CS283: **Robotics Spring 2023: Localization**

Sören Schwertfeger / **师泽仁**

ShanghaiTech University

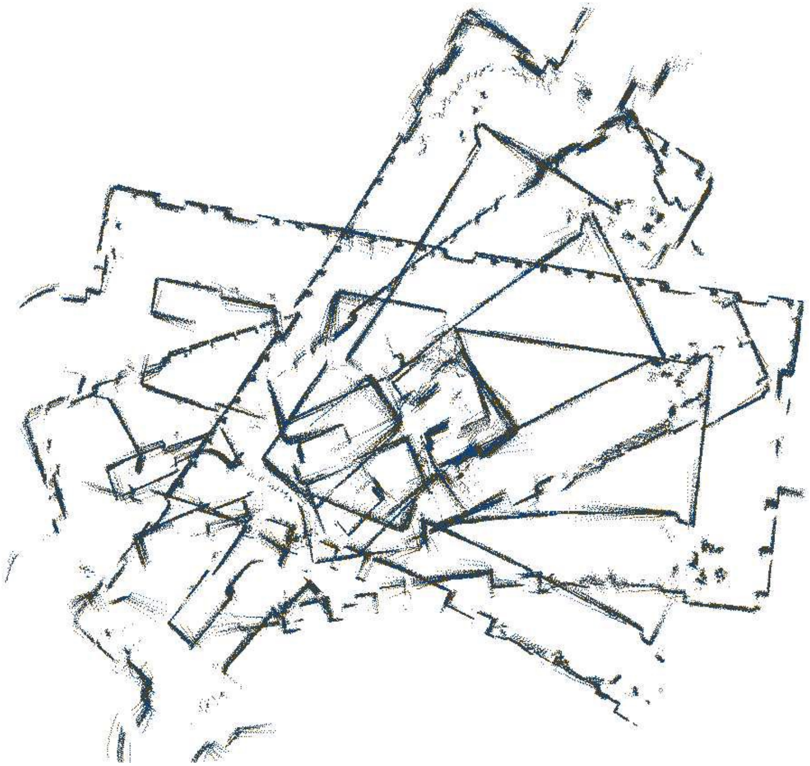
Mapping

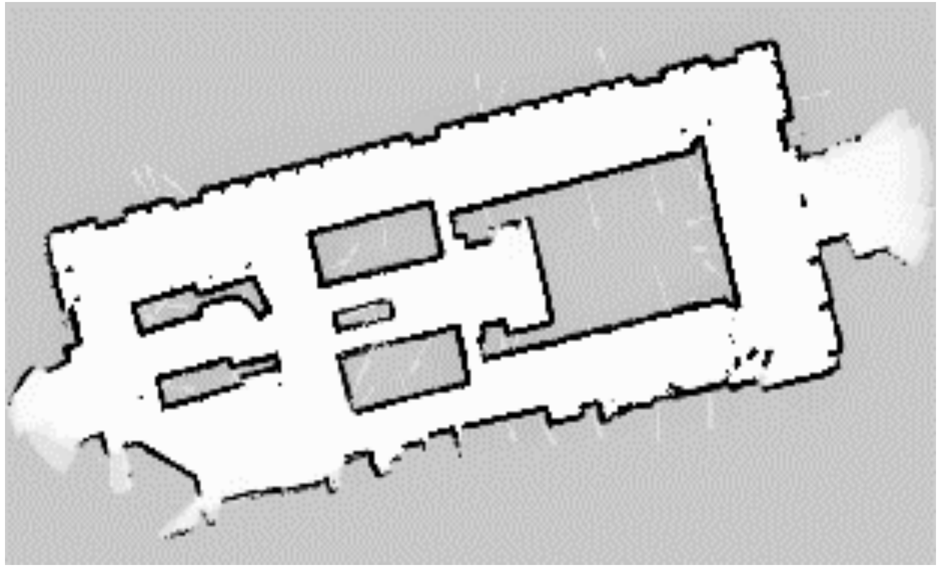
- Process of building a map
- Basic principle:
  1. Initialize the map with unknown or free
  2. Take a sensor scan
  3. Maybe pre-process it (e.g. plane detection)
  4. Localize the robot w.r.t. the map frame (<u>maybe difficult!</u>)
  5. Transform the (processed) sensor scan to the global frame
  6. "Merge" the new data with the old map data, e.g.:
     - Add scanned points to map point cloud
     - Update cells in a probabilistic occupancy grid
  7. Sometimes: Also do ray-casting to mark all cells from sensor to obstacle as free
  8. Repeat for every new sensor scan

- Localization step may need the map (e.g. matching the scan against the map) => both should be done at the same time =>
- Simultaneous Localization and Mapping : SLAM

Cyclic Environments

- Small local error accumulate to arbitrary large global errors!
- This is usually irrelevant for navigation
- However, when closing loops, global error does matter



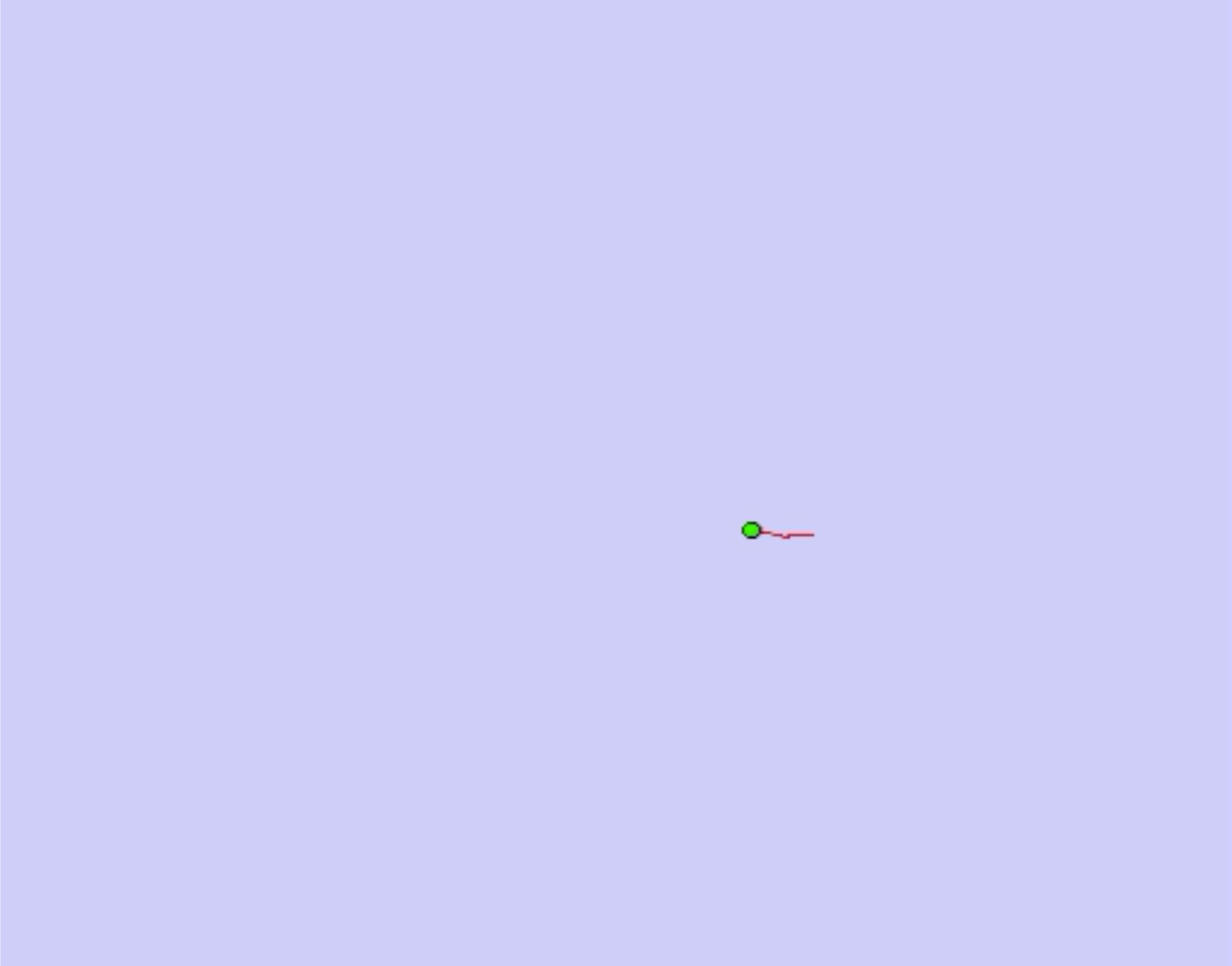


Raw Odometry

- Famous Intel Research Lab dataset (Seattle) by Dirk Hähnel

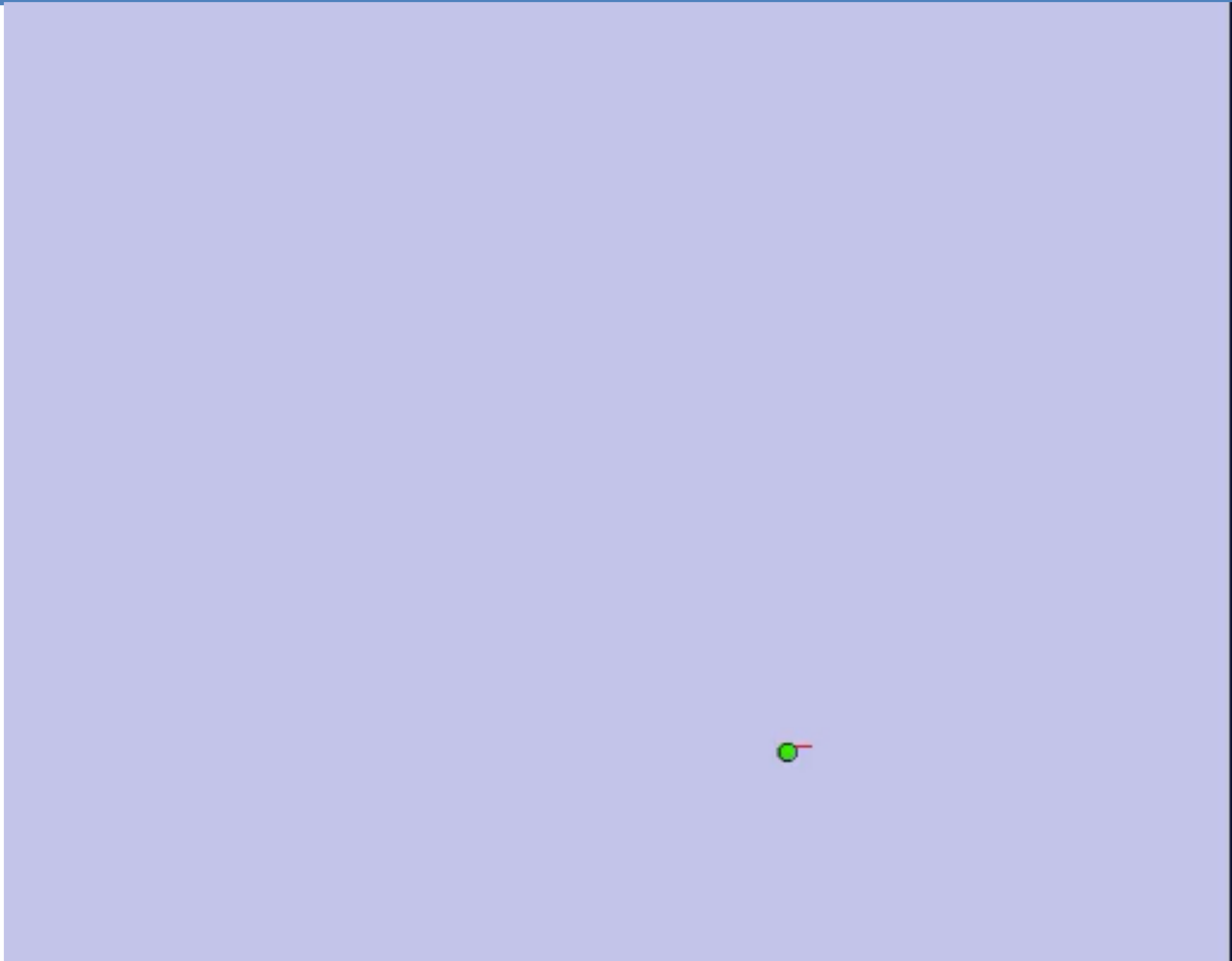
Courtesy of S. Thrun

http://robots.stanford.edu/videos.html

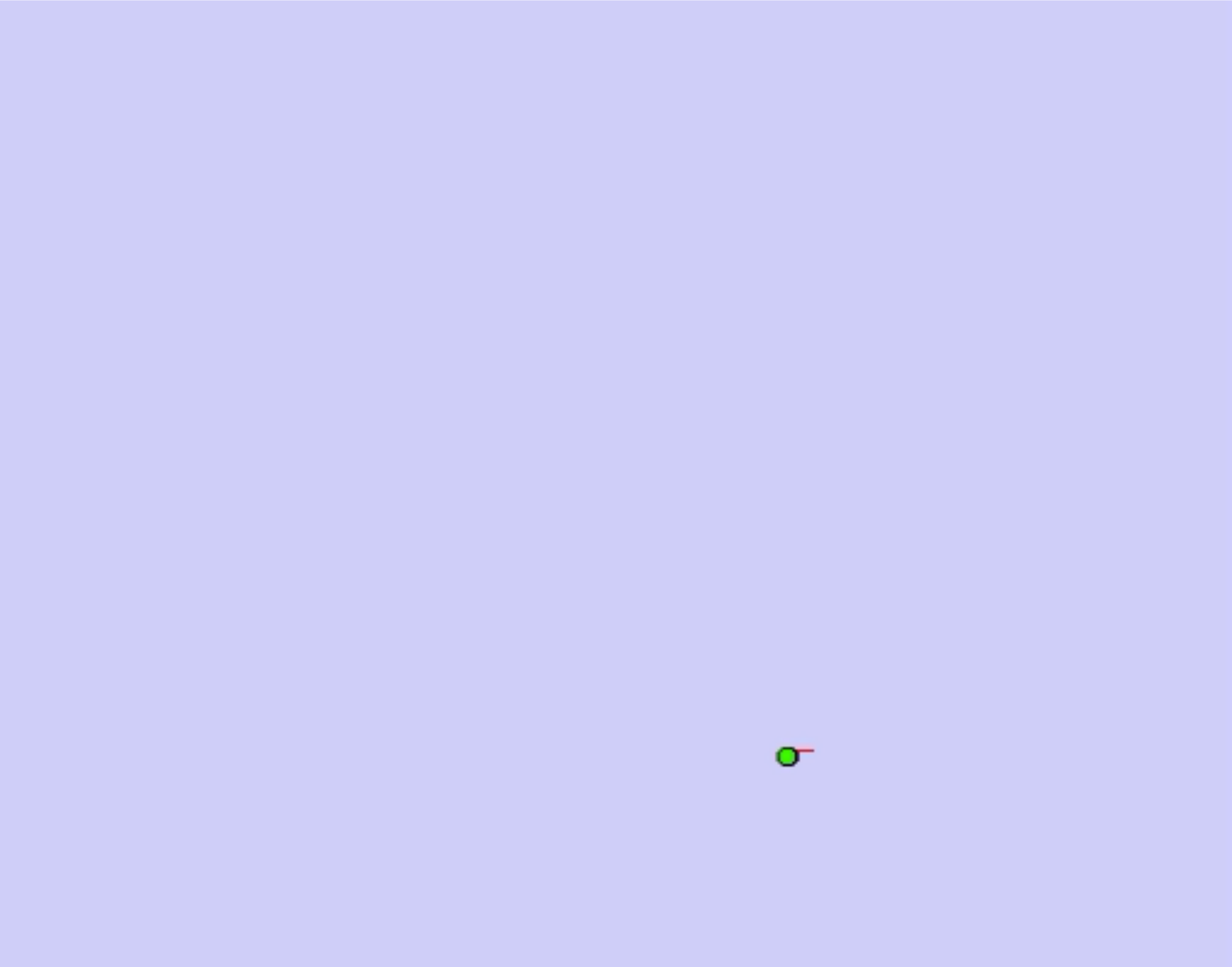


Scan Matching: compare to sensor data from previous scan

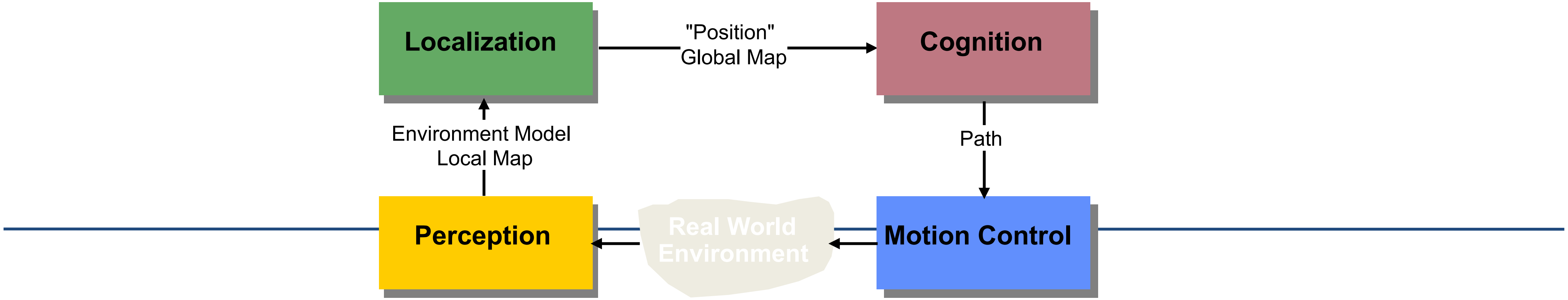
Courtesy of S. Thrun



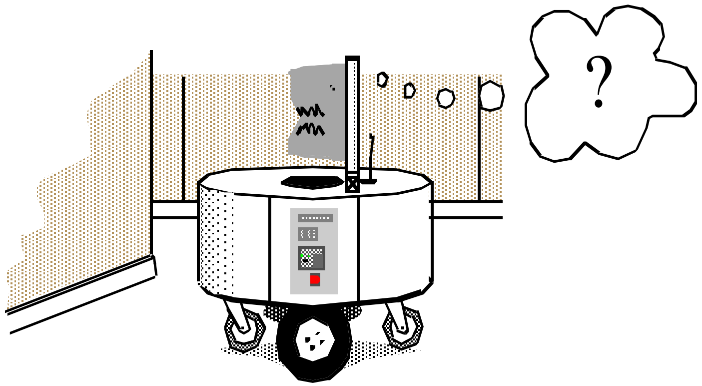
FastSLAM: Particle-Filter SLAM



Courtesy of S. Thrun



LOCALIZATION



Problem: NOISE!

- Exteroceptive Sensor Noise
  - Sensor noise is mainly influenced by environment
    e.g. surface, illumination …
  - and by the measurement principle itself
    e.g. interference two Kinects
  - Sensor noise drastically reduces the useful information of sensor readings. The solution is:
    - to model sensor noise appropriately
    - to take multiple readings into account
    - employ temporal and/or multi-sensor fusion

Effector Noise: Odometry, Deduced Reckoning

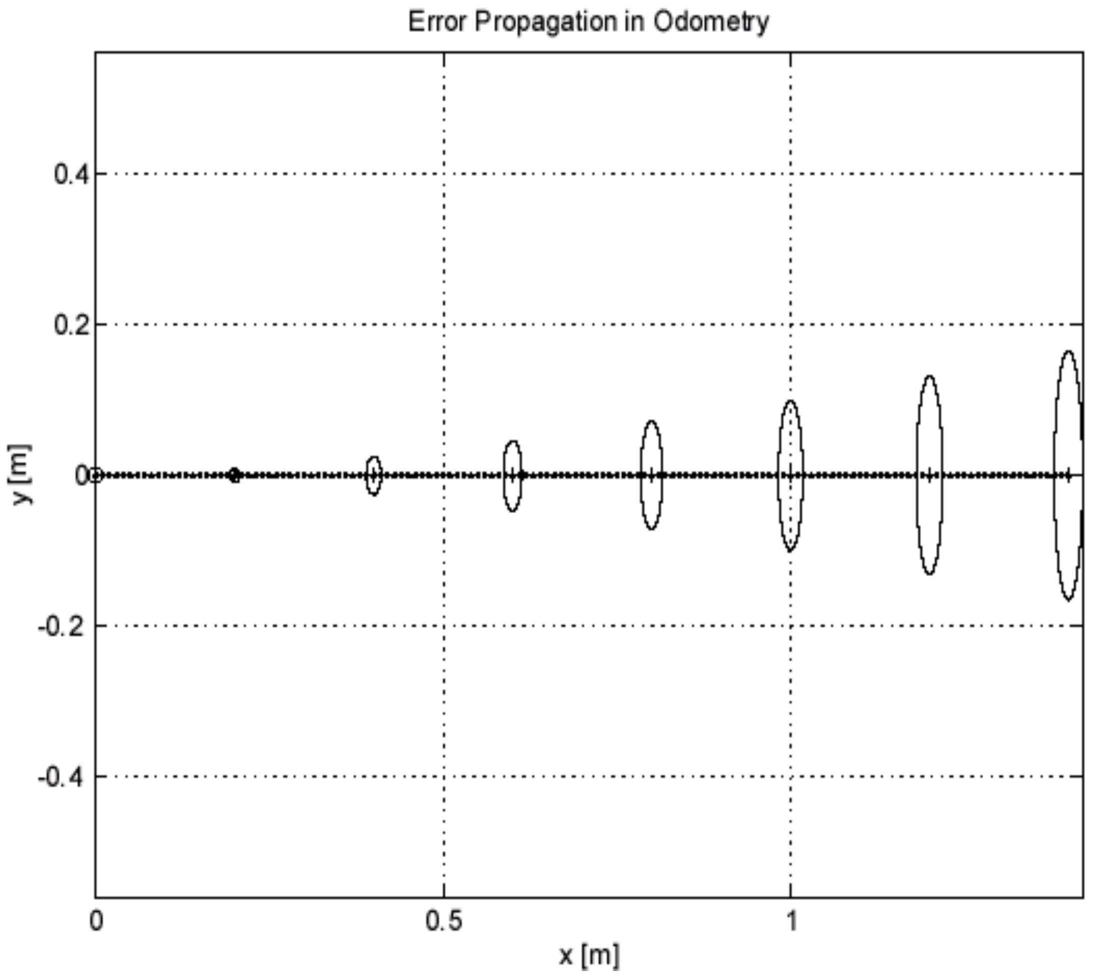
- Odometry and dead reckoning:
  Position update is based on proprioceptive sensors
  - Odometry: wheel sensors only
  - Dead reckoning: also heading sensors

- The movement of the robot, sensed with wheel encoders and/or heading sensors is integrated to the position.
  - Pros: Straight forward, easy
  - Cons: Errors are integrated -> unbound

- Using additional heading sensors (e.g. gyroscope) might help to reduce the cumulated errors, but the main problems remain the same.

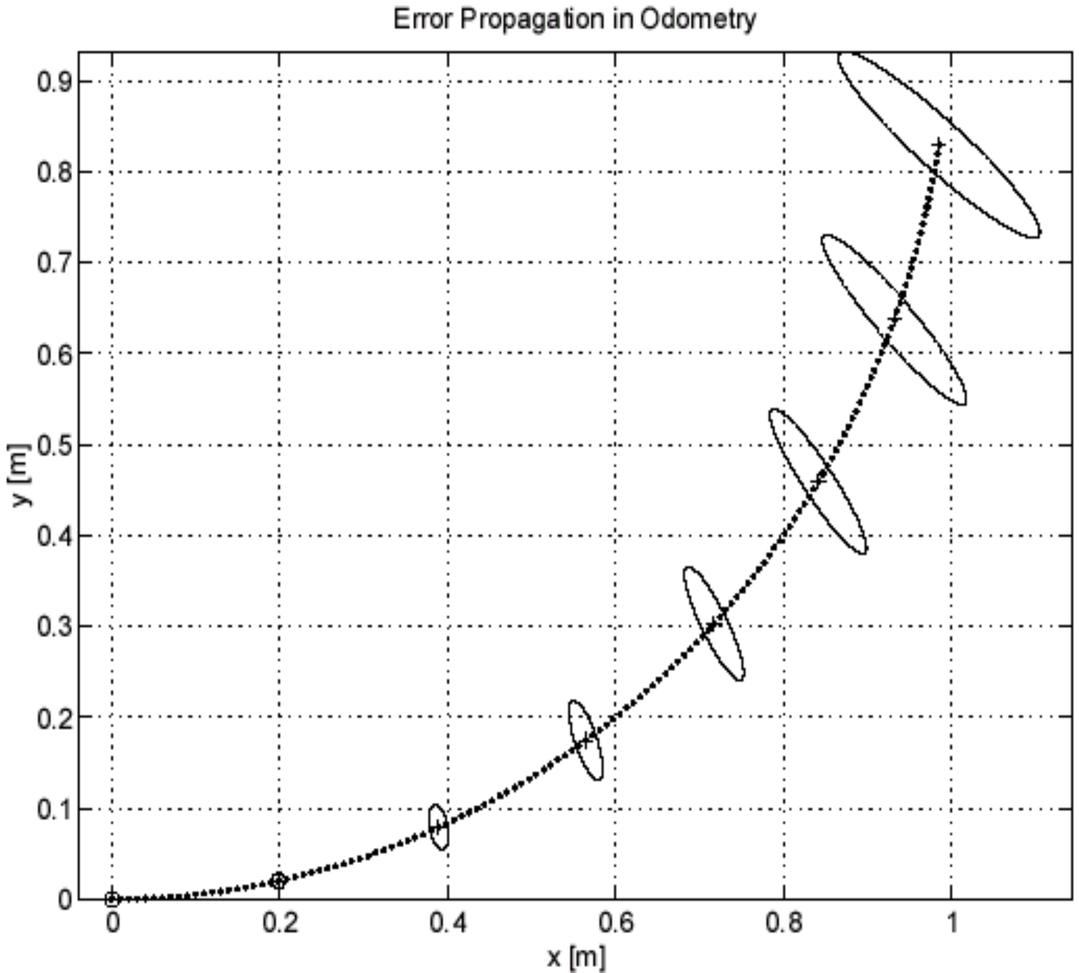
Odometry: Growth of Pose uncertainty for Straight Line Movement

- Note: Errors perpendicular to the direction of movement are growing much faster!



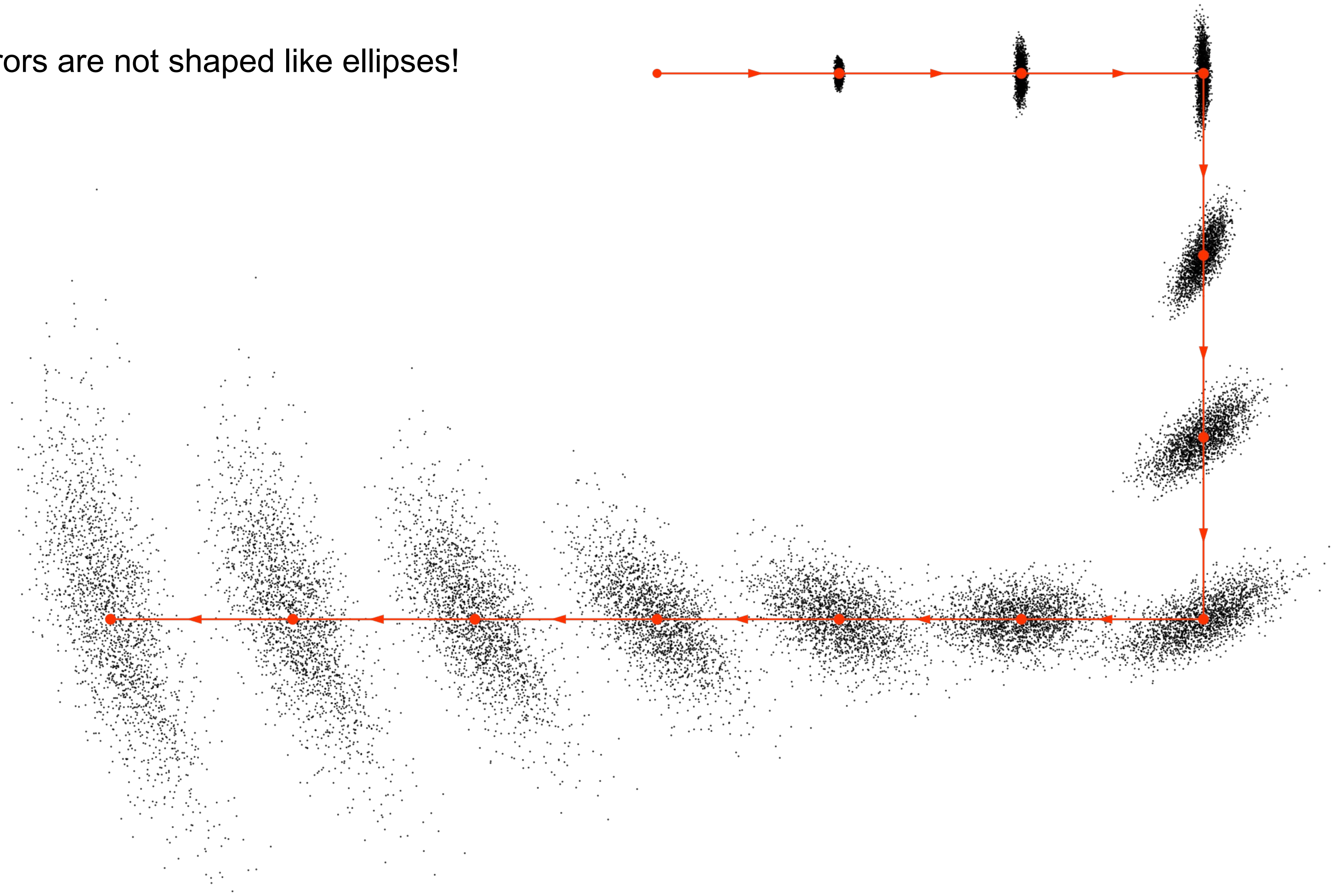
Odometry: Growth of Pose uncertainty for Movement on a Circle

- Note: Errors ellipse in does not remain perpendicular to the direction of movement!



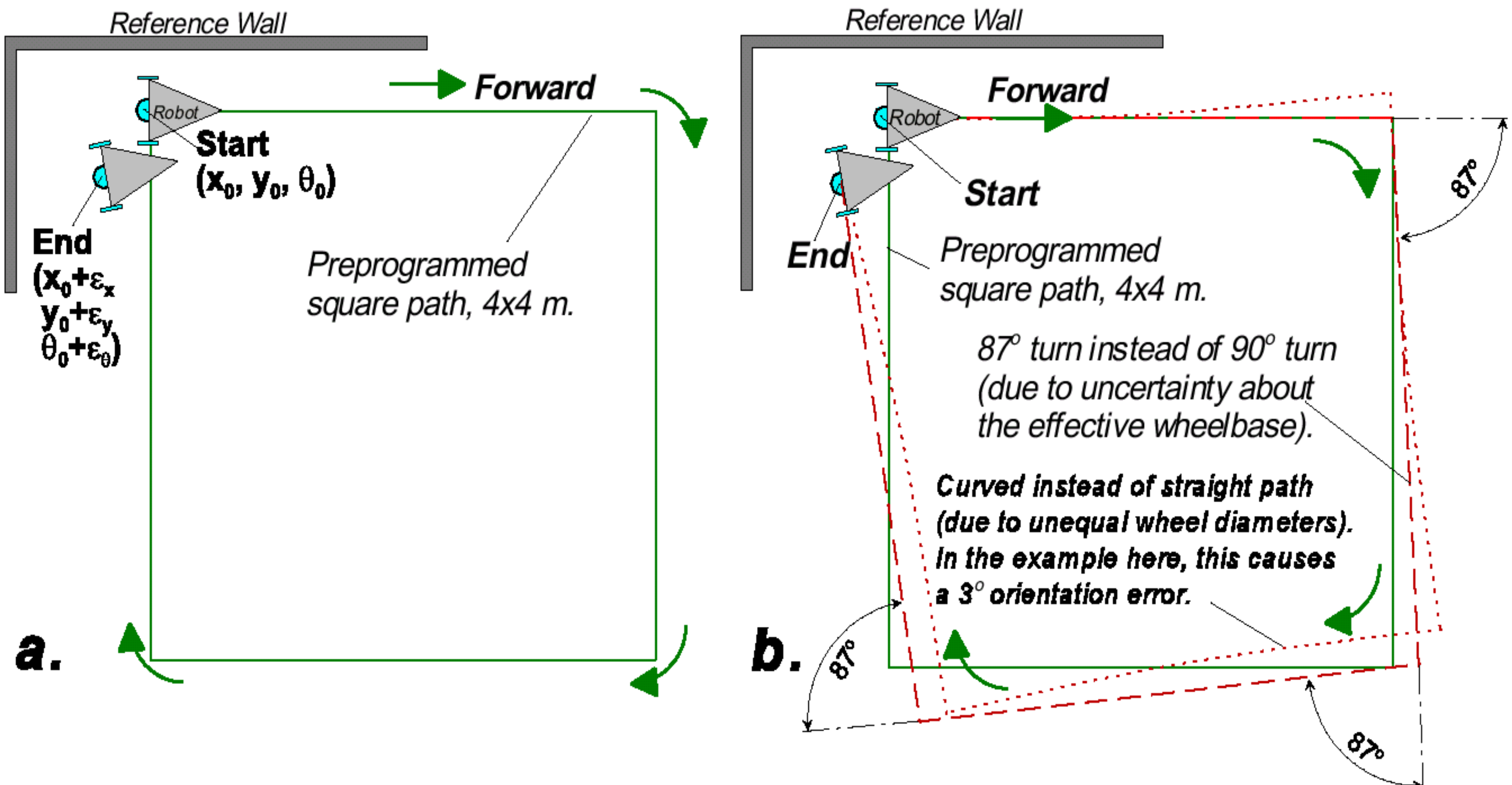
Odometry: example of non-Gaussian error model

- Note: Errors are not shaped like ellipses!



Odometry: Calibration of Errors

- The unidirectional square path experiment



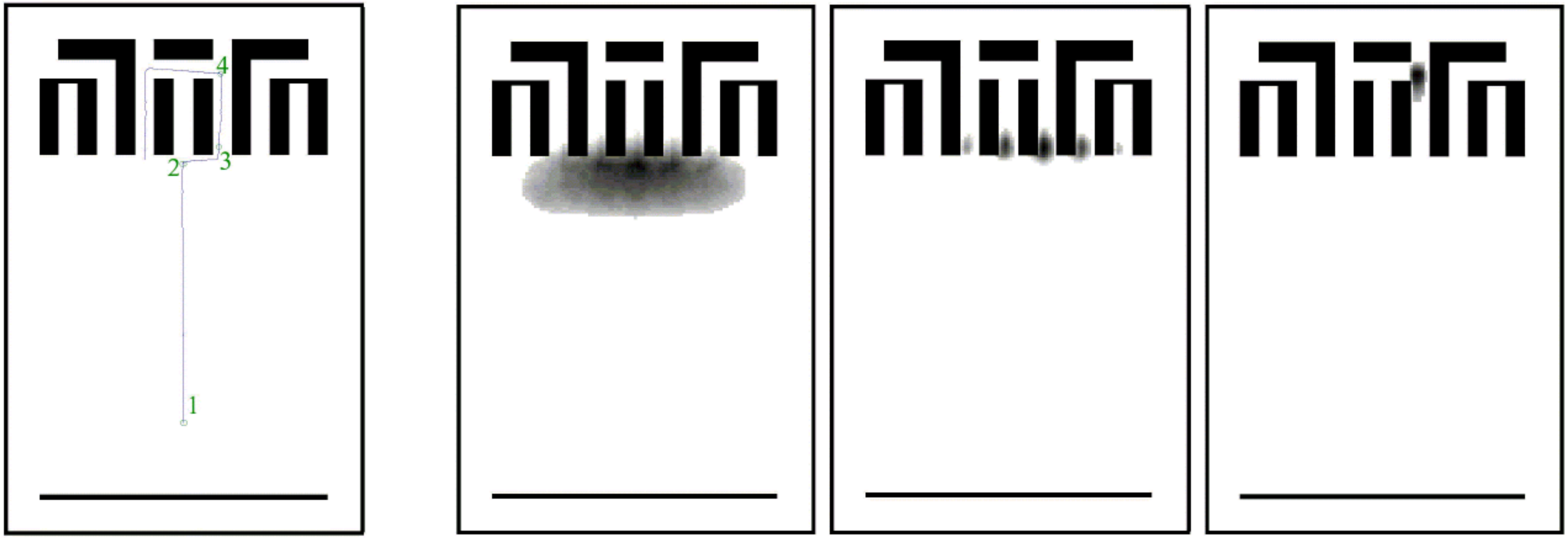
LOCALIZATION METHODS

Localization

- Based on control commands => Open Loop!
- Wheel odometry
  - Compass, Accelerometer, Gyro => IMU
- Scan Matching of Range Sensors == Registration (rigid => no scaling or shearing)
  - ICP: scan to scan or scan to map
    - Needs good initial guess
  - NDT registration
  - Feature-based registration
  - Direct/ optimization based registration
- Grid-based Localization
- Kalman Filter Based Localization
- Monte-Carlo Localization (MCL) == Particle Filter
  - Adaptative MCL => AMCL
- Visual Odometry (VO)
  - With IMU: Visual Inertial Odometry (VIO)
- SLAM techniques
- 3D Reconstruction
  - Structure from Motion/ Bundle Adjustment
  - Localization is by-product
- Absolute Localization:
  - GPS
  - Markers (e.g. QR code)
  - Landmarks (e.g. ShanghaiTech Tower)

Grid-based Localization - Multi Hypothesis

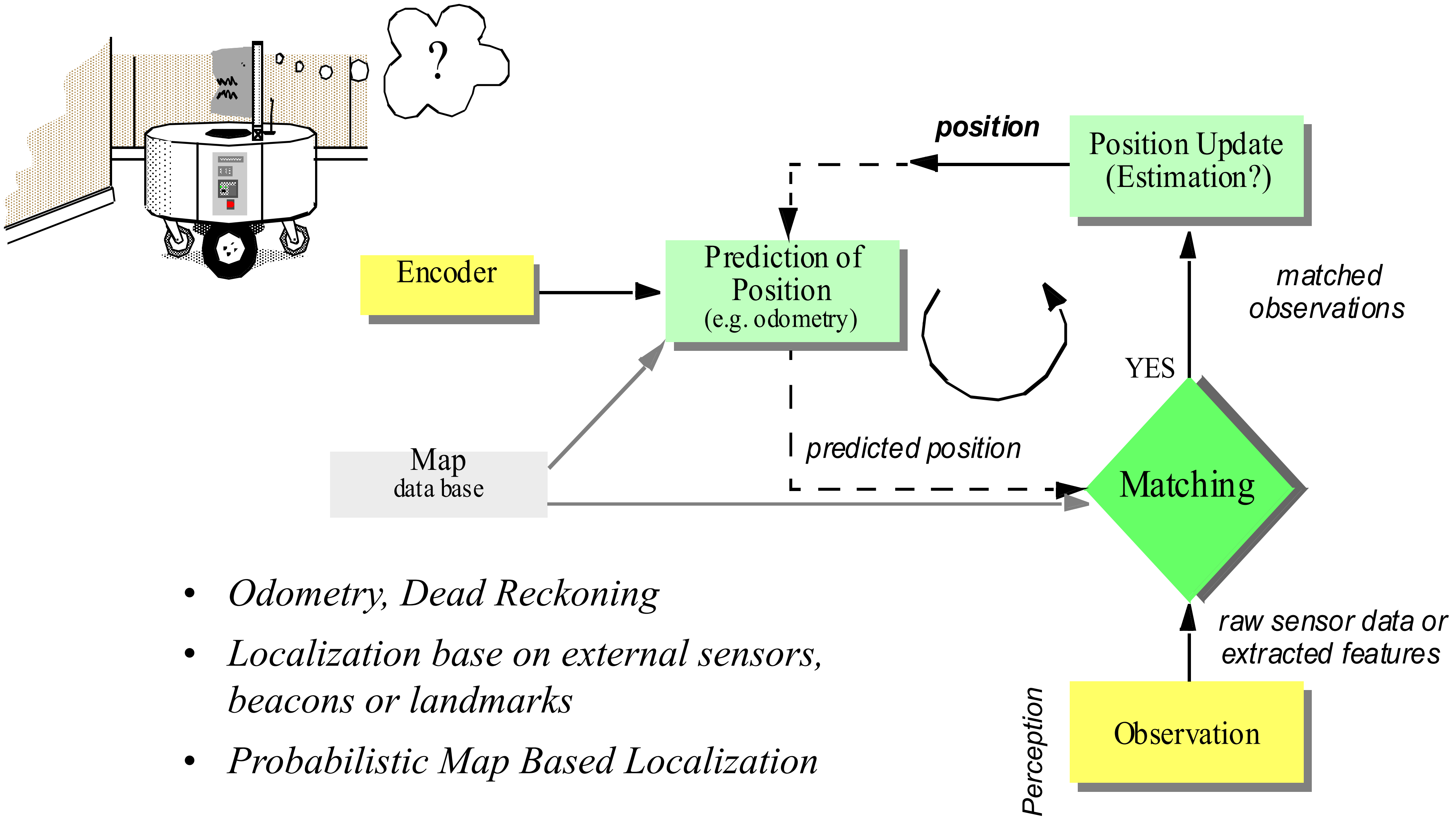
Probability of robot location saved in grid cells – based on combination of:
1) cell values of previous step; 2) odometry; 2) scan matching



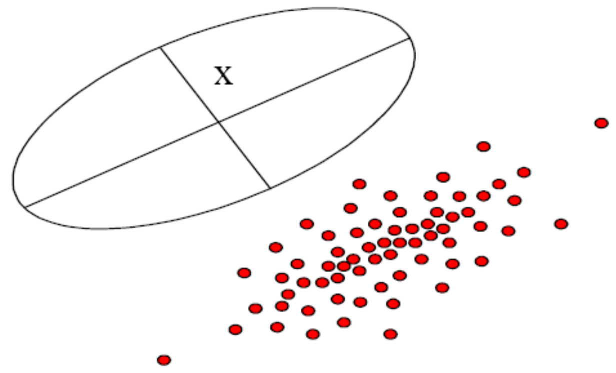
Path of the robot *Belief states at positions 2, 3 and 4*

Courtesy of W. Burgard

Map based localization



- *Odometry, Dead Reckoning*
- *Localization base on external sensors, beacons or landmarks*
- *Probabilistic Map Based Localization*



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

Monte Carlo Localization (MCL)

- Input: Global, known map and laser scan
- Particle filter: set of particles representing a robot state
  - Here: robot pose (position & orientation)
  - Particle filter SLAM (e.g. FastSLAM): also map!
  - Particles are sampled based on probability distribution
- Assign weights (scores) to particles based on how well the scan matches to the map, given this pose
- Markov property: Current state only depends on previous state

- Algorithm:

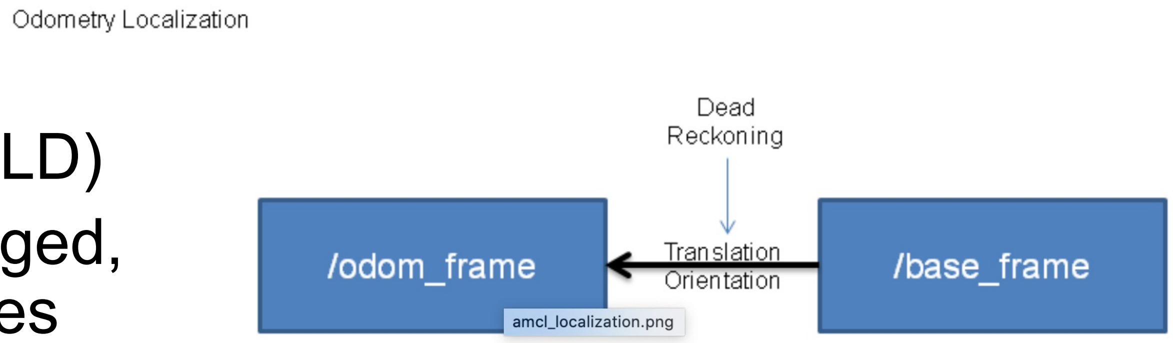
1. For all particles:
   1. Apply motion update (e.g. odometry)
   2. Apply the sensor update (scan match) and calculate new weights
2. Re-Sample particles based on their weights

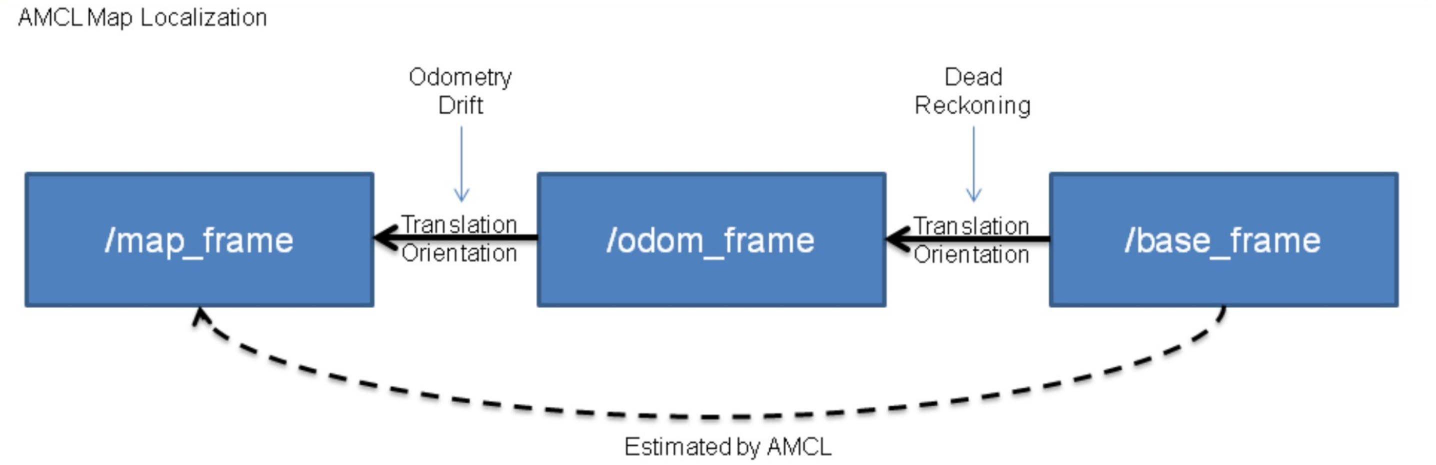
- Can solve the kidnapped robot problem (also wake-up robot problem)
- Problem: Particle of correct pose might not exist…

Adaptive Monte Carlo Localization (AMCL)

- Sample particles adaptively
  - Based on error estimate
  - Kullback-Leibler divergence (KLD)
  - => when particles have converged, have a fewer number of particles

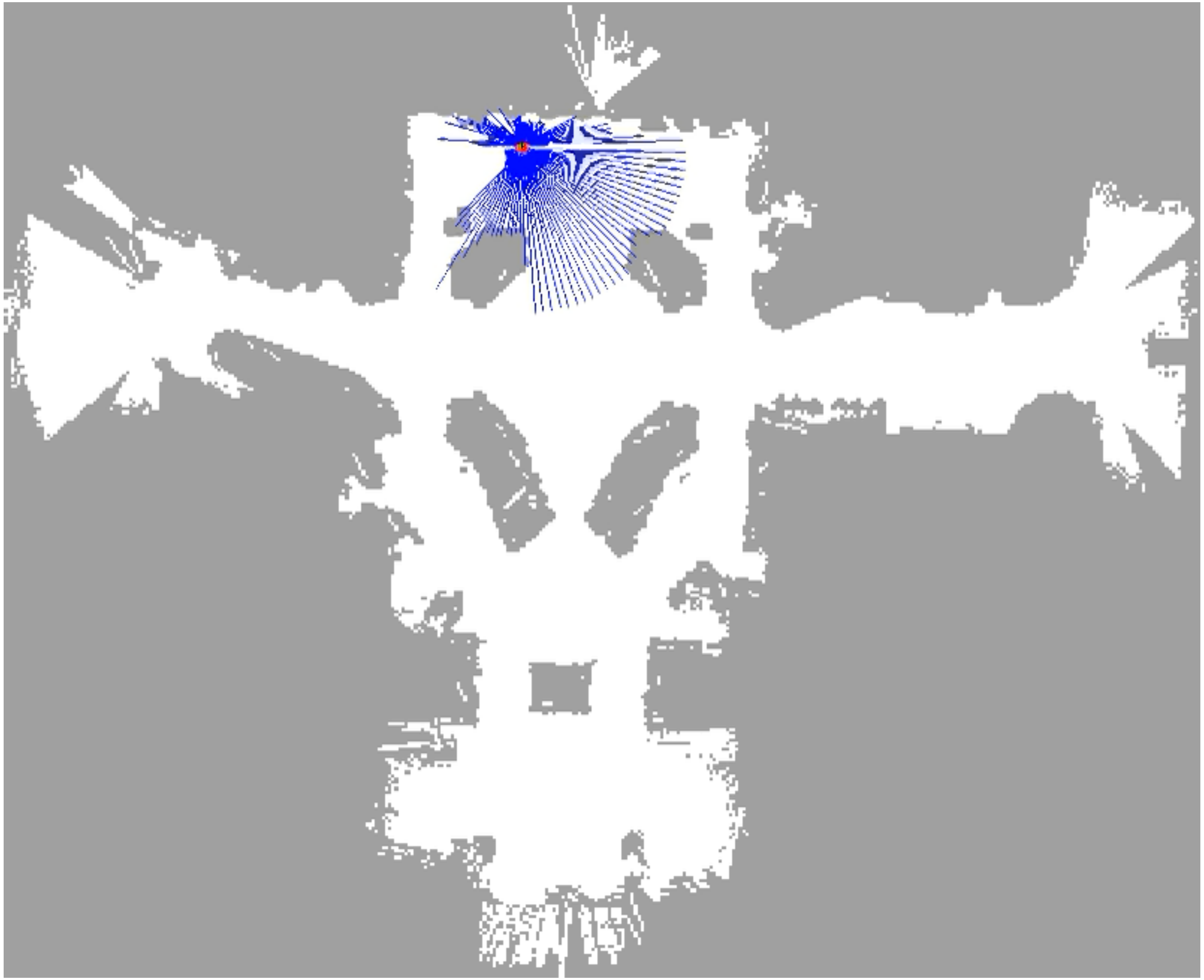
  - Sample size is re-calculated each iteration



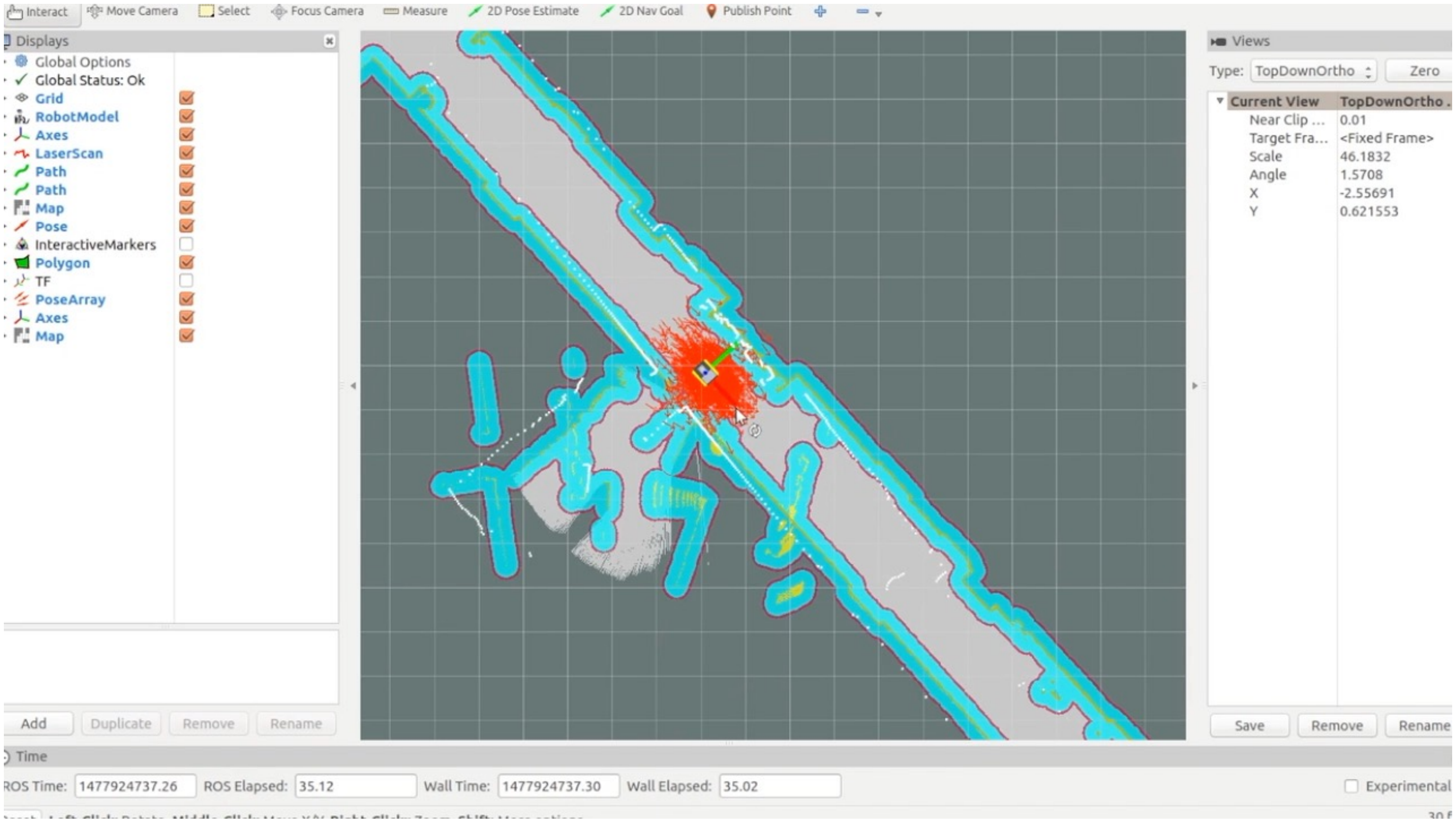


- http://wiki.ros.org/amcl
- Used by the ROS Navigation stack

MCL & Robot Kidnapping



AMCL in ROS

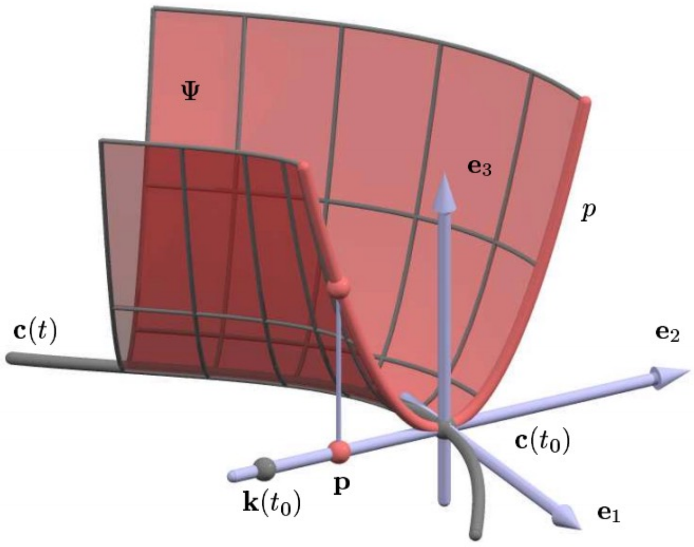

Interact
Move Camera
Select
Focus Camera
Measure
2D Pose Estimate
2D Nav Goal
Publish Point
Displays
Global Options
Global Status: Ok
Grid
RobotModel
Axes
LaserScan
Path
Path
Map
Pose
InteractiveMarkers
Polygon
TF
PoseArray
Axes
Map
Add
Duplicate
Remove
Rename
Views
Type: TopDownOrtho
Zero
Current View TopDownOrtho
Near Clip ... 0.01
Target Fra... <Fixed Frame>
Scale 46.1832
Angle 1.5708
X -2.55691
Y 0.621553
Save
Remove
Rename
Time
ROS Time: 1477924737.26
ROS Elapsed: 35.12
Wall Time: 1477924737.30
Wall Elapsed: 35.02
Experimental

Scan Matching/ Registration

- Take one sensor scan
- Match against:
  - Another sensor scan
  - Against the map
- Output:
  - The Transform (2D: 3DoF; 3D: 6DoF; each maybe with scale)
  - Uncertainty about the result (e.g. covariance matrix) and/ or registration error/ fitting error
- Used for Localization
- Most famous algorithm: ICP (Iterative Closest Point)

Registration Methods for Range Data

- ICP
- NDT
- Robust point matching (soft point correspondences)
- Coherent point drift
- Kernel correlation
- Approximations of the squared distance functions to curves and surfaces
- Direct Methods/ Optimization based (also for images)

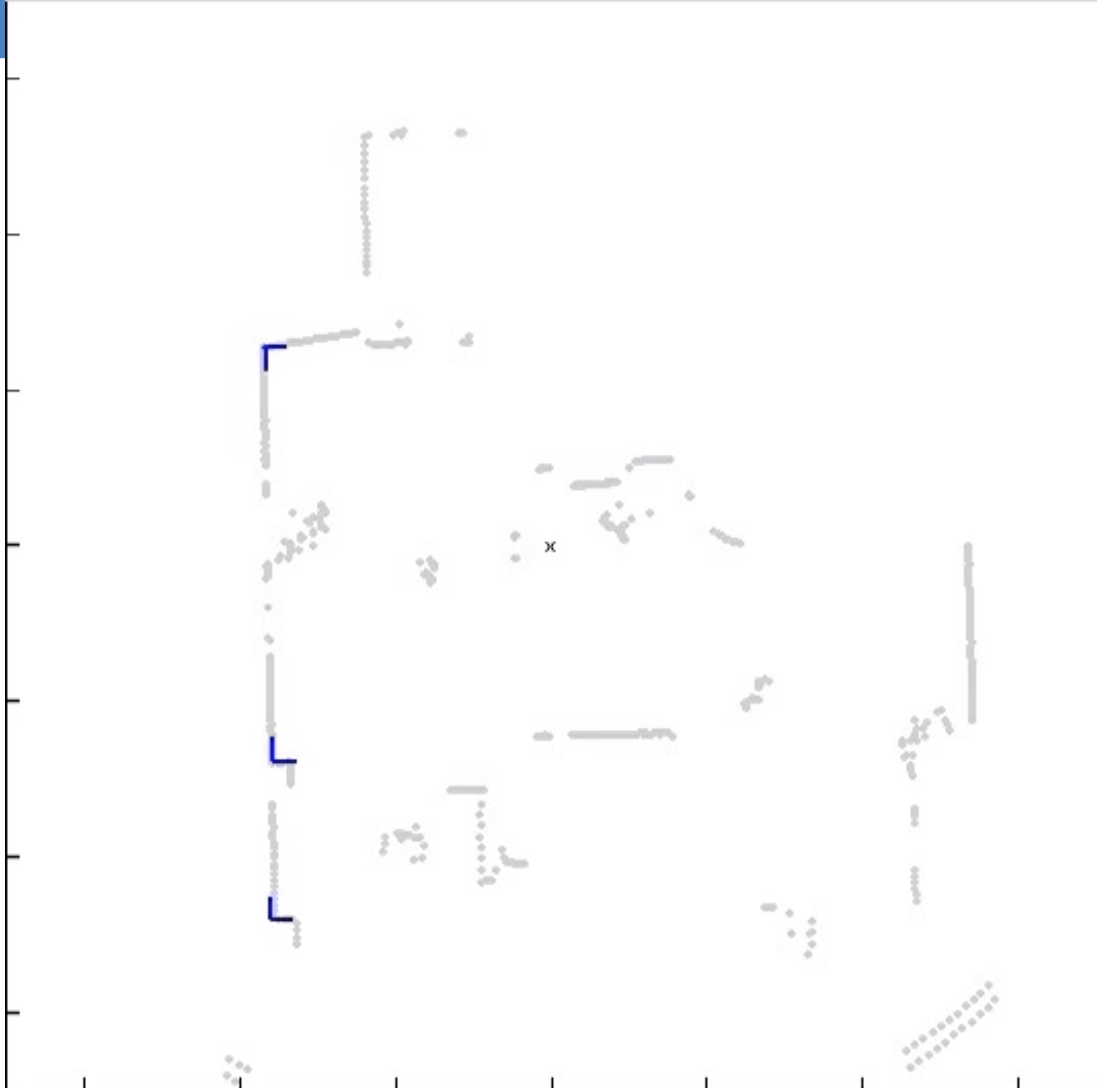


- Feature extracting methods (also for images)
  - Corners in point clouds
  - Lines
  - Planes
  - Feature Descriptors/ also via Deep Learning

- Spectral methods (also for images)

SLAM using corner structures

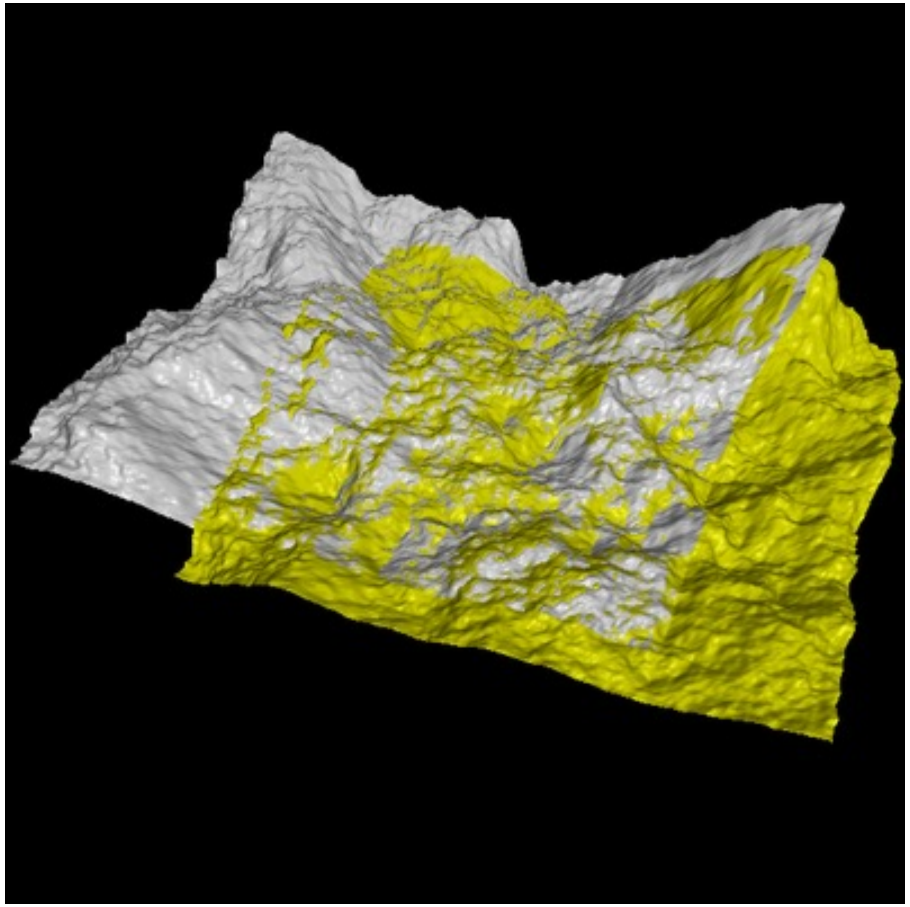
- 2D LRF Scan
- Detect corners in the scan
- Map corners, localization against corners



ICP

ICP: Iterative Closest Points Algorithm

- Align two partially-overlapping point sets (2D or 3D)
- Given initial guess for relative transform
- Warning: Using 3D ICP for 2D data may mirror the data (e.g. 180 degree roll)!
  - Use 2D ICP!
- ROS: Point Cloud Library (PCL)



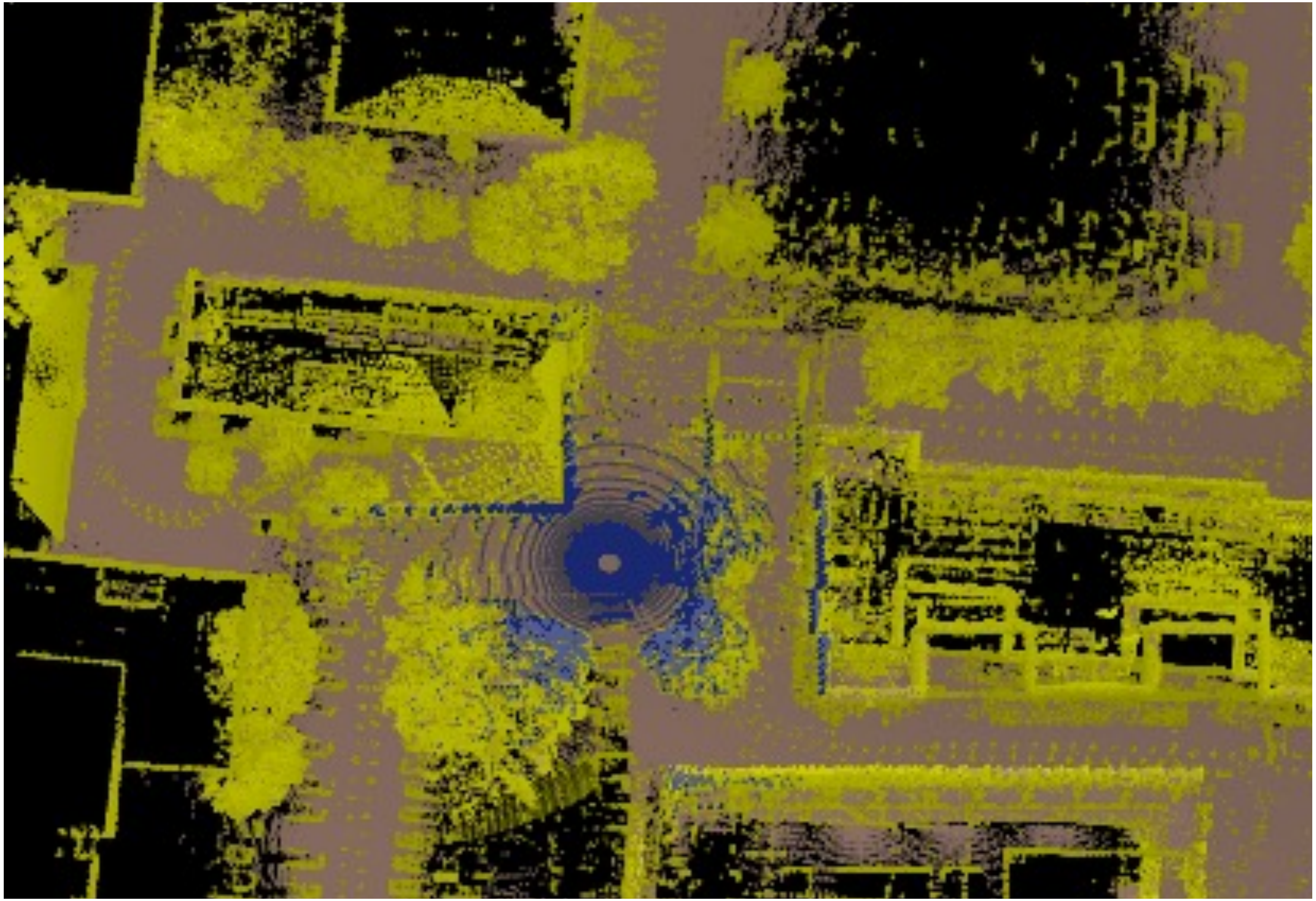
Material derived from Ronen Gvili : *www.cs.tau.ac.il/~dcor/Graphics/adv-slides/**ICP**.ppt*

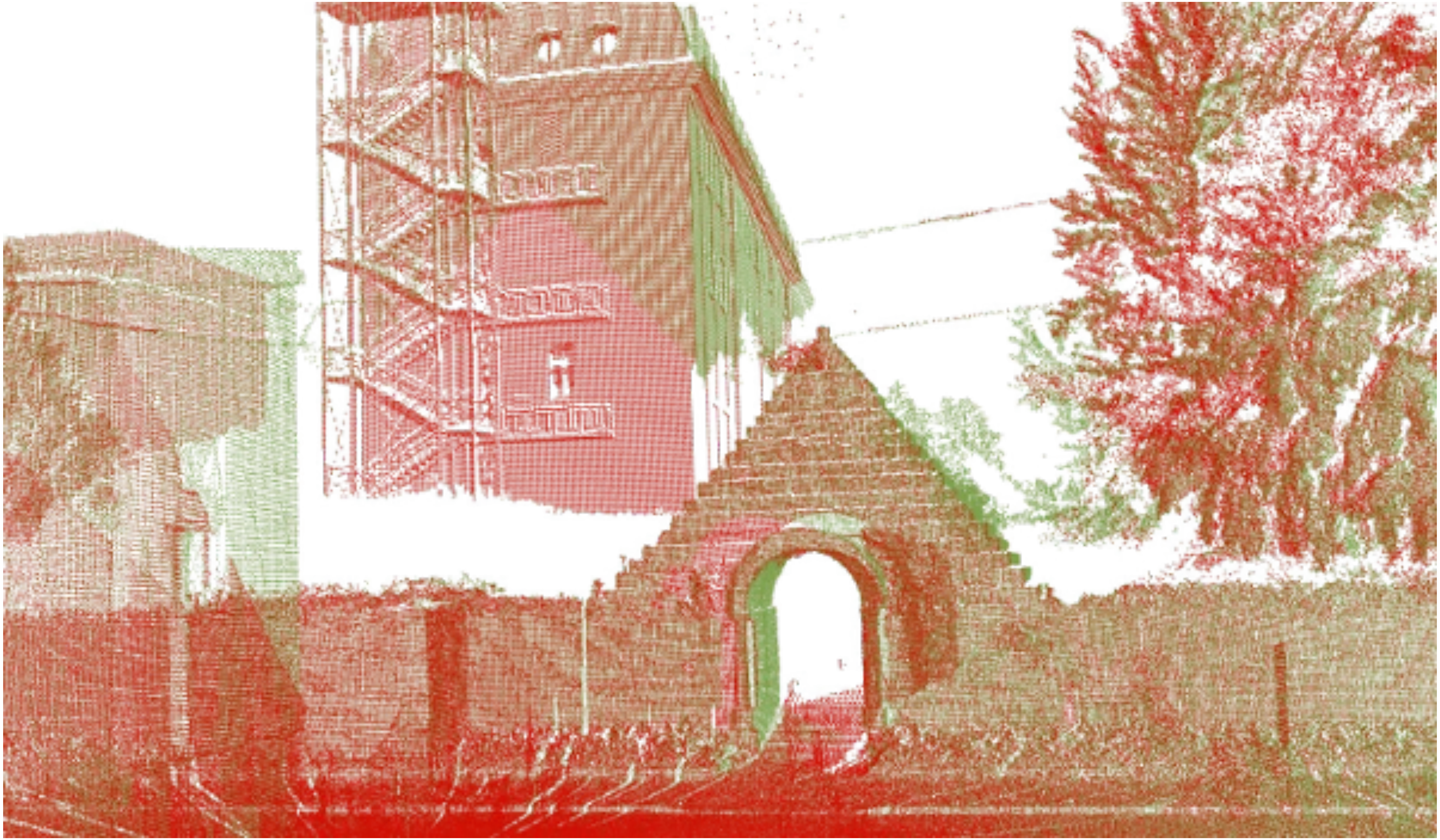
Data Types

- Point sets
- Line segment sets (polylines)
- Implicit curves : $f(x,y,z) = 0$
- Parametric curves : $(x(u),y(u),z(u))$
- Triangle sets (meshes)
- Implicit surfaces : $s(x,y,z) = 0$
- Parametric surfaces $(x(u,v),y(u,v),z(u,v)))$

Motivation

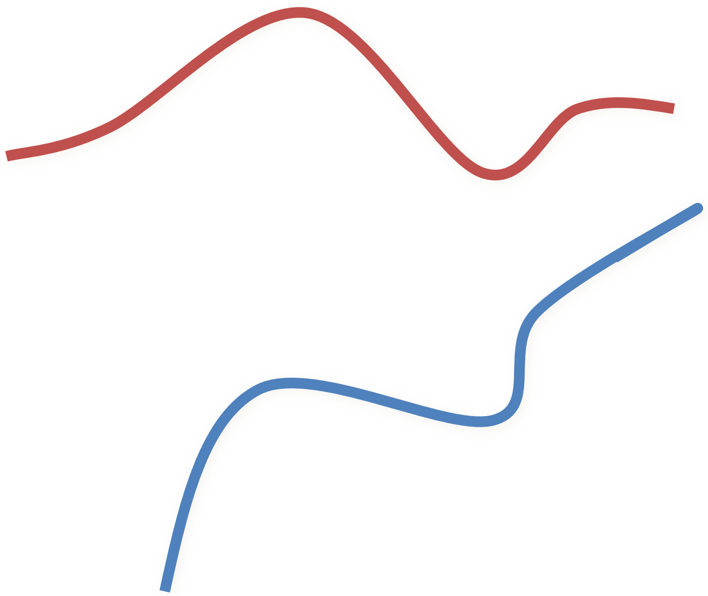
- Scan Matching - Registration
- Shape inspection
- Motion estimation
- Appearance analysis
- Texture Mapping
- Tracking





Aligning 3D Data

- Continuous lines or a set of points…

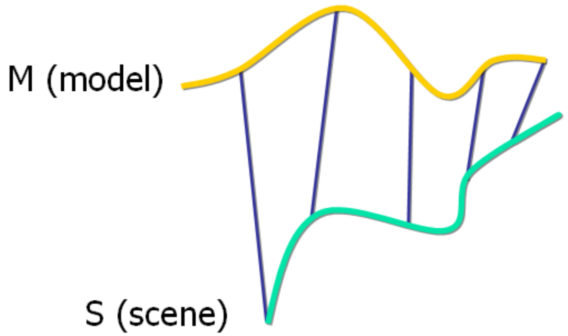


Corresponding Point Set Alignment

- Let M be a model point set. (or map or previous scan)
- Let S be a scene point set. (current scan)

We assume :

1. $N_M = N_S$.
2. Each point S_i correspond to M_i .



Corresponding Point Set Alignment

The Mean Squared Error (MSE) objective function :

$$f(R,T) = \frac{1}{N_S}\sum_{i=1}^{N_S}\left\| m_i - Rot(s_i) - Trans \right\|^2$$

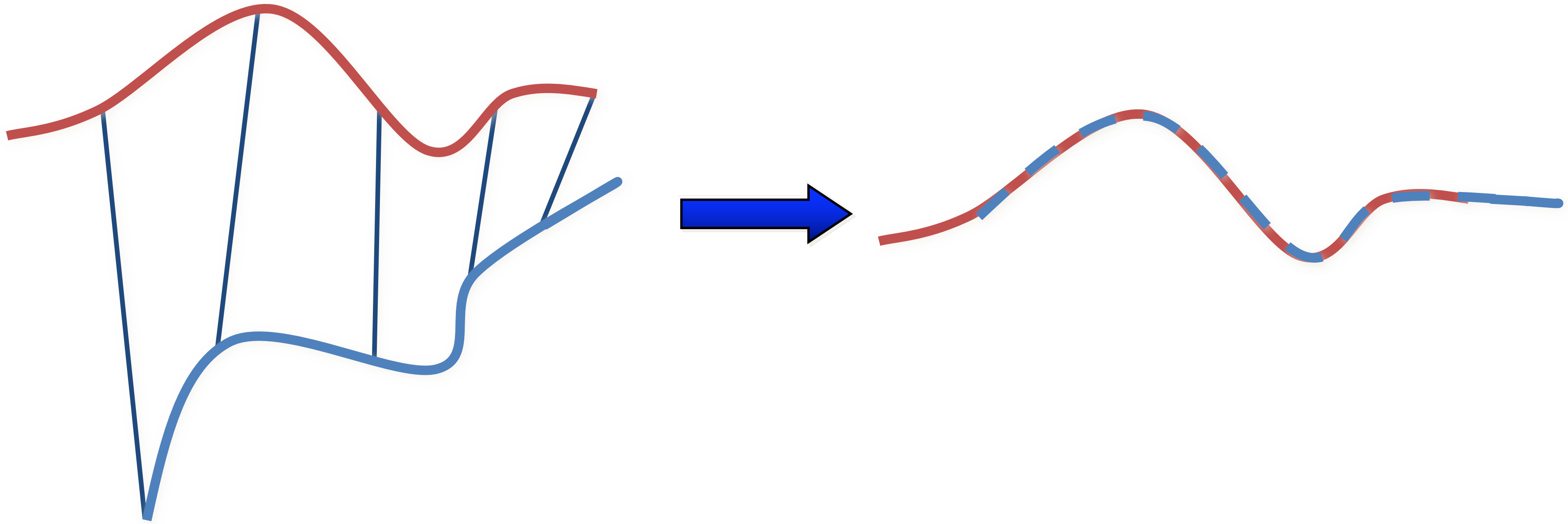
$$f(q) = \frac{1}{N_S}\sum_{i=1}^{N_S}\left\| m_i - R(q_R)s_i - q_T \right\|^2$$

The alignment is :

$$(rot, trans, d_{mse}) = \Phi(M, S)$$

Aligning 3D Data

- If correct correspondences are known, can find correct relative rotation/ translation as closed from solution:
  - **Horn's quaternion method**
  - SVD Arun et al.
  - Orthonormal matrices Horn et al.
  - Dual quaternions Walker et al.

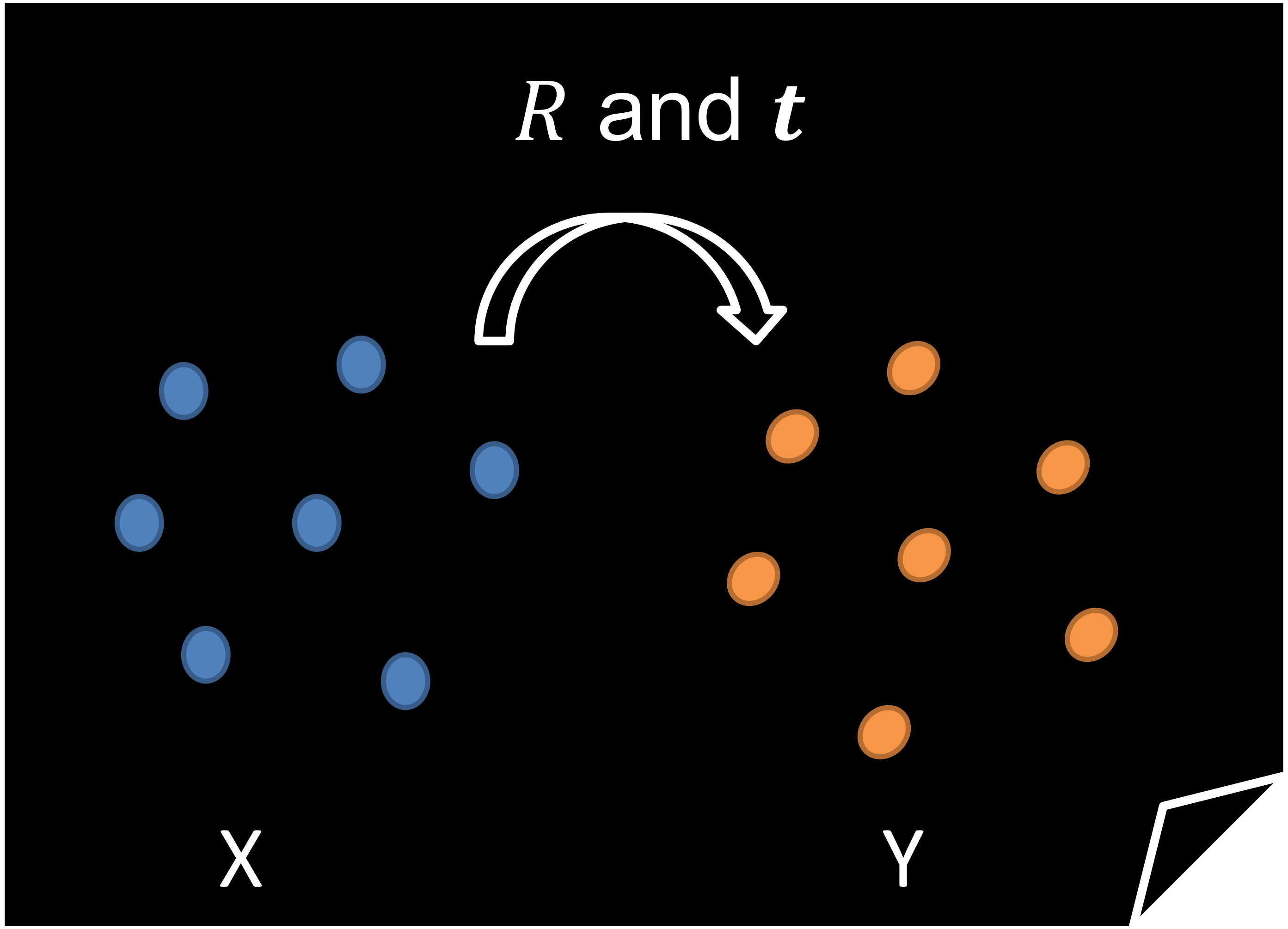


See:
A. Lorusso, D. Eggert, and R. Fisher.
A Comparison of Four Algorithms for Estimating 3-D Rigid Transformations.
In *Proceedings of the 4th British Machine Vision Conference (BMVC '95)*, pages 237 - 246, Birmingham, England, September 1995.

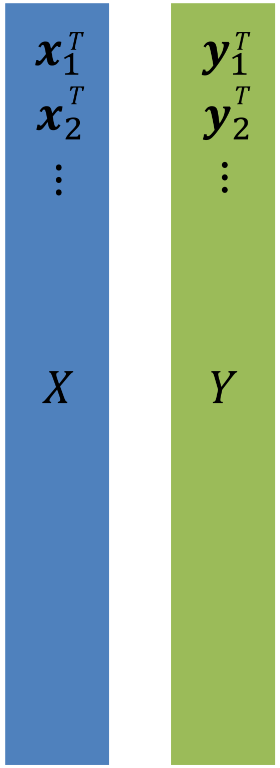
Horn's method

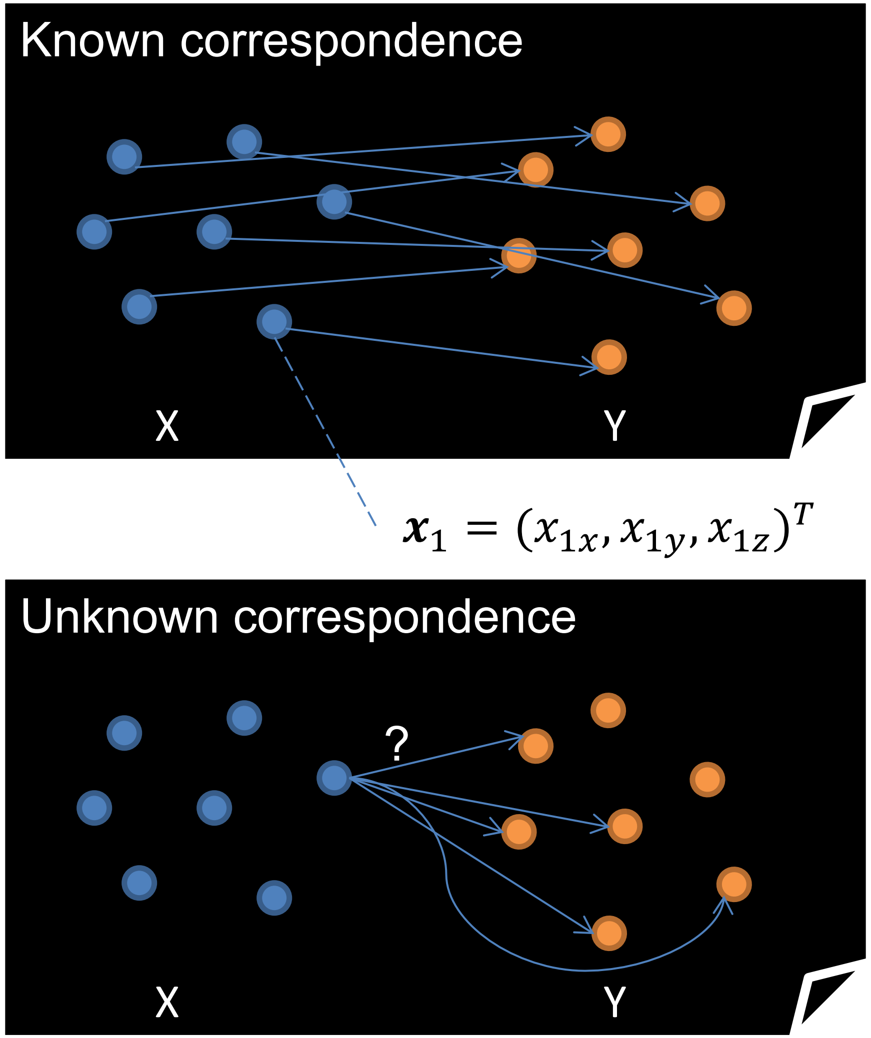
Material by Toru Tamaki, Miho Abe, Bisser Raytchev, Kazufumi Kaneda

- Input
  - Two point sets: X and Y
- Output
  - Rotation matrix R
  - Translation vector $\boldsymbol{t}$
  - Fitting error



Horn’s method: correspondence is known.





Horn's method: correspondence is known.

1 Compute centers

$$X = \begin{pmatrix} \boldsymbol{x}_1^T \\ \boldsymbol{x}_2^T \\ \vdots \end{pmatrix} \Rightarrow \bar{\boldsymbol{x}} \qquad Y = \begin{pmatrix} \boldsymbol{y}_1^T \\ \boldsymbol{y}_2^T \\ \vdots \end{pmatrix} \Rightarrow \bar{\boldsymbol{y}}$$

2 Centering

$$\hat{X} = X - \bar{\boldsymbol{x}} \qquad \hat{Y} = Y - \bar{\boldsymbol{y}}$$

3

$$S = \hat{X}\,\hat{Y}$$

$$\begin{pmatrix} S_{xx} & S_{xy} & S_{xz} \\ S_{yx} & S_{yy} & S_{yz} \\ S_{zx} & S_{zy} & S_{zz} \end{pmatrix}$$

4

$$K = \begin{pmatrix} S_{xx}+S_{yy}+S_{zz} & S_{yz}-S_{zy} & S_{zx}-S_{xz} & S_{xy}-S_{yx} \\ S_{yz}-S_{zy} & S_{xx}-S_{yy}-S_{zz} & S_{xy}+S_{yx} & S_{zx}+S_{xz} \\ S_{zx}-S_{xz} & S_{xy}+S_{yx} & S_{yy}-S_{xx}-S_{zz} & S_{yz}+S_{zy} \\ S_{xy}-S_{yx} & S_{zx}+S_{xz} & S_{yz}+S_{zy} & S_{zz}-S_{xx}-S_{yy} \end{pmatrix}$$

5

Compute 1st Eigenvector $\boldsymbol{q}$

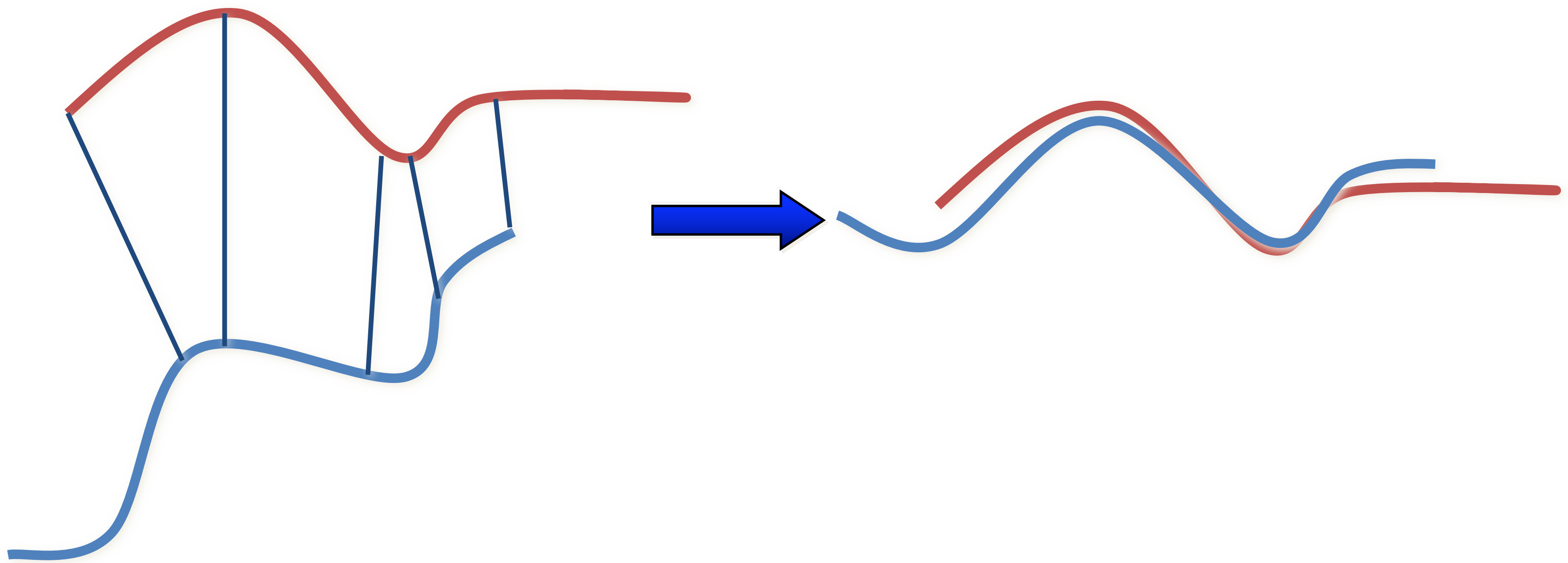
: quaternion q

Convert q to R

$$\boldsymbol{t} = \bar{\boldsymbol{x}} - R\bar{\boldsymbol{y}}$$

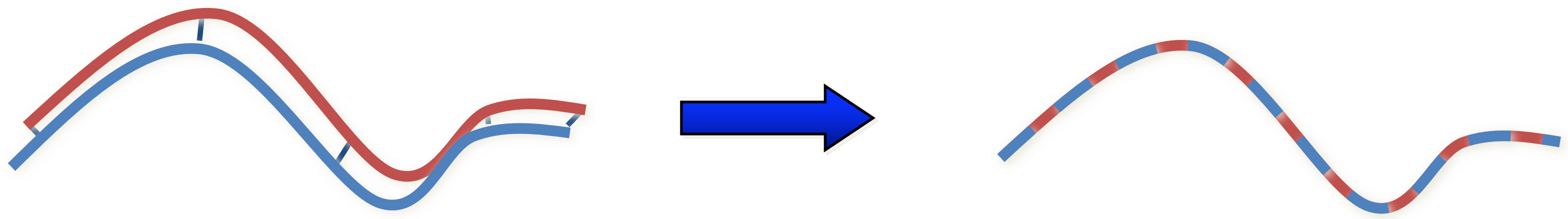
Aligning 3D Data

- How to find correspondences: User input? Feature detection? Signatures?
- Alternative: assume closest points correspond



Aligning 3D Data

- Converges if starting position "close enough"



Closest Point

- Given 2 points r_1 and r_2, the Euclidean distance is:

$$d(r_1, r_2) = \|r_1 - r_2\| = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}$$

- Given a point r_1 and set of points A, the Euclidean distance is:

$$d(r_1, A) = \min_{i \in 1..n} d(r_1, a_i)$$

Finding Matches

- The scene shape S is aligned to be in the best alignment with the model shape M.
- The distance of each point s of the scene from the model is :

$$d(s, M) = \min_{m \in M} d\|m - s\|$$