Content of the presentation:

1. **Introduction**
   - What is P-SLAM?
2. **Problem formulation**
   - prediction of an unexplored region with a built up map
   - Use of predicted Map
3. **Environmental structure prediction**
   - Search for reference region
     a. Feature extraction
     b. Homogenous transformation matrix
     c. Similarity measurement
4. **P-SLAM versus SLAM**
   - Bayesian formulation of P-SLAM
   - P-SLAM with an RBPF
5. **Experimental results**
   - Computer simulation
   - Experiment on a pioneer 3-DX robot
6. **conclusion**

P-SLAM: simultaneous Localization and Mapping with environmental- structure Prediction

Sepideh Hadadi

Probabilistic Robotics

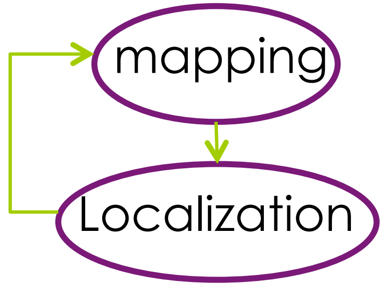
Master in computer vision (MSCV), semester 2, Centre universitaire Condorcet, Le Creusot

22-May 2017

Introduction

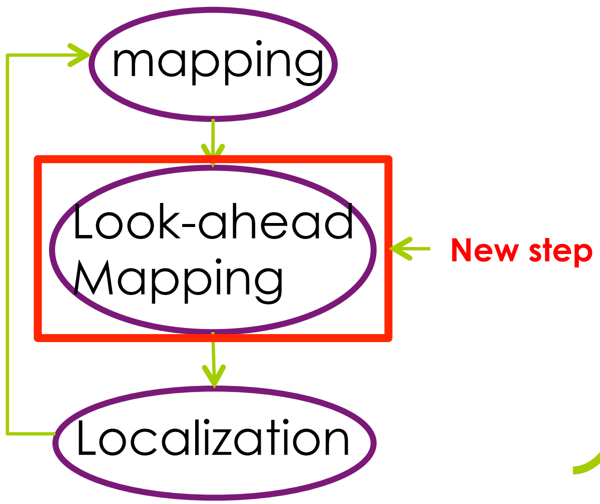
What is P-SLAM?

SLAM



Application: the entire region is explored

P-SLAM

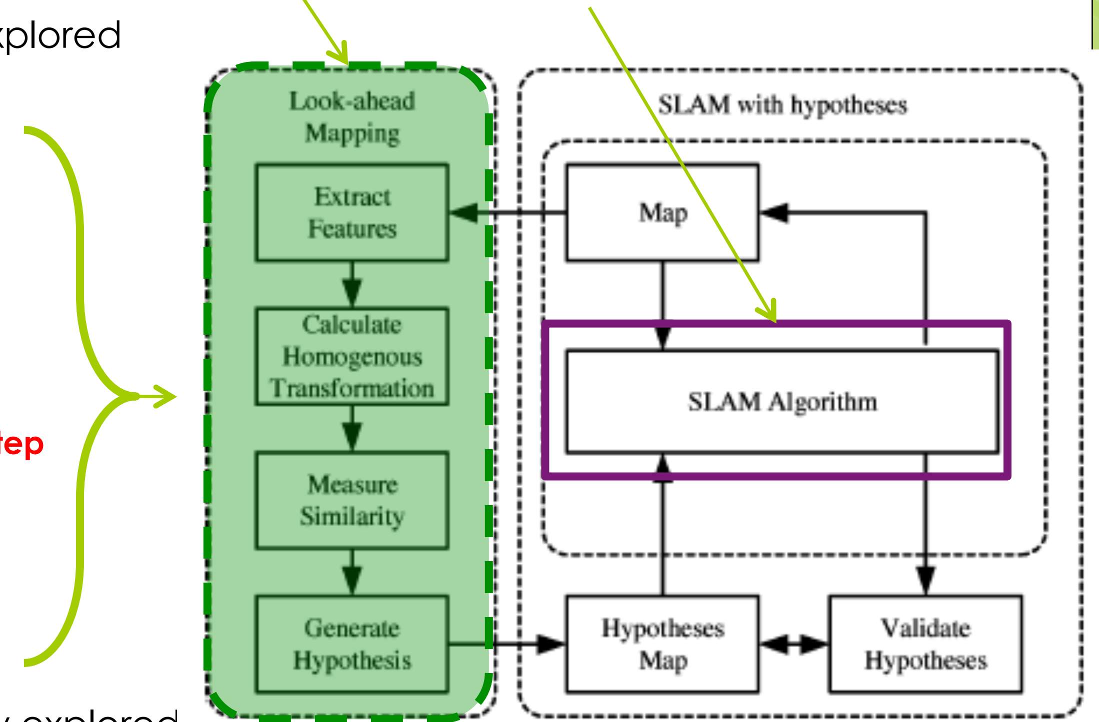


Application: the region is partially explored

P-SLAM working structure

New step (subject of the paper)

SLAM



Prediction of an unexplored region

- The the proposed P-SALM focuses on predicting a structure of an unexplored region.
- To identify where the unexplored region is, P-SLAM adopts the occupancy-grid map.
- In the occupancy- grid map the prediction can be divided into four major steps:
  1. **Locate a target frontier cell to predict**
  2. **Collect structure information near the target region(feature)**
  3. **Search for similar structures in the built map**
  4. **Generate a hypothesis if a similarly match exist**
- **The above four steps can be formulated as an optimization problem**

$$C_{f'} = \arg\max_{C_{f'} \in \mathcal{M}, f' \neq f} \{\Psi(C_{f'}, S_f)\}$$

All the parameters are known except **f'**

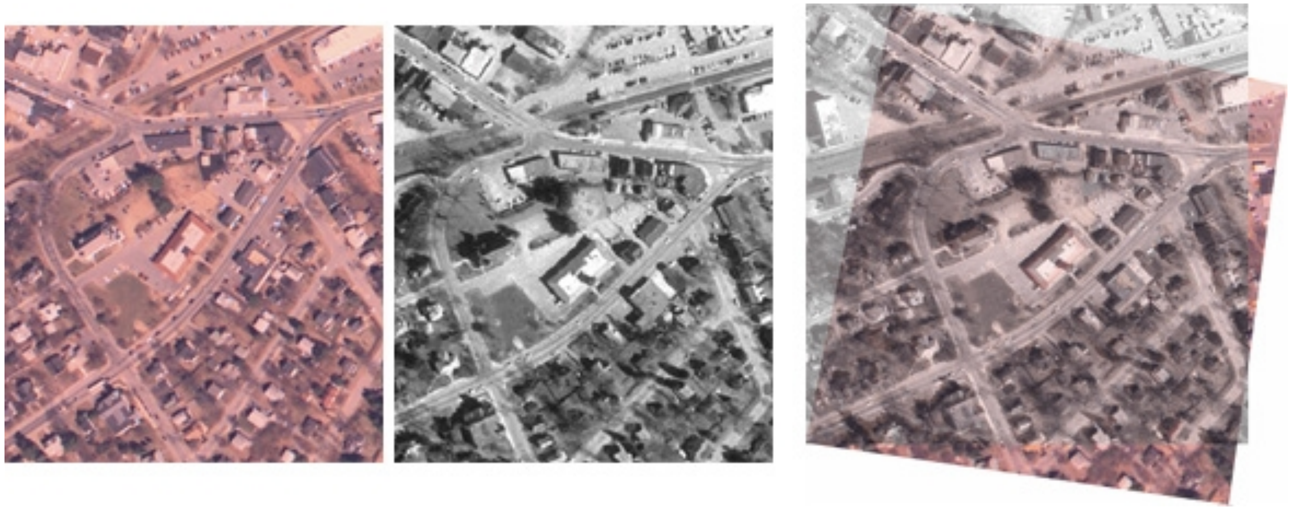
Problem: finding optimization solution is very time consuming and can not be done in real-time (3600s for instance)

Alternative solution to the previous problem

- An alternative solution to overcome the above problem is to use image processing technique:

image registration algorithm

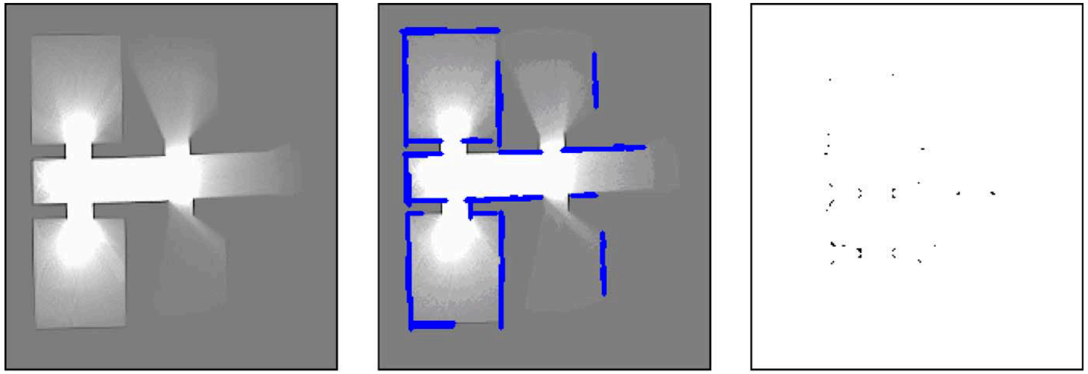
- Image registration consist of following steps
  1. **Feature extraction**
  2. **Feature matching**
  3. **Calculation of transformation matrices**



Environmental structure prediction

feature extraction

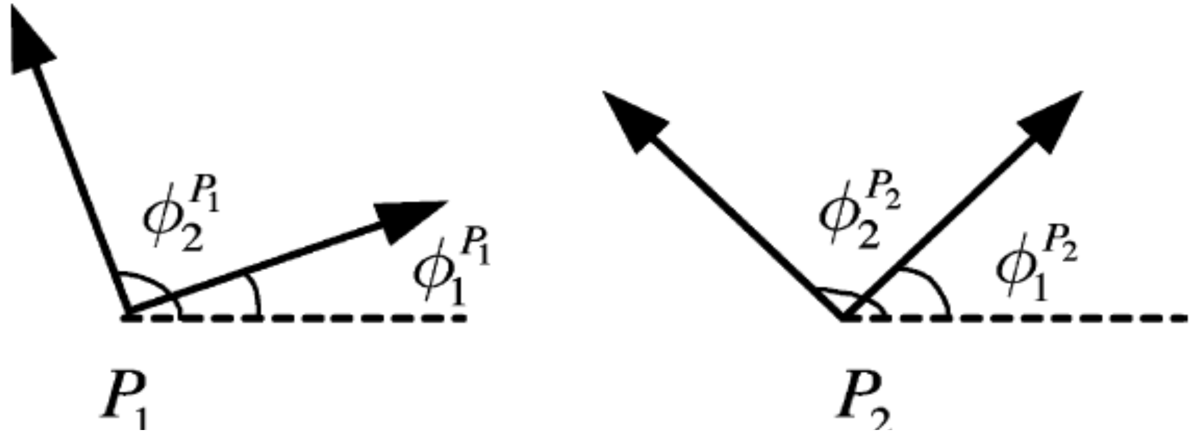
- The entire paper is discussing about indoor move of robot
- Lines and corners are selected as features because they are the elementary representation of walls, hallways or rooms



Extracted features

Part of target indoor path of robot

Homogenous transformation matrix



P_1 and P_2 are control points extracted from corner features. The angles $\phi_1^{P_1}$, $\phi_2^{P_1}$, $\phi_1^{P_2}$, and $\phi_2^{P_2}$ are extracted from the line features.

$$\Gamma = \begin{bmatrix} \cos\theta & -\sin\theta & p_x^1 - p_x^2 \\ \sin\theta & \cos\theta & p_y^1 - p_y^2 \\ 0 & 0 & 1 \end{bmatrix}$$

The angle θ is the difference between $\Phi_1^{P1} - \Phi_1^{P2}$ and P_x, P_y is the projection of each vector P on x and y axis

Similarity measurement

Similarity is measured based on following equations:

$$I(i,j) = \begin{cases} 1, & \text{if } S_f(i,j) \text{ and } \tilde{C}_{\tilde{f}'}(i,j) \text{ are occupied} \\ 0, & \text{else} \end{cases}$$

$$J(R,i,j) = \begin{cases} 1, & \text{if } R(i,j) \text{ is occupied} \\ 0, & \text{else} \end{cases}$$

$$\Psi(S_f, \tilde{C}_{\tilde{f}'}) = \frac{2 \times \sum_{i=1}^{d_s} \sum_{j=1}^{d_s} I(i,j)}{\sum_{i=1}^{d_s} \sum_{j=1}^{d_s} J(S_f, i, j) + \sum_{i=1}^{d_s} \sum_{j=1}^{d_s} J(\tilde{C}_{\tilde{f}'}, i, j)}$$

Hypothesis: If the similarity measurement of every possible reference region is below the threshold the prediction process is terminated until the next target is determined. The selected target regions will be part of the mapping

$$H_k = \{h_1, h_2, \ldots, h_k\} = \{H_{k-1}, h_k\}.$$

SLAM predictor

$$x_k = f_k(x_{k-1}, u_{k-1}) + w_{k-1},$$ State estimation

$$z_k = h_k(x_k) + v_k.$$ measurement

- prediction

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1}$$

- update

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})}.$$

SLAM Algorithm

Algorithm: SLAM

{- Pose initialization}

$x_0^B = \hat{x}_0^B;\ P_0^B = \hat{P}_0^B;$

$[z_0, R_0] = get\_measurements;$

$[x_0^B, P_0^B] = add\_new\_features(x_0^B, P_0^B, z_0, R_0);$

for k=1 to steps **do**

$[u_{R_k}^{R_{k-1}}, Q_k] = get\_odometry$

{-EKF prediction}

$[x_{k|k-1}^B, P_{k|k-1}^B] = move\_vehicle(x_{k-1}^B, P_{k-1}^B, x_{R_k}^{R_{k-1}}, Q_k)$

$[z_k, R_k] = get\_measurements$

$\mathcal{H}_k = data\_association(x_{k|k-1}^B, P_{k|k-1}^B, z_k, R_k);$

{-EKF update}

$[x_k^B, P_k^B] = update\_position(x_{k|k-1}^B, P_{k|k-1}^B, z_k, R_k);$

$[x_k^B, P_k^B] = add\_new\_features(x_k^B, P_k^B, z_k, R_k, \mathcal{H}_k);$

end for

predictor

Depending on the process model, there is three possibility:

Here, last condition is met and SLAM use FP of Bayesian filter

h, f linear	w, v Gaussian	KF	
h, f non-linear	w, v Gaussian	EFK	
h, f non-linear	w, v non-Gaussian	PF, Bayesian	✔

Bayesian P-SLAM

Standard Bayesian SLAM has following recursive equations:

$$P(x_k, \mathcal{M}_k | Z_k, U_k, x_0)$$
$$= \kappa \times P(z_k | x_k, \mathcal{M}_k) \times \Lambda$$
$$\Lambda = \int P(x_k | x_{k-1}, u_k) P(x_{k-1}, \mathcal{M}_{k-1} | Z_{k-1} U_{k-1}, x_0) dx_{k-1}$$

Above equation were updated by the author to construct new set of equations for P-SLAM.
Bayesian P-SLAM will have following recursive equations:

$$P(x_k, \boxed{H_k}, \mathcal{M}_k | Z_k, U_k, x_0)$$
$$= \kappa' P\left(z_k^e | \mathcal{M}_k, x_k\right) \boxed{P\left(h_k | z_k^u, x_k\right)} \Lambda'$$
$$\Lambda' = \int P(x_k | x_{k-1}, u_k) P(x_{k-1}, \boxed{H_{k-1}, \mathcal{M}_{k-1}} | Z_{k-1}, U_{k-1}, x_0) dx_{k-1}$$

RBPF P-SLAM

The recursive equation of RBPF SLAM is formulated in the following reference:

A. Doucet, J. de Freitas, K. Murphy, and S. Russel, "Rao-Blackwellized particle filtering for dynamic Bayesian networks," in Proc. Conf. Uncertainty Artif. Intell., 2000, pp. 499–516.

The recursive equation of RBPF SLAM is updated for P-SLAM as follow:

Robot pose $$x_k^{(n)} = A\left(u_{k-1}, x_{k-1}^{(n)}\right)$$

Map explored $$m_k^{(n)} = M\left(z_k, x_k^{(n)}\right) + m_{k-1}^{(n)}$$

Map unexplored $$h_k^{(n)} = V\left(m_k^{(n)}, h_{k-1}^{(n)}\right) + H\left(m_k^{(\text{best})}, x_k^{(\text{best})}, x_k^{(n)}, T_k\right)$$

Weight update eq. $$w_k^{(n)} = S\left(z_k, x_k^{(n)}, m_{k-1}^{(n)}, h_k^{(n)}\right) w_{k-1}^{(n)}$$

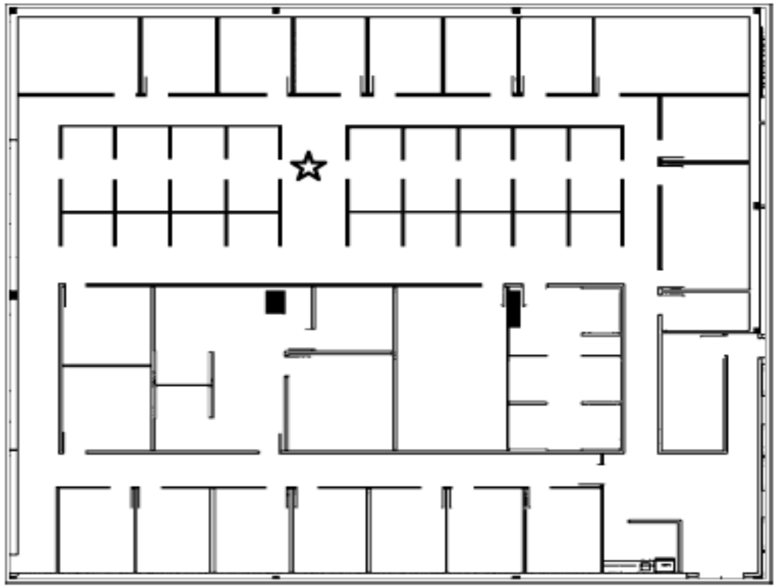
Sensor model for explored region

Sensor model for unexplored region

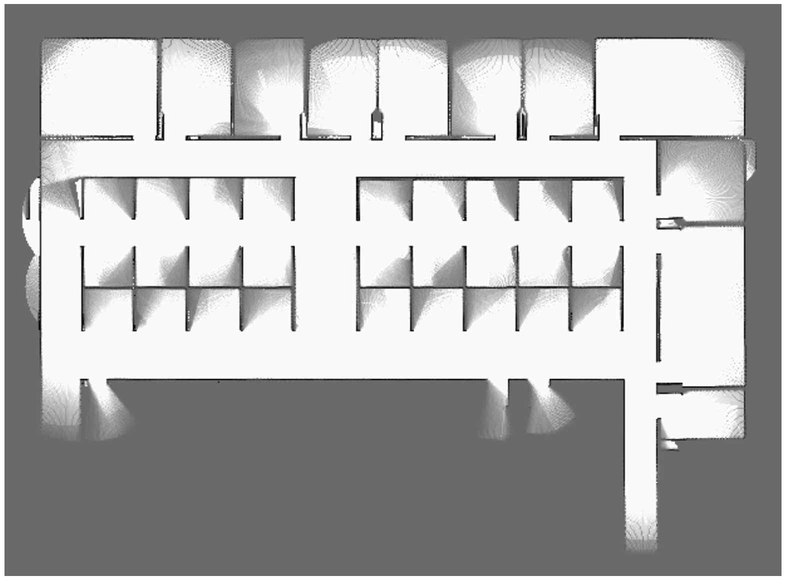
Sensor model $$S\left(z_k, x_k^{(n)}, m_{k-1}^{(n)}, h_k^{(n)}\right) = \boxed{S_1\left(z_k^e, x_k^{(n)}, m_{k-1}^{(n)}\right)} \times \boxed{S_2\left(z_k^u, x_k^{(n)}, h_k^{(n)}\right)}$$

Weighting update eq. $$w_k^{(n)} = w_{k-1}^{(n)} \boxed{P\left(z_k^e | x_k^{(n)}, m_{k-1}^{(n)}\right)} \boxed{P\left(z_k^u | h_k^{(n)}, x_k^{(n)}\right)}$$

Simulation result



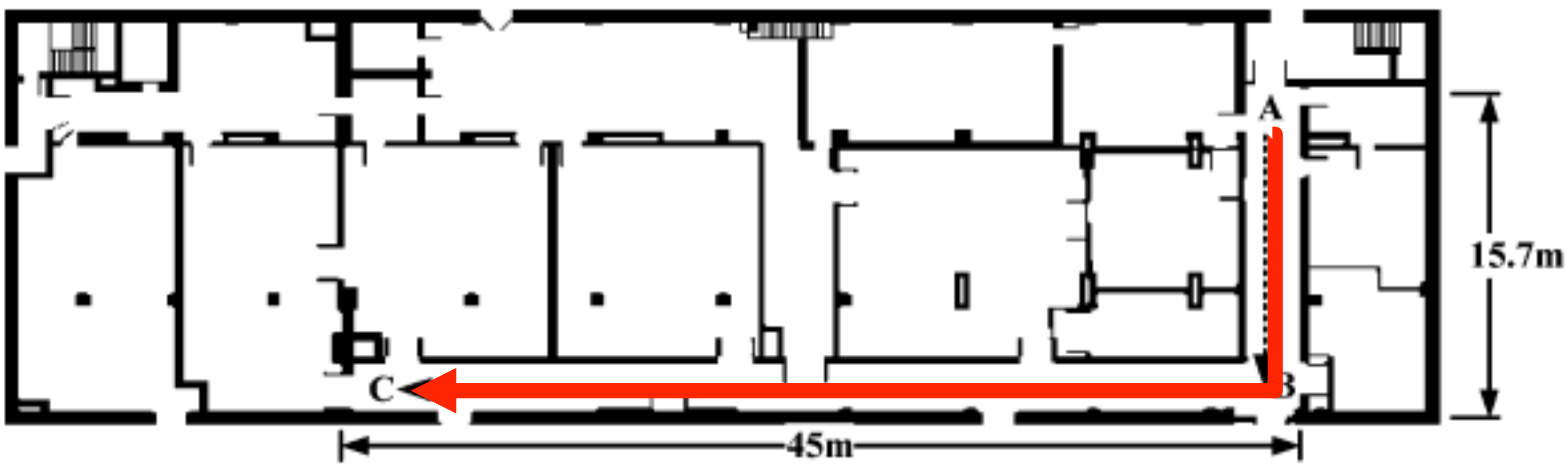
Office environment used in the computer simulation. The star indicates the initial location of the mobile robot.



Map generated by the proposed P-SLAM of the upper-office environment. The predictions in the unexplored regions were also added in this map, such as the leftmost part, which cannot be reached by the robot.

Experimental result

Real-time result using Pioneer 3-DX robot



experimental environment is shown above (tope view). The mobile robot explored the L-shaped corridor starting from location A and ending at location C.

conclusion

improvement

- Experimental result is shown that the essential problem of time is been resolved
- The proposed algorithm based on Bayesian filter and Rao-Blackwellized Particle Filter (RBPF) are very efficient in practice.
- Using image processing algorithm(image registration) is an alternative solution for robotics mapping problem
- The algorithm has been tested for indoor.