Universidad Zaragoza

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Probabilistic Semi-Dense Mapping from Highly Accurate Feature-Based Monocular SLAM

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1. Monocular SLAM approaches

Feature-Based SLAM	Direct SLAM
Extract features on the images	Use directly pixel's intensity
Minimize **reprojection error**	Minimize **photometric error**
Sparse map	**Semi-dense/Dense** map

2. Comparison in the TUM RGB-D Benchmark

KeyFrame Position RMSE (cm)

✗ Tracking Failure

	ORB-SLAM	PTAM	LSD-SLAM
fr1_xyz	**0.90**	1.15	9.00
fr2_xyz	0.30	**0.20**	2.15
fr1_floor	**2.99**	✗	38.07
fr1_desk	**1.69**	✗	10.65
fr2_360_kidnap	3.81	**2.63**	✗
fr2_desk	**0.88**	✗	4.57
fr3_long_office	**3.45**	✗	38.53
fr3_nstr_tex_near	**1.39**	2.74	7.54
fr3_str_tex_far	**0.77**	0.93	7.95
fr3_str_tex_near	1.58	**1.04**	✗
fr2_desk_person	**0.63**	✗	31.73
fr3_sit_xyz	**0.79**	0.83	7.73
fr3_sit_halfsph	**1.34**	✗	5.87
fr3_walk_xyz	**1.24**	✗	12.44
fr3_walk_halfsph	**1.74**	✗	✗

Feature-Based SLAM

PTAM
G. Klein and D. Murray. ISMAR 2007

ORB-SLAM
R. Mur-Artal, J. M. M. Montiel and J. D. Tardós. ArXiv 2015

Direct SLAM

LSD-SLAM
J. Engel, T. Schöps and D. Cremers. ECCV 2014

Our ORB-SLAM is +Robust and +Accurate!

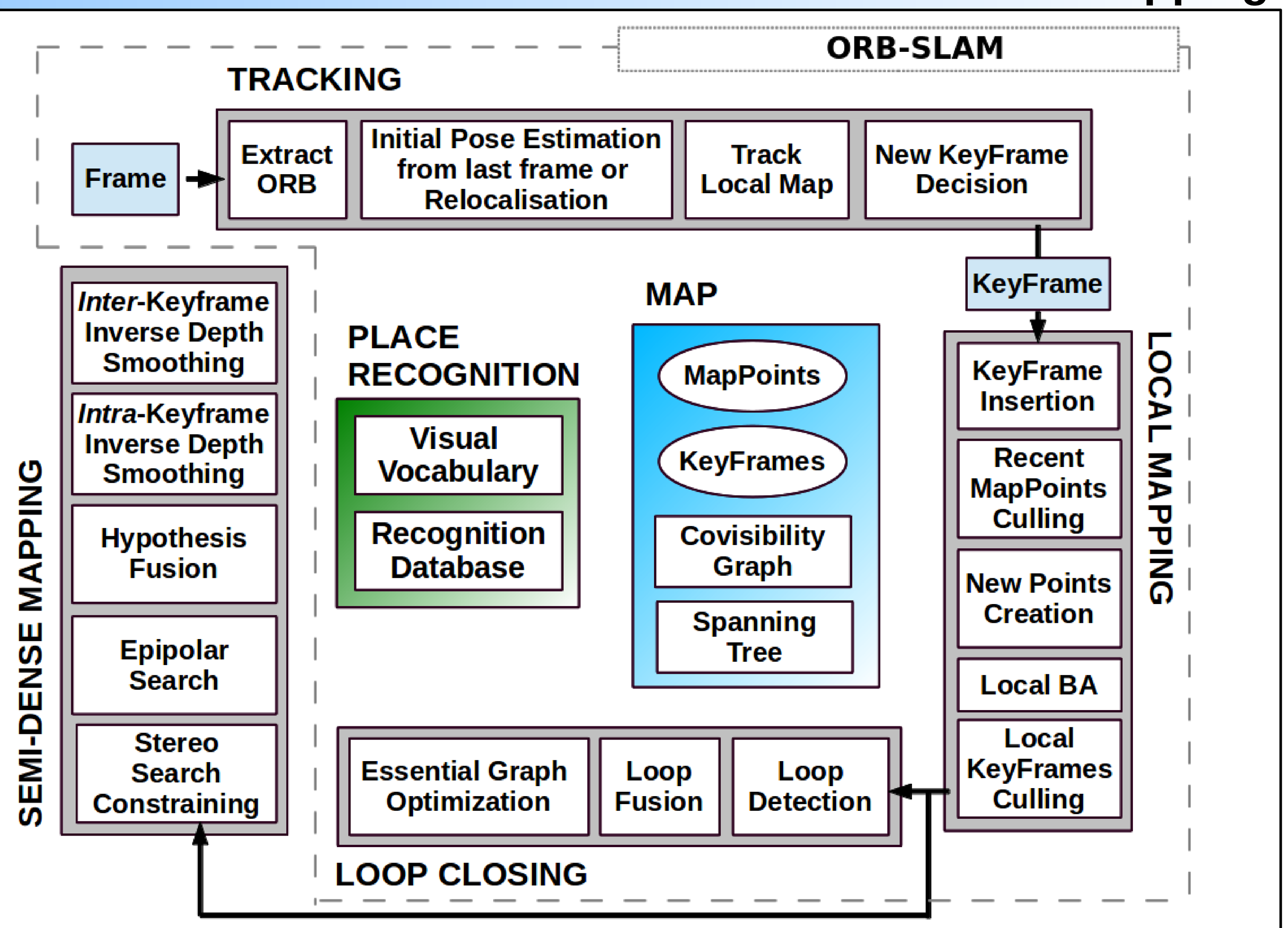
Surprising for a Feature-Based Technique.

3. Benefits of Feature-Based SLAM

- **Bundle adjustment (joint optimization of map-trajectory).**
  +Accuracy
- **Good invariance to viewpoint and illumination.**
  +Accuracy (wider matches), +Robustness
- **Less affected by auto-gain, auto-exposure and rolling shutter.**
  +Robustness
- **Less affected by dynamic elements.**
  +Robustness
- **BoW place recognition for relocalisation and loop closing.**
  +In ORB-SLAM it is fully integrated using the same features

But Sparse Reconstructions...

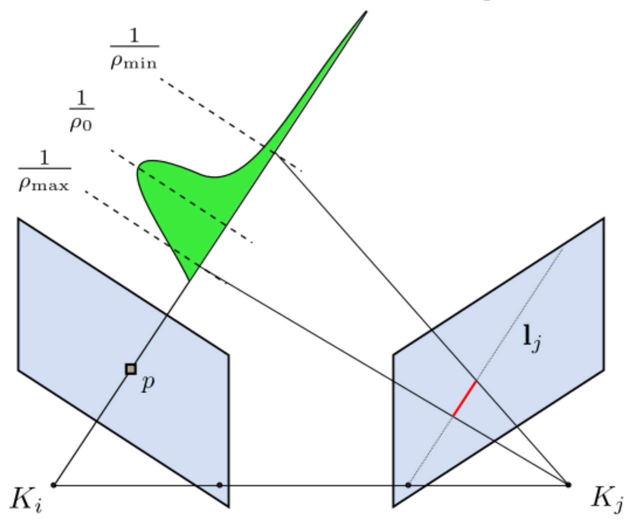
4. Solution: ORB-SLAM + Probabilistic Semi-Dense Mapping

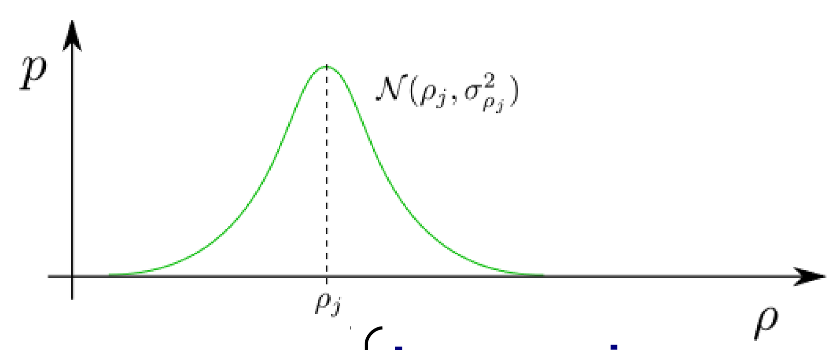


5. Probabilistic Semi-Dense Mapping

Goal: For each pixel with high gradient, compute the probability distribution of its inverse-depth.

1. Stereo search in *N* neighbor keyframes

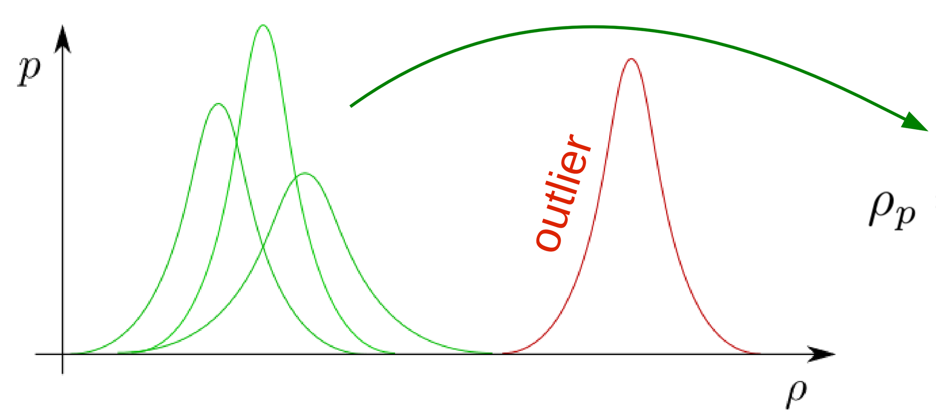




Compare { **Intensity**, **Gradient modulo**, **Gradient direction** }

Uncertainty { **Image noise**, **Parallax**, **Matching ambiguity** }

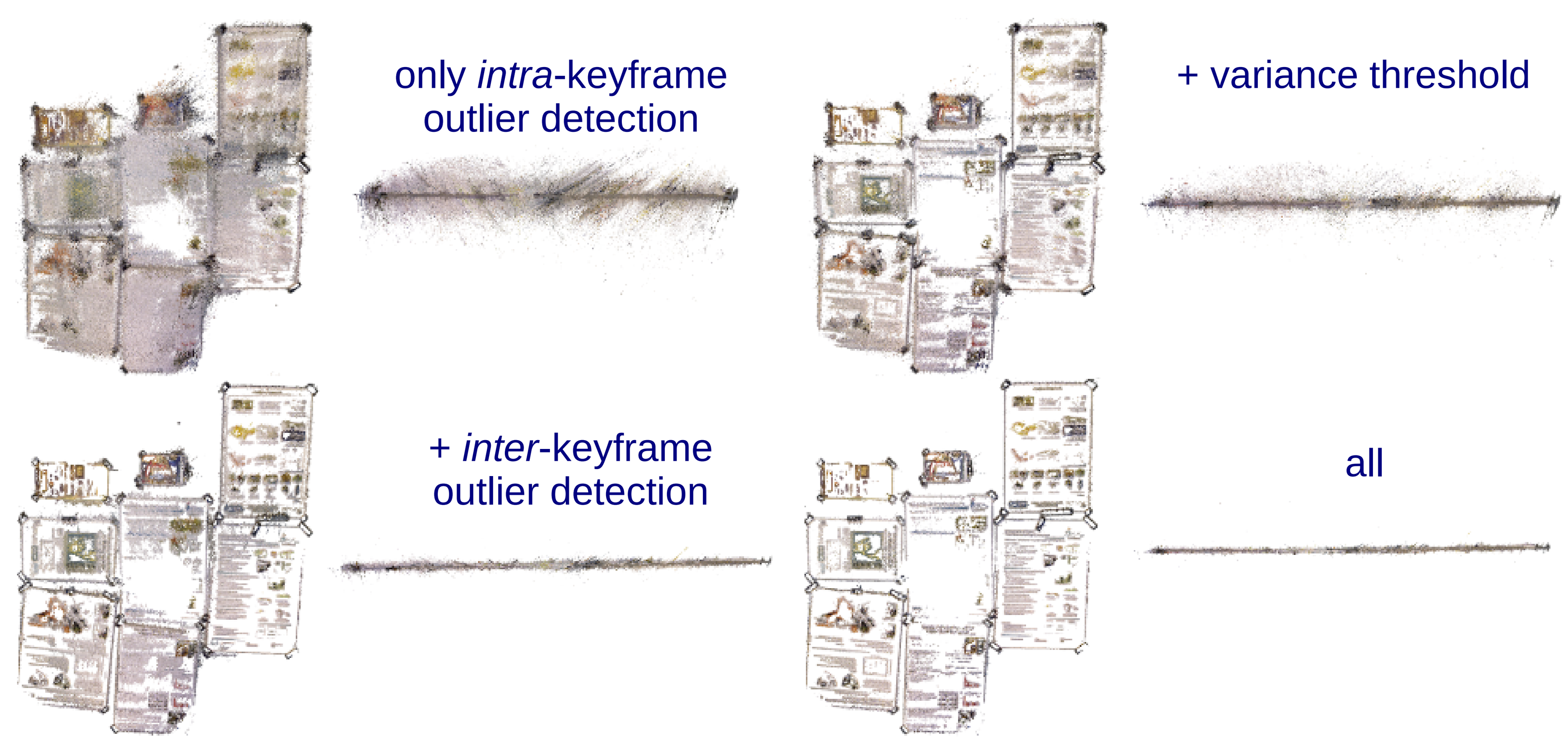
2. Hypothesis Fusion



$$\rho_p = \frac{\sum_n \frac{1}{\sigma^2_{\rho_j}} \rho_j}{\sum_n \frac{1}{\sigma^2_{\rho_j}}}, \quad \sigma^2_{\rho_p} = \frac{1}{\sum_n \frac{1}{\sigma^2_{\rho_j}}}$$

3. *Intra* and *Inter* KeyFrame Outlier Detection and Smoothing

Check compatibility of pixel's inverse-depth distribution with neighbor pixels. If compatible, average distribution, discard otherwise.
Intra: Neighbors in the same keyframe.
Inter: Neighbors around projection in neighbor keyframes.



6. Real-Time (No GPU) Results in the TUM RGB-D Benchmark