A Compact Spherical RGBD Keyframe-based Representation

T. Gokhool, R. Martins, P. Rives, N. Despré

Inria Sophia Antipolis

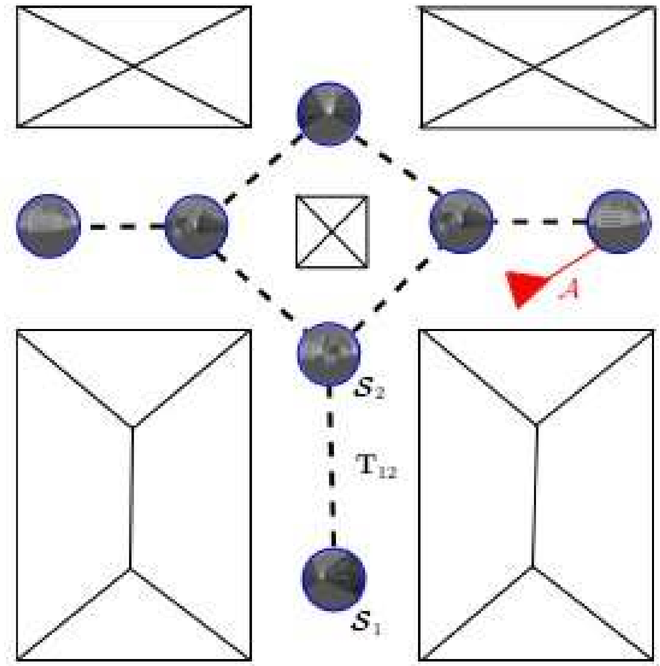
http://team.inria.fr/lagadic

May 29, 2015

Building Large Scale Scene RGB-D Models

Context and Motivation

- Map as ego-centered hybrid topo-metric graph
- The need for compact representations
- Dealing with static and dynamic errors: measurement uncertainties, occlusion, wrong pose estimation $\rightarrow$ result in odometry failures if not anticipated
- Map with fine properties (accuracy, observability, completeness, ...): fundamental to ensure convergence of visual localization and visual servoing tasks
- How to place and generate a sub-set of keyframe spheres



Learning indoor/outdoor map

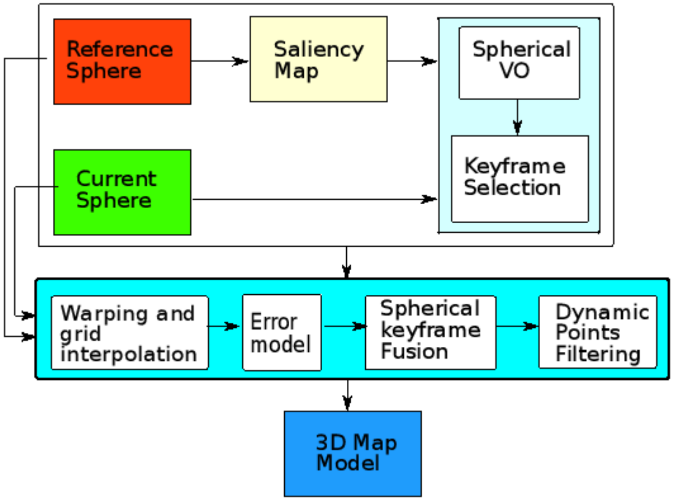
Key Contributions

- Generic spherical uncertainty error modelling
- Dynamic 3D points rank stability

Overall Approach Pipeline

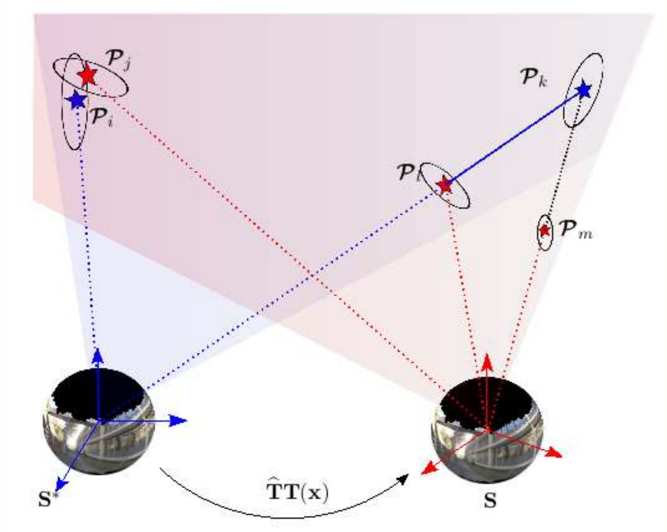
Approach

- Warping $\mathcal{S}$ and its resulting model error propagation
- Data fusion with occlusions and outlier rejection
- An improved 3D point selection technique based on stable salient points



3 – Point Stability Ranking

- Pixels observability from subsequent views: markovian process
- Points perceived over several frames are made permanent
- Salient map is updated only with consistent features

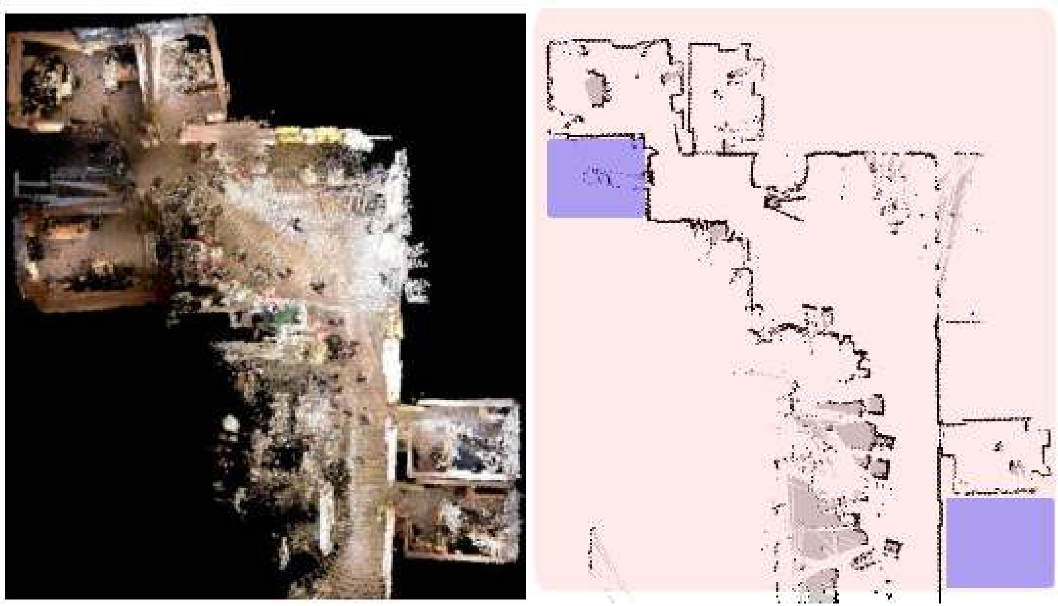


Main Results: Topo-metric Graph

	Only MAD	*Proposed Approach*
Keyframe criteria α	0.96	0.78
Keyframe reduction ($\%$)	$-$	$\mathbf{75.2}$
Mean convergence error	0.5889	$\mathbf{0.2413}$
Mean nos. iterations	28.3	$\mathbf{23.5}$

Table: Methods comparison

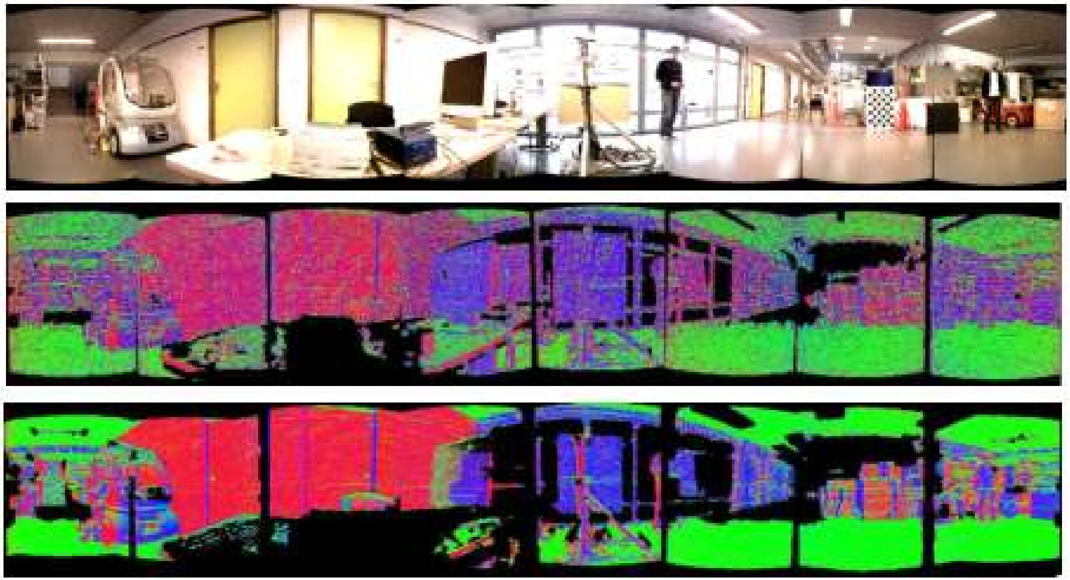
270 Keyframes initially recorded without fusion is reduced to 67



Comparison between vision and laser maps

Conclusions

- improvement of $10\% - 30\%$ in the depth map
- reduction of keyframes, giving a sparser representation
- better overall consistency of the map
- emergence of two new entities: uncertainty and stability maps



Node comparison pre and post filtering

Thank you for your attention!