

Online Variational Bayesian Motion Averaging

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Introduction

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

Given *noisy relative transformations*

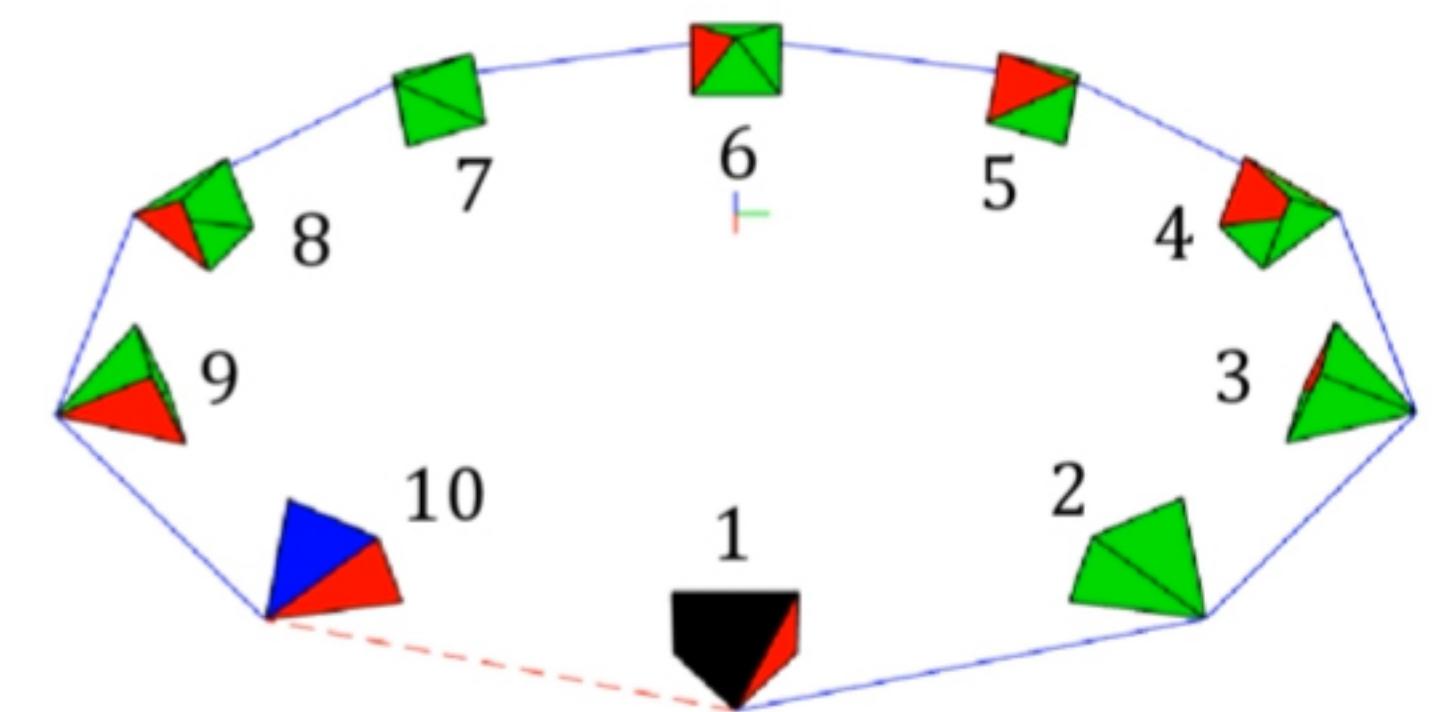
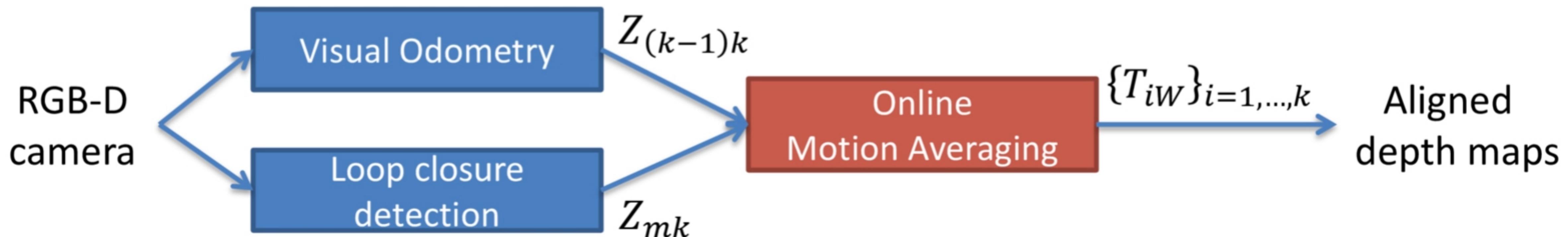
$$\{Z_{mn} \in G\}_{1 \leq m < n \leq N}$$



Estimate *absolute transformations*

$$\{T_{iW} \in G\}_{i=1,\dots,N}$$

Example of application: RGB-D mapping



Aligned
depth maps

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

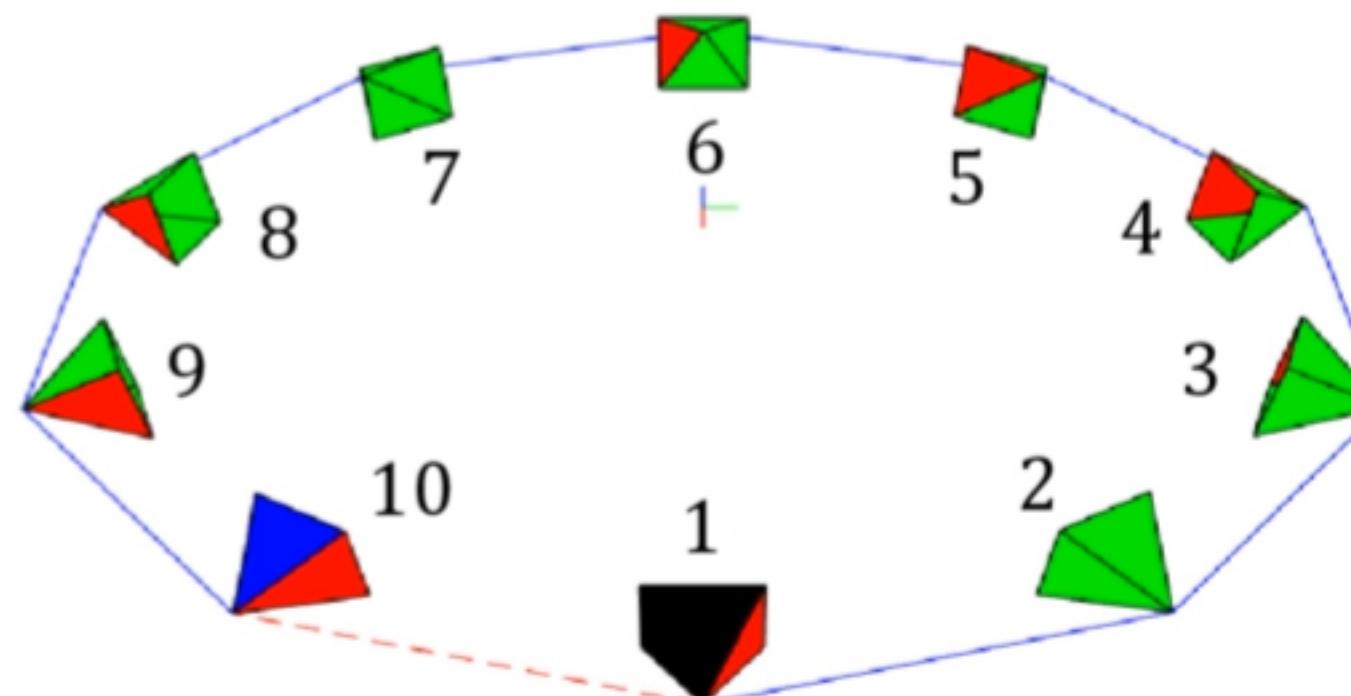
Our approach

The absolute transformations can be reparametrized as follows:

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

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

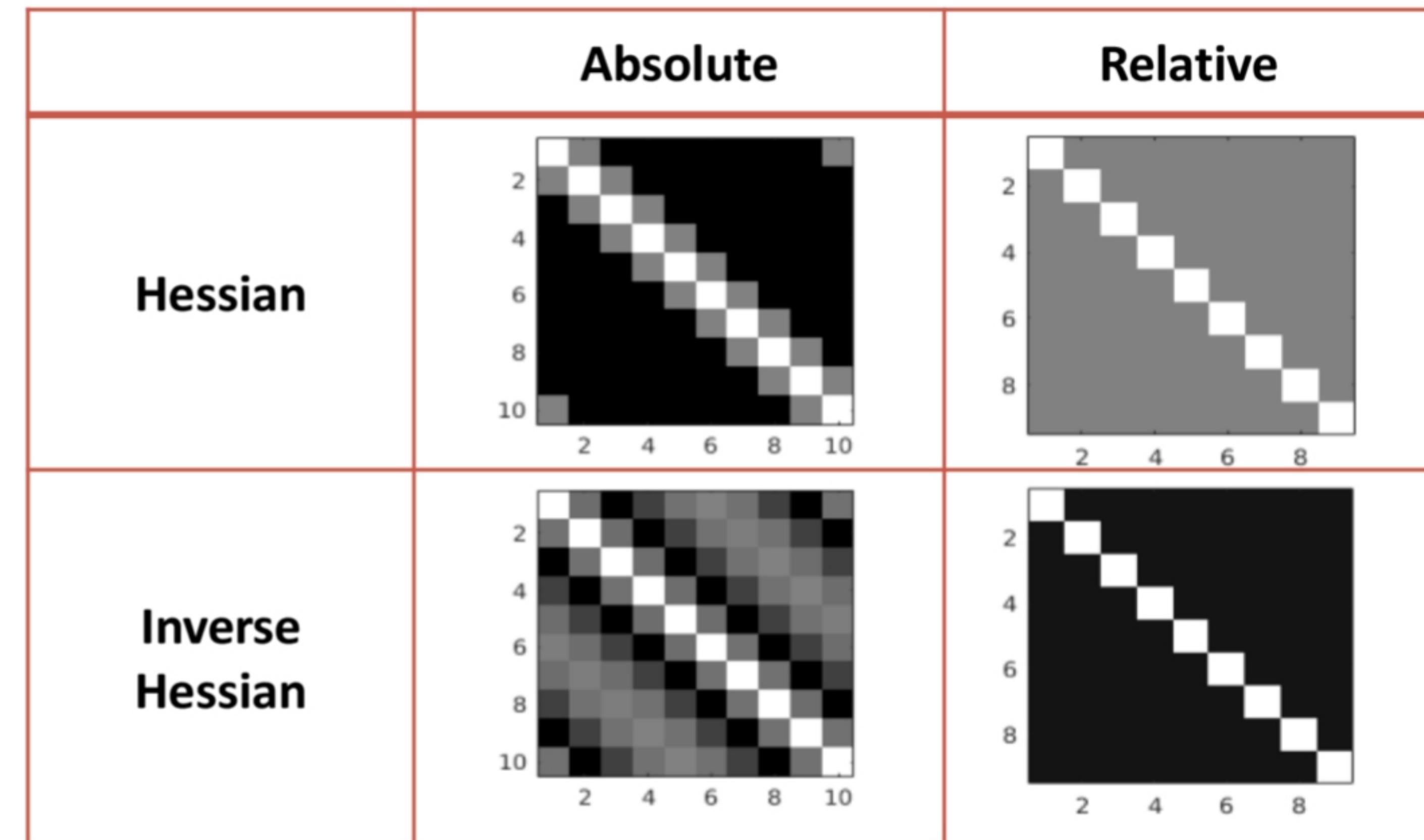
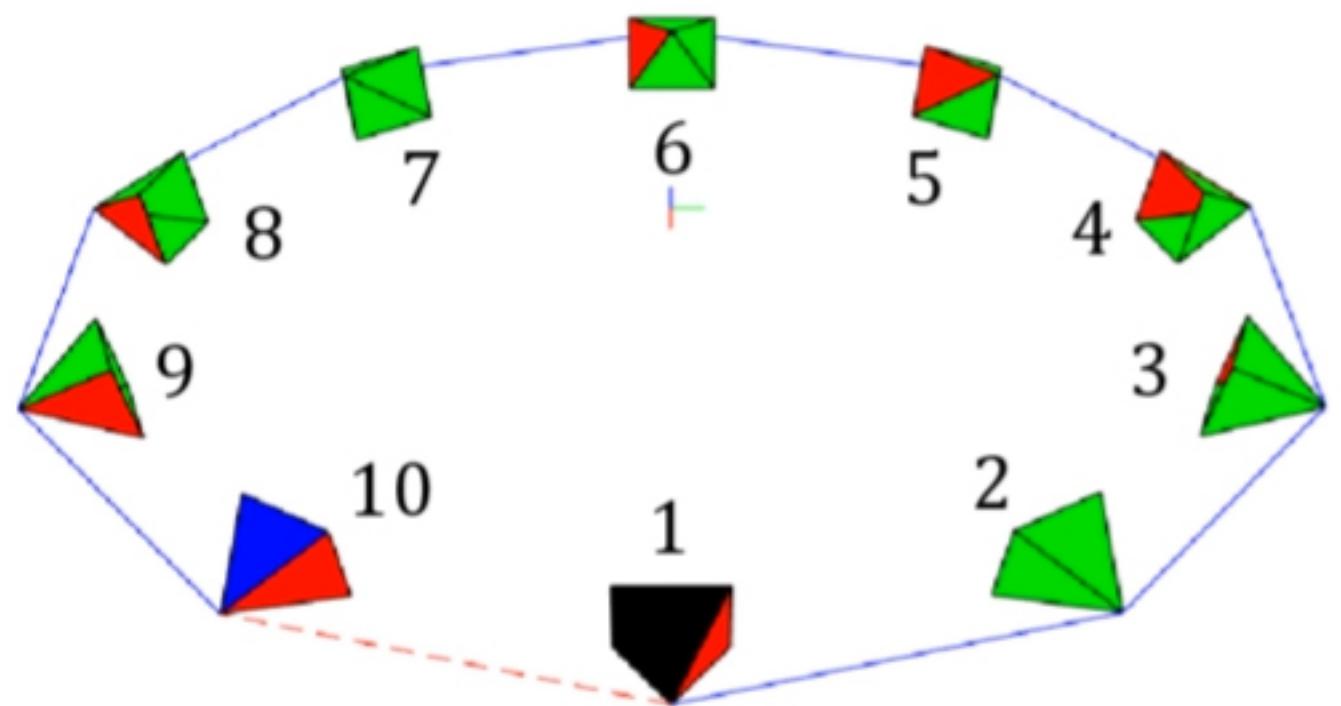
Case of a single loop:



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

Our approach cont'd

Case of a single loop:

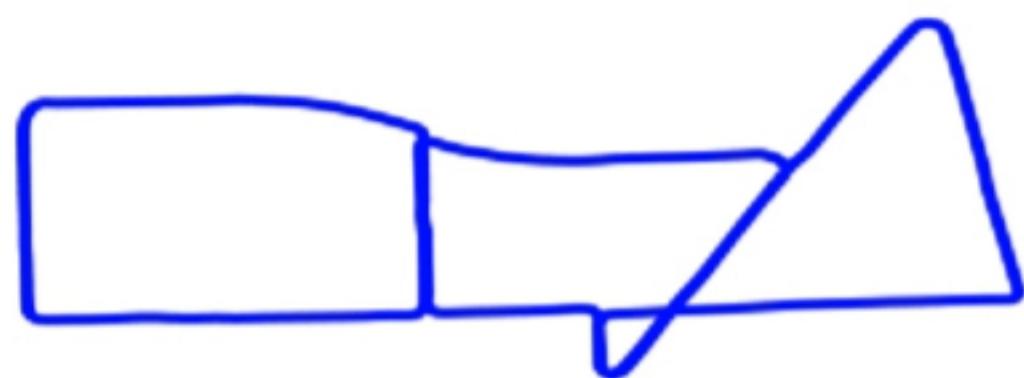


The relative parametrization induces very small correlations!

Motivation for a variational Bayesian approximation of the posterior distribution assuming independent relative transformations (see paper)

Results

$G = \text{Sim}(3)$: Monocular Visual SLAM, sequence KITTI 13



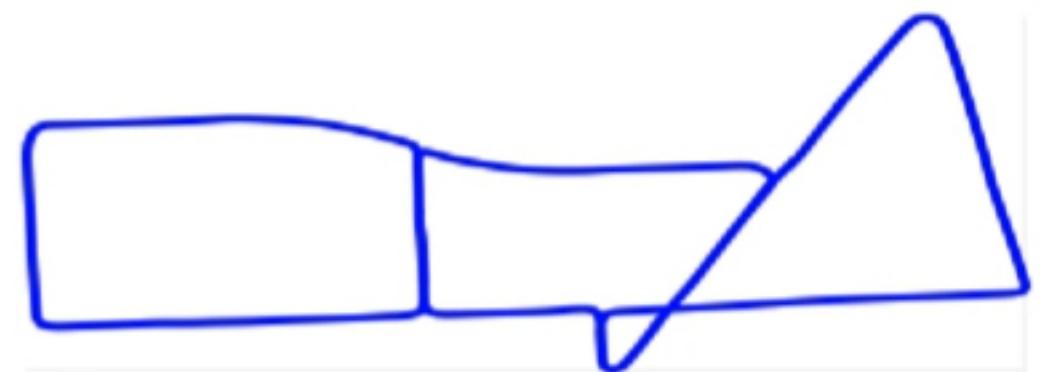
Ground truth (Lidar)



Visual Odometry

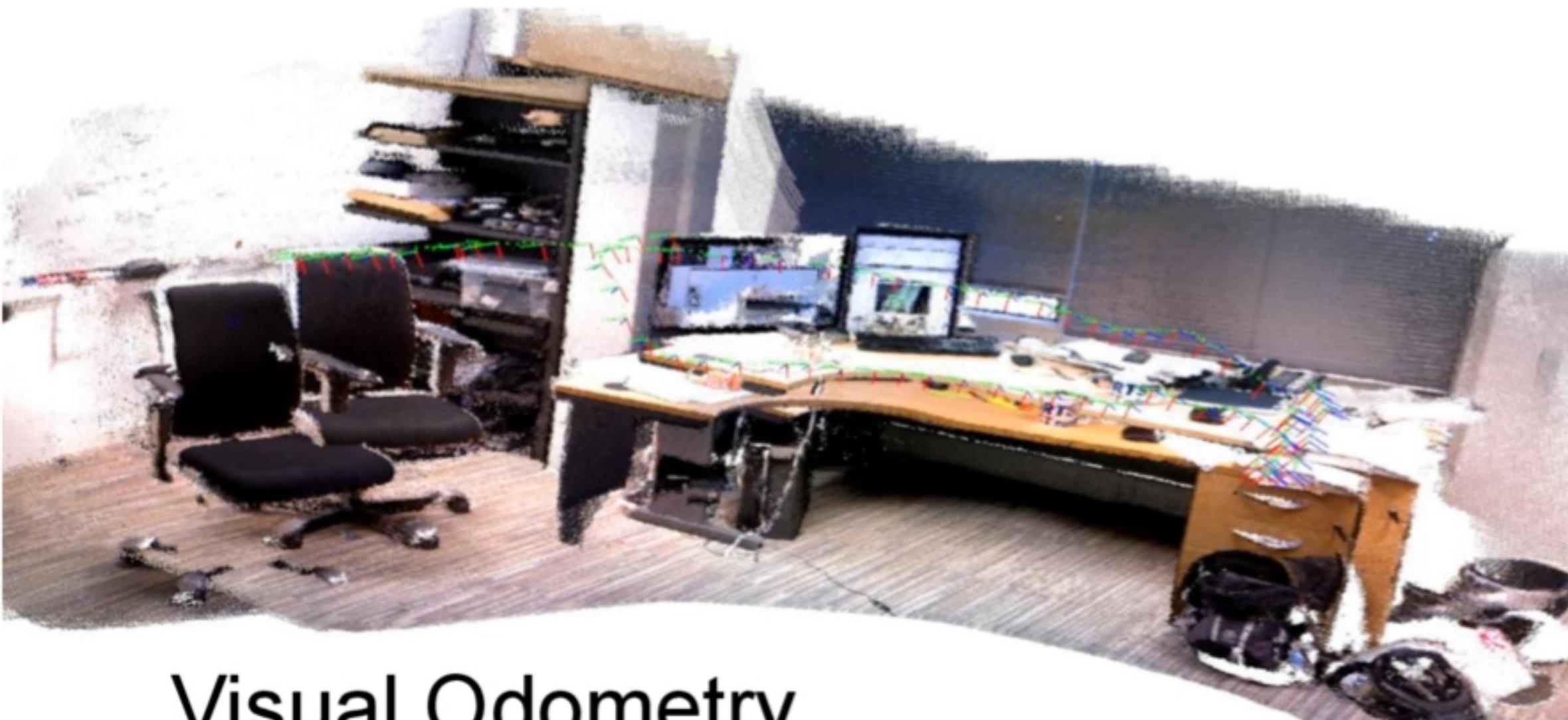


COP-SLAM

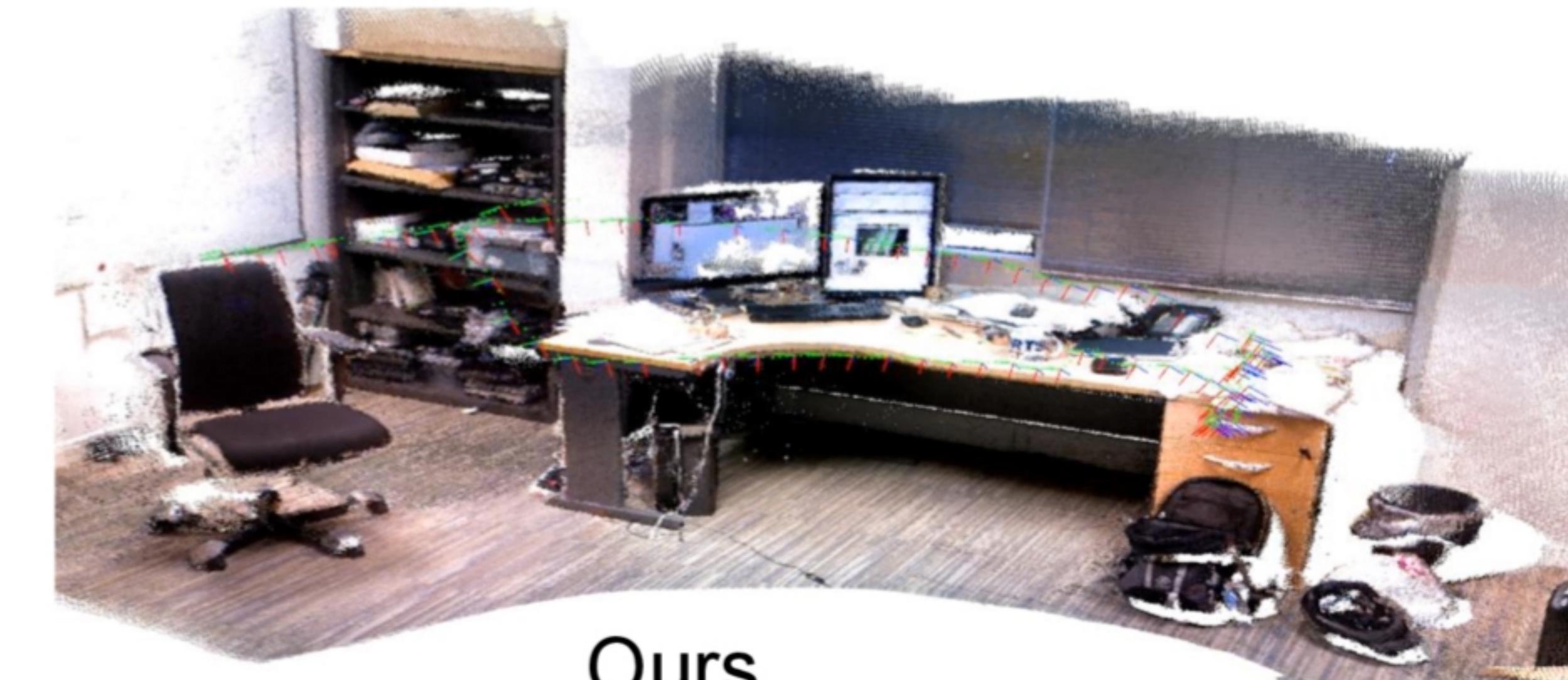


Ours

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



Visual Odometry



Ours