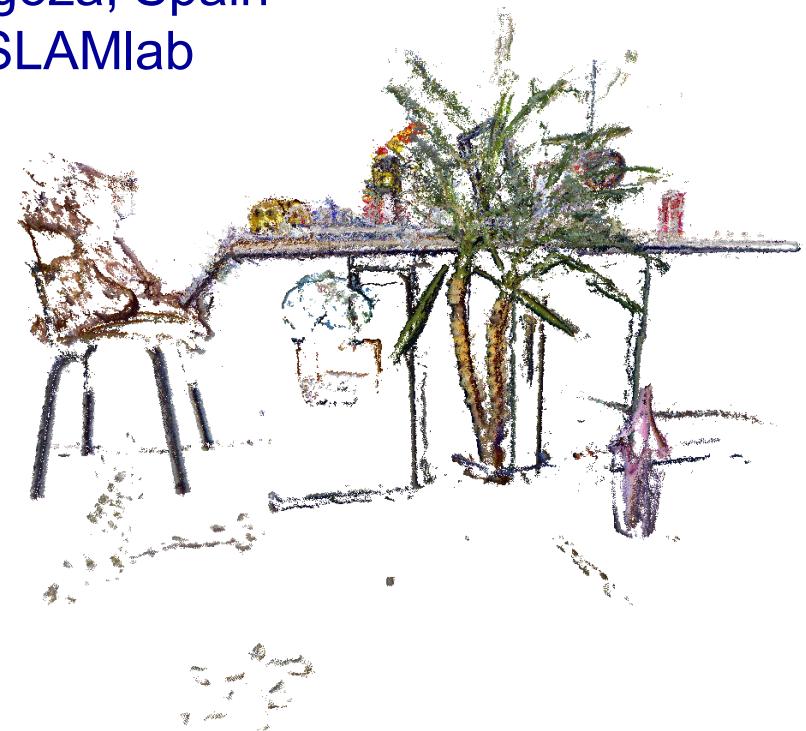


# ORB-SLAM: a Real-Time Accurate Monocular SLAM System

Juan D. Tardós, Raúl Mur Artal, José M.M. Montiel  
Universidad de Zaragoza, Spain  
[robots.unizar.es/SLAMlab](http://robots.unizar.es/SLAMlab)



# Outline

- Motivation
- ORB-SLAM: Feature-Based Visual SLAM
- Robustness and Accuracy
- Application to VR
- Discussion and Future Work

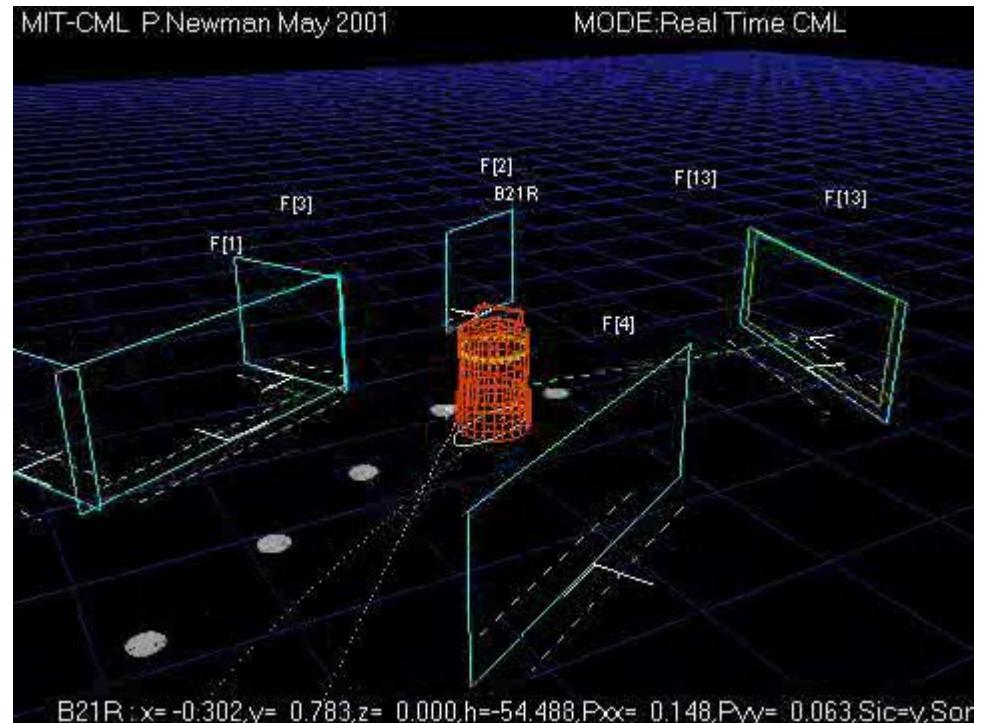
# SLAM: Simultaneous Localization and Mapping

The SLAM problem:

- a robot moving in an unknown environment

Use sensor data to:

- **build a map** of the environment
- and **at the same time**
- use the map to compute the **robot location**



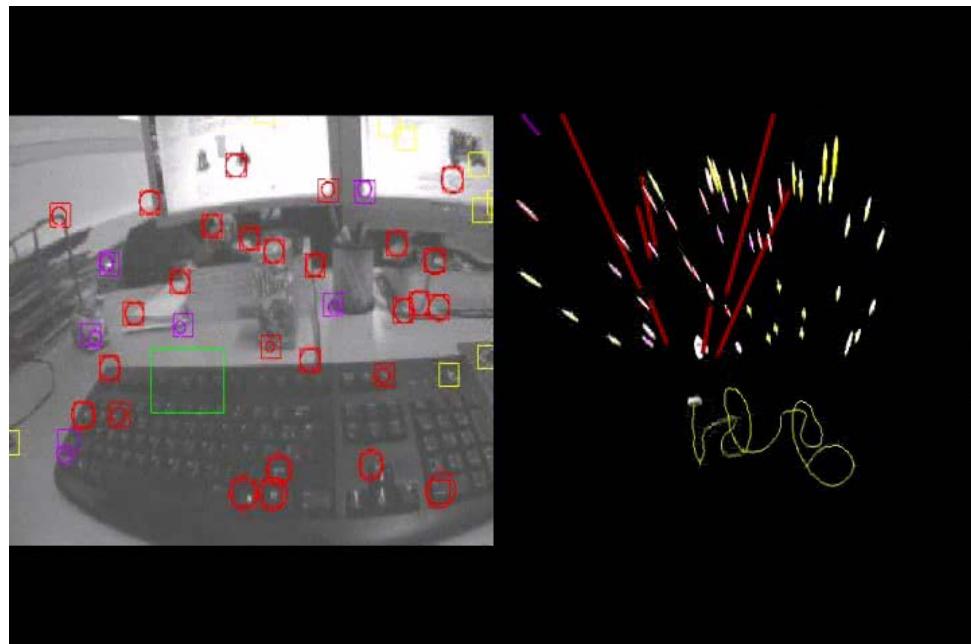
P. Newman, J.J Leonard, J.D. Tardos, J. Neira:  
**Explore and return: Experimental validation of real-time concurrent mapping and localization.**  
IEEE Int. Conf. Robotics and Automation, 2002

# Motivation

- Head tracking in VR
  - Orientation tracking
  - Based on IMU
  - Slow drift
  - Position tracking with external camera
    - » Limited by the field of view



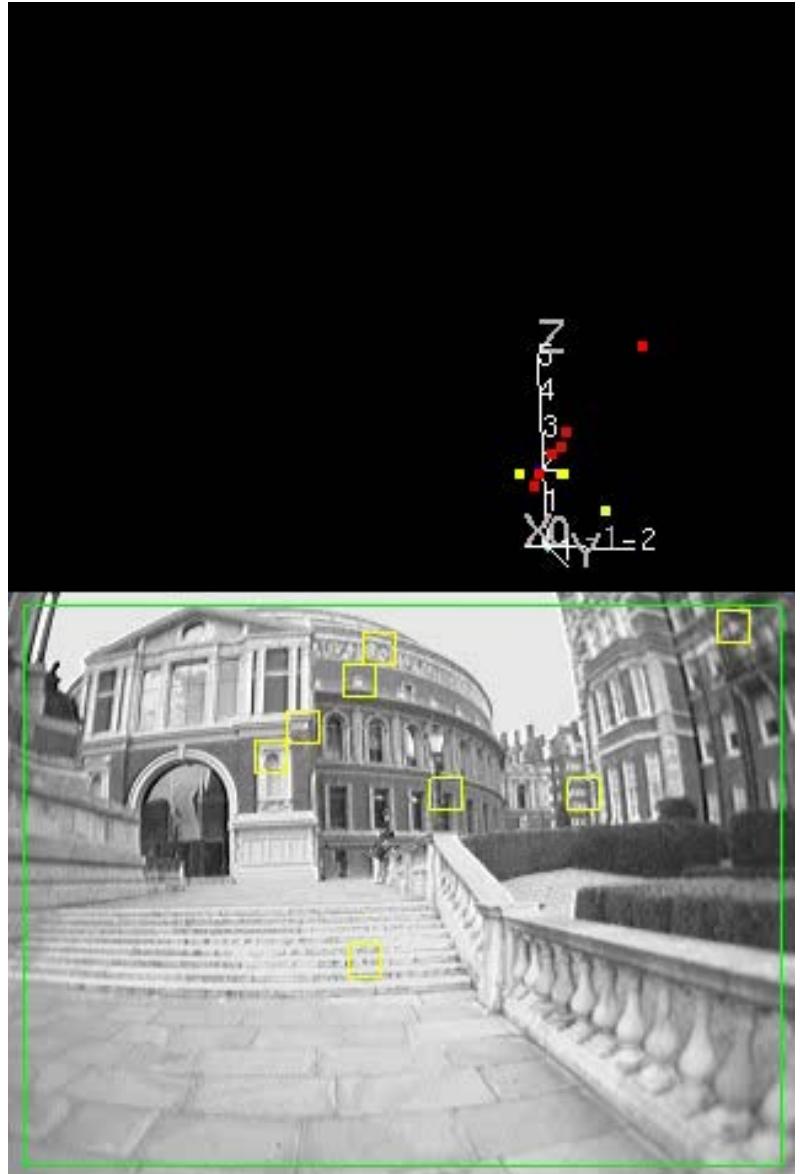
- Real-time Visual SLAM
  - 6DOF camera tracking
  - Monocular, stereo, RGB-D
  - Zero drift
  - Unlimited area
  - And gives a Map



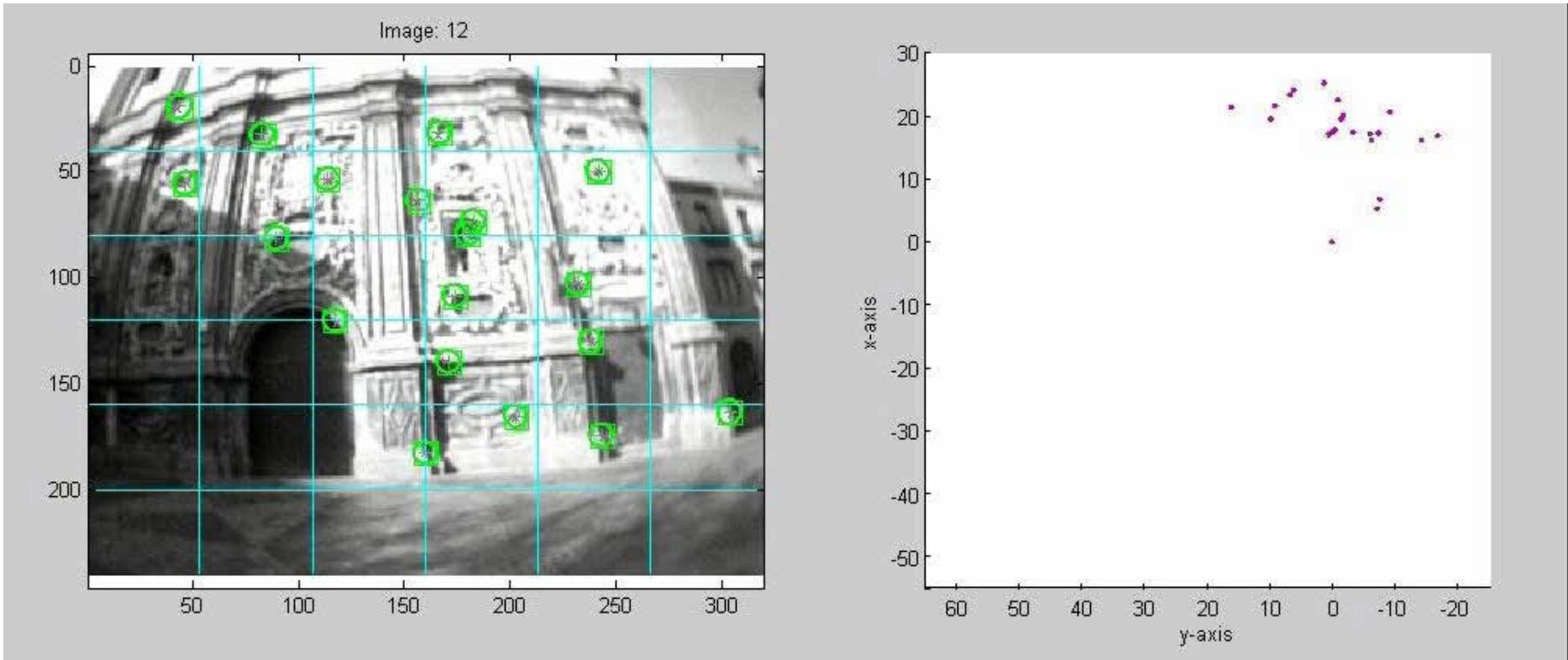
# Monocular SLAM with EKF



L.A. Clemente, A.J. Davison, I.D. Reid, J  
Neira, J.D. Tardós, **Mapping Large Loops  
with a Single Hand-Held Camera.**  
Robotics: Science and Systems, June 2007



# Monocular SLAM with EKF

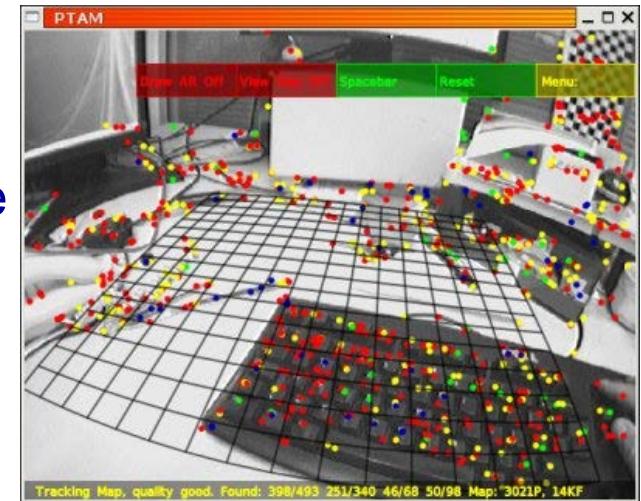


P. Piniés, J.D. Tardós, **Large-scale SLAM building conditionally independent local maps: Application to monocular vision**, IEEE Transactions on Robotics, 24 (5), 1094-1106, 2008

# PTAM: Keyframe-Based SLAM

- *Parallel Tracking and Mapping for Small AR Workspaces*  
*G. Klein and D. Murray, ISMAR 2007*

- First Keyframe-Based Monocular SLAM
- Bundle Adjustment is possible in real-time
- Still considered a reference system

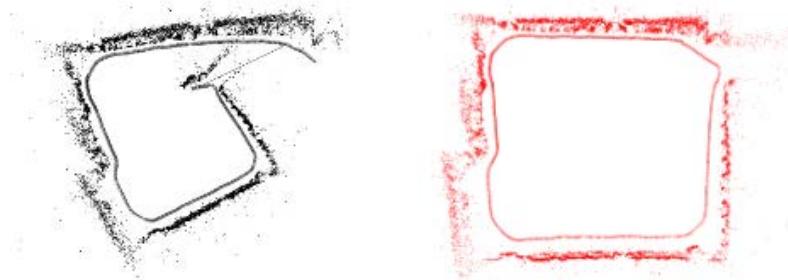


- Limitations:
  - Relocalisation with little invariance to viewpoint
  - No loop detection
  - Small scale operation
  - Initialization in planar scenes, with human intervention

# Recent Key Ideas

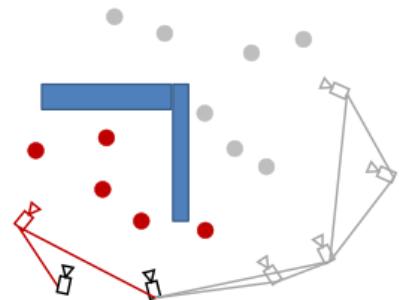
- Scale Drift-Aware Loop Closing

H. Strasdat, J.M.M. Montiel and A.J. Davison  
*Scale Drift-Aware Large Scale Monocular SLAM*  
RSS 2010



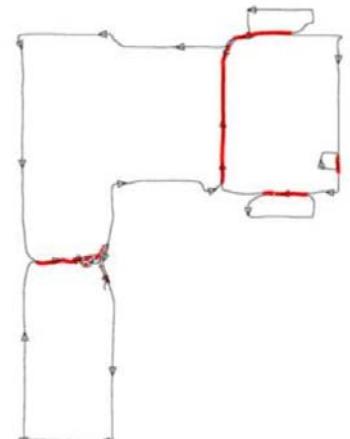
- Covisibility Graph

H. Strasdat, A. J. Davison, J. M. M. Montiel , K. Konolige  
*Double Window Optimization for Constant Time Visual SLAM*  
ICCV 2011

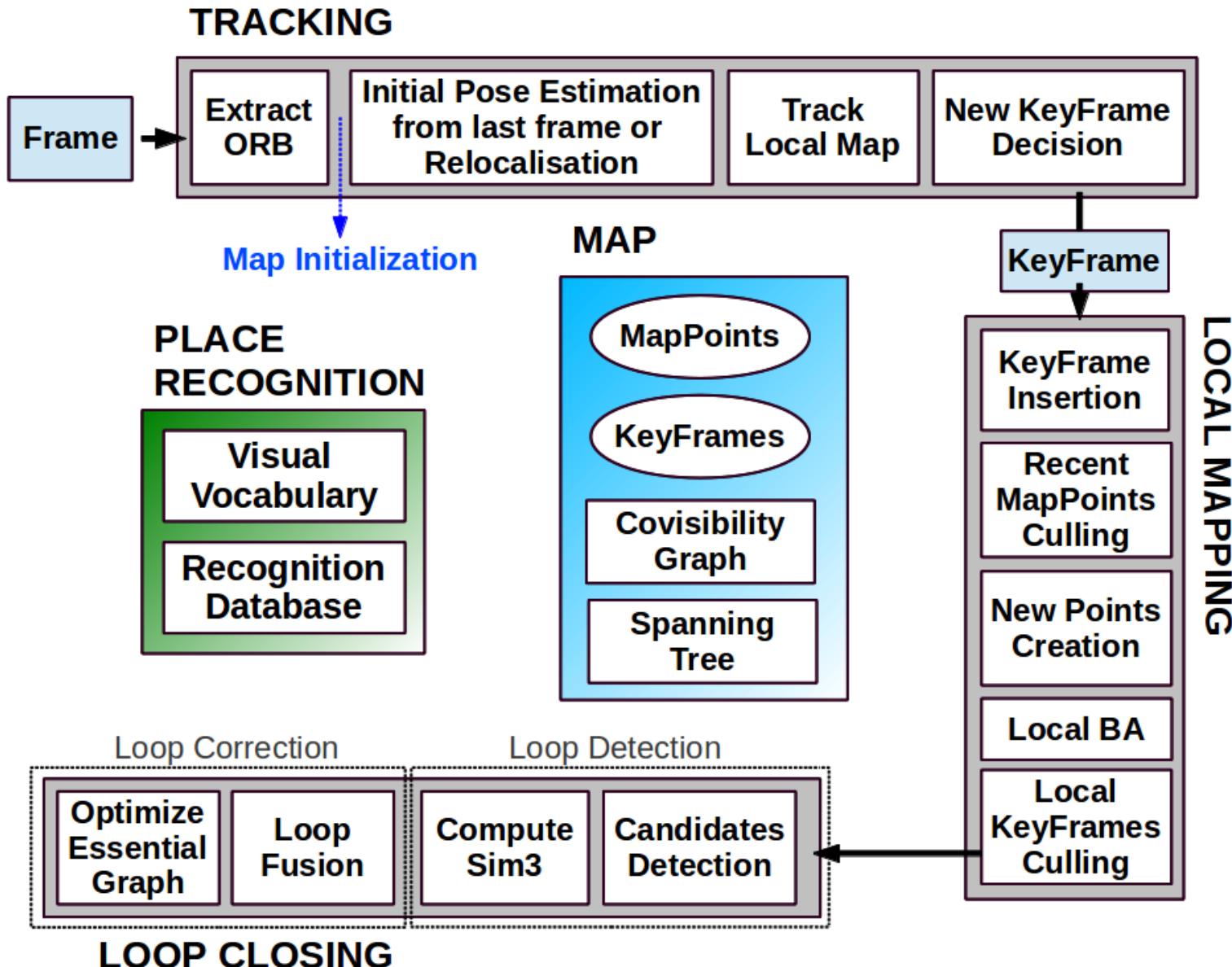


- Bags of Binary Words (DBoW)

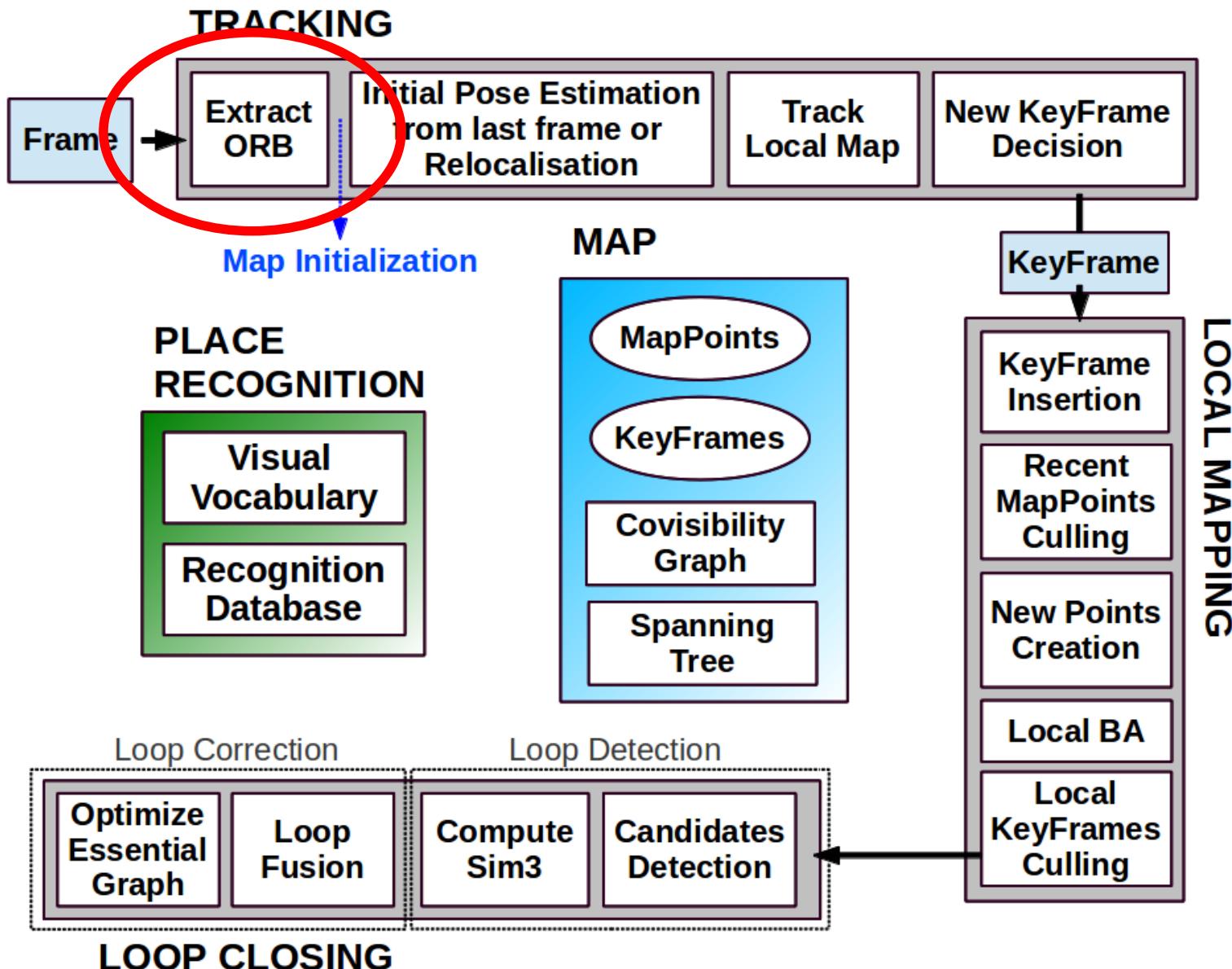
D. Gálvez-López and J. D. Tardós  
*Bags of Binary Words for Fast Place Recognition in Image Sequences*, IEEE Transactions on Robotics 2012



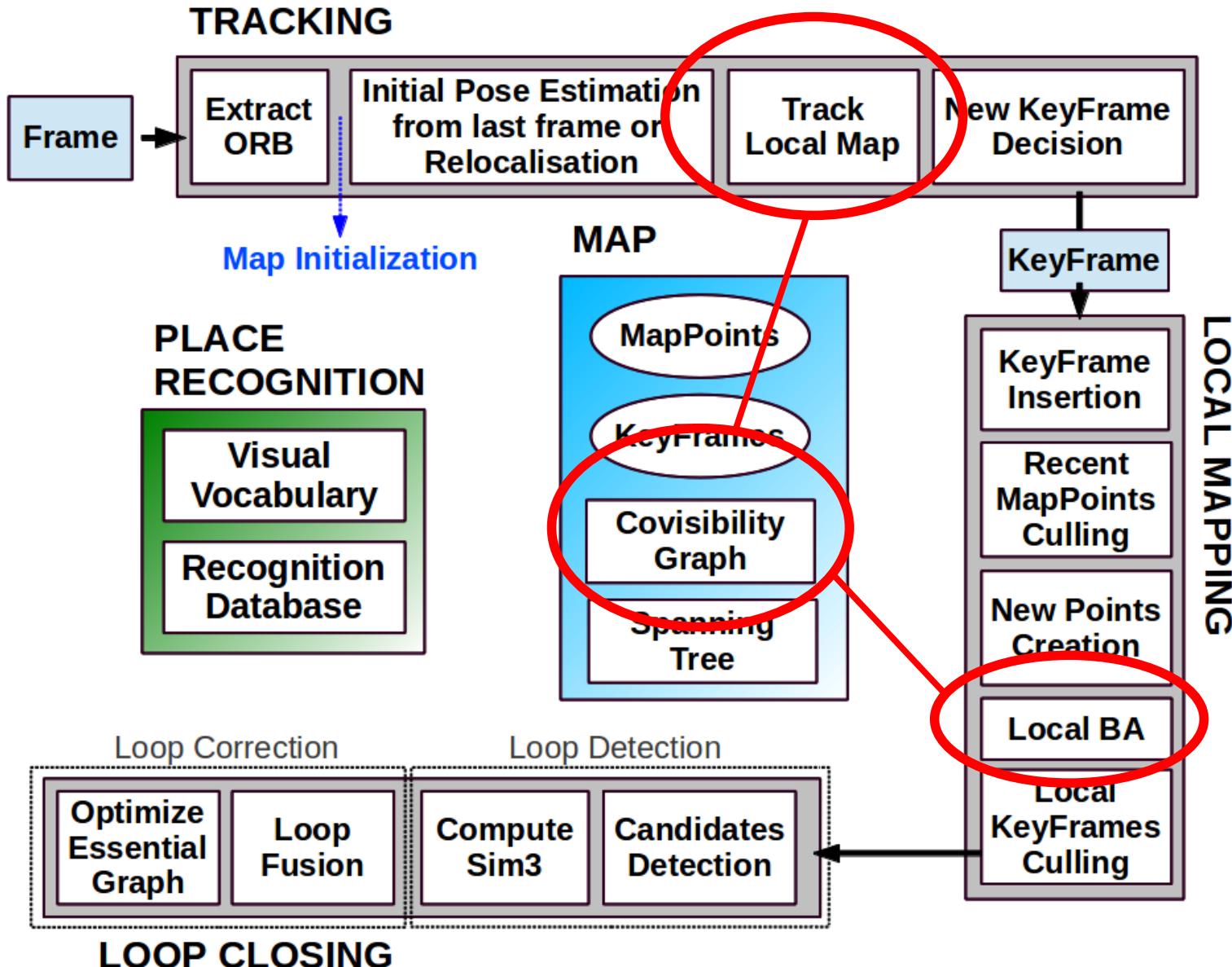
# ORB-SLAM: Real-Time Monocular SLAM



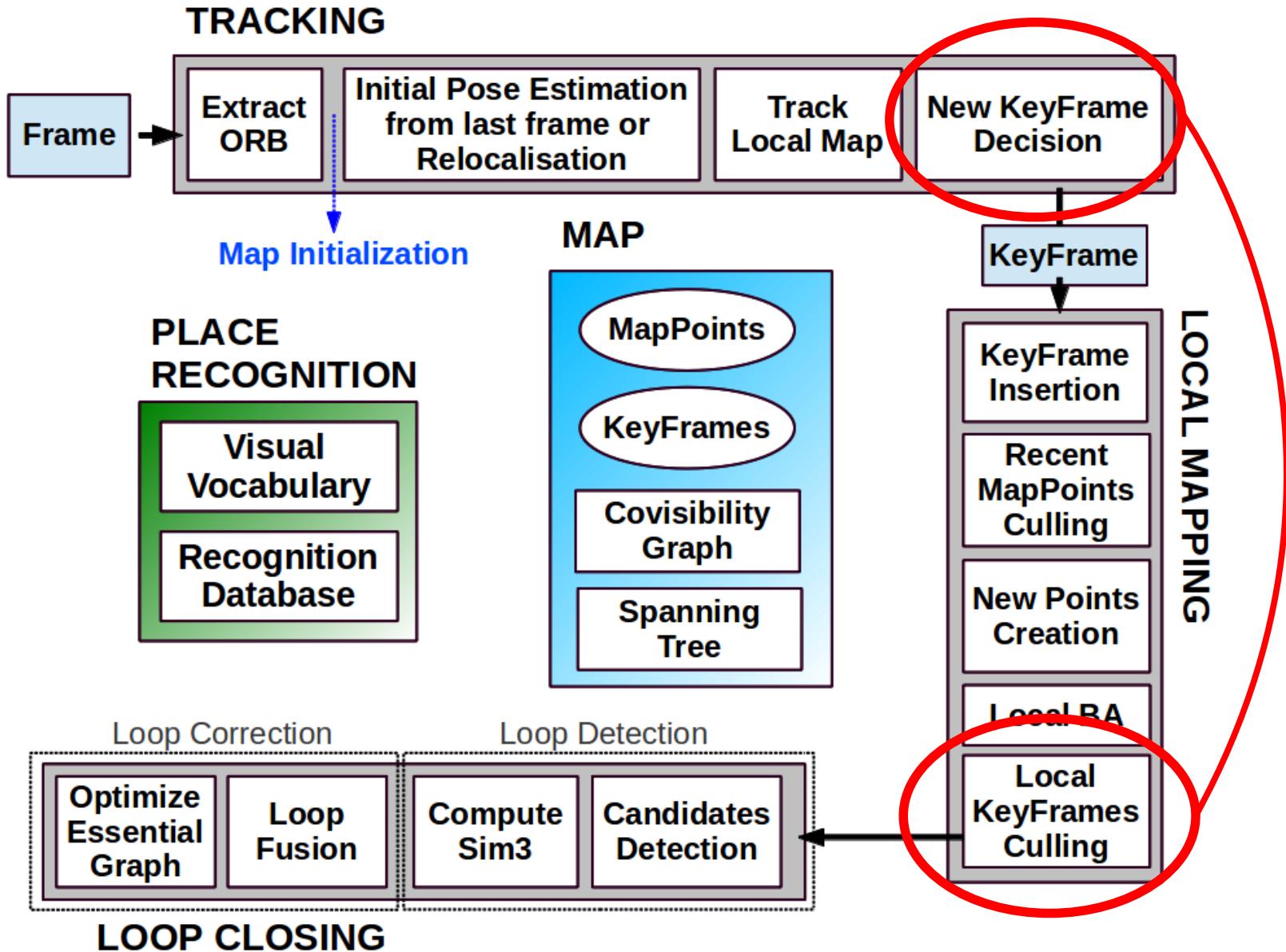
# ORB-SLAM: Real-Time Monocular SLAM



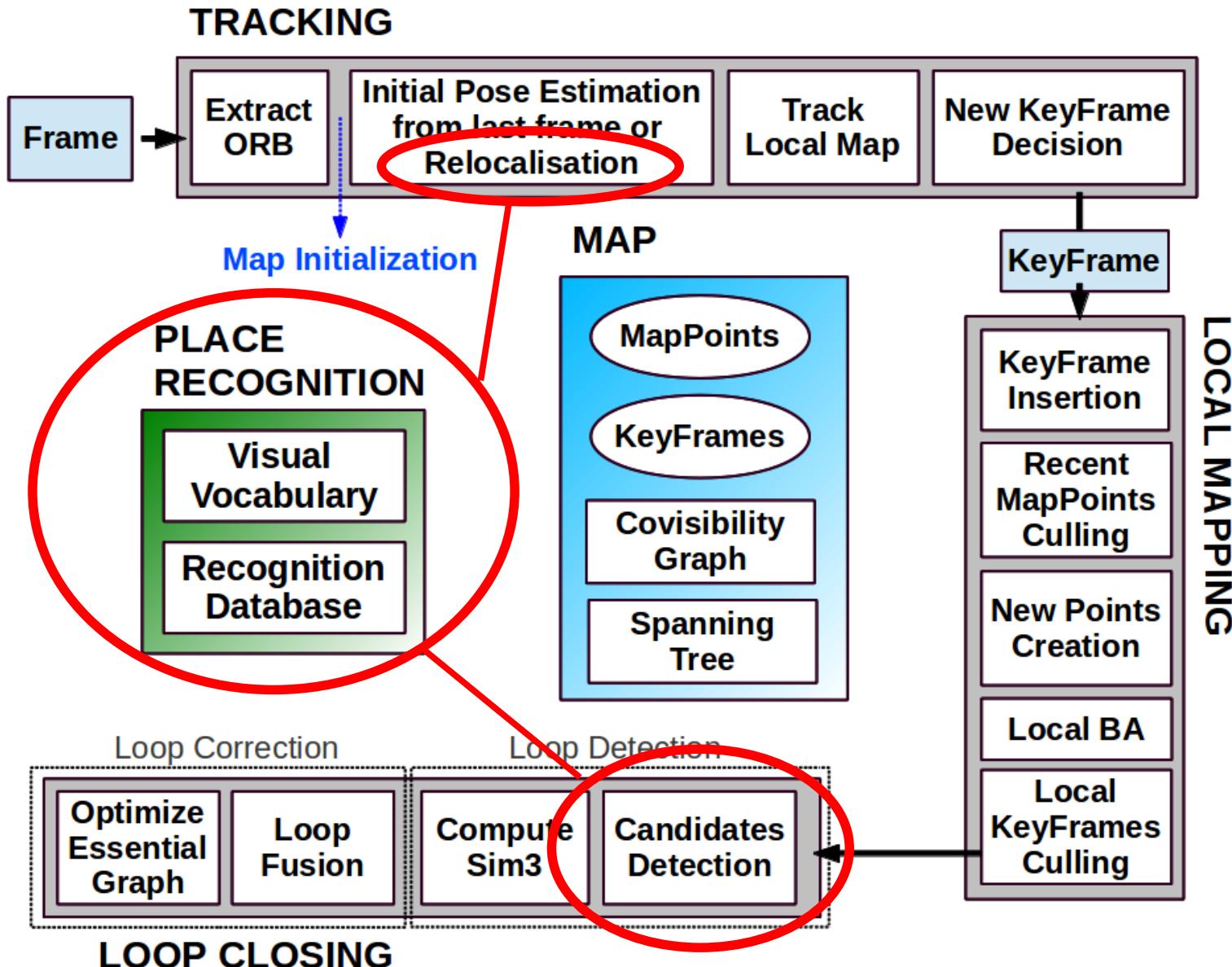
# ORB-SLAM: Real-Time Monocular SLAM



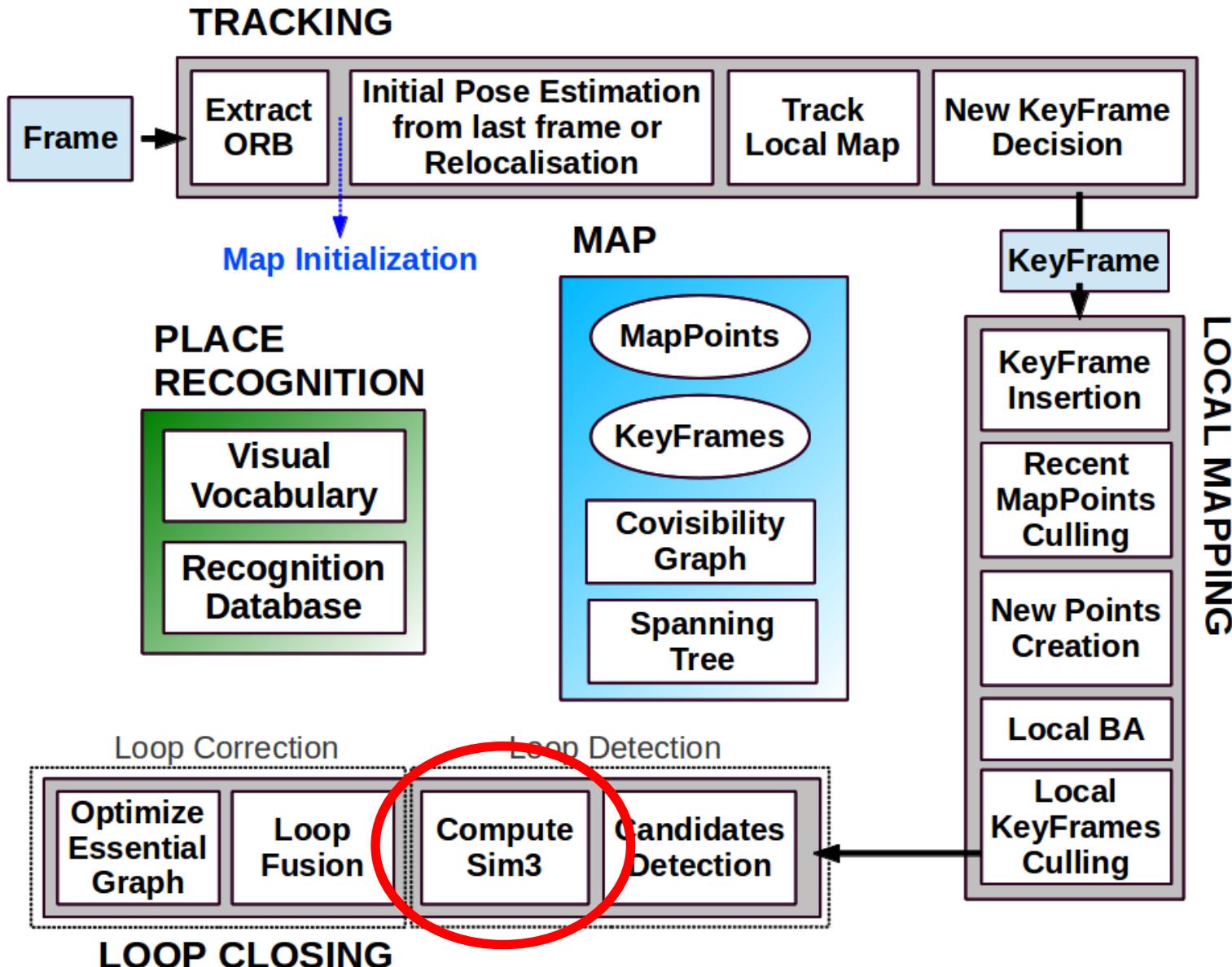
# ORB-SLAM: Real-Time Monocular SLAM



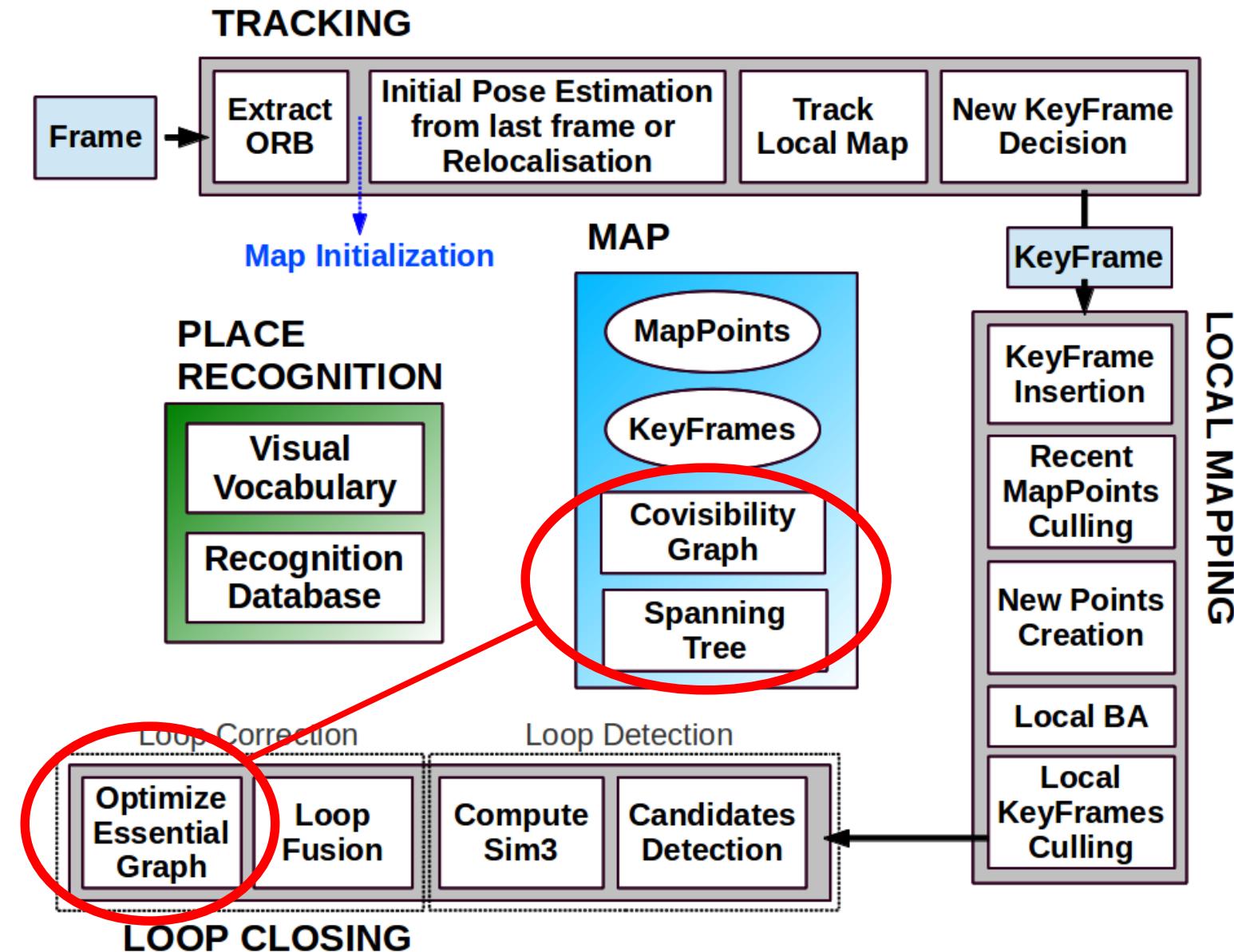
# ORB-SLAM: Real-Time Monocular SLAM



# ORB-SLAM: Real-Time Monocular SLAM



# ORB-SLAM: Real-Time Monocular SLAM



# Automatic Map Initialization

## Model Selection

**Homography**  
(Planar, Low Parallax)

**Fundamental Matrix**  
(General)

ORB-SLAM

PTAM

# Tracking I: Occlusion Handling

## Covisibility Graph

Track only a local map  
(potentially visible)

## Point Viewing Direction

Do not project if  
further than 60°

ORB-SLAM

PTAM

# Tracking II: Fast KeyFrame Insertion

## Survival of the Fittest KeyFrame Selection

Fast Keyframe Insertion  
(no distance threshold)

Culling of redundant  
Keyframes

ORB-SLAM

PTAM

# Relocalisation

## Bags of Binary Words

Same ORBs used in  
Tracking and Mapping

Good Viewpoint  
Invariance (ORB)

ORB-SLAM

PTAM

# ORB-SLAM indoors: TUM RGB-D dataset

	ORB-SLAM	PTAM
fr1_xyz	0.90	1.15
fr2_xyz	0.30	0.20
fr1_floor	2.99	<del> </del>
fr1_desk	1.69	<del> </del>
fr2_360_kidnap	3.81	2.63
fr2_desk	0.88	<del> </del>
fr3_long_office	3.45	<del> </del>
fr3_nstr_tex_near	1.39	2.74
fr3_str_tex_far	0.77	0.93
fr3_str_tex_near	1.58	1.04
fr2_desk_person	0.63	<del> </del>
fr3_sit_xyz	0.79	0.83
fr3_sit_halfsph	1.34	<del> </del>
fr3_walk_xyz	1.24	<del> </del>
fr3_walk_halfsph	1.74	<del> </del>

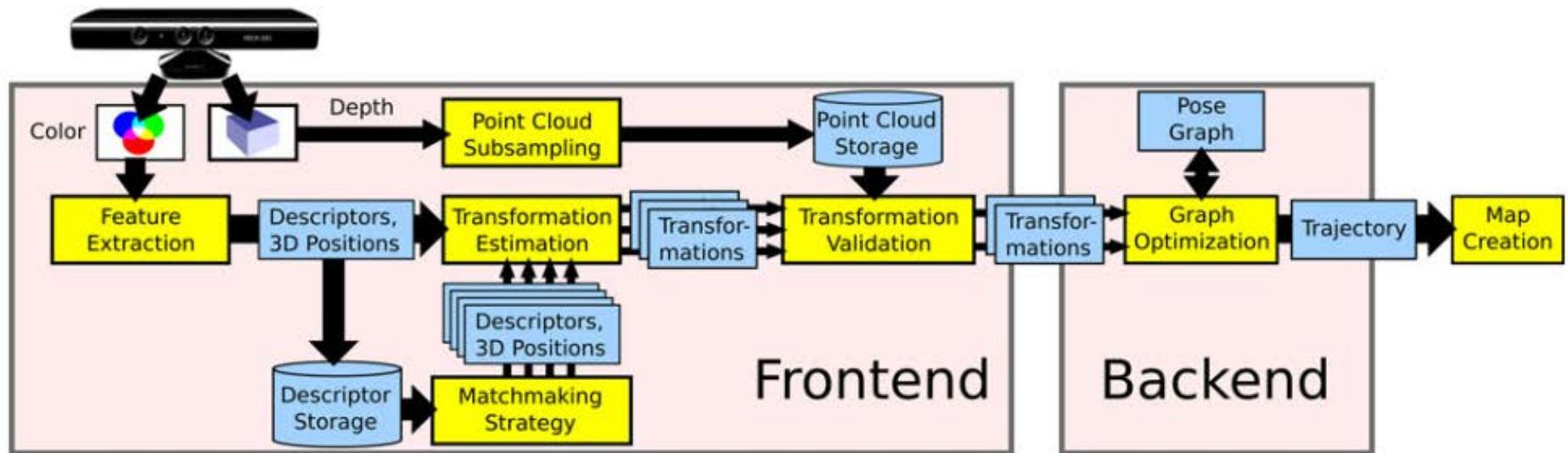
## TUM RGB-D Benchmark

RMS KeyFrame Position Error  
(cm)

*Median over 5 executions*

# Comparison with RGB-D SLAM

Use depth information!



F. Endres, J. Hess, J. Sturm, D. Cremers and W. Burgard  
***3-D Mapping with an RGB-D Camera***  
IEEE Transaction on Robotics, 2014.

	ORB-SLAM	PTAM	RGBD-SLAM
fr1_xyz	<b>0.90</b>	1.15	1.34
fr2_xyz	0.30	<b>0.20</b>	1.42
fr1_floor	<b>2.99</b>	<del>2.99</del>	3.51
fr1_desk	<b>1.69</b>	<del>1.69</del>	2.52
fr2_360_kidnap	3.81	<b>2.63</b>	100.5
fr2_desk	<b>0.88</b>	<del>0.88</del>	3.94
fr3_long_office	<b>3.45</b>	<del>3.45</del>	-
fr3_nstr_tex_near	<b>1.39</b>	2.74	-
fr3_str_tex_far	<b>0.77</b>	0.93	-
fr3_str_tex_near	1.58	<b>1.04</b>	-
fr2_desk_person	<b>0.63</b>	<del>0.63</del>	2.00
fr3_sit_xyz	<b>0.79</b>	0.83	-
fr3_sit_halfsph	<b>1.34</b>	<del>1.34</del>	-
fr3_walk_xyz	<b>1.24</b>	<del>1.24</del>	-
fr3_walk_halfsph	<b>1.74</b>	<del>1.74</del>	-

## TUM RGB-D Benchmark

RMSE (cm)

RGB-D SLAM results taken from the benchmark website

# Comparison with LSD-SLAM

Use directly pixel intensities!

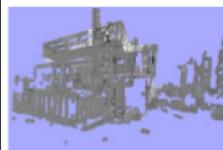
## Tracking

New Image  
(640 x 480 at 30Hz)



### Track on Current KF:

→ estimate SE(3) transformation



$$\min_{\xi \in \text{se}(3)} \sum_{\mathbf{p}} \left\| \frac{r_p^2(\mathbf{p}, \xi)}{\sigma_{r_p}^2(\mathbf{p}, \xi)} \right\|_{\delta}$$

tracking reference

## Depth Map Estimation

Take KF?

yes

Create New KF  
→ propagate depth map  
to new frame  
→ regularize depth map

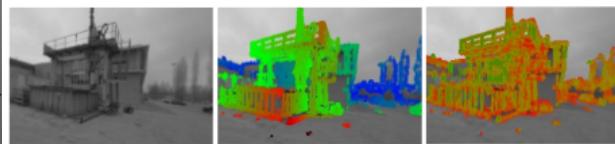
no

Refine Current KF  
→ small-baseline stereo  
→ probabilistically  
merge into KF  
→ regularize depth map

replace KF

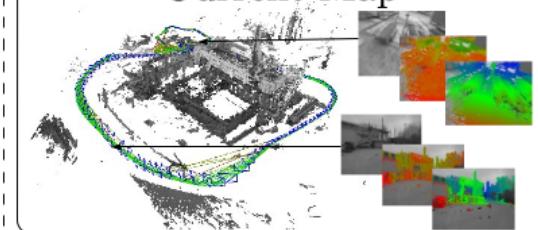
refine KF

### Current KF



## Map Optimization

### Current Map

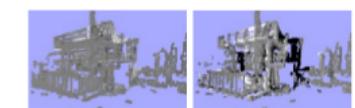


add to map

### Add KF to Map

→ find closest keyframes  
→ estimate Sim(3) edges

$$\min_{\xi \in \text{sim}(3)} \sum_{\mathbf{p}} \left\| \frac{r_p^2(\mathbf{p}, \xi)}{\sigma_{r_p}^2(\mathbf{p}, \xi)} + \frac{r_d^2(\mathbf{p}, \xi)}{\sigma_{r_d}^2(\mathbf{p}, \xi)} \right\|_{\delta}$$



J. Engel, T. Schöps, D. Cremers  
**LSD-SLAM: Large-Scale Direct Monocular SLAM**  
European Conference on Computer Vision (ECCV), 2014.

State-of-the-art in Direct SLAM

# Comparison with LSD-SLAM

fr3/structure\_texture\_near

ORB-SLAM

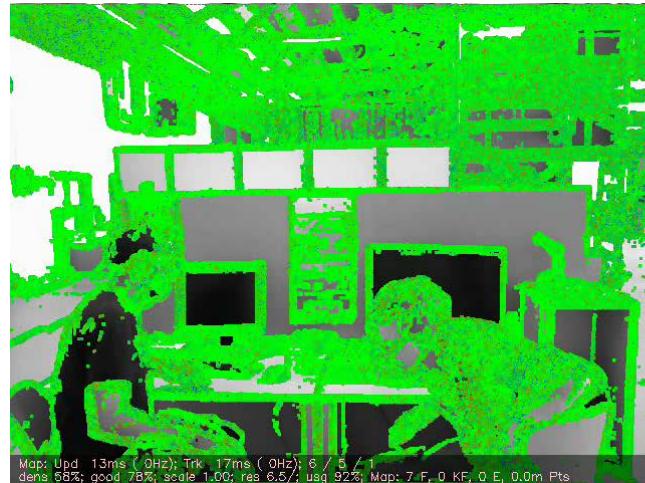
LSD-SLAM



# Comparison with LSD-SLAM

fr3/walking\_halfsphere

LSD-SLAM



**TUM RGB-D  
Benchmark**

**RMSE (cm)**

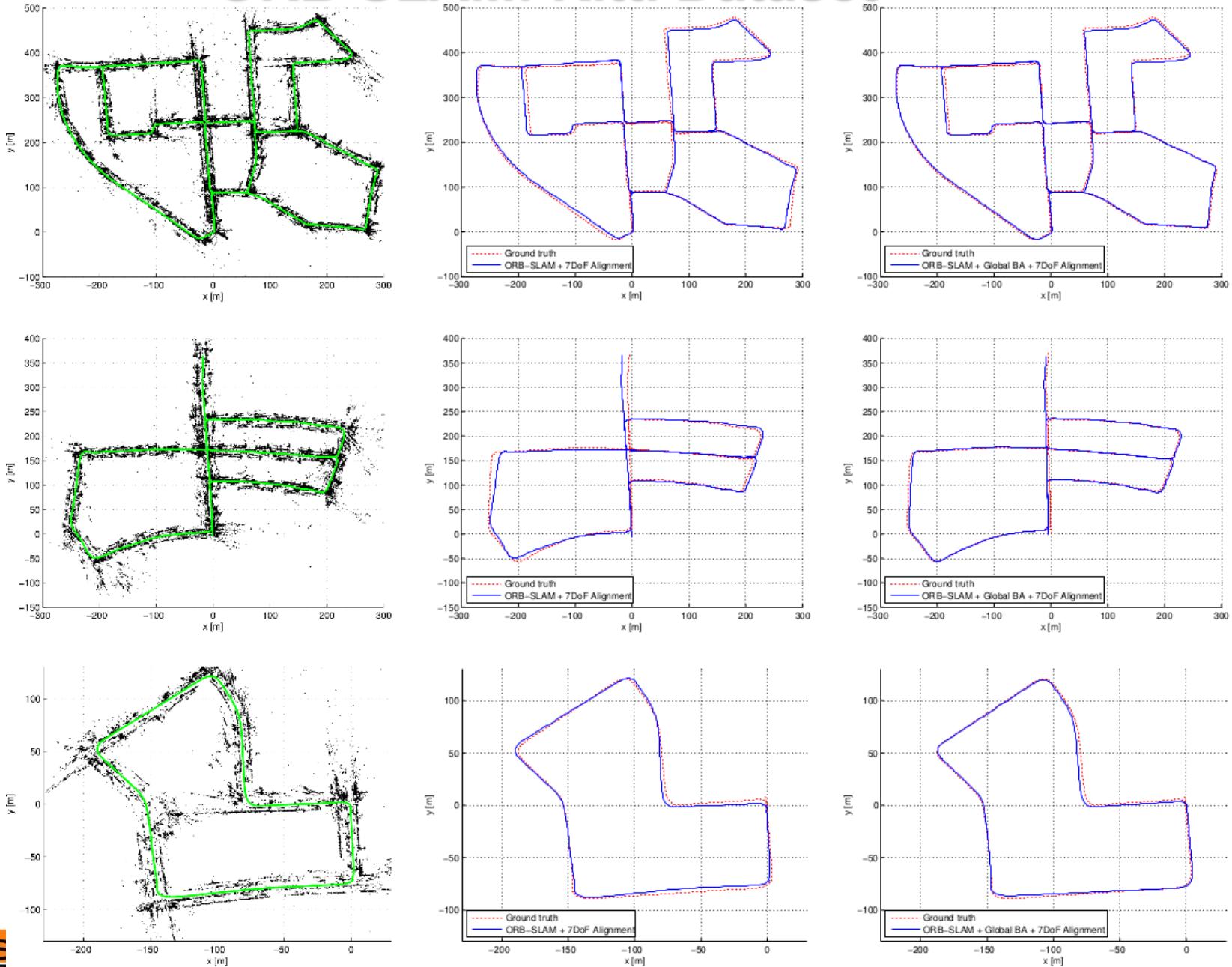
	ORB-SLAM	PTAM	RGBD-SLAM	LSD-SLAM
fr1_xyz	<b>0.90</b>	1.15	1.34	9.00
fr2_xyz	0.30	<b>0.20</b>	1.42	2.15
fr1_floor	<b>2.99</b>	<del>2.99</del>	3.51	38.07
fr1_desk	<b>1.69</b>	<del>1.69</del>	2.52	10.65
fr2_360_kidnap	3.81	<b>2.63</b>	100.5	<del>2.63</del>
fr2_desk	<b>0.88</b>	<del>0.88</del>	3.94	4.57
fr3_long_office	<b>3.45</b>	<del>3.45</del>	-	38.53
fr3_nstr_tex_near	<b>1.39</b>	2.74	-	7.54
fr3_str_tex_far	<b>0.77</b>	0.93	-	7.95
fr3_str_tex_near	1.58	<b>1.04</b>	-	<del>1.04</del>
fr2_desk_person	<b>0.63</b>	<del>0.63</del>	2.00	31.73
fr3_sit_xyz	<b>0.79</b>	0.83	-	7.73
fr3_sit_halfsph	<b>1.34</b>	<del>1.34</del>	-	5.87
fr3_walk_xyz	<b>1.24</b>	<del>1.24</del>	-	12.44
fr3_walk_halfsph	<b>1.74</b>	<del>1.74</del>	-	<del>1.74</del>

# Feature-Based .vs. Direct SLAM

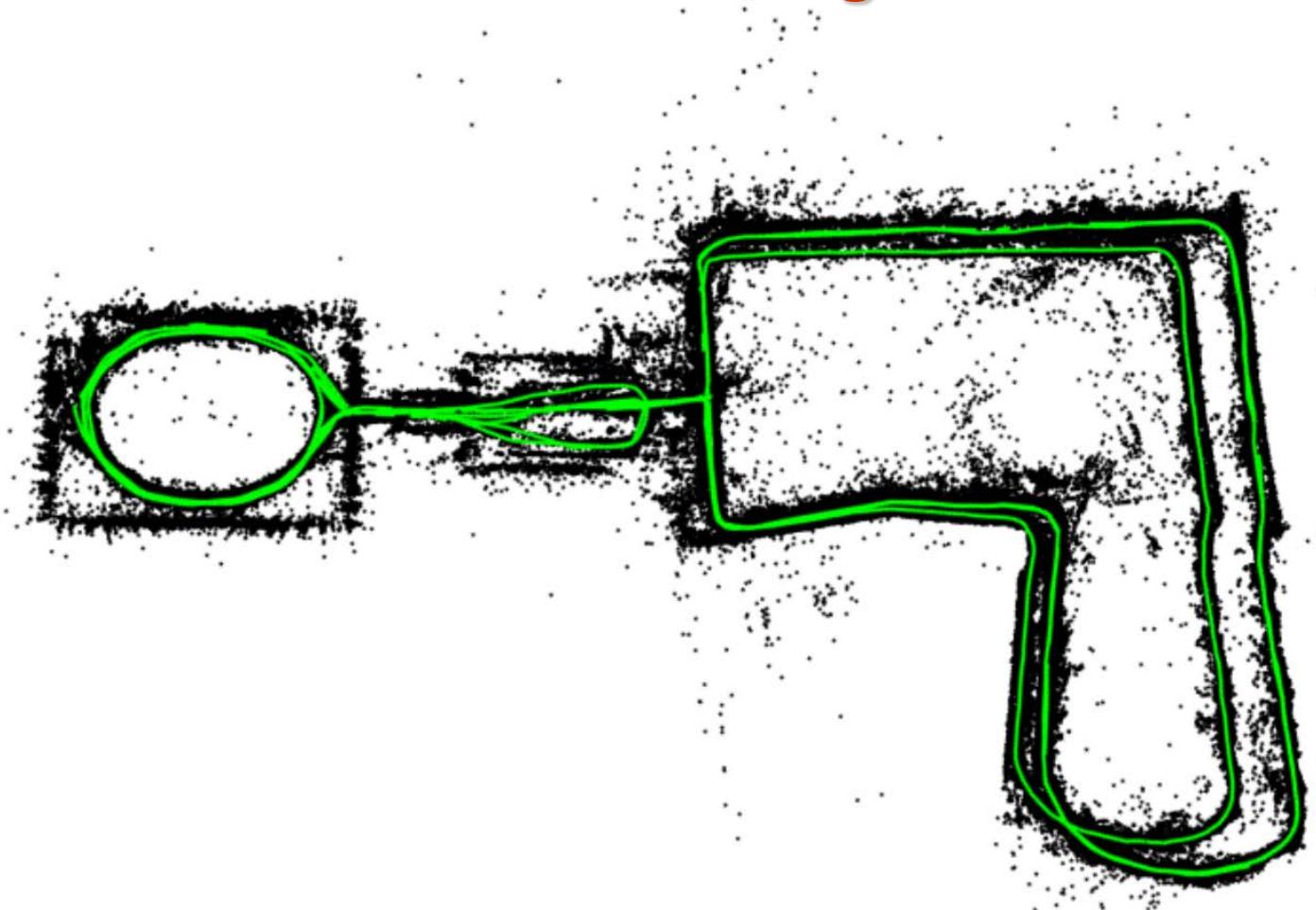
	Feature-Based SLAM (ORB-SLAM)	Direct SLAM (LSD-SLAM)
<b>Matching</b>	Illumination/viewpoint invariance <i>Wide baseline</i>	Photometric consistency <i>Narrow baseline</i>
<b>Map Optimization</b>	Local BA + Global Pose Graph	Global Pose Graph
<b>Loop Detection</b>	Integrated Place Recognition	Need Features (FabMap)
<b># Points</b>	~300	~100K
<b>Strengths</b>	Excellent accuracy Robust in dynamic scenes Robust initialization	Robust in low texture areas Robust under defocus/motion blur
<b>Weakness</b>	Low texture areas Motion blur	Dynamic Objects Strong viewpoint/illumination changes Rolling-shutter cameras

# ORB-SLAM outdoors: Kitti Dataset

# ORB-SLAM: Kitti Dataset



# ORB-SLAM: New College Dataset



Median Tracking Time per Frame: 30ms  
Median Mapping Time per KeyFrame: <400ms

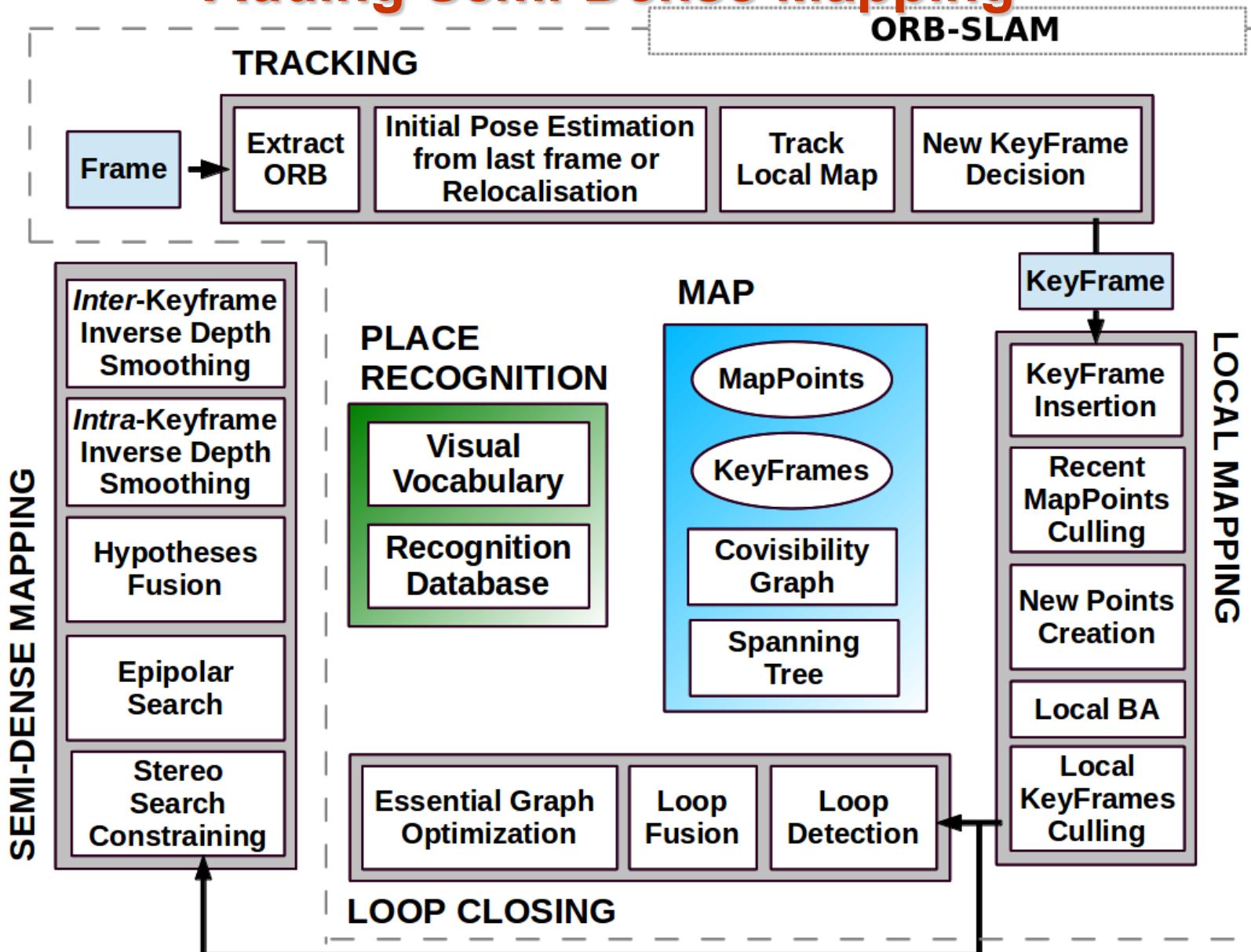
Intel Core i7 @ 2.4 GHz  
(4 cores)

# Limitations and Extensions

- Limitations
  - Monocular → the absolute scale is unknown
    - » Include in the map a known-size object
  - Requires a reasonably lit area
  - Needs texture: will fail with large plain walls
  - Map is too sparse for interaction with the environment
- Extensions
  - Improve agility using IMU
  - Stereo camera: real scale and robustness to quick motions
  - RGB-D camera: track with features + dense map
  - Semi-dense or dense mapping

# Adding Semi-Dense Mapping

ORB-SLAM



# ORB-SLAM + Semi-Dense Mapping

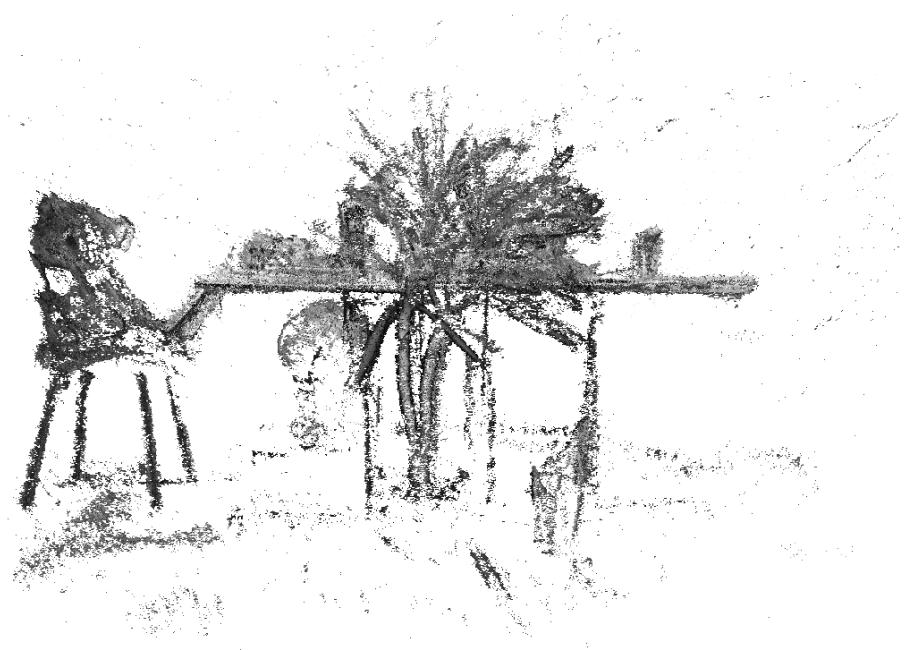
# Comparison with LSD-SLAM

fr2/desk

ORB-SLAM



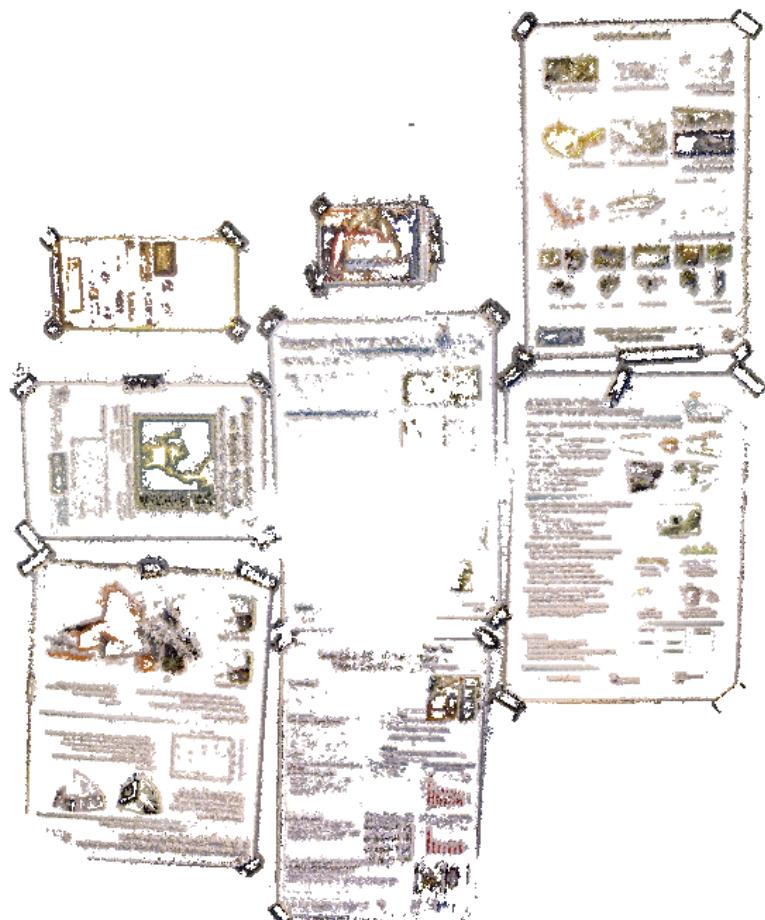
LSD-SLAM



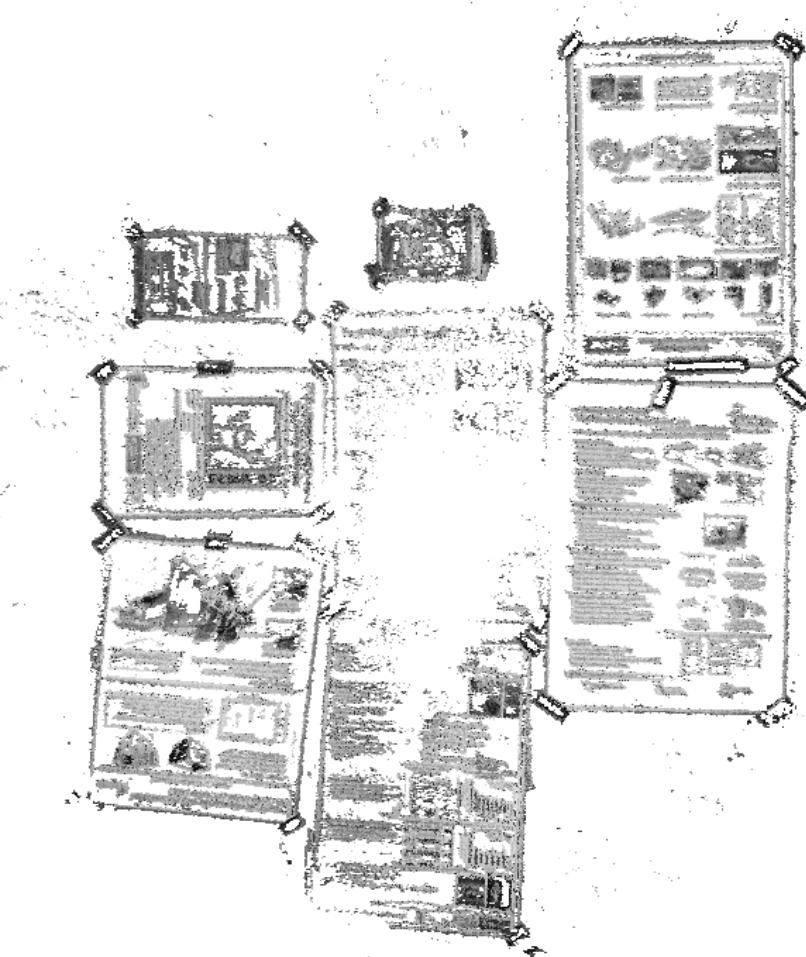
# Comparison with LSD-SLAM

fr3/nostructure\_texture\_near\_withloop

ORB-SLAM



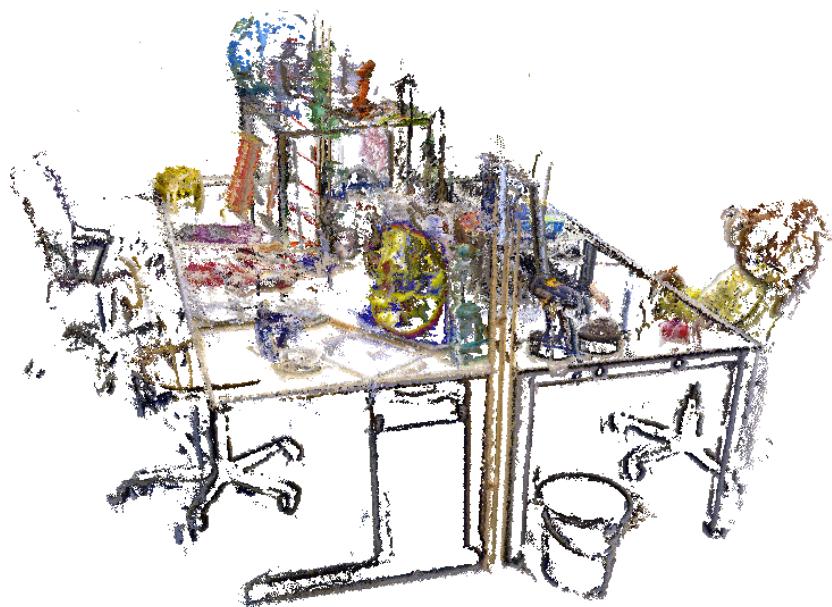
LSD-SLAM



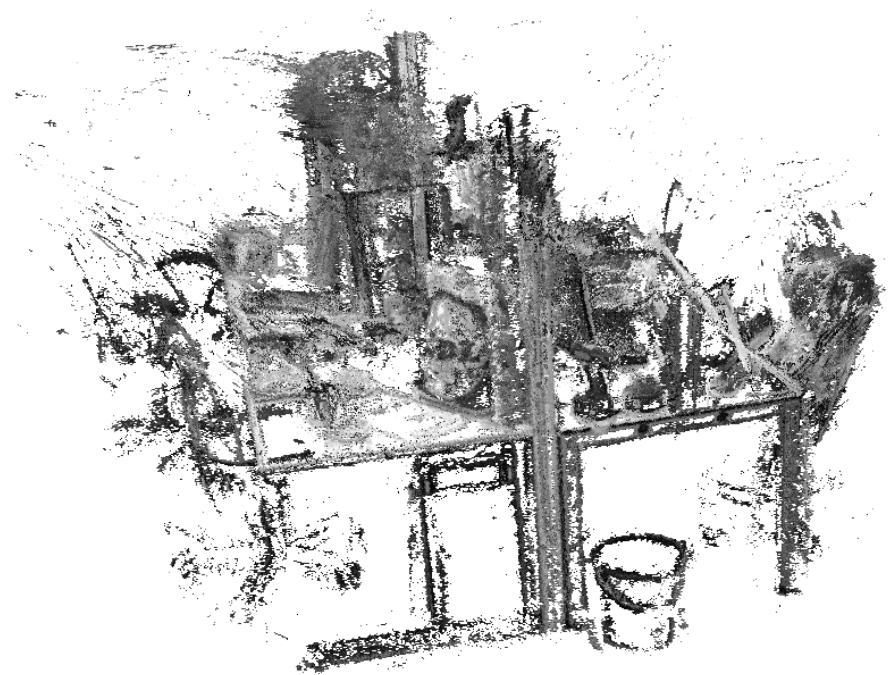
# Comparison with LSD-SLAM

fr3/long\_office\_household

ORB-SLAM



LSD-SLAM



# Comparison with LSD-SLAM

fr3/structure\_texture\_near

ORB-SLAM



LSD-SLAM

**TRACKING  
FAILURE**

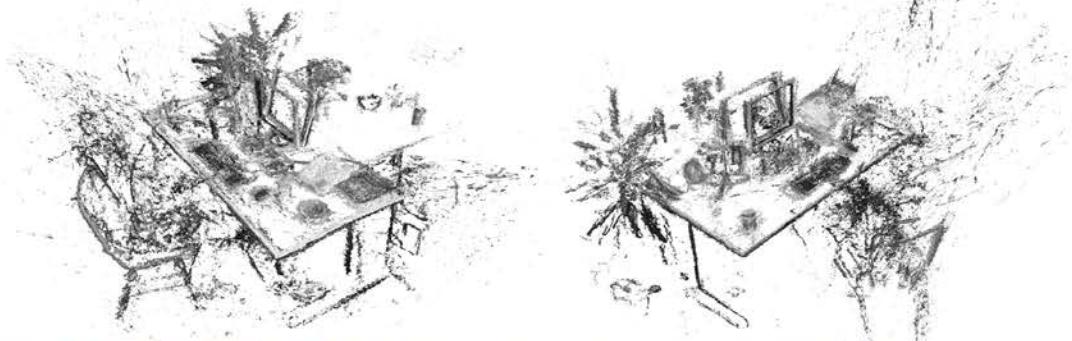
# Comparison with LSD-SLAM

fr2/desk\_with\_person

Our Approach



LSD-SLAM



# Application to VR

- ORB-SLAM: Feature-Based monocular SLAM
  - Tracking with ORB in <30ms
  - Local mapping: survival of the fittest for keyframes
  - Relocation and loop closing with good viewpoint invariance
- Application to Virtual Reality:
  - Map creation in real-time
  - Viewpoint tracking
    - » Mapping and loop closing can be disabled
    - » Zero-drift tracking
    - » Typical accuracy indoors: 1-3cm
    - » Possible to track multiple users, with different cameras

# Some VR Projects using Visual SLAM

- Project Tango (Google)

- Visual-inertial odometry
  - Area learning (SLAM)
  - RGB-D sensor



- Hololens (Microsoft)

- RGB-D sensor



- Magic Leap

- ???

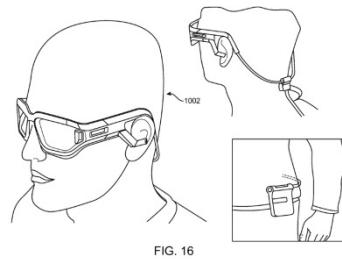
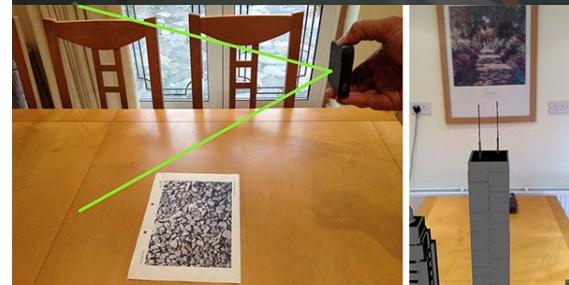
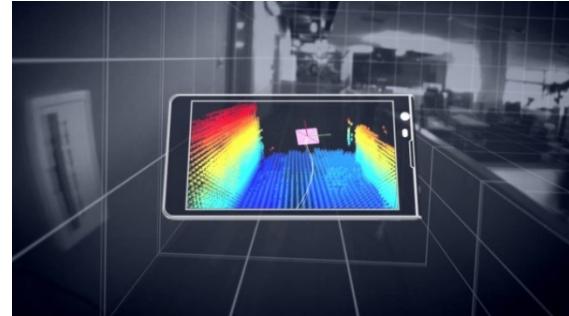


FIG. 16

- Vuforia (Qualcomm)

- Extended tracking (monocular SLAM)



- Apple (metaio), Oculus (surrealVision),

# Monocular SLAM for AR in Medicine

## Computer Vision Distance Measurement from Endoscopic Sequences. Prospective Evaluation in Laparoscopic Ventral Hernia Repairs.

### 3 - Computer-Vision-Based Measurement Method

Hospital Clínico Universitario  
"Lozano Blesa"

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S. Casado: [scasado@salud.aragon.es](mailto:scasado@salud.aragon.es)  
I. Gil: [igil@unizar.es](mailto:igil@unizar.es)

Instituto de Investigación en  
Ingeniería de Aragón (I3A)

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J. M. M. Montiel: [josemari@unizar.es](mailto:josemari@unizar.es)



*This work was supported by Spanish MICINN Grants DPI2009-07130 and DPI2012-32168*

# Summary

- ORB-SLAM: Feature-Based monocular SLAM
  - Large-scale operation
  - Loop closing and relocation
  - Robust operation, indoors, outdoors
  - Excellent precision
  - Open-source version released under GPLv3
- More Information:
  - Raúl Mur-Artal and Juan D. Tardós  
*Fast Relocalisation and Loop Closing in Keyframe-Based SLAM*,  
ICRA 2014
  - Raúl Mur-Artal, J.M.M. Montiel and Juan D. Tardós  
ORB-SLAM: A Versatile and Accurate Monocular SLAM System,  
IEEE Transactions on Robotics (under review), arXiv:1502.00956
  - Raúl Mur-Artal and Juan D. Tardós  
Probabilistic Semi-Dense Mapping from Highly Accurate Feature-Based  
Monocular SLAM, RSS 2015

<http://webdiis.unizar.es/~raulmur/orbslam/>

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