Information Based Adaptive Robotic Exploration

Presented by Morten Rufus Blas

Massachusetts Institute of Technology

Overview / Agenda / Outline

- Motivation
- Introduction
- Related work
- Defining problem and model
- Solution:
  - Minimizing localization error
  - Maximize gain in explored map
  - Combined Information Utilities
  - Integrated Adaptive Information-based Exploration Algorithm
- Results
- Conclusion
  - Novelty
  - Problems
  - Extensions

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Motivation

- SLAM:
  - "There is little value in a robot exploring and mapping new areas when it has no idea of how accurately it knows its own location."
  - Come up with an algorithm to adapt controls to do better exploration.

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Introduction

- They attempt to maximize the accuracy and speed of their map building process.
  - How well does the robot know its pose?
  - How well have different areas been explored?
  - In this paper:

F. Bourgault, A. Makarenko, S.B. Williams, B. Grocholsky, H.F. Durrant-Whyte, "Information Based Adaptive Robotic Exploration", presented at IEEE/RSJ Intl. Workshop on Intelligent Robots and Systems, 2002

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Related work

- H.J.S. Feder, J.J. Leonard, and C.M. Smith. Adaptive mobile robot navigation and mapping. *Int. Journal of Robotics Research*, 18(7):650–668, 1999.
- T.M. Cover and J.A. Thomas. *Elements of information theory*. Wiley series in telecommunications. Wiley, New York, 1991.

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Defining problem and model

- Problem:
  - Optimize control step in order to:
    - Minimize localization error.
    - Maximize gain in explored map.
- Model:
  - Solve problem by maximizing information gain.

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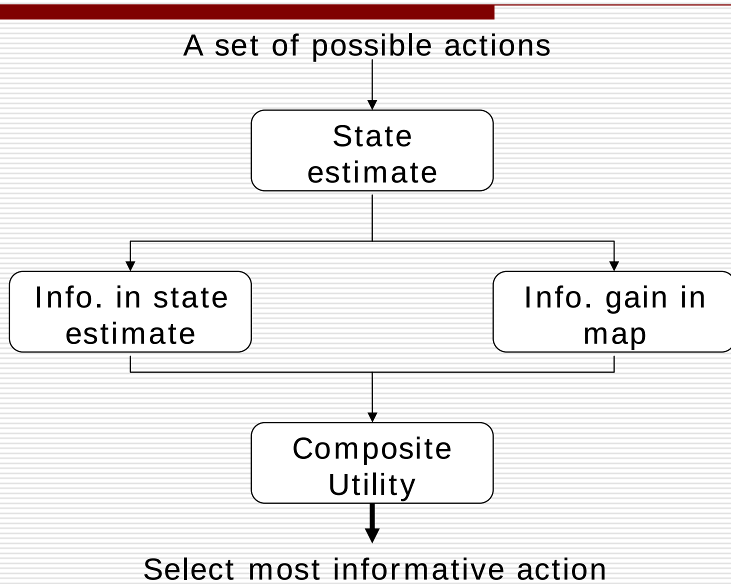
Defining problem and model

- We will be using:
  - EKF to model localization (Extended Kalman Filter).
  - OG to represent map (Occupation Grid).
  - Entropy map (more about this later).

Defining problem and model



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Solution: Minimizing localization error

- Localization is linked to two uncertainties:
  - Measurement,
  - And navigational uncertainty.
- Adaptively choose actions to maximize information about:
  - Robot position.
  - Feature positions (the map).

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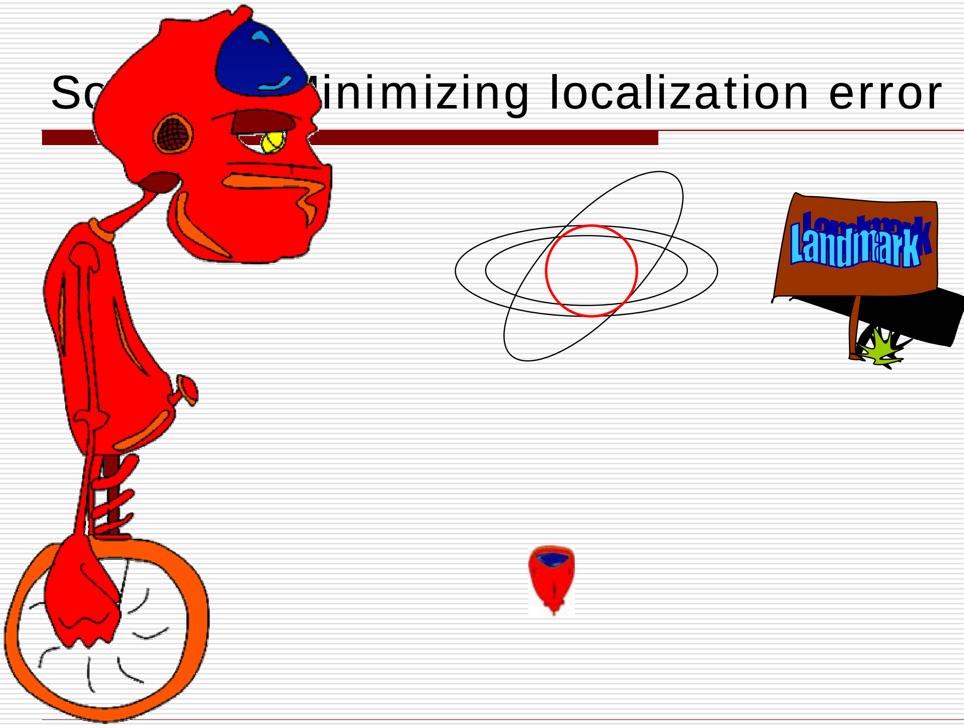
Sc inimizing localization error



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Solution: Minimizing localization error

- This can be modeled using a cost function C(**P**):

$$C(\mathbf{P}) = \pi \prod_j \sqrt{\lambda_j(\mathbf{P}_{vv})} + \pi \sum_{i=1}^{n_f} \prod_j \sqrt{\lambda_j(\mathbf{P}ii)}$$

$$= \pi \sqrt{\det(\mathbf{P}_{vv})} + \pi \sum_{i=1}^{n_f} \sqrt{\det(\mathbf{P}_{ii})} \qquad (14)$$

- Maximizing information about a state estimate is equivalent to minimizing the determinant of the corresponding covariance matrix.

- C(**P**) represents the sum of the uncertainty ellipses of both features and robot after the expected observation from the predicted state.

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Solution: Maximize gain in explored map

Entropy map:

0.0	0.0	0.693
0.693	0.693	0.693
0.693	0.693	0.693

Occupation Grid:

1.0 (OCC)	0.0 (EMP)	0.5
0.5	0.5	0.5
0.5	0.5	0.5

Solution: Maximize gain in explored map

- The a priori entropy at time t_k for grid cell i:

$$H_{k,i} \equiv -E[\ln P_i(x_i)] = -\sum_{x_i \in X_i} P_i(x_i) \ln P_i(x_i)$$

- Given two possible states (OCC, EMP) for OG map this becomes:

$$H_{k,i} = -P_i(OCC)\ln P_i(OCC) - P_i(EMP)\ln P_i(EMP)$$

Solution: Maximize gain in explored map

$$H_{k,i} = -P_i(OCC)\ln P_i(OCC) - P_i(EMP)\ln P_i(EMP)$$

- So for unexplored cell at time t_k:

$$H_k = -0.5\ln 0.5 - 0.5\ln 0.5$$
$$= 0.693$$

- For occupied explored cell at t_k:

$$H_k = -1\ln 1 - 0$$
$$= 0$$

  - Analogous for empty explored cell.

Solution: Maximize gain in explored map

- Expected mutual information gain for cell i:

$$\hat{I}_i(x_i) \equiv -E\left[\ln \frac{P_i(x_i|z_k)}{P_i(x_i)}\right] = H_i - \overline{H}_i(x_i|z_k)$$

Information gain = current entropy – new predicted entropy

Solution: Maximize gain in explored map

- Mean conditional entropy over all possible observations:

$$\overline{H}_i \equiv E[H_i(z_k)] = \int H_i(z_k) P_i(z_k) dz_k$$

  - It is the expectation of entropy left after an observation.

Solution: Maximize gain in explored map

- Conditional entropy for cell i after observation z_k at time t_k:

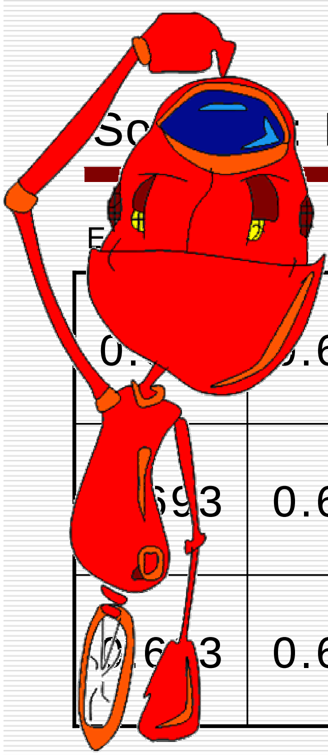
$$H_i(z_k) \equiv -E[\ln P_i(x_i|z_k)] = -\sum_{x_i \in X_i} P_i(x_i|z_k) \ln P_i(x_i|z_k).$$

- Where Bayes rule says:

$$P_i(x_i|z_k) = \frac{P_i(z_k|x_i)P_i(x_i)}{P_i(z_k)}.$$

- Using our two states (OCC, EMP) the conditional entropy can be rewritten as:

$$H_{k,i}(z_k) = -P_i(OCC|z_k)\ln P_i(OCC|z_k) - P_i(EMP|z_k)\ln P_i(EMP|z_k)$$



So[illegible]: Maximize gain in explored map

E[illegible]

0.[illegible]	[illegible].693	0.693
[illegible]3	0.693	0.693
[illegible]6[illegible]3	0.693	0[illegible]3

Occupation Grid:

0.5	0.5	0.5
0.5	0.5	0.5
0.5	0.5	0.5

Solution: Maximize gain in explored map

Entropy map:

0.693	0.693	0.693
0.693	0.693	0.693
0.693	0.693	[illegible]

[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	0.5
0.5	0.5	0.0

Information gain going up = 0.693 – 0.0

Going left = 0.693 – 0.0

Solution: Maximize g[illegible]

Entropy map:

0.693	0.693	0.693
0.693	0.693	[illegible]
0.693	0.693	0.0

[illegible]	[illegible]	0.5
0.5	0.5	0.0
0.5	0.5	0.0

Information gain going up = 0.693 – 0.0

Going left = 0.693 – 0.0

Going down = 0.0 – 0.0

Solution: Maximize gain in explored map

Entropy map:

0.693	0.693	()
0.693	0.693	0.0
0.693	0.693	0.0

Occupation Grid:

0.5	0.5	0.0
0.5	0.5	0.0
0.5	0.5	0.0

Solution: Maximize gain in explored map

- Total expected information gain from doing a specific action:

$$\hat{I}_{S_j}(x_i|z_k) = \sum_{i \in S_j} I_i(x_i|z_k)$$ = sum of information gain for each explored cell

  - Where S_j are the cells covered by scan.

- After you have done an action you update entropy map with measurements.

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Combined Information Utilities

- Constructed by linear combination:

$$\begin{aligned} U_k &= I_{composite}(\mathbf{x}, \mathbf{x}_c, \mathbf{u}_j(k)) \qquad (23) \\ &= w_1 I_{SLAM}(\mathbf{x}, \mathbf{u}_j(k)) + w_2 I_{OG}(\mathbf{x}_c, \mathbf{u}_j(k)) \end{aligned}$$

$$w_1(k) = \alpha / I_{SLAM_{MAX}}(k) \qquad w_2 = (1-\alpha)/I_{OG_{MAX}}$$

  - $SLAM_{MAX}$ is an upper bound for the SLAM covariance matrix given a number of landmarks.
  - OG_{MAX} is total information of a perfectly known OG map.
  - Increasing alpha increases accuracy of OG map. Reducing it increases amount of exploration.

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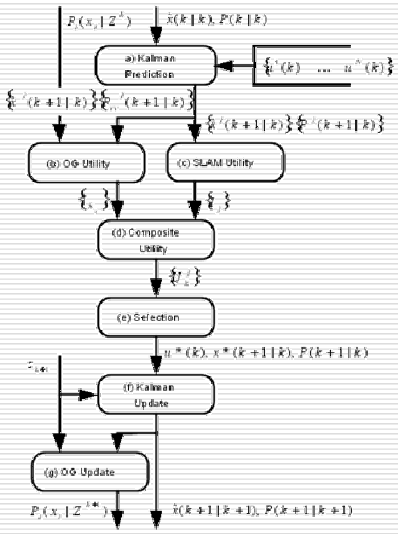
Integrated Adaptive Information-based Exploration Algorithm



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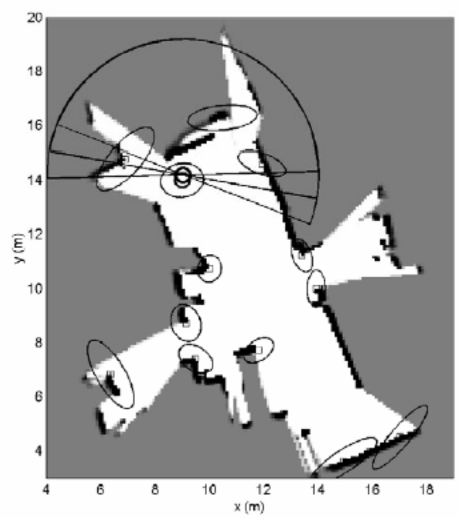
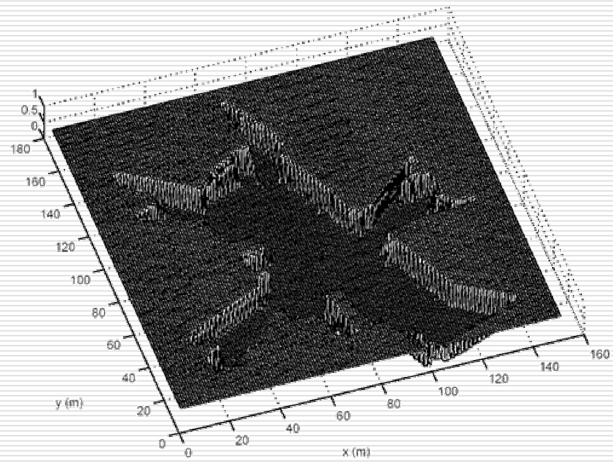
Results: OG map



Results: Entropy map



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Conclusion: Novelty

- Present an information based approach for exploration.
- Present a scheme for combining different types of information.
- Outline the Integrated Adaptive Information-based Exploration Algorithm
- Tests on an actual robot indicate the validity of these approaches.

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Conclusion: Problems

- Local Minima:
  - They claim it is robust, but is it?
- Global optimization:
  - Can be used in multi-step solutions such as path planning but:
    - Computational costs grows very rapidly with amount of look-ahead.
- No notion of “closing the loop”.

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Conclusion: Extensions

- Can easily be extended with other types of information metrics.
- It is certainly interesting to extend this for multi-robot systems.
- Further reading/different approaches:
  - R. Sim and N. Roy. “Active Exploration Planning for SLAM using Extended Information Filters”. ‘04 *Submitted to the Conference on Uncertainty in Artificial Intelligence.*