Robots for the real world

The strengths and weaknesses of EKF-SLAM

Link to the live slides:
https://docs.google.com/presentation/d/1fJXPY5fIXk3cORBzvNFWIbSa8QTznq3_B6MvLm-IMzs/edit?usp=sharing

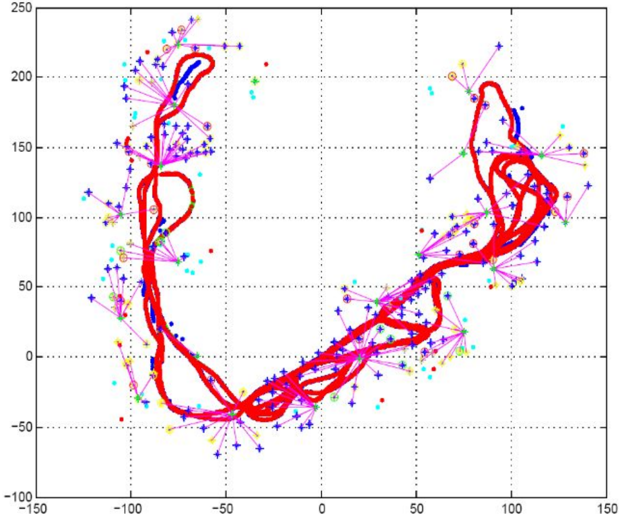
Feras Dayoub

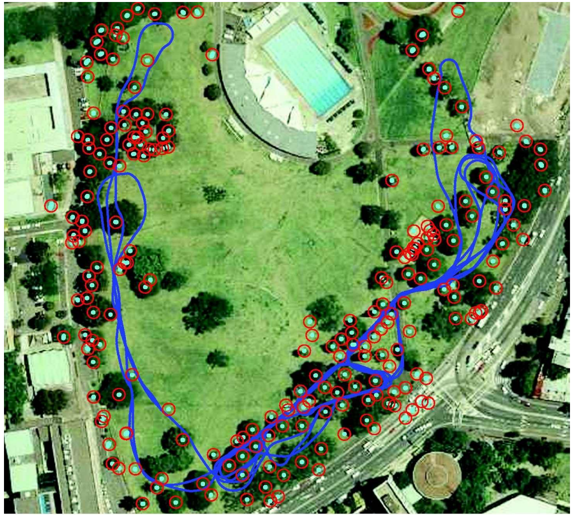
Learning objectives

- The strengths and weaknesses of EKF-SLAM.
- The other flavours of the SLAM algorithm.

EKF-SLAM: Strengths

- Easy to implement.
- Simple parameterization using only the mean and the covariance matrix.





Guivant, J., Nebot, E., & Durrant-Whyte, H. **(2000, July)**. Simultaneous localization and map building using natural features in outdoor environments. In *Intelligent Autonomous Systems* (Vol. 6, No. 1, pp. 581-586).

Simultaneous Localization and Map Building Using Natural features in Outdoor Environments

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Abstract. This work presents efficient algorithms for real time Simultaneous Localization and Map Building (SLAM). The accuracy of the algorithm is investigated with respect to standard localization algorithms using a 1cm kinematic GPS as ground truth. The issue of algorithm convergence when running in large areas of operation and for long period of time is investigated. Experimental results in unstructured environment are presented using more than 200 natural features. The complexity of feature extraction is also investigated with an approach to identify common types of outdoor natural features.

Guivant, J., Nebot, E., & Durrant-Whyte, H. **(2000, July)**. Simultaneous localization and map building using natural features in outdoor environments. In *Intelligent Autonomous Systems* (Vol. 6, No. 1, pp. 581-586).

2 Navigation System

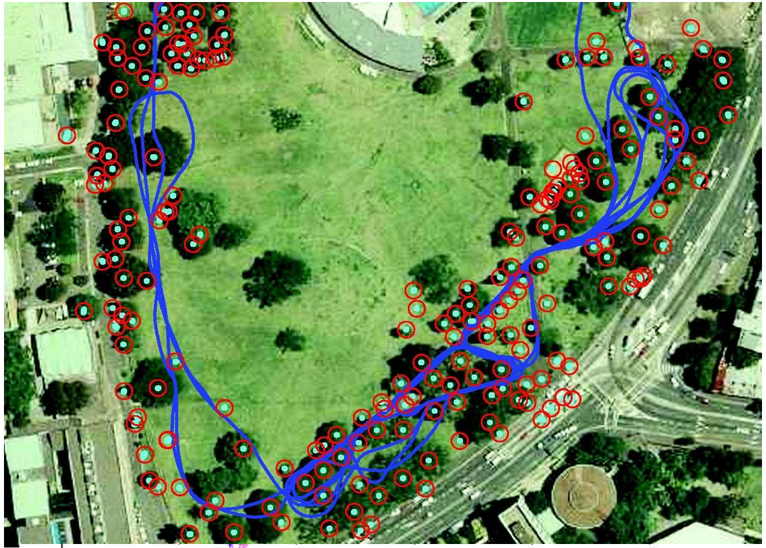
The navigation loop is based on encoders and range / bearing information provided by a laser sensor. A simple kinematic model is used for this experimentation [6]. The trajectory of the centre of the back axle is given by:

$$\begin{bmatrix} \dot{x}_c \\ \dot{y}_c \\ \dot{\phi}_c \end{bmatrix} = \begin{bmatrix} v_c \cdot \cos(\phi) \\ v_c \cdot \sin(\phi_c) \\ \frac{v_c}{L} \cdot \tan(\alpha) \end{bmatrix} \tag{1}$$

where v_c is the velocity of the centre of the back axle and α is the orientation of the front wheels with respect to the forward direction. The equation that relates the observation with the states is

$$\begin{bmatrix} z_r^i \\ z_\beta^i \end{bmatrix} = h(X, x_i, y_i) = \begin{bmatrix} \sqrt{(x_L - x_i)^2 + (y_L - y_i)^2} \\ \operatorname{atan}\left(\frac{(y_L - y_i)}{(x_L - x_i)}\right) - \phi + \pi/2 \end{bmatrix} \tag{2}$$

where z and $[x, y, \phi]$ are the observation and state values respectively, and (x_i, y_i) are the positions of the beacons or natural landmarks.

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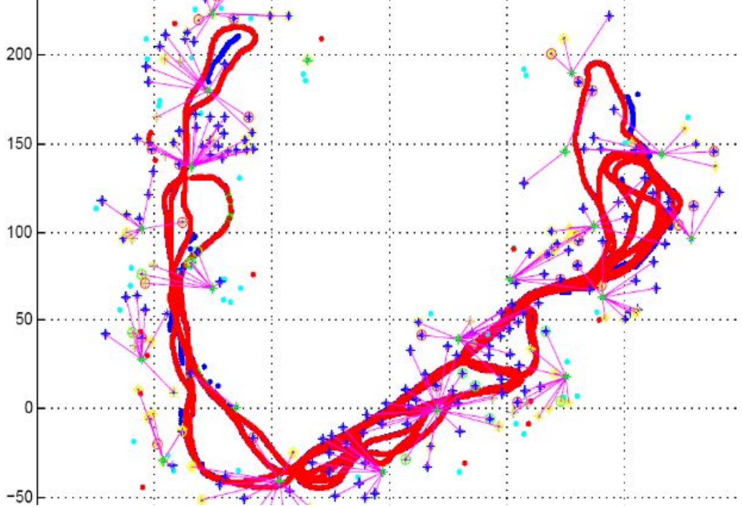
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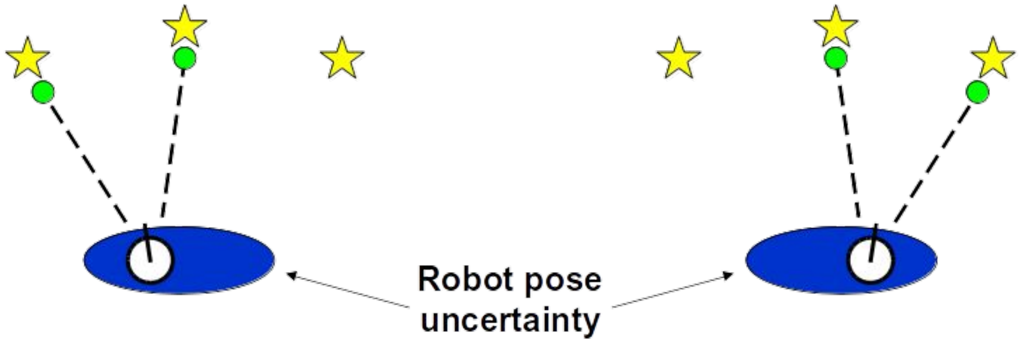
EKF-SLAM: Weaknesses

- The data association problem.
- The global localization problem.
- The linearization problem.
- The non-Gaussian world problem.
- The loop closing problem.
- The increase in complexity with the number of the landmarks problem.

The data association problem

- The problem of determining whether or not two landmarks observed at different points in time correspond to one and the same object in the physical world.
- In this unit, we assumed that the robot can determine the correspondences between its observations and the landmarks with absolute certainty. In reality, this is rarely the case.



The data association problem

- Solving this problem in a robust way is crucial for the success of SLAM.
  - **The simplest strategy is finding the maximum likelihood correspondence.**
- Most deployed SLAM algorithms construct maps with tens of thousands of landmarks, or more.
- EKF-SLAM can handle small number of landmarks (less than 1000). Above that the landmarks need to be easy to detect and the association with the measurements is not ambiguous.

Maximum Likelihood Data Association

- Compute the probability that the current measurement corresponds to each landmark in the map.
- Then choose the landmark with the highest probability of correspondence and assumes it is the correct association.

for all measurements $z_t^i = [r_t^i \ \phi_t^i]^T$ do

for all landmarks k in the map m do

$$q = (m_{k,x} - \bar{\mu}_{t,x})^2 + (m_{k,y} - \bar{\mu}_{t,y})^2$$

$$\hat{z}_t^k = \begin{bmatrix} \sqrt{q} \\ \operatorname{atan2}(m_{k,y} - \bar{\mu}_{t,y},\ m_{k,x} - \bar{\mu}_{t,x}) - \bar{\mu}_{t,\theta} \end{bmatrix}$$

$$H_t^k = \begin{bmatrix} -\frac{m_{k,x} - \bar{\mu}_{t,x}}{\sqrt{q}} & -\frac{m_{k,y} - \bar{\mu}_{t,y}}{\sqrt{q}} & 0 \\ \frac{m_{k,y} - \bar{\mu}_{t,y}}{q} & -\frac{m_{k,x} - \bar{\mu}_{t,x}}{q} & -1 \end{bmatrix}$$

$$S_t^k = H_t^k \bar{\Sigma}_t [H_t^k]^T + Q_t$$

endfor

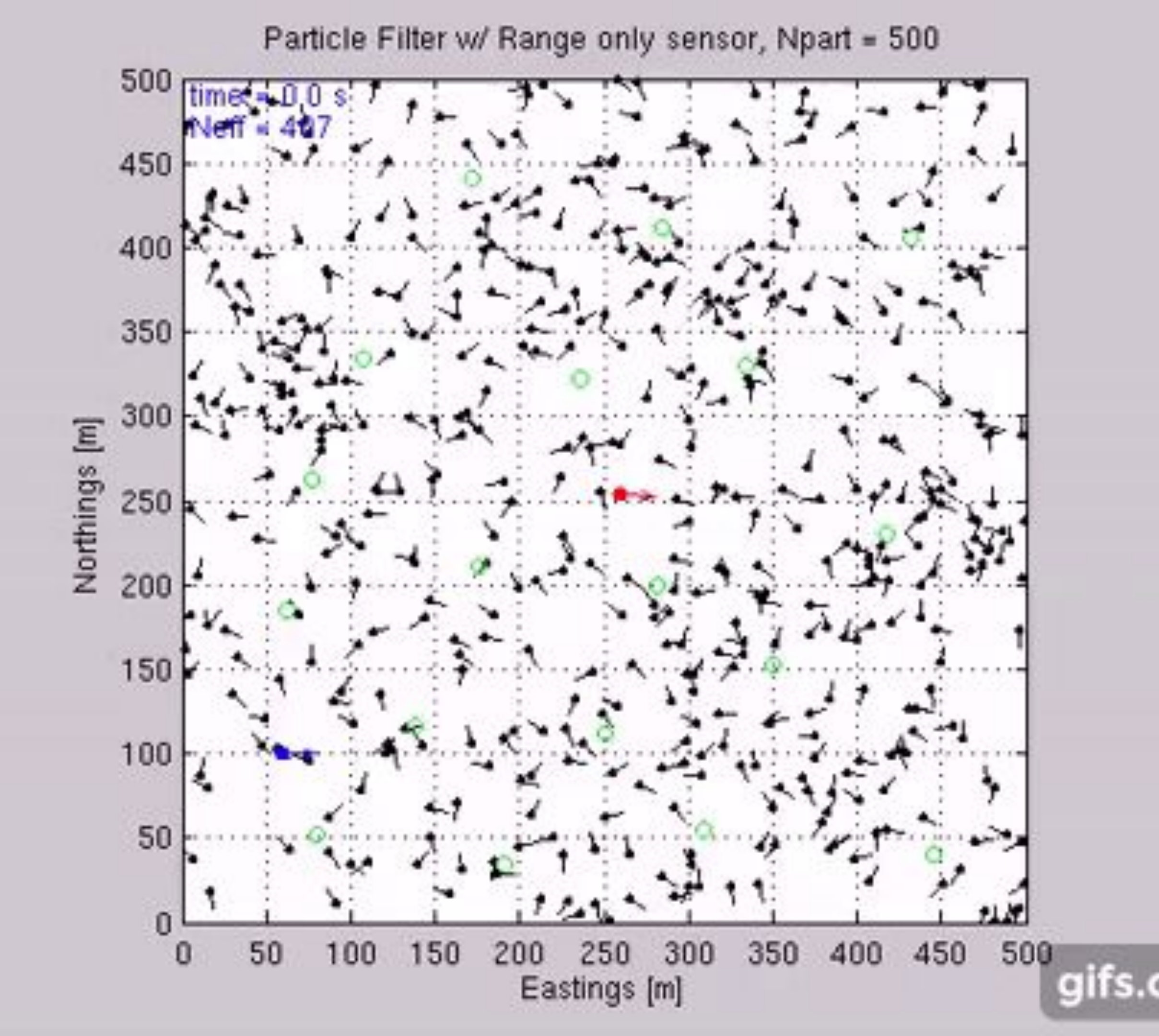
$$j(i) = \operatorname{argmax}_k \ \det(2\pi S_t^k)^{-\frac{1}{2}} \exp\{-\frac{1}{2}(z_t^i - \hat{z}_t^k)[S_t^k]^{-1}(z_t^i - \hat{z}_t^k)^T\}$$

endfor

The global localization problem

- The type of localization we did in this unit is called **position tracking**. It assumes that the initial robot pose is known or in the case of SLAM, we define the starting point. We also approximated the **pose uncertainty by an unimodal Gaussian distribution** (i.e it has one peak). This type of localization is called local, since the uncertainty is confined to region near the robot's true pose.
- **Global localization** is the problem where the <u>initial pose of the robot is unknown inside of a known frame of reference</u>. Unimodal probability distributions are usually inappropriate.

The global localization problem



The global localization problem (kidnapped robot)

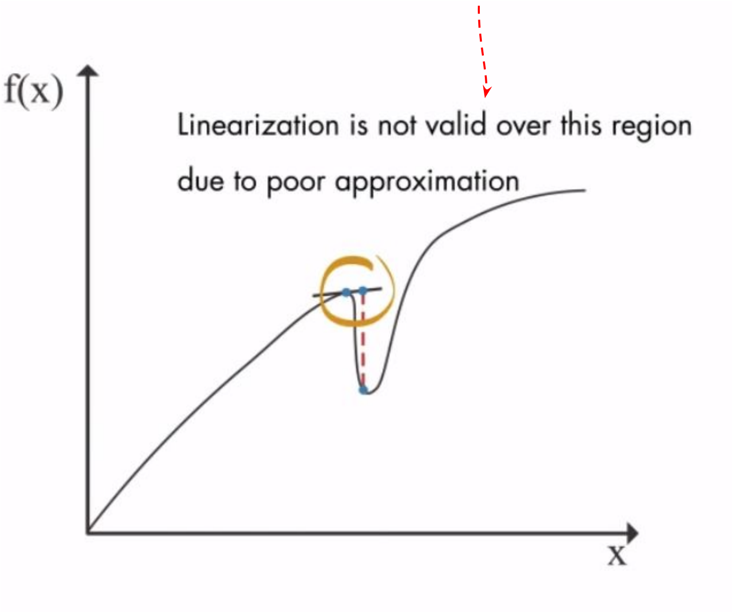
This problem is harder than both local and global localization. In this scenario, the robot can get kidnapped and teleported to some other location.

This problem is difficult because the robot do not know that it is been teleported.

EKF-SLAM can not handle this case which means it can not recover from catastrophic failures. The ability to recover from failures is essential for truly autonomous robots. The kidnapped robot case is a test for the ability of any SLAM algorithm to recover from global localization failures.

The nonlinearity problem

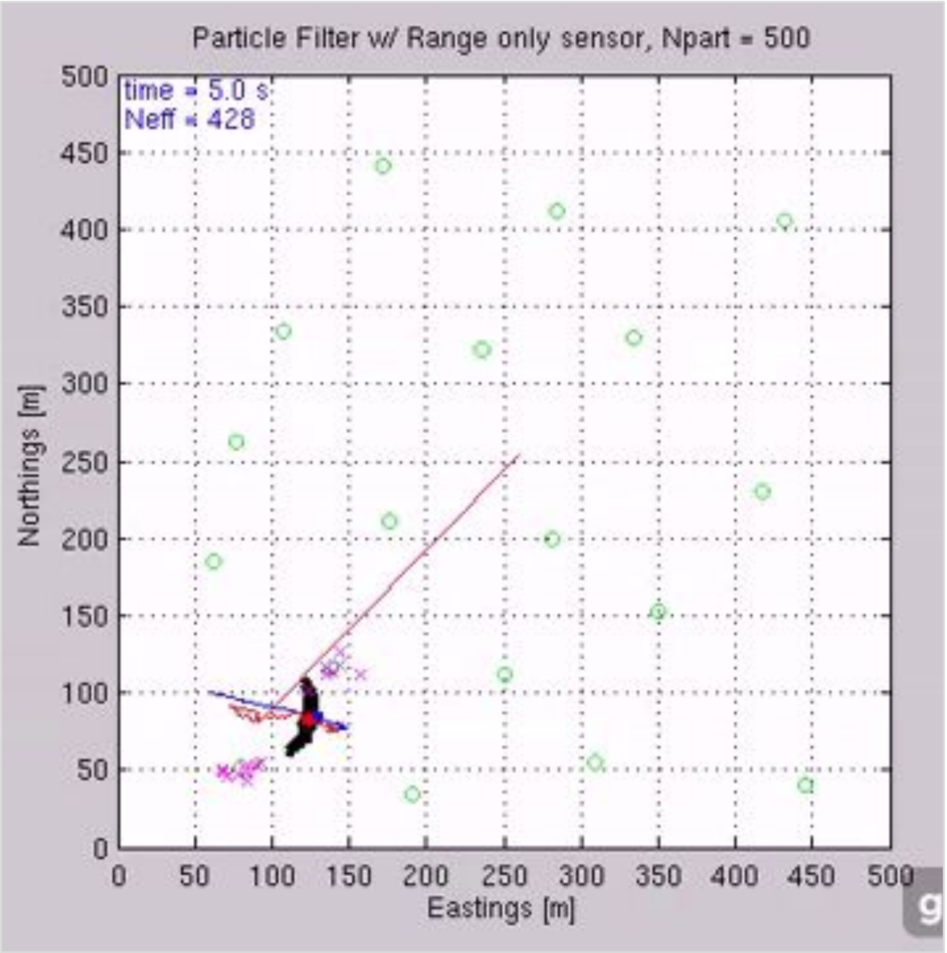
- EKF works well for **moderate nonlinearity** with small uncertainty.



- Linearizations is good in a close range to the linearization point (e.g if the standard deviation on the heading of the robot is larger than 20 degrees, linearization will make the EKF-SLAM fail)

The non-Gaussian world problem

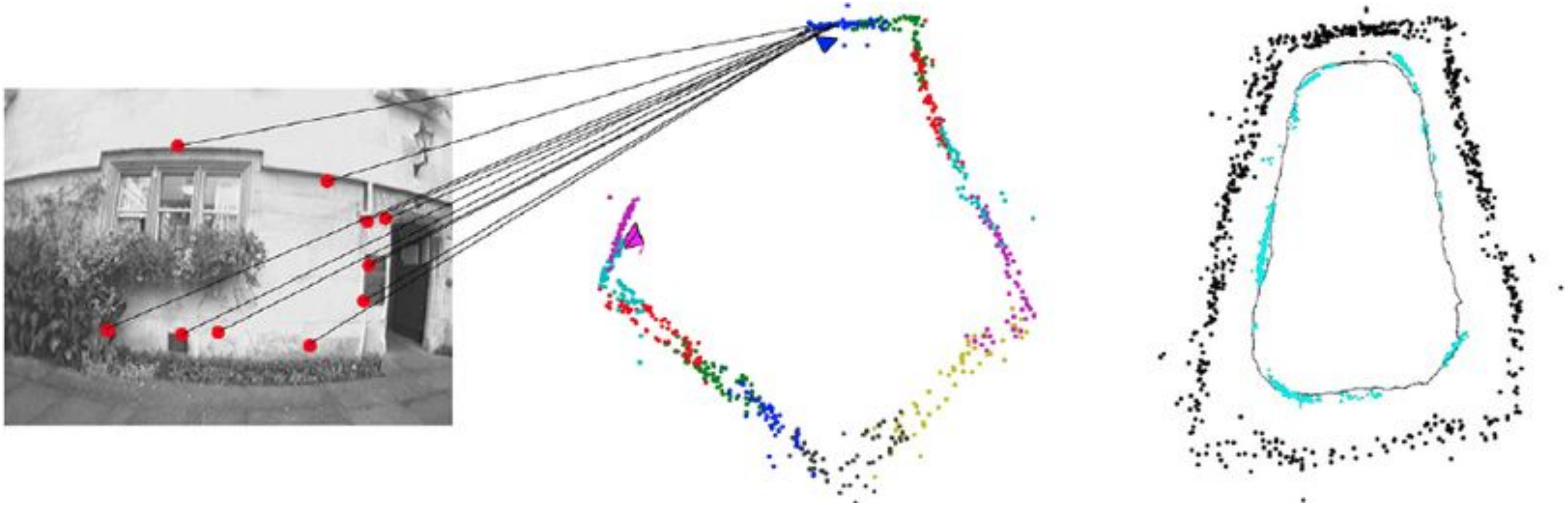
- **In this unit** we modeled **the robot pose**, **the odometry noise** and **measurement noise** as Gaussians and we used a trick to handle the nonlinearity in the system. This was good enough to perform SLAM in our green arena however EKF cannot be applied when there is high non-linearities involved in the models or when the **noise is non-Gaussian**.
- A popular alternative to EKF-SLAM are **nonparametric filters**, on of which is called the **Particle filter**.
- Particle filters are able to capture the non-Gaussian and multi-modal posterior distributions and also deal with nonlinear models.



Particle filters are able to capture the non-Gaussian and multi-modal posterior distributions and also deal with nonlinear models

The loop closing problem

- Loop closure happen when the robot traverses a large area and then revisit an already mapped section of it.




gifs.com

The loop closing problem

- Depending on the quality of the odometry and the sensors the system will accumulate error resulting in drifts.
- When returning to a known area, the robot will see the old landmarks but assumes they are new and initializes them in the map.
- The other scenario is when the robot close the loop incorrectly because of an alias environment.
- Wrong loop closures leads to divergence in the EKF-SLAM and the filter will fail.

The increase in complexity with the number of the landmarks problem

- Maintaining a multivariate Gaussian requires time quadratic in the number of features in the map.
- EKF-SLAM is computationally intractable for large maps (> 1000 landmarks).
- One solution is to decompose the problem of building one large map into a collection of smaller maps, which can be updated more efficiently.

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OpenSLAM

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What's SLAM?

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People

Acknowledgment

Datasets & Links

What is OpenSLAM.org?

The simultaneous localization and mapping (SLAM) problem has been intensively studied in the robotics community in the past. Different techniques have been proposed but only a few of them are available as implementations to the community. The goal of OpenSLAM.org is to provide a platform for SLAM researchers which gives them the possibility to publish their algorithms. OpenSLAM.org provides to every interested SLAM researcher a subversion (svn) repository and a small webpage in order to publish and promote their work. In the repository, only the authors have full access to the files; other users are restricted to read-only access. OpenSLAM.org does not really aim to provide a repository for the daily development process of early SLAM implementations. Published algorithm should have a certain degree of robustness.

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Click to submit your SLAM algorithm.

The OpenSLAM Team
Cyrill Stachniss, Udo Frese, Giorgio Grisetti

disclaimer

Translations of this page

- French

Real Time Example

Large Scale Outdoors with multiple Loops

Dataset: KITTI (Odometry benchmark)

Sequence: 00

Dimensions: 564 x 496 meters

Image Resolution: 1241 x 376 pixels

Camera fps: 10 Hz

Motion: Car

ORB-SLAM
Raúl Mur-Artal, J. M. M. Montiel and Juan D. Tardós

Universidad Zaragoza

The END