Online Variational Bayesian Motion Averaging

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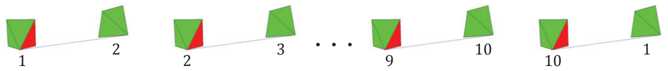
ECCV '16

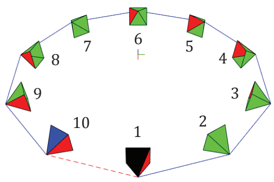
Introduction

Motion averaging (aka pose-graph inference for $G = SE(3)$)

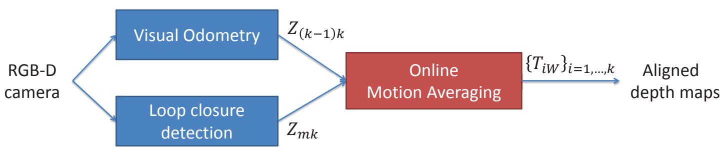
Given *noisy relative transformations* $\{Z_{mn} \in G\}_{1 \le m < n \le N}$



Estimate *absolute transformations* $\{T_{iW} \in G\}_{i=1,\dots,N}$



Example of application: RGB-D mapping



Contributions

To perform **online motion averaging on large scale problems**, we propose an algorithm that is:

1. **Computationally efficient:** process the measurements one by one
2. **Memory efficient:** approximate the posterior distribution of the absolute transformations with a number of parameters that grows at most linearly over time
3. **Robust:** detect and remove wrong loop closures

Reparametrization of the absolute transformations

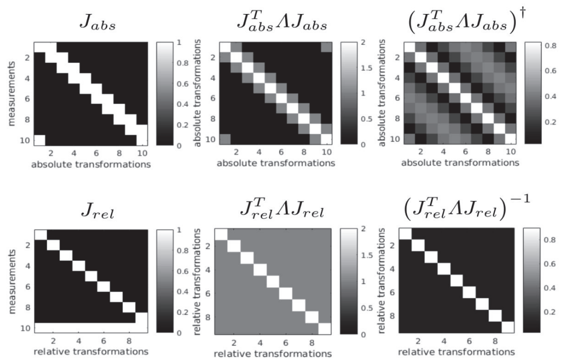
$$T_{i(i+1)} = T_{iW} T_{(i+1)W}^{-1}$$

	Absolute	Relative
Estimated transformations at time instant k	$\{T_{iW}\}_{i=1,\dots,k}$	$\{T_{i(i+1)}\}_{i=1,\dots,k-1}$

Case of a single loop

$$\underset{\{T_{iW}\}_{i=1,\dots,k}}{\operatorname{argmin}} \underbrace{\left\| \log_G\left(Z_{1N}^{-1} T_{1W} T_{NW}^{-1}\right) \right\|_{\Sigma_{1N}}^2}_{\text{loop closure}} + \underbrace{\sum_{i=1}^{N-1} \left\| \log_G\left(Z_{i(i+1)}^{-1} T_{iW} T_{(i+1)W}^{-1}\right) \right\|_{\Sigma_{i(i+1)}}^2}_{\text{odometry}}$$

$$\underset{\{T_{i(i+1)}\}_{i=1,\dots,k-1}}{\operatorname{argmin}} \underbrace{\left\| \log_G\left(Z_{1N}^{-1} \prod_{i=1}^{N-1} T_{i(i+1)}\right) \right\|_{\Sigma_{1N}}^2}_{\text{loop closure}} + \underbrace{\sum_{i=1}^{N-1} \left\| \log_G\left(Z_{i(i+1)}^{-1} T_{i(i+1)}\right) \right\|_{\Sigma_{i(i+1)}}^2}_{\text{odometry}}$$



The relative parametrization induces very small correlations!

Motivation for a variational Bayesian approximation of the posterior distribution assuming independent relative transformation.

Online Variational Bayesian Motion Averaging Algorithm

- Approximated posterior at time $k-1$

$$p(\mathcal{X}_{k-1} | \mathcal{D}_{\text{odo},k-1}, \mathcal{D}_{\text{LC},k-1}) = \prod_{i=1}^{k-2} \mathcal{N}_G\left(T_{i(i+1)}; \overline{T}_{i(i+1)}, P_{i(i+1)}\right)$$

- Processing of a new odometry measurement

$$p(\mathcal{X}_{k} | \mathcal{D}_{\text{odo},k}, \mathcal{D}_{\text{LC},k-1}) = \prod_{i=1}^{k-1} \mathcal{N}_G\left(T_{i(i+1)}; \overline{T}_{i(i+1)}, P_{i(i+1)}\right)$$

where $\overline{T}_{(k-1)k} = Z_{(k-1)k}$ and $P_{(k-1)k} = \Sigma_{(k-1)k}$

- Validation gating of a new loop closure measurement

$$p(Z_{lk} | \mathcal{D}_{\text{odo},k}, \mathcal{D}_{\text{LC},k-1}) \approx \mathcal{N}_G\left(Z_{lk}; \prod_{i=l}^{k-1} \overline{T}_{i(i+1)}, \Sigma_{(k-1)k} + \sum_{i=l}^{k-1} J_{li} P_{i(i+1)} J_{li}^T\right)$$

- Processing of a new loop closure measurement

$$p(\mathcal{X}_{k} | \mathcal{D}_{\text{odo},k}, \mathcal{D}_{\text{LC},k-1}, Z_{lk}) \approx \prod_{i=1}^{k-1} \mathcal{N}_G\left(T_{i(i+1)}; \breve{T}_{i(i+1)}, \Xi_{i(i+1)}\right)$$

where $\{\breve{T}_{i(i+1)}\}_{i=1,\dots,k-1}$ is obtained via a Gauss-Newton

and $\{\Xi_{i(i+1)}\}_{i=1,\dots,k-1}$ is computed via a Variational Bayesian approximation

Results

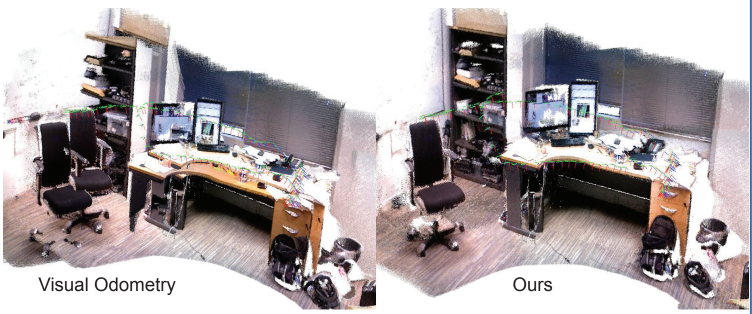
$G = SE(3)$: Binocular 6D SLAM

	RMSE position (m)			Time (ms)		
	Sphere	KITTI 00	KITTI 02	Sphere	KITTI 00	KITTI 02
Ours	**2,1**	**2,7**	**13,6**	971	65	29
COP-SLAM	6,0	3,8	19,7	**350**	**7**	**2**
LG-IEKF	0,8	2,0	13,6	n/a	n/a	n/a
g²o	0,2	2,4	13,8	40000	1336	693

$G = Sim(3)$: Monocular Visual SLAM (KITTI 13)

Ground truth (Lidar) | Visual Odometry | COP-SLAM | Ours

$G = SE(3)$: RGB-D Mapping



Visual Odometry | Ours

$G = SL(3)$: Video Mosaicing (see supplementary material)