

Recovering Cholesky Factor in Smoothing and Mapping

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June 27th, 2018

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Problem Definition

Simultaneous Localisation and Mapping (SLAM)

- Robot localising itself while mapping an unknown environment
- Pose (\mathbf{s}) and map of landmarks ($\mathcal{M} = \{\mathbf{l}_1, \mathbf{l}_2, \dots\}$) given observations (\mathbf{z}) and odometry (\mathbf{u})

Problem Definition

Current State of the Art

Incremental reordering

- Reorder affected nodes
- Resumed Cholesky

Full reordering

- Reorder all nodes
- Cholesky

Current Work - Propositions

Proposition 1 : numerical changes

When two adjacent column in C change position, the new Cholesky factor \bar{L} can be recovered from L as follows:

Current Work - Propositions

Proposition 2 and 3 - Structural Changes

- The elimination tree needs to be update
- The multiplicity of column elements may need to be updated

indep. columns($\max\{\pi^{-1}(j)\} < k < \pi(j)$)

$$\begin{aligned}\bar{\pi} &= \pi|_{\pi(\pi^{-1}(j))} = k \\ \bar{\mathcal{L}}_j^\# &= \mathcal{L}_k^\# \\ \bar{\mathcal{L}}_k^\# &= \mathcal{L}_j^\#\end{aligned}$$

dependent columns($\pi(j) = j + 1$)

$$\begin{aligned}\bar{\pi}(l) &= \begin{cases} j+1 & l \in \{\pi^{-1}(j)\} \setminus \mathcal{U}_c \\ j & l \in \{\pi^{-1}(j+1)\} \setminus \mathcal{U}_c \\ \pi(l) & \text{otherwise} \end{cases} \\ \bar{\mathcal{L}}_{j+1}^\# &= \mathcal{L}_{j+1}^\# - \mathcal{L}_j + \sum_{i \in \mathcal{U}_c} \mathcal{L}_i \\ \bar{\mathcal{L}}_j^\# &= \mathcal{L}_j^\# + \bar{\mathcal{L}}_{j+1} - \sum_{i \in \mathcal{U}_c} \mathcal{L}_i\end{aligned}$$

Current Work - summary

Hybrid Cholesky

- All nodes can be reordered
- Fraction of the cost of Full Cholesky (ordering dependent)

Results - Datasets Description

- Popular datasets in the literature
- Indoor/Outdoor, Experimental/Simulated

Dataset	Size	Loop Closings	Total Reordering	Reordered Using Factor Recovery	Author	Source
10k	64311	1431	32	6	Grisetti et al.	SLAM++ ¹
City10k	20687	10688	13	3	M. Kaess et al.	SLAM++
CityTrees10k	14442	4343	13	0	C. Stachniss	SLAM benchmarking ²
CSAIL	1172	128	11	8	C. Stachniss	SLAM benchmarking
FR079	1217	229	8	8	C. Stachniss	SLAM benchmarking
FRH	2820	1505	13	13	B, Steder et al.	SLAM benchmarking
Intel	1835	895	19	9	D. Hahnel Freiburg	SLAM++
Killian	3995	2055	11	8	M. Bosse and J. Leonard	SLAM++
Victoria Park	10608	3489	14	6	Jose Guivant	SLAM++

¹L. Polok and I. Violela, *Slam++*, 2015.

²R. Kummerle, B. Steder, C. Dornhege, et al., *Slam benchmarking*, 2015. 

Results - Datasets Summary

- Performance gain, fact. time excluding overhead : 11.68%
- Performance gain, total time including overhead: -1.9%
- Density reordering has high variability (< 12 samples)
- Overhead is a significant portion of the cost
- Overhead is higher for outdoor datasets
- Total runtime performance of CSAIL is unexpected

Results - Improved Cost Function Summary

- Performance gain, factorisation time : 12.21%
- Performance gain, total time : 1.9%
- Performs better than initial threshold
- Factorisation performance gain positive for almost all datasets

Results - Optimised Cost Function Threshold Selection

Table: Calculated and Optimized Thresholds

Dataset	Threshold	
	Calculated	Optimized
10k	1	1.57
City10k	32	56.98
CityTrees10k	15	13.70
CSAIL	144	208.82
FR079	40	56.04
FRH	96	4.99
Intel	20	41.01
Killian	53	25.97
Victoria Park	9	8.44

Navigation icons: back, forward, search, etc.

Results - Optimised Cost Function Summary

- Average performance gain, total time: 1.9%
- Performance gain, factorisation time: 17.6%
- Varying performance improvement over previous threshold
- Normalizing effect on the data

Contributions

- Factor Recovery
 - Perform full reordering
 - Fraction of the cost of Full Cholesky
- Hybrid Cholesky³
 - Chooses between Factor Recovery and Full Cholesky
 - The best method is selected
- Comparison
 - Comparison with Full Cholesky
 - Multiple datasets spanning a variety of situations

³S. Touchette, W. Gueaieb, and E. Lantegne, "Efficient cholesky factor recovery for column reordering in simultaneous localisation and mapping", *Journal of Intelligent & Robotic Systems*, vol. 84, no. 1, pp. 859–875, Dec. 2016, ISSN: 1573-0409. DOI: 10.1007/s10846-016-0367-7.

Future Work

Possible avenues of research include

- Further integrate in SLAM algorithm
- Correlate threshold to dataset characteristics
- Refine cost function

Questions and Comments

Thank you.