



上海科技大学
ShanghaiTech University

CS283: Robotics Spring 2026: SLAM I

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ShanghaiTech University

ADMIN

Midterm; April 16; during class hours

- Midterm: “test-run” for the final...
- Content:
 - Everything till (including) today’s lecture.
 - Take a look at facts, algorithms, concepts
 - Take a look at the homeworks again
 - Sample exam: https://robotics.shanghaitech.edu.cn/sites/default/files//files/final_Example.pdf
- You are allowed to bring 3 A4 sheets (so 6 pages) of info to the Final – for the Midterm you can bring **2** A4 sheets. You can write/ print anything on those sheets. On top of **every page** (so 6 times) there needs to be your **name (pinyin), student ID and ShanghaiTech email** address. We will check every cheat sheet before the exam and **confiscate** every sheet without name or with a name that is not yours.
- No electronics/ calculator/ smartwatch allowed

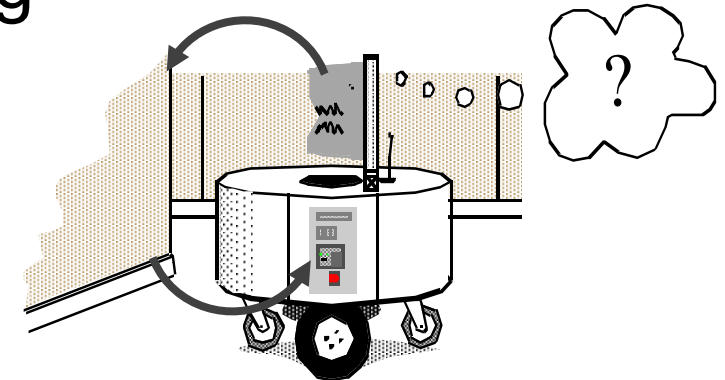
Presentation

- Upload your pdf/ ppt to your group git latest April 20 23:59!
- If you want to use your own pdf/ ppt later you'll loose 30% of that score.
- Be present at all 3 presentation slots – listen carefully – everybody needs to ask in total at least 3 questions (for 3 different presentations)

DEFINITION OF SLAM

What is SLAM?

- **Localization:** inferring location given a map
- **Mapping:** inferring a map given locations
- **SLAM:** learning a map and locating the robot simultaneously
- SLAM has long been regarded as a chicken-and-egg problem:
 - a map is needed for localization and
 - a pose estimate is needed for mapping

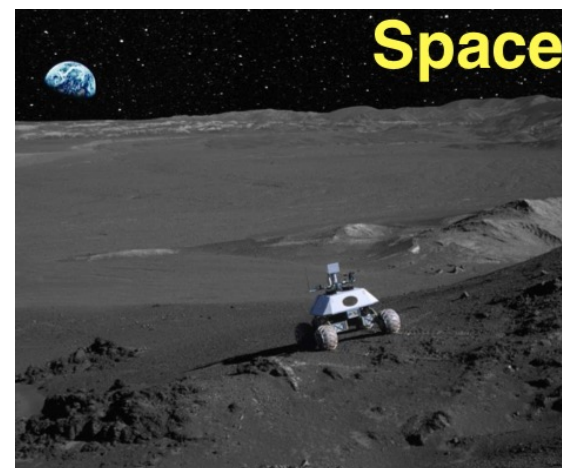


Material derived from Wolfram Burgard:

<http://ais.informatik.uni-freiburg.de/teaching/ss20/robotics/slides/13-slam.pdf>

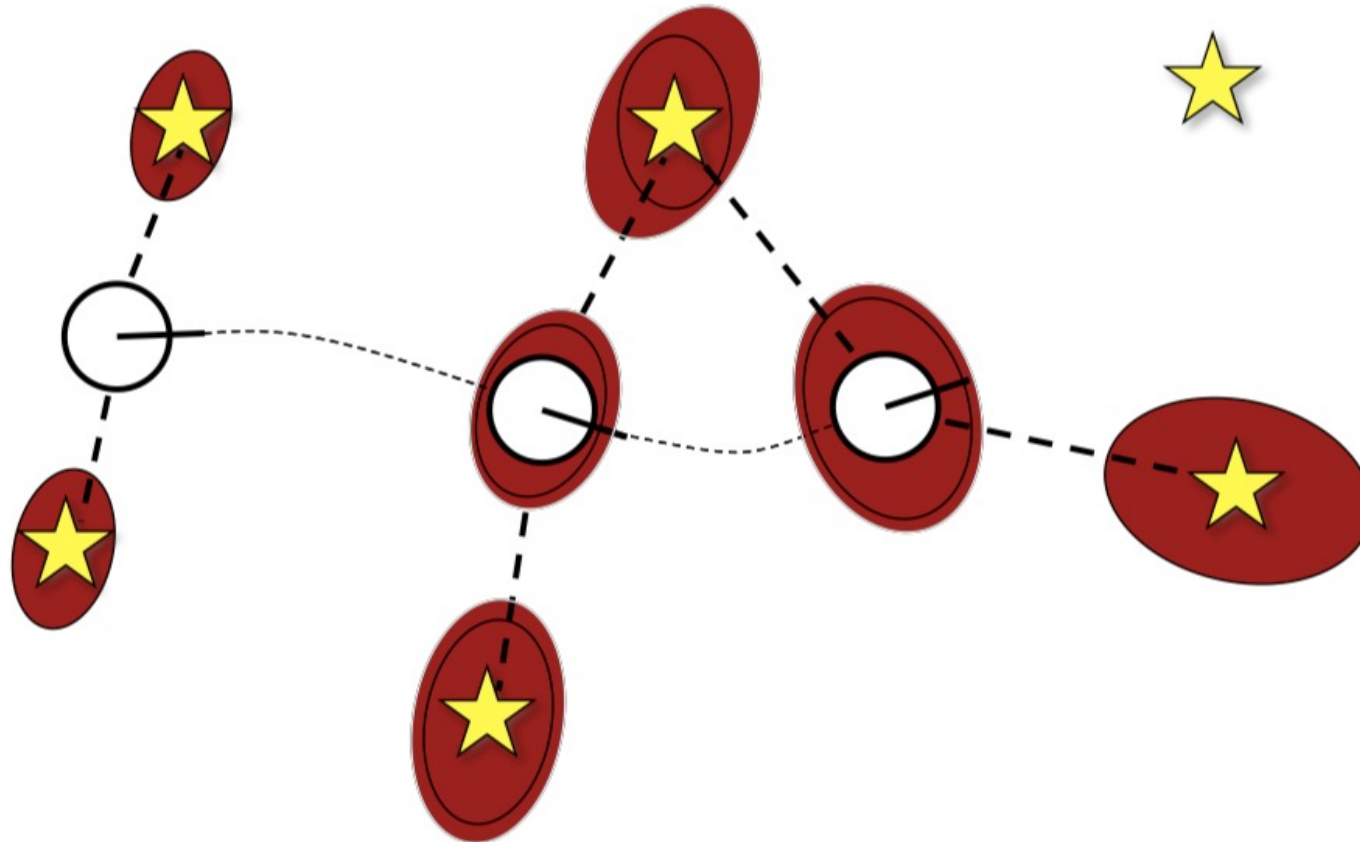
SLAM Applications

- At home: vacuum cleaner, lawn mower
- Air: surveillance with unmanned air vehicles
- Underwater: reef monitoring
- Underground: exploration of mines
- Space: terrain mapping for localization
-



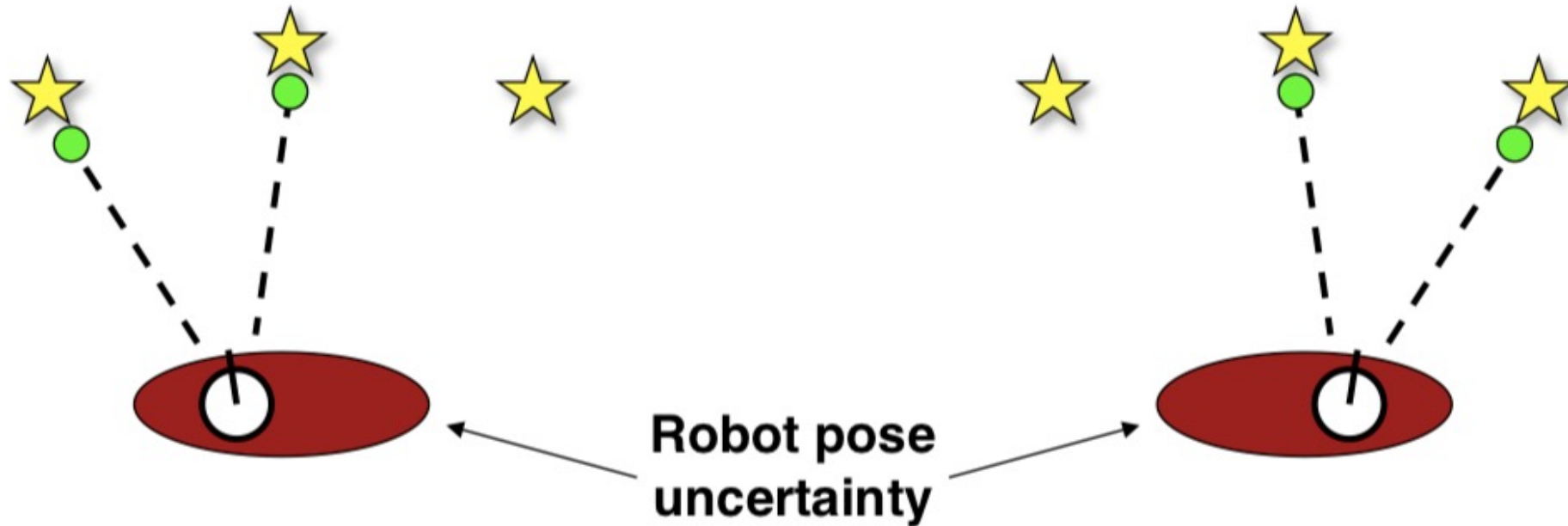
Why is SLAM a Hard Problem?

- Robot path and map are both unknown
- Errors in map and pose estimates correlated



Why is SLAM a Hard Problem?

- The mapping between observations and landmarks is unknown
- Picking wrong data associations can have catastrophic consequences (divergence)



Overview of SLAM Methods

- Camera

- Feature-Based Methods
 - MonoSLAM
 - PTAM
 - ORB-SLAM
- Direct Methods
 - DTAM
 - LSD-SLAM
 - DSO
- Semi-Direct Methods
 - SVO
- Others
 - PoseNet
 - CNN-SLAM
 - ...

- Laser

- Pose Graph
 - Cartographer
 - Karto-SLAM
 - Hector-SLAM
 - BLAM
 - LIO
- Particle Filter
 - FastSLAM
 - Gmapping
- Extended Kalman Filter
 - EKF-SLAM
 - LINS
- Others
 - LOAM
 - IMLS-SLAM
 - ...

SLAM Front-end & Back-end

- Front-end
 - calculate relative poses between several frames/ to map
 - scan matching
 - image registration
 - ...
 - estimate absolute poses
 - construct the local map
- Back-end
 - optimize the absolute poses and mapping
 - only if a loop was closed



FRONT END – LASER - ICP

FRONT END - CAMERA

Methods

- **Feature-based Methods**

- SIFT
- ORB (ORB-SLAM)
- BRISK
- AKAZE

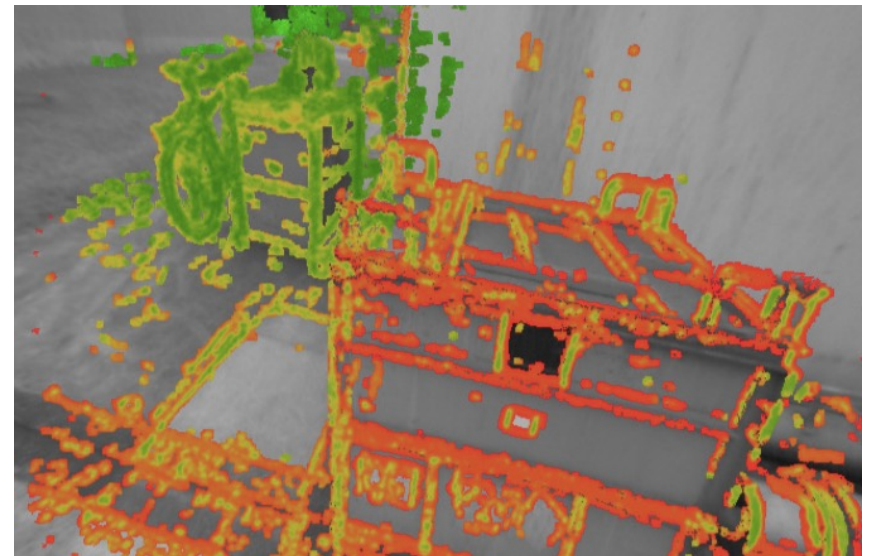
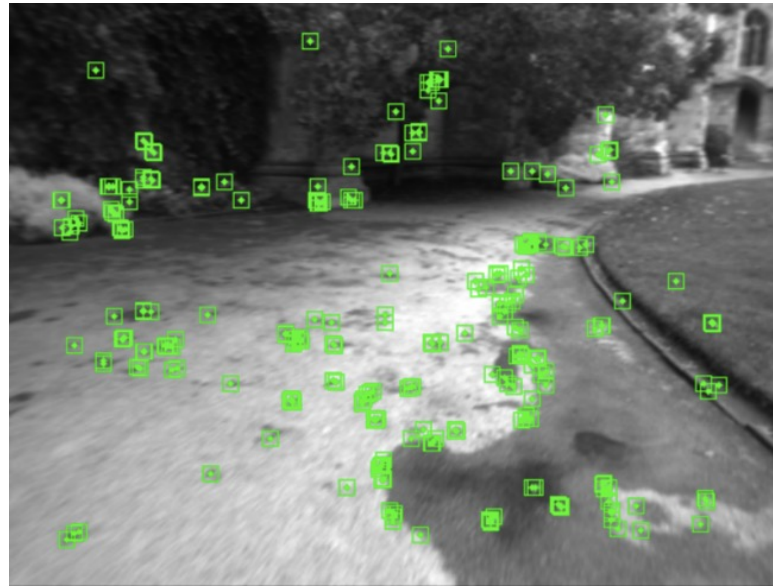
- **Direct Methods**

- Optical Flow
- Inverse Depth (LSD-SLAM)
- Fourier-Mellin Transform

- **Semi-Direct Methods**

- SVO

more details in the next lectures

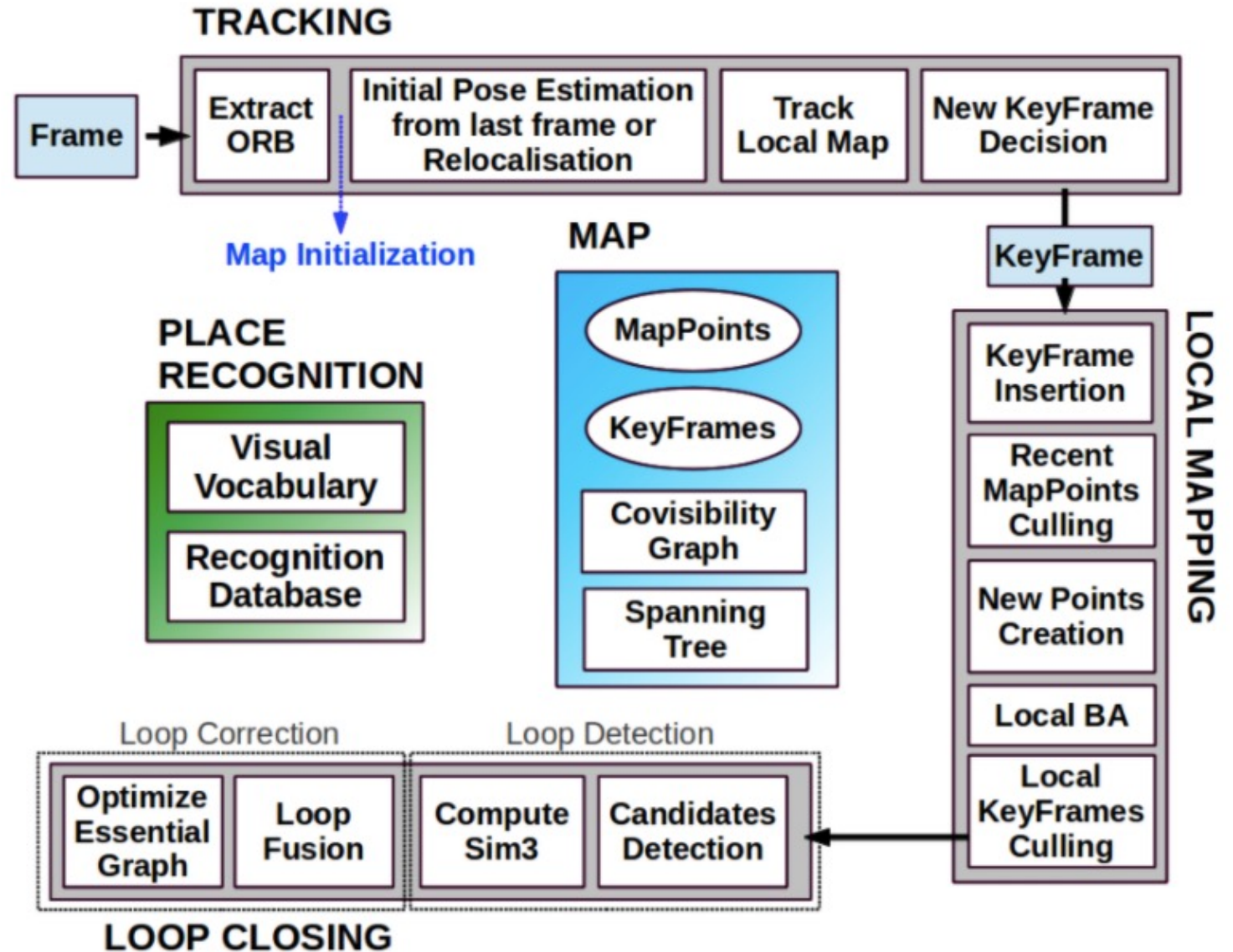


Feature-based Methods

- Feature Extraction
 - Feature Detectors & Feature Descriptor; more in vision lectures
 - ORB, SIFT, AKAZE, BRISK, etc ...
- Feature Matching
 - BFM, KNN, etc ...
- Relative Pose Calculation
 - 5-pt, 7-pt, 8-pt, PnP, etc ...

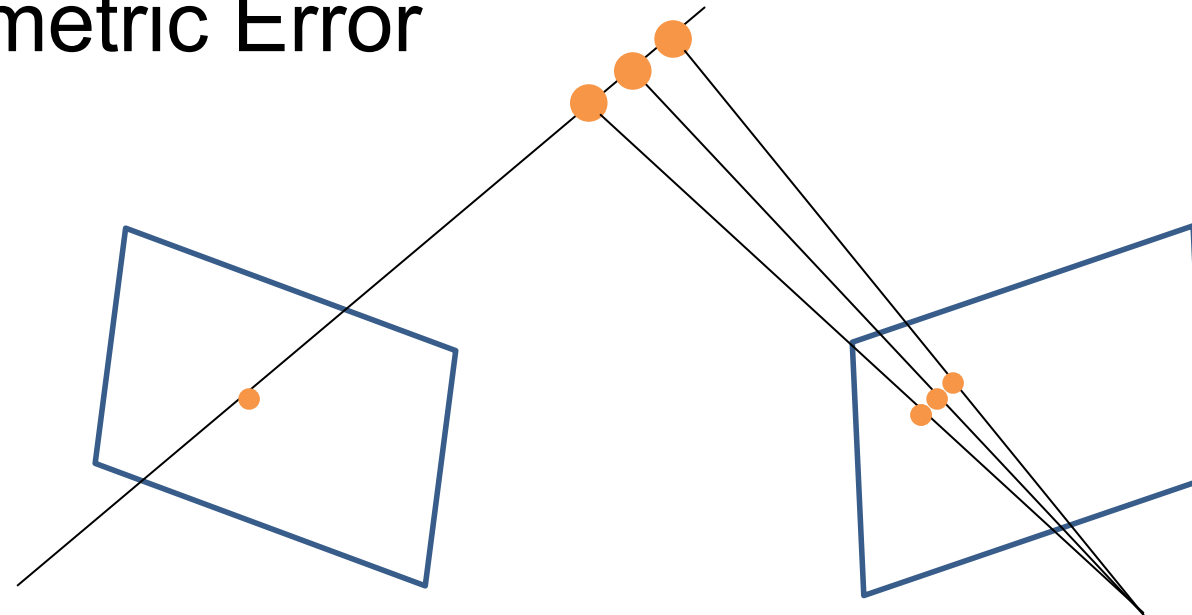
Feature-based Method: ORB-SLAM

Mur-Artal R, Montiel J M M, Tardos J D. ORB-SLAM: a versatile and accurate monocular SLAM system[J]. IEEE transactions on robotics, 2015, 31(5): 1147-1163.



Direct Method: LSD-SLAM

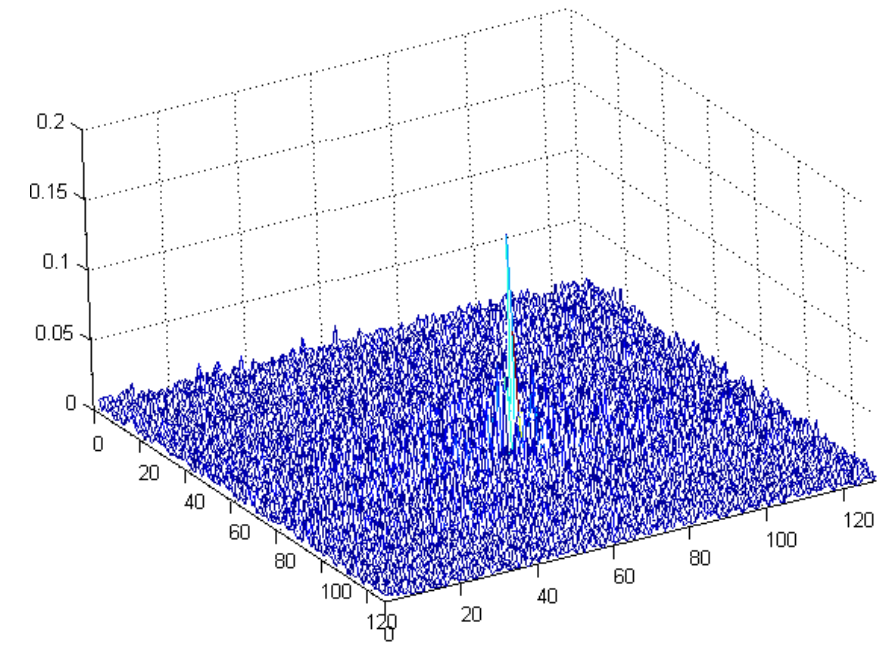
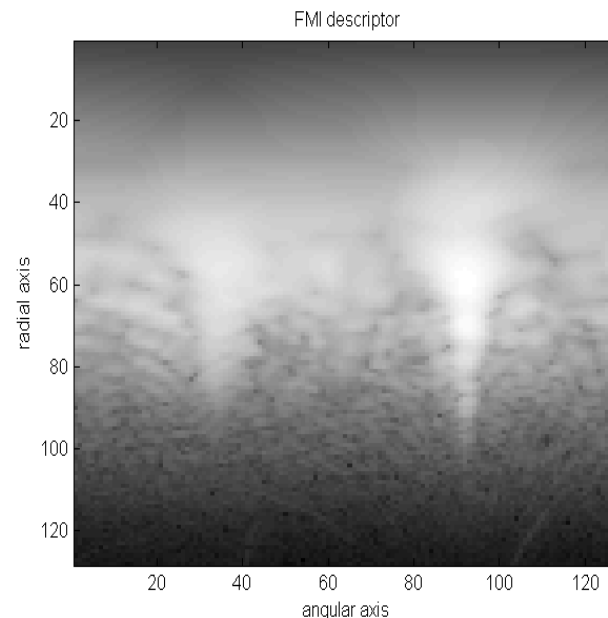
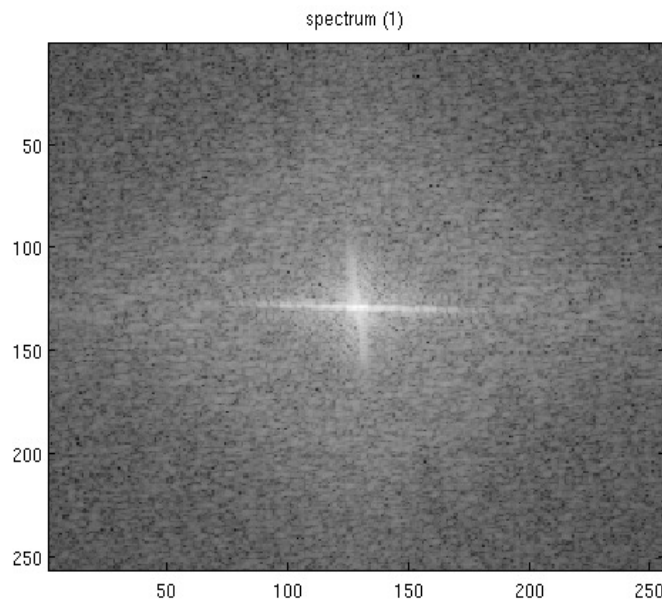
- Construct Photometric Error



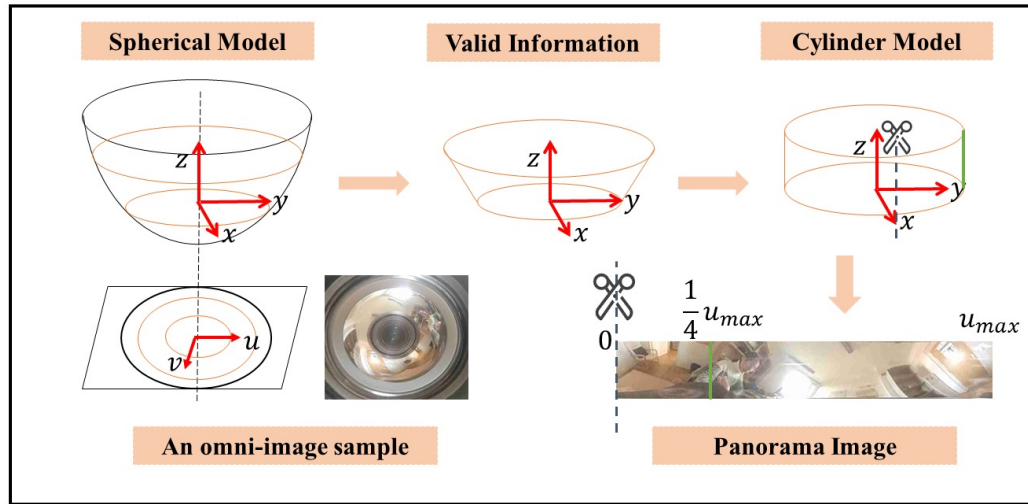
- Construct Depth Error
- Minimize Objective Error Function

Direct Method: Fourier Mellin Transform

- Spectral based registration: detection of scaling, rotation and translation in 2 subsequent frames
- Processing spectrum magnitude decouples translation from affine transformations
 - Detection of signal shift between 2 signals by phase information
 - Resampling to polar coordinates → Rotation turns into signal shift !
 - Resampling the radial axis from linear to logarithmic presentation → Scaling turns into signal shift !
 - Calculate a Phase Only Match Filter (POMF) on the resampled magnitude spectra



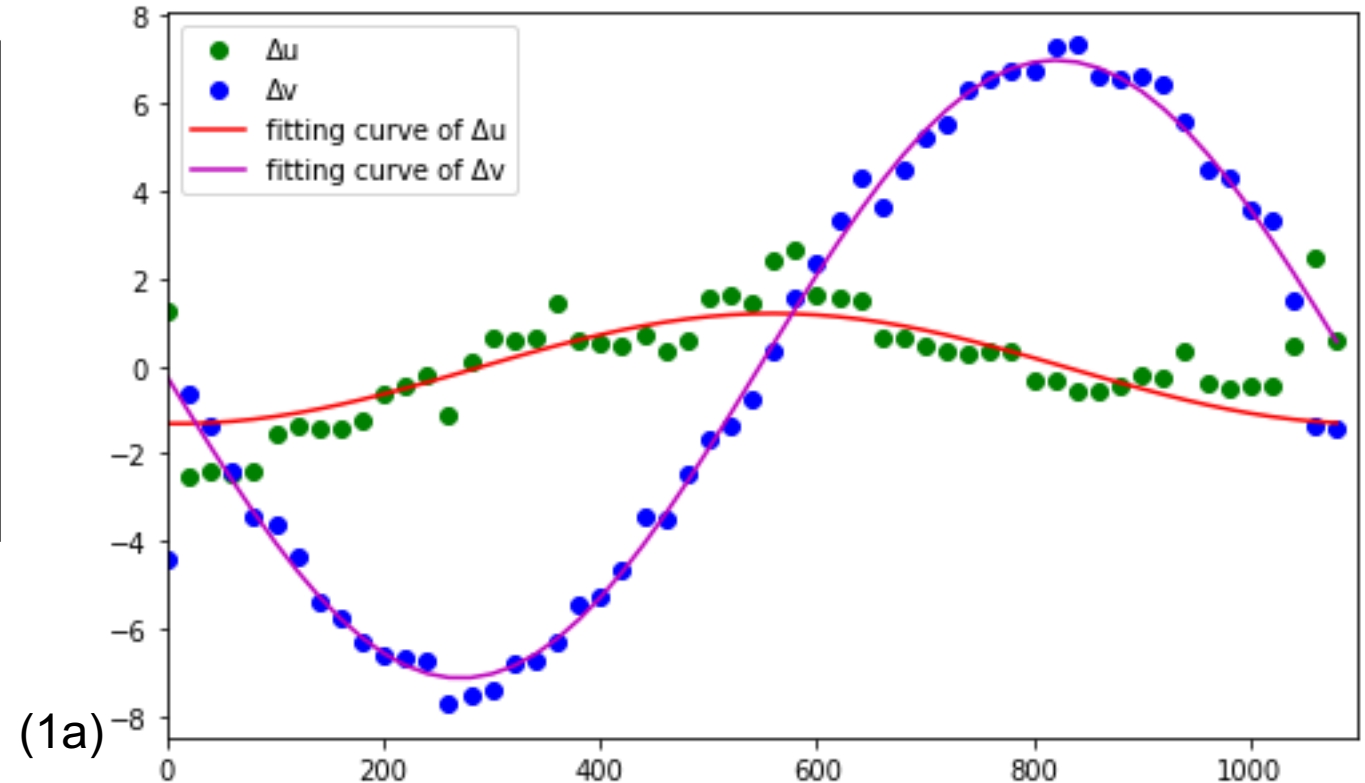
Pose Estimation for Omni-directional Cameras using Sinusoid Fitting



$$y = B + A \sin(\omega x + \phi)$$

$$\Delta v(u_p) = \lambda_p t_z + \gamma \left\| \left\| P_{xy}(R) \cdot \sin(\gamma u_p + \frac{P_{xy}(R)}{\|P_{xy}(R)\|}) \right\| \right\|$$

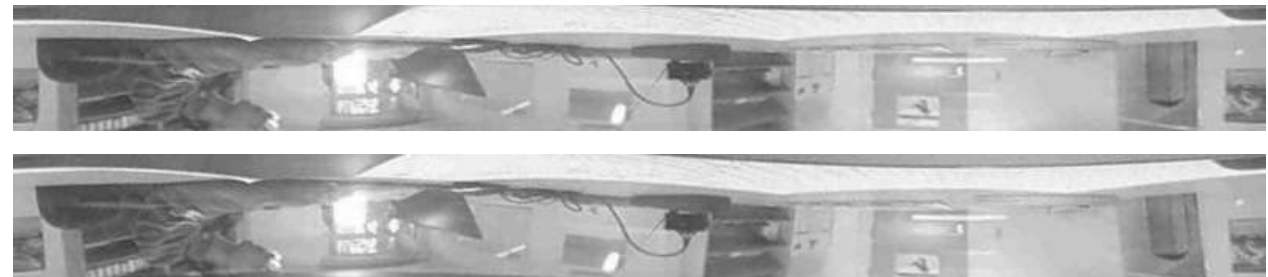
$$\Delta u(u_p) = \gamma P_z(R) + \lambda_p \|P_{xy}(t)\| \cdot \sin(\gamma u_p + \hat{t}_{xy})$$



(1a)

(1b)

(1c)



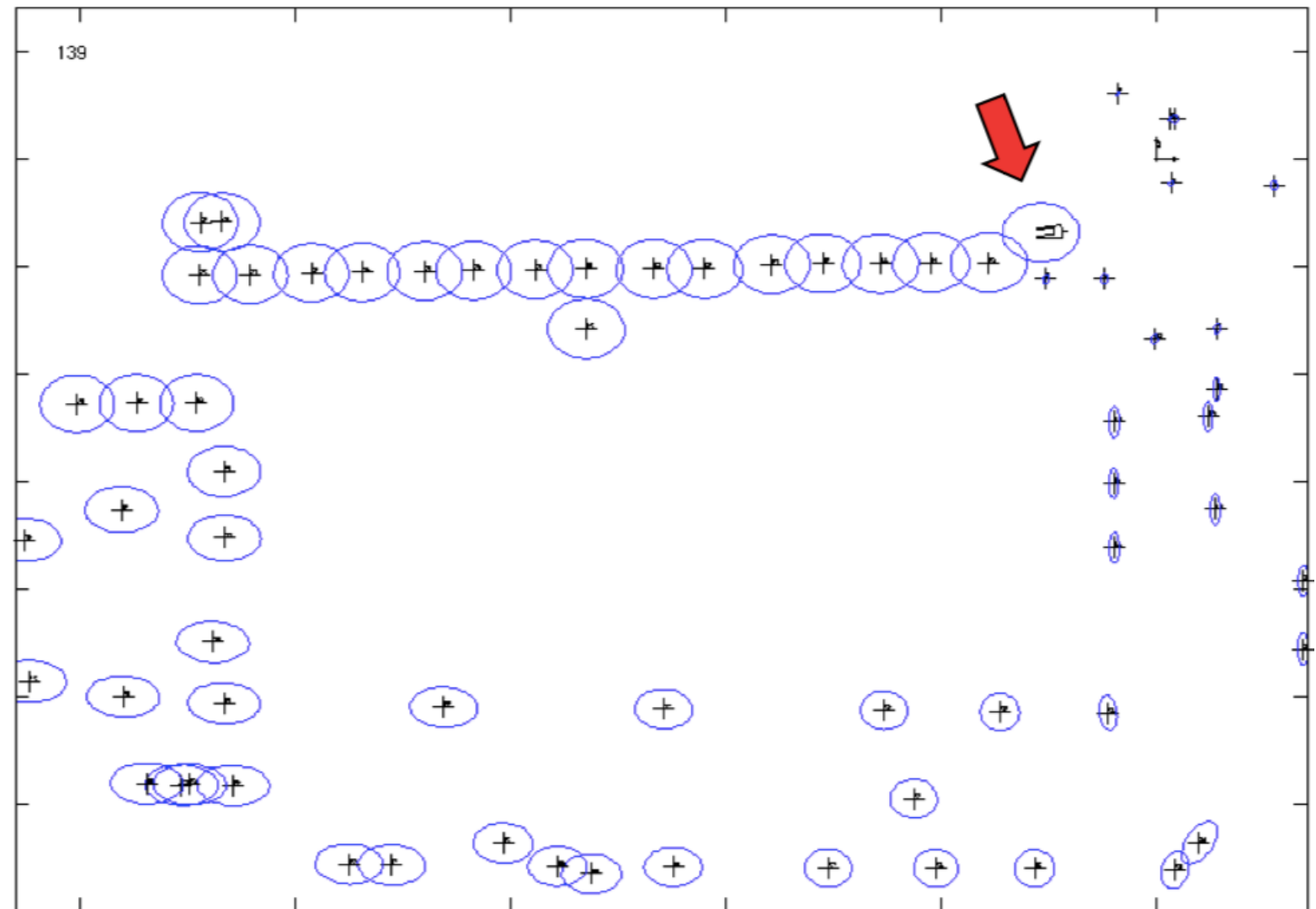
BACK END

Overview of Back-end

- Loop Detection
 - Find candidates of scan pairs/ scan with old map
 - E.g. based on global pose estimated (chain rule) OR image similarity (bag of words)
- Loop Closure
 - E.g. use scan matching to find the transform AND its uncertainty
- Optimization
 - Pose Graph optimization (e.g. minimize error of poses, based on uncertainty)
 - Bundle Adjustment
- Map Rendering
 - E.g. generate grid map based on optimized graph

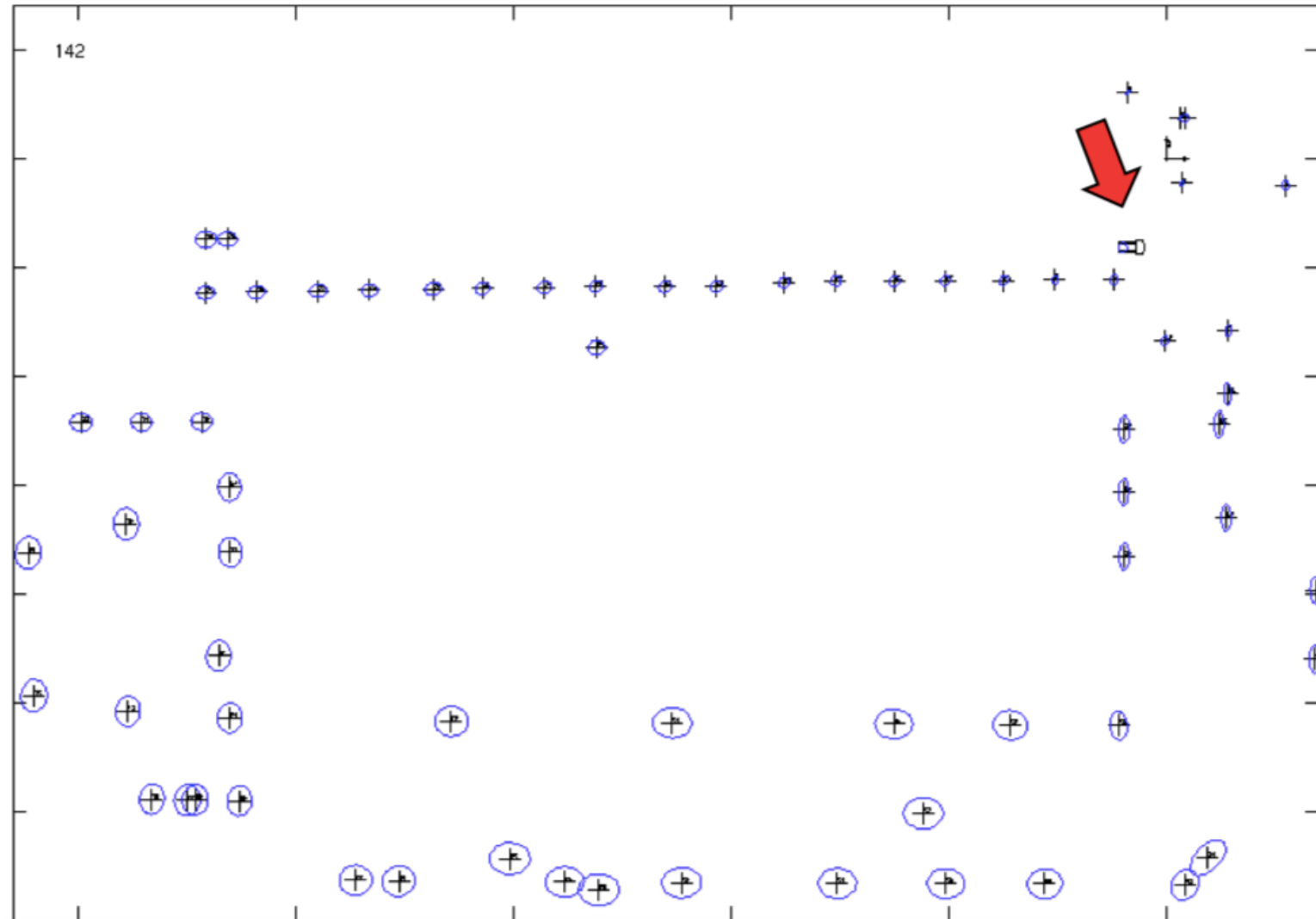
Loop Closure

- Before loop closure



Loop Closure

- After loop closure



Loop Closure

- Recognizing an already mapped area, typically after a long exploration path (the robot “closes a loop”)
- Structurally identical to data association, but
 - high levels of ambiguity
 - possibly useless validation gates
 - environment symmetries
- Uncertainties collapse after a loop closure (whether the closure was correct or not)

Loop Closure

- By revisiting already mapped areas, uncertainties in robot and landmark estimates can be reduced
- This can be exploited when exploring an environment for the sake of better (e.g. more accurate) maps
- Exploration: the problem of where to acquire new information

Robust Loop Closing over Time for Pose Graph SLAM

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OVERVIEW: THREE SLAM PARADIGMS

The Three SLAM Paradigms

- Most of the SLAM algorithms are based on one of the following three different approaches:
 - Extended Kalman Filter SLAM: (called EKF SLAM)
 - Particle Filter SLAM: (called FAST SLAM)
 - Graph-Based SLAM

EKF SLAM: overview

- **Extended state vector** y_t : robot pose x_t + position of all the features m_i in the map:

$$y_t = [x_t, m_0, \dots, m_{n-1}]^T$$

- Example: 2D line-landmarks, size of $y_t = 3 + 2n$: three variables to represent the robot pose + $2n$ variables for the n line-landmarks having vector components

$$(\alpha_i, r_i)$$

$$y_t = [x_t, y_t, \theta_t, \alpha_0, r_0, \dots, \alpha_{n-1}, r_{n-1}]^T$$

- As the robot moves and takes measurements, the state vector and covariance matrix are updated using the standard equations of the extended Kalman filter
- Drawback: EKF SLAM is computationally very expensive.

Particle Filter SLAM: FastSLAM

- **FastSLAM approach**

- Using particle filters.
- Particle filters: mathematical models that represent probability distribution as a set of discrete particles that occupy the state space.

- **Particle filter update**

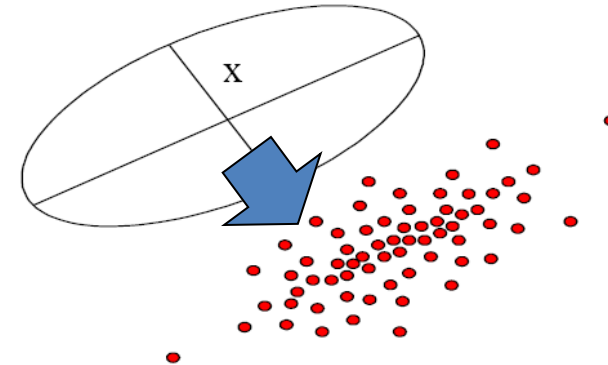
- Generate new particle distribution using motion model and controls

- a) For each particle:

1. Compare particle's prediction of measurements with actual measurements
2. Particles whose predictions match the measurements are given a high weight

- b) Filter resample:

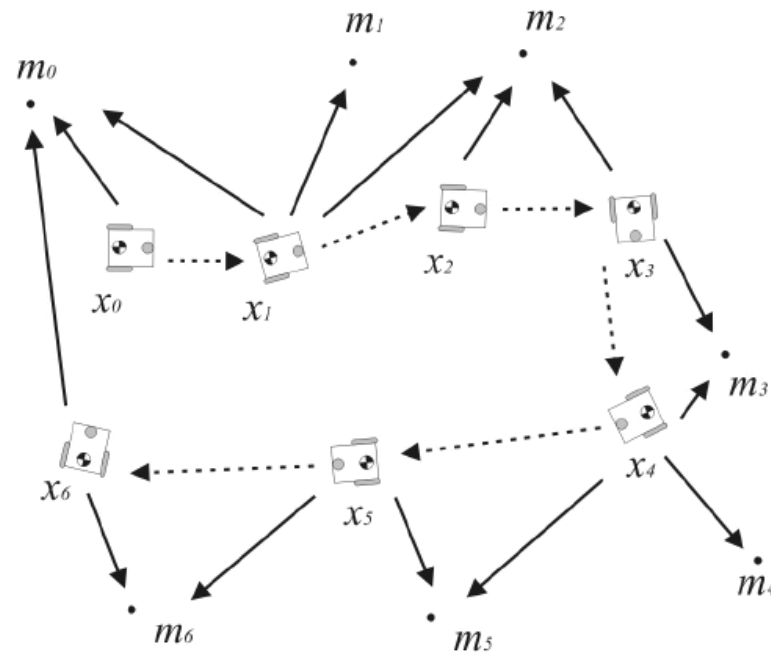
- Resample particles based on weight
- Filter resample
 - Assign each particle a weight depending on how well its estimate of the state agrees with the measurements and randomly draw particles from previous distribution based on weights creating a new distribution.



probability distribution (ellipse) as particle set (red dots)

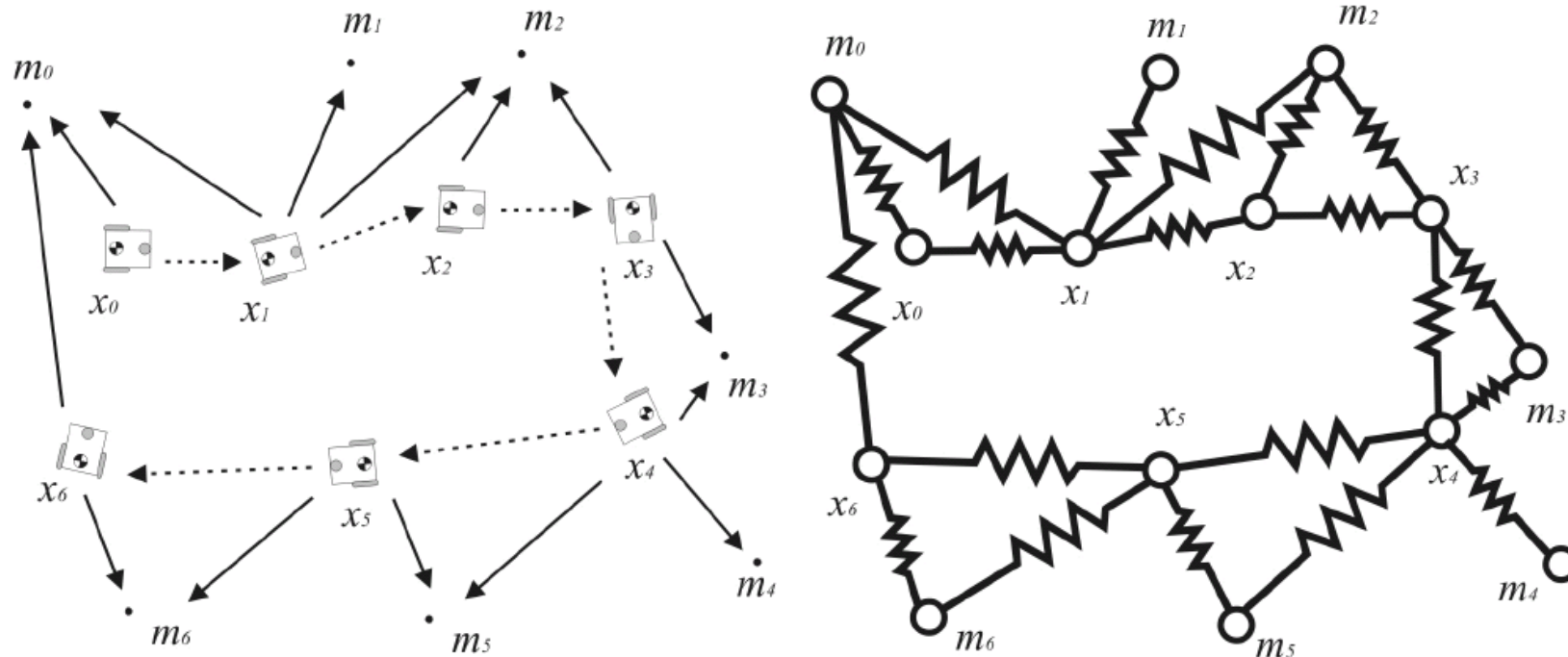
Graph-Based SLAM (1/3)

- SLAM problem can be interpreted as a sparse graph of nodes and constraints between nodes.
- The nodes of the graph are the robot locations and the features in the map.
- Constraints: relative position between consecutive robot poses, (given by the odometry input \mathbf{u}) and the relative position between the robot locations and the features observed from those locations.



Graph-Based SLAM (2/3)

- Constraints are not rigid but soft constraints!
- Relaxation: compute the solution to the full SLAM problem =>
 - Compute best estimate of the robot path and the environment map.
 - Graph-based SLAM represents robot locations and features as the nodes of an elastic net. The SLAM solution can then be found by computing the state of minimal energy of this net



Graph-Based SLAM (3/3)

- Significant advantage of graph-based SLAM techniques over EKF SLAM:
 - EKF SLAM: computation and memory for to update and store the covariance matrix is quadratic with the number of features.
 - Graph-based SLAM: update time of the graph is constant and the required memory is linear in the number of features.
- However, the final graph optimization can become computationally costly if the robot path is long.
- Libraries for graph-based slam: g2o, ceres

SLAM EXAMPLES

Jacobs 3D Mapping – Plane Mapping

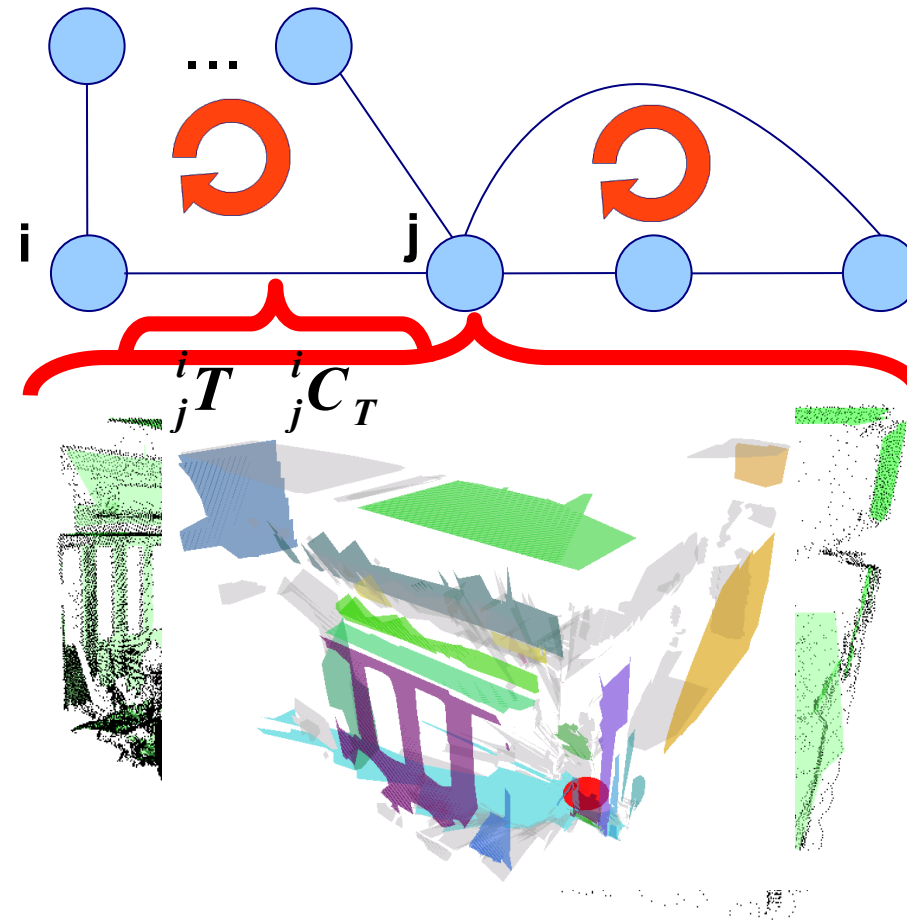
Pose Graph

3D Range Sensing

Plane Extraction

Planar Scan Matching

Relax Loop-Closing Errors



Plane Extraction from 3D Point Clouds

- **Plane Fitting**

- Assumes 3D sensor has radial Gaussian noise dependent on range
- Uses Approximate Least Squares solution to find the best fit.
- Estimates covariance matrix of the plane parameters

- **Range Image Segmentation**

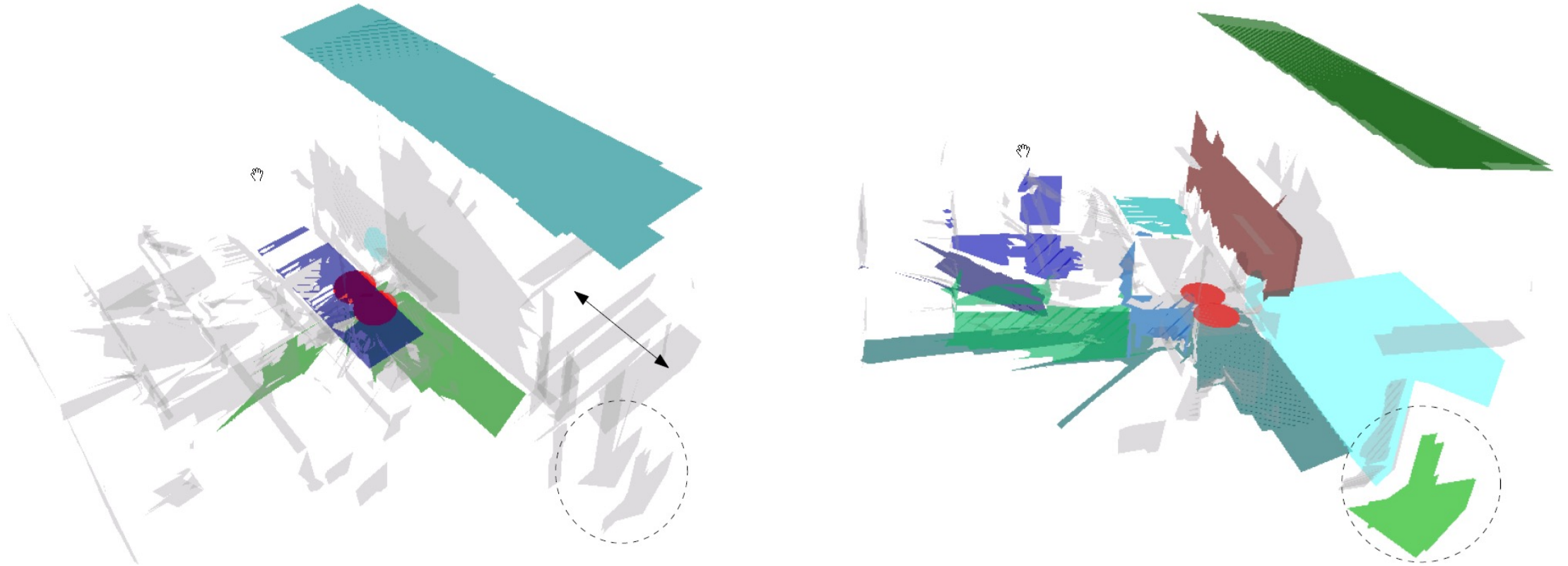
- Is based on region growing algorithm
- Uses incremental formulas, therefore is fast
- Has linear computational complexity

Given a range image, returns a polygonal model i.e. a set of planar features and boundaries.

Plane Registration (Scan Matching)

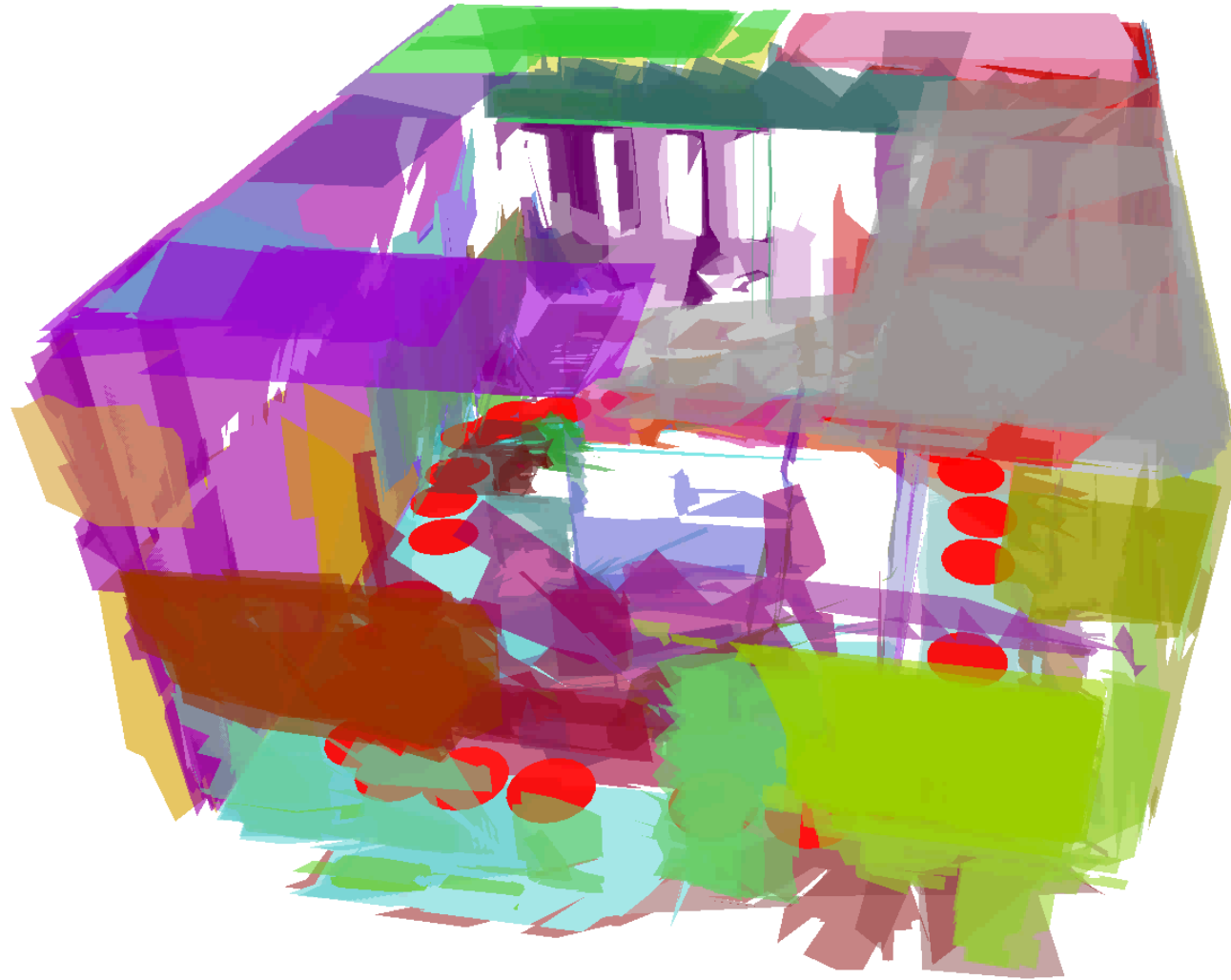
- Determining the correspondence set maximizing the global rigid body motion constraint.
- Finding the optimal decoupled rotations (Wahba's problem) and translations (closed form least squares) with related uncertainties.
- No motion estimates from any other source are needed.
- Very fast
- MUMC: Finding Minimally Uncertain Maximal Consensus
 - Of matched planes
- Idea: select two non-parallel plane matches \Rightarrow fixes rotation and only leaves one degree of translation!

Relaxation of Errors (Translation)



- **Only translation errors are relaxed**
 - Good rotation estimates from the plane matching
 - Non-linear optimization can be exchanged with linear if rotation is assumed to be known precisely.
 - This leads to a fast relaxation method

Experiment Lab Run: 29 3D point-clouds; size of each: $541 \times 361 = 195,301$





Universidad
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en Ingeniería de Aragón
Universidad Zaragoza

ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras

Raúl Mur-Artal and Juan D. Tardós

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LOAM: Lidar Odometry and Mapping in Real-time

(Open Source Code and Open Datasets)

The Field Robotics Center
At the Robotics Institute of Carnegie Mellon University

