
Sensor Based Robotics

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- Introduction
- Exploration and SLAM
- Optimal navigation
- Object finding
- Pursuit-evasion
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Introduction

- Our ideas are centered on the development of mobile robotic systems that perform sensor-based tasks.



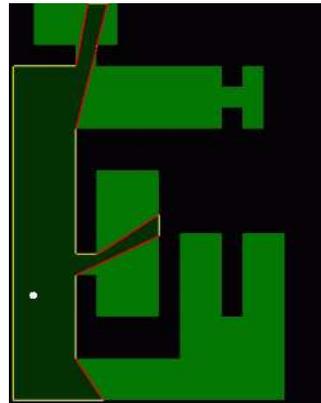
Environment Representation



Optimal Navigation



Target Finding and Tracking



Visibility

Computer Vision for SLAM



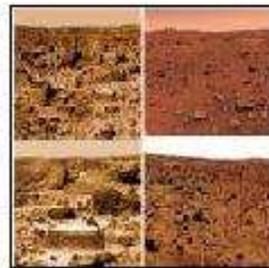
Forest

Snowed Forest

Prairie



Moon



Mars



Desert

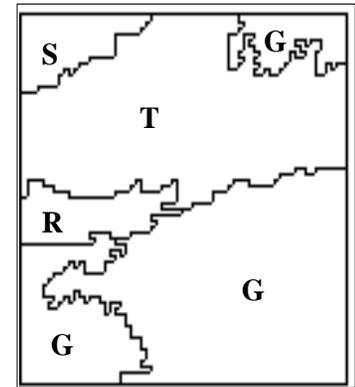


Test Image

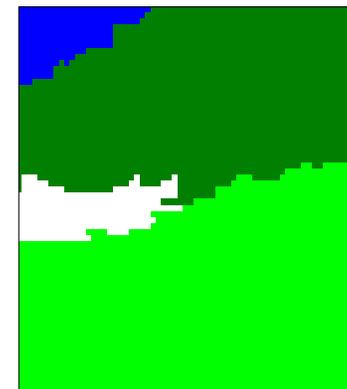
Environment Recognition



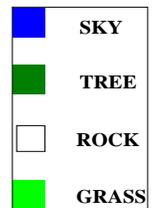
(a) Original Image



(b) Segmentation and Identification



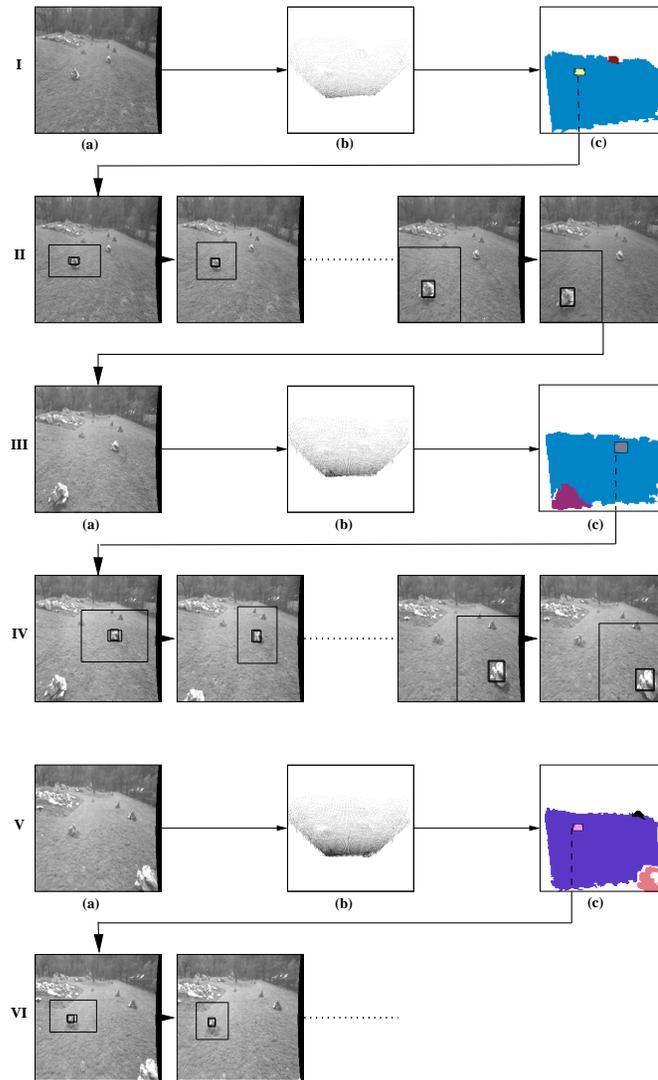
(c) Final Model



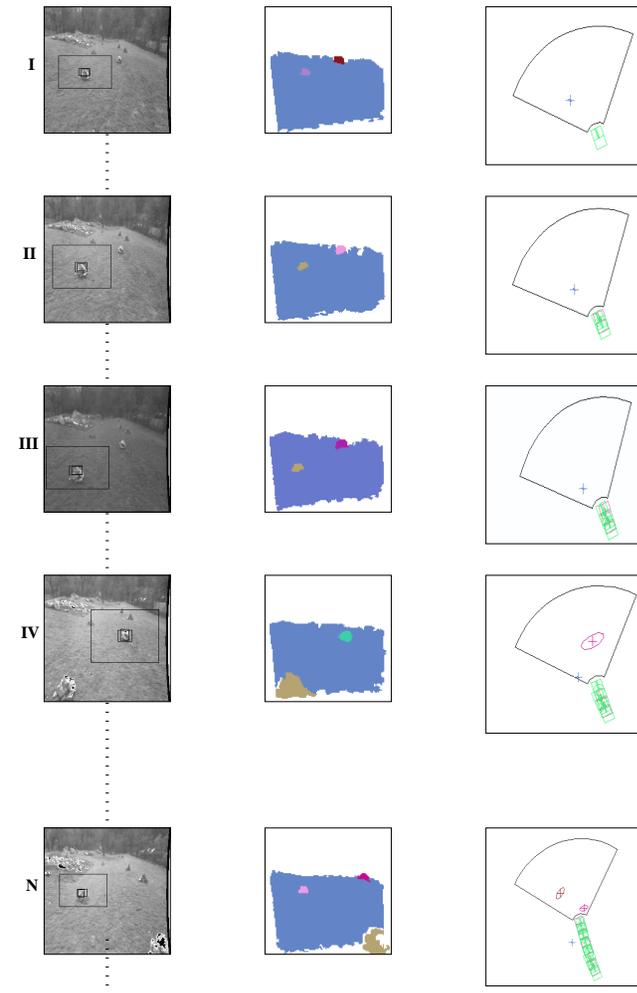
(d) Classes

Scene Modeling

Outdoor Landmark based Navigation and SLAM



Landmark-Based Visual Navigation



Landmark-Based SLAM

Outdoor Landmark based Navigation and SLAM

- Visual Navigation in Natural Environments: From Range and Color Data to a Landmark-based Model, R. Murrieta-Cid, C. Parra and M. Devy, **Journal Autonomous Robots, Vol. 13, No. 2, pages 143-168, September 2002.**
- Building Multi-level Models: From Landscapes to Landmarks, R. Murrieta-Cid, C. Parra, M. Devy, B. Tovar, C. Esteves, **In Proc IEEE International Conference on Robotics and Automation, pages 4346-4353, Washington D.C., USA, ICRA 2002.**

Planning Exploration Strategies for SLAM

- A mobile sensor (the observer) must define a motion strategy to efficiently build a map of an indoor environment.
- We have developed a randomized motion planner that selects the next best view from a set based on maximizing a utility function.
- The final result of the exploration is a multi-representational map consisting of polygons, landmarks and a road map.

Planning Exploration Strategies for SLAM

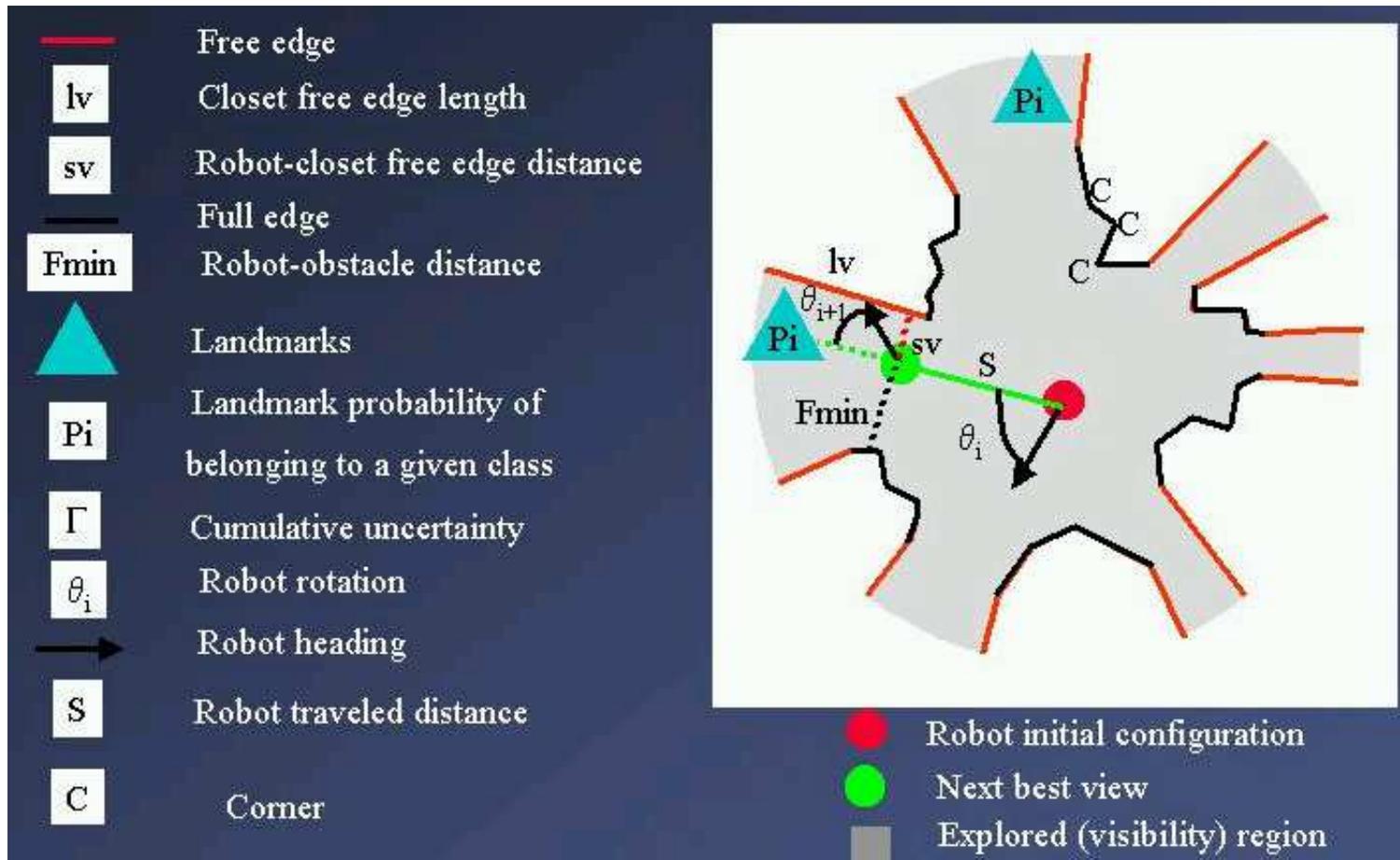
A multi-objective optimization problem:

$$\mathcal{T} = e^{l_v - (s + s_v)} \left(\frac{e^{-|\theta|}}{\Gamma + \sqrt{s} + 1} \right) \left(\frac{1}{n} \sum_{j=1}^n p_j + N_e \right) f_{min}(d_l).$$

l_v	Length of the closest free edge
s	Distance from the robot to the next possible position
s_v	Distance from the next possible position to the closest free edge
θ	Orientation change to reach the next robot's configuration
Γ	Cumulative uncertainty
p_j	Object identification probability
n	Number of landmarks inside a visibility region
N_e	Number of corners inside a visibility region
f_{min}	A function that penalizes configurations that like near an obstacle.
d_l	Minimum distance from a full edge

Definitions of variables used in the utility function.

Planning Exploration Strategies for SLAM



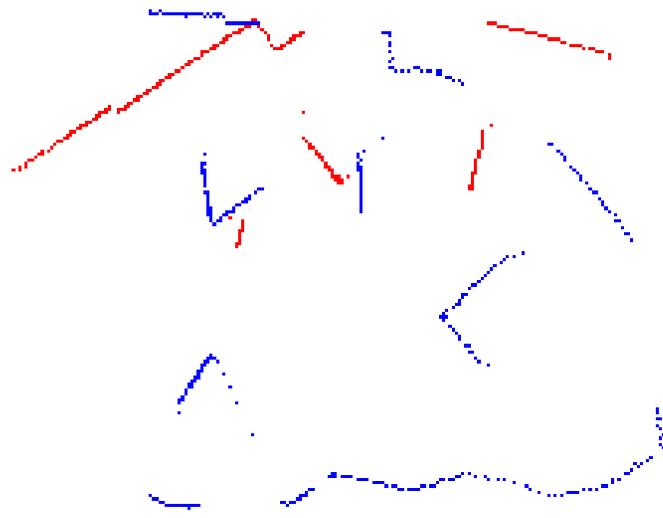
Planning Exploration Strategies for SLAM

- Given two sets of points P and Q , the Hausdorff distance is used to find the matching and update robot localization

$$H(P, Q) = \max(h(P, Q), h(Q, P))$$

$$h_M(P, Q) = M_{p \in P} \min_{q \in Q} \|p - q\|$$

Planning Exploration Strategies for SLAM

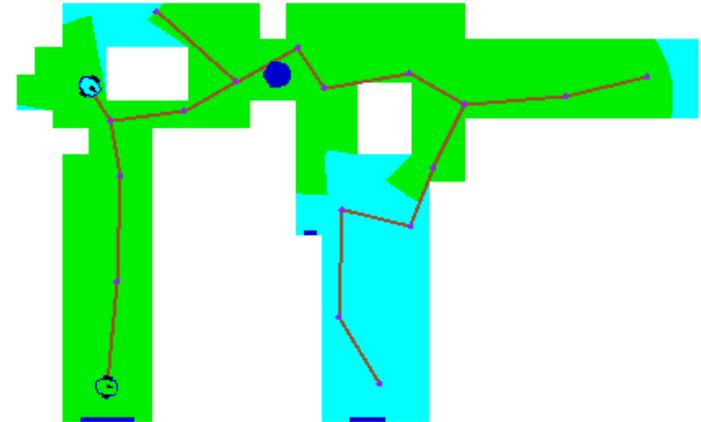


(a)
(a) Laser data

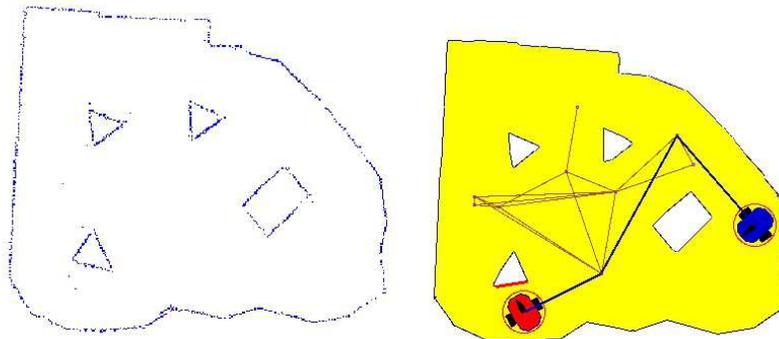


(b)
(b) Model matching

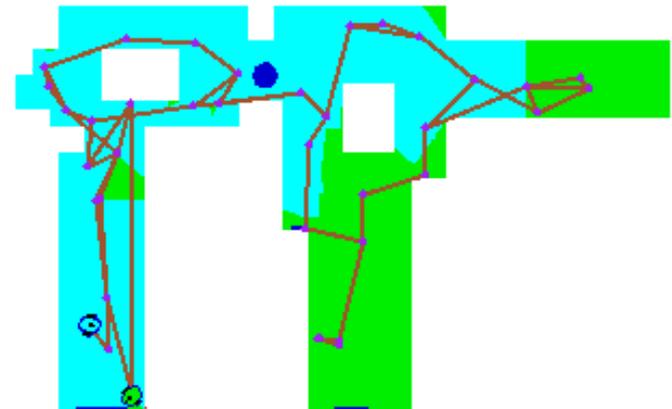
Planning Exploration Strategies for SLAM



Omnidirectional and infinite range sensor



Experiments in Real Robot



180 degrees field of view and limited range

Exploration with Multiple Heterogeneous Robots

Observation model

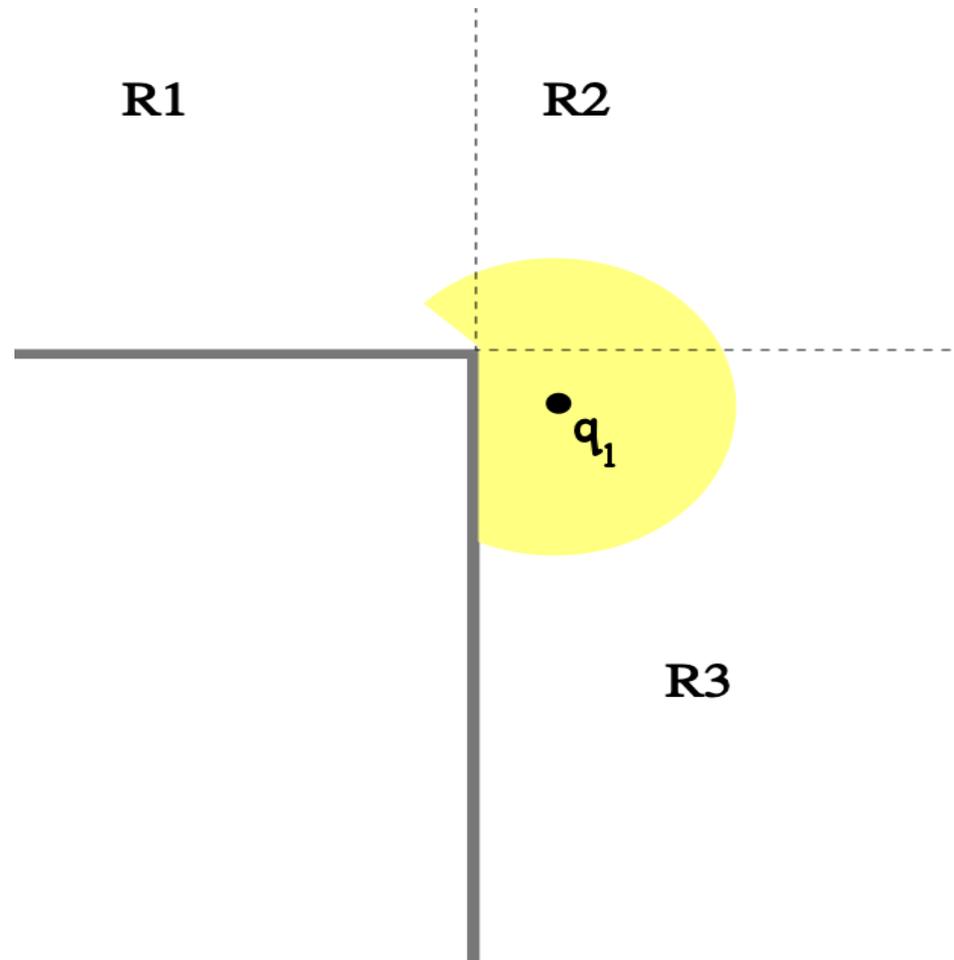
- $z = h(x)$

- Our observation model is a classifier.

$$h : x = q \times (T : S(q) \rightarrow e^{tp}) \rightarrow z \sim tp$$

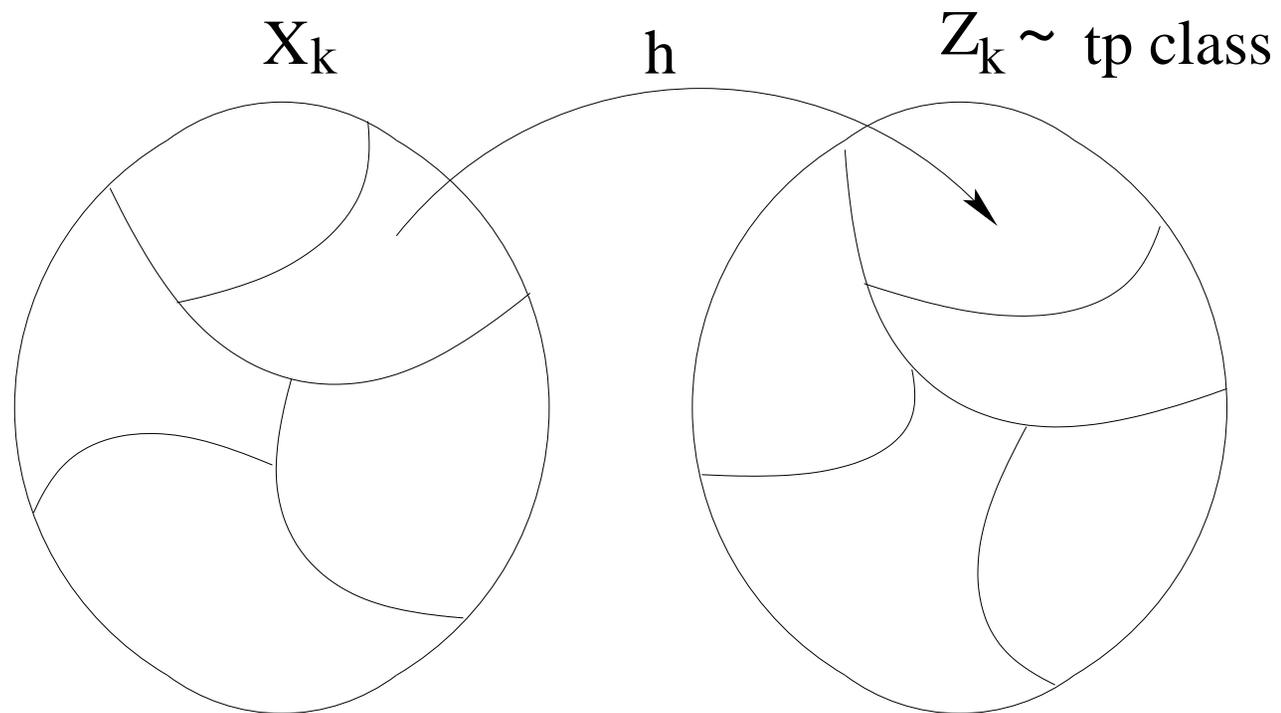
- T estimates a type (class) of local map e^{tp} by virtue of the nearest neighbor method using the partial Hausdorff distance as metric.
- h estimates the type (class) of observation tp using the Bayes rule.

Exploration with Multiple Heterogeneous Robots



Exploration with Multiple Heterogeneous Robots

Observation model



Exploration with Multiple Heterogeneous Robots

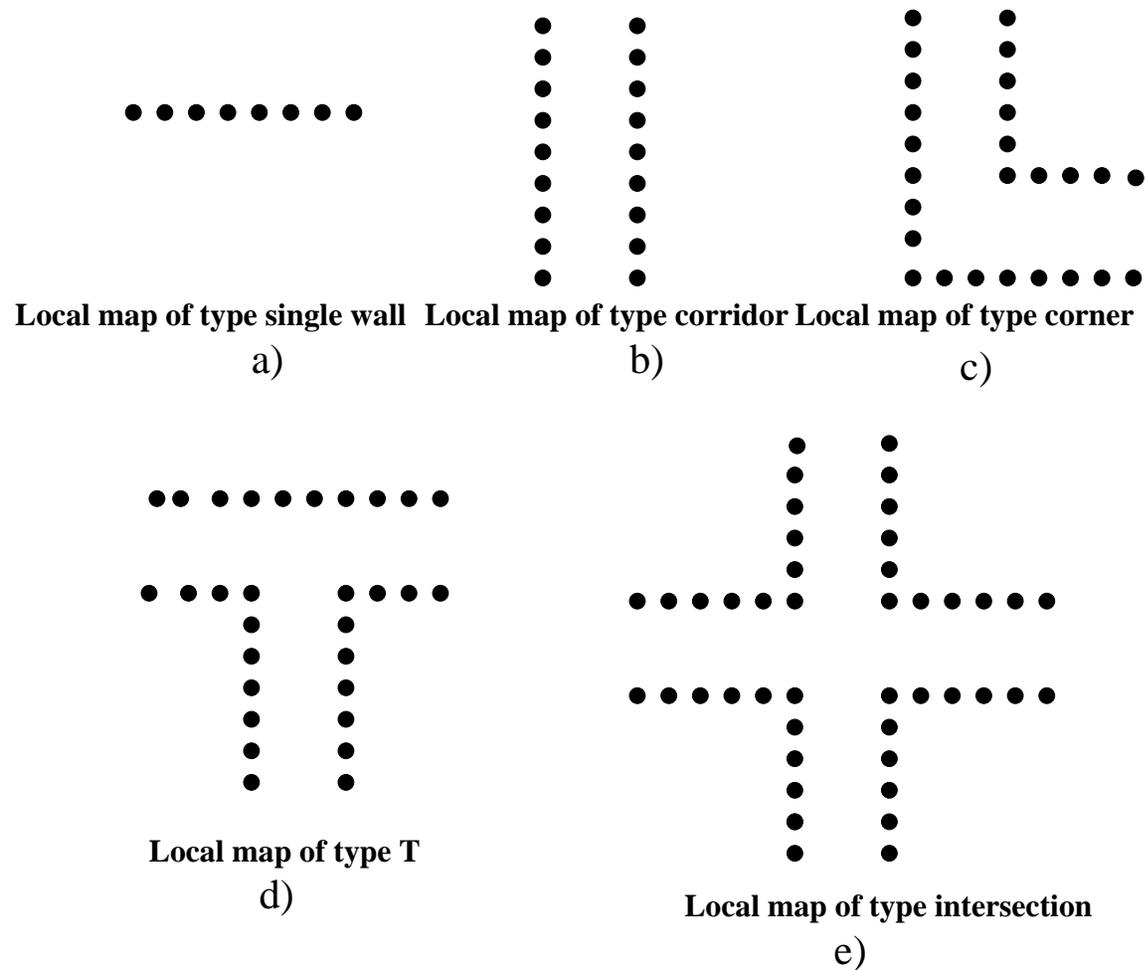
- The Bayes rule is used to estimate $p(z_{k+1}|x_{k+1})$

$$P(z_{k+1}|x_{k+1}) = \frac{p(x_{k+1}|z_{k+1})p(z_{k+1})}{\sum_{z_{k+1}} p(x_{k+1}|z_{k+1})p(z_{k+1})}$$

- MAP

$$p(z_{k+1}|x_{k+1}) = \max\{P(z_{k+1}|x_{k+1})\}$$

Exploration with Multiple Heterogeneous Robots



The training data considers some variants of each one of the five main patterns

Exploration with Multiple Heterogeneous Robots

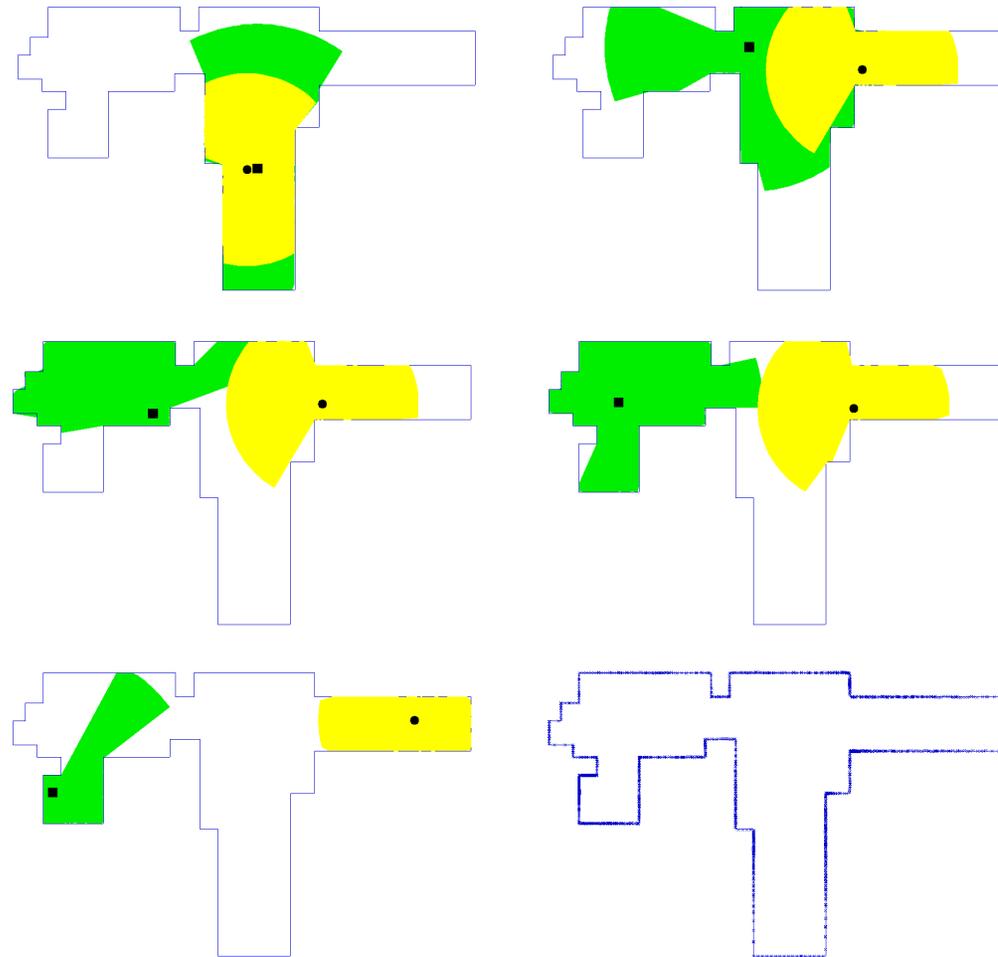
- Dynamic programming in states with imperfect information is used to select the system action u_k [Bertsekas 00].

$$J_k(I_k) = \max_{u_k} [g(I_k, u_k) + E_{z_{k+1}} \{J_{k+1}(I_k, z_{k+1}, u_k) | I_k, u_k\}]$$

- $g(I_k, u_k) = \sum_{x_k} p(x_k | I_k) g(x_k, u_k)$

- $p(x_{k+1} | I_{k+1}) = \frac{p(z_{k+1} | u_k, x_{k+1}) \sum_{x_k} p(x_k | I_k) p(x_{k+1} | x_k, u_k)}{\eta}$

Exploration with Multiple Heterogeneous Robot



15 over 20 times robot $R1$ (the one with better sensing capabilities) has explored the left part of the environment and robot $R2$ (having better control capabilities) the right part.

Planning Exploration Strategies for SLAM

- The crux of our method is a sampling-based motion planner algorithm that, given a partial map of the environment, selects where to move the robot next.
- We balance the desire to see as much of the as-yet-unseen environment as possible, while at the same time having enough overlap and landmark information with the scanned part of the building to guarantee good registration and robot localization.
- Visibility is used to bias the sampling generation.
- With heterogeneous robots, the ones with good sensing capabilities are selected to explore visually rich local maps, and robots with good control capabilities are used to explore local maps, which are hard to be matched with the global map.

Planning Exploration Strategies for SLAM

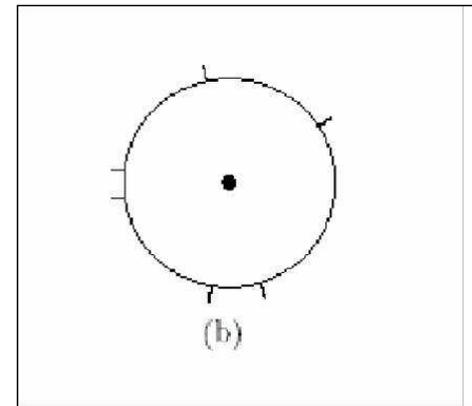
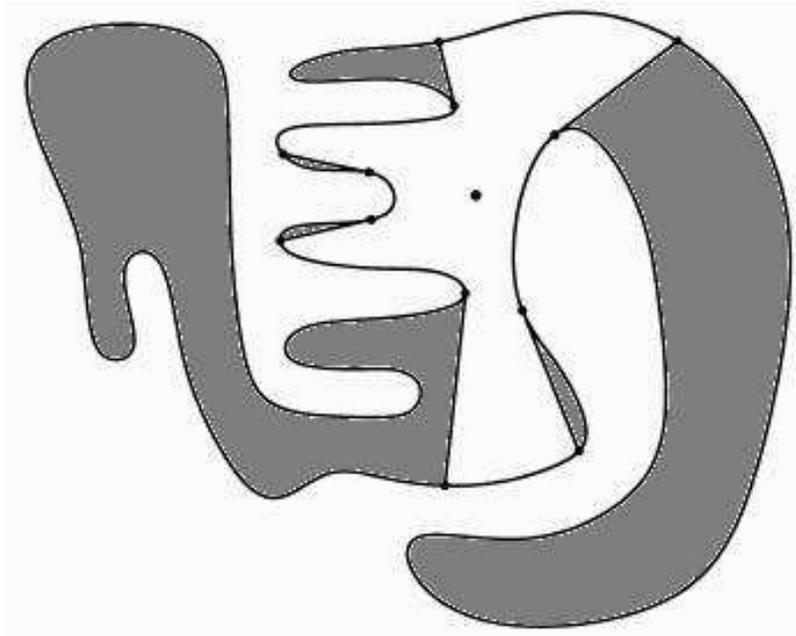
- Exploration and Map-Building under Uncertainty with Multiple Heterogeneous Robots, L. Muñoz, M. Alencastre, R. Lopez and R. Murrieta-Cid, **Proc IEEE International Conference on Robotics and Automation**, pages 2295-2301, Shanghai China, ICRA 2011.
- Planning Exploration Strategies for Simultaneous Localization and Mapping, B. Tovar, L. Muñoz-Gomez, R. Murrieta-Cid, M. Alencastre, R. Monroy and S. Hutchinson, **Journal on Robotics and Autonomous Systems**, Vol. 54, No 4, pages 314-331, April, 2006.
- Robot Motion Planning for Map Building, B. Tovar, R. Murrieta-Cid and C. Esteves, **Proc IEEE/RSJ International Conference on Intelligent Robots and Systems**, pages 673-680, Lausanne Switzerland, IROS 2002.

Optimal Navigation

What is the minimal information required to navigate in an environment with obstacles?

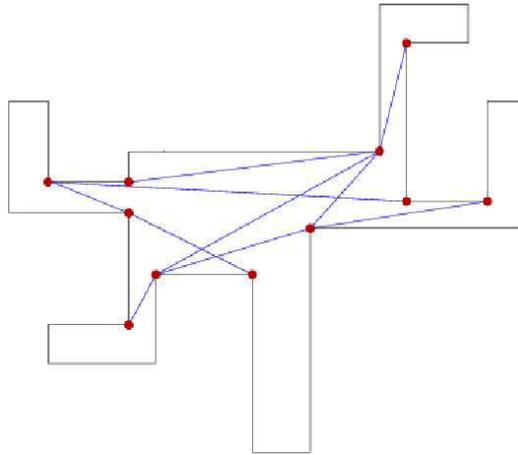
- We propose a sensor feedback motion strategy for robot navigation.
- We developed a data structure and algorithm that captures the topology of the environment and enables a robot to navigate optimally.
- This data structure is a dynamic tree that encodes enough information to generate optimal paths, although only information of gap critical events is used.

Optimal Navigation

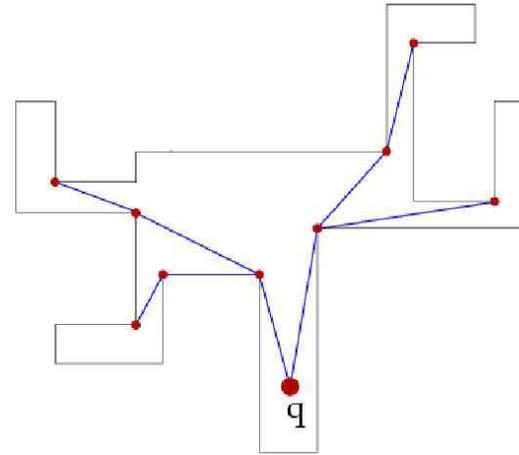


The robot view of the environment

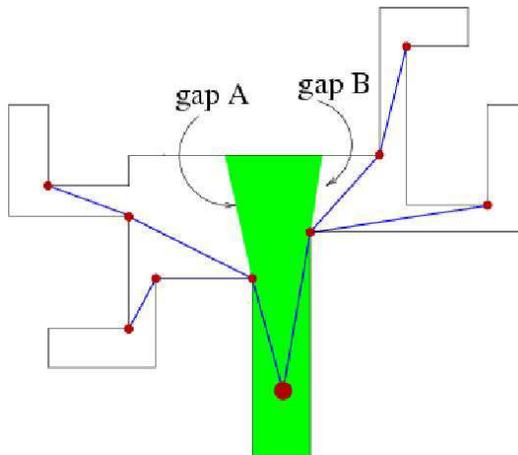
Optimal Navigation



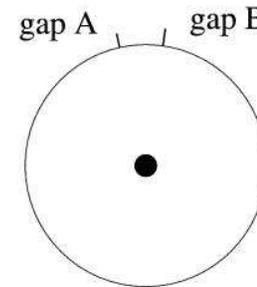
Reduced visibility graph



Visibility tree at point q $T(q)$

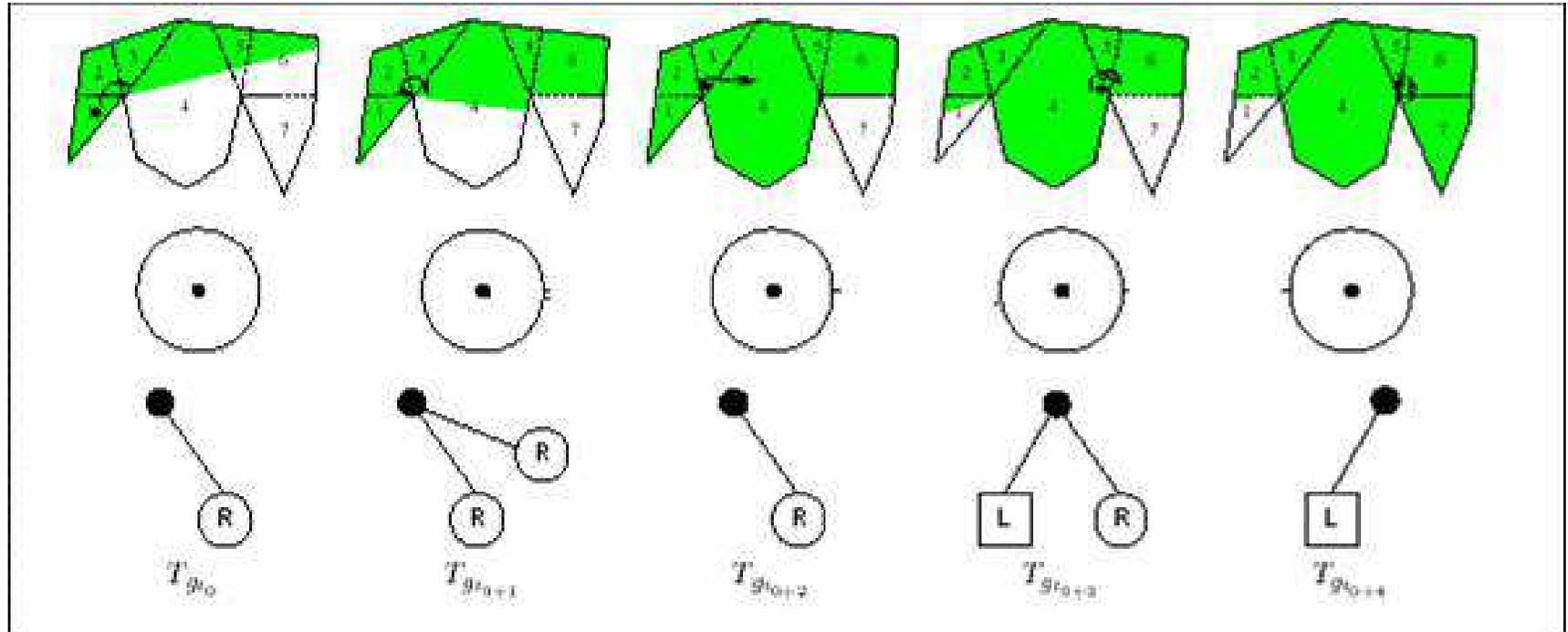


Visibility region



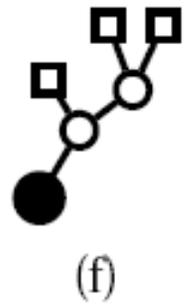
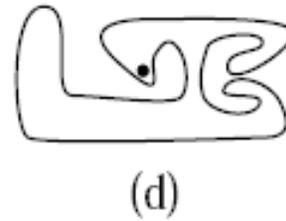
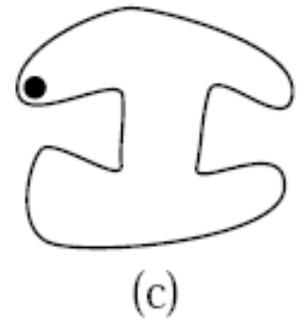
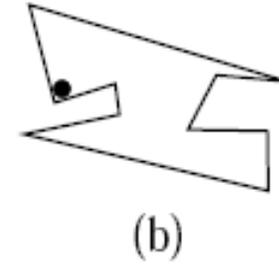
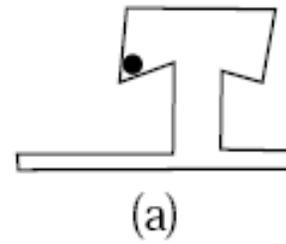
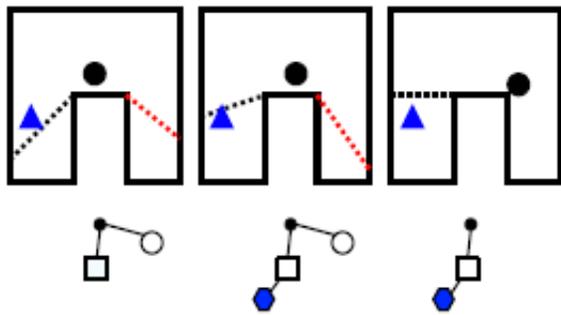
Measurement of the gap sensor

Optimal Navigation

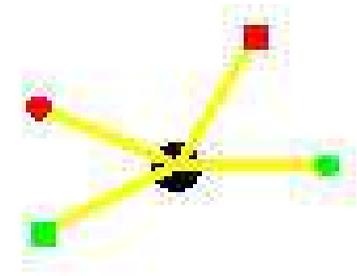
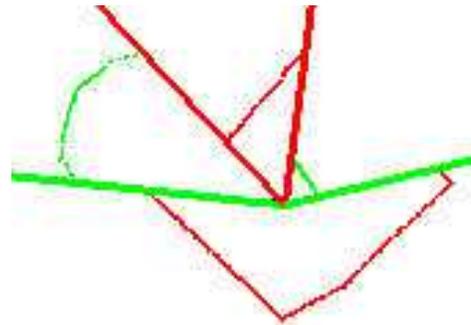


Learning T_g

Optimal Navigation



Optimal Navigation



Experiments with real robots

Simulations and Experiments

Optimal Navigation

Main results

- Theorem 1: If R is simply connected and the robot is at a point in S , then the path encoded in the GNT between the root and any point is globally optimal in Euclidean distance.
- Theorem 2: The extended GNT encodes a path to any object or landmark in the environment from the current position of the robot.

Optimal Navigation

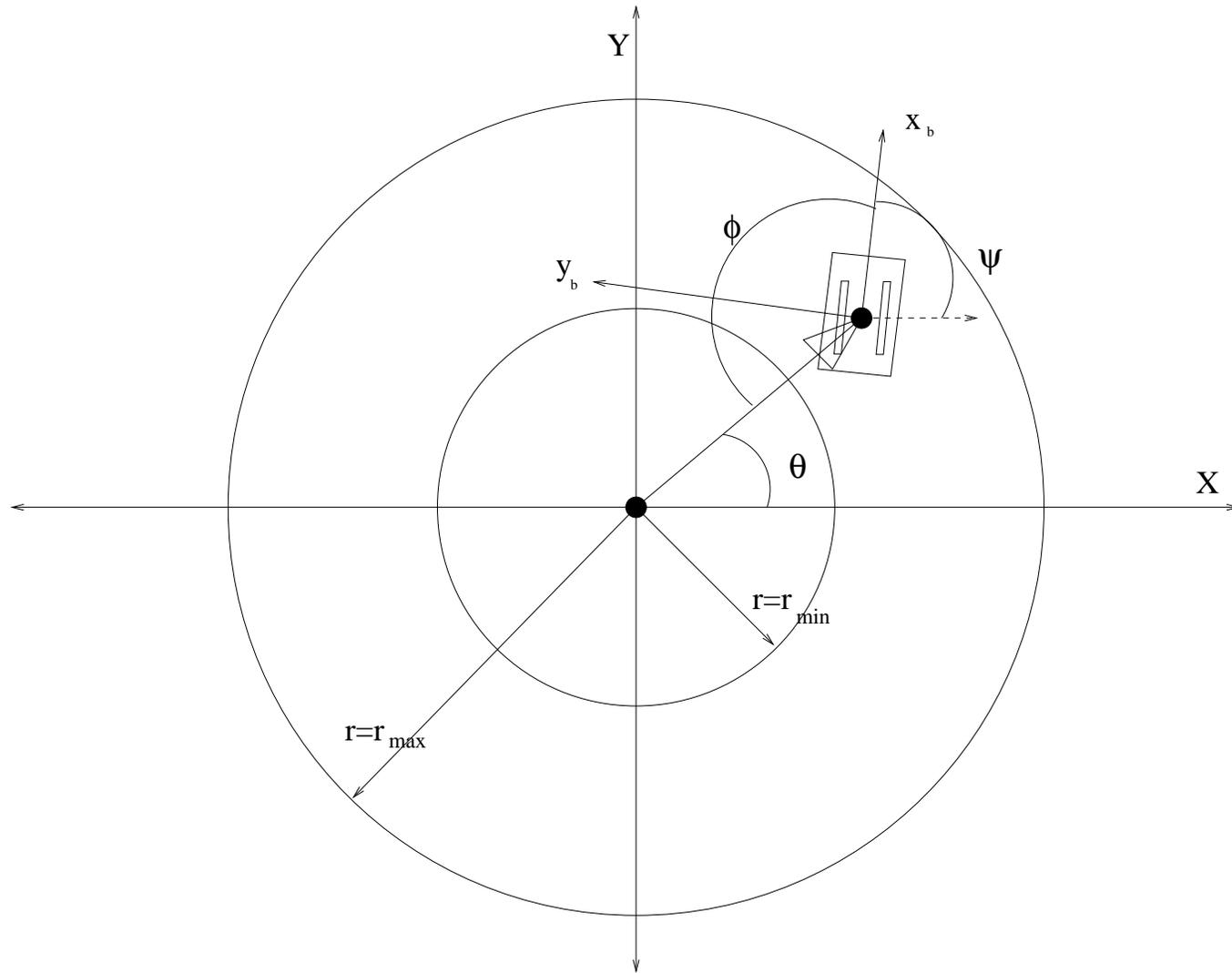
- Distance-Optimal Navigation in an Unknown Environment without Sensing Distances, B. Tovar, R. Murrieta-Cid and S. M. LaValle, **IEEE Transactions on Robotics, Vol. 23, No. 3, pages 506-518, June 2007.**
- Optimal Navigation and Object Finding without Geometric Maps or Localization, B. Tovar, S. M. LaValle, and R. Murrieta-Cid, **IEEE International Conference on Robotics and Automation, pages 464-470, Taipei Taiwan, ICRA 2003.**
- Locally-Optimal Navigation in Multiply-Connected Environments without Geometric Maps, B. Tovar, S. M. LaValle, and R. Murrieta-Cid, **IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 3491-3497, Las Vegas USA, IROS 2003.**

Optimal Navigation II

Problem Definition: Path Planning for a Differential Robot –Minimal Length Paths–.

- A mobile robot navigates while maintaining view of a fixed landmark.
- The robot has sensing constraints namely, limited angle of view.
- The robot is a nonholonomic system, differential drive robot.
- Our goal is to find the path that is optimal in sense of distance between a given start and a goal position.

Optimal Navigation II



Controllability and Optimality

- **Controllability**

Theorem 1: Between any two admissible configurations, there exists a path that satisfies sensor constraints.

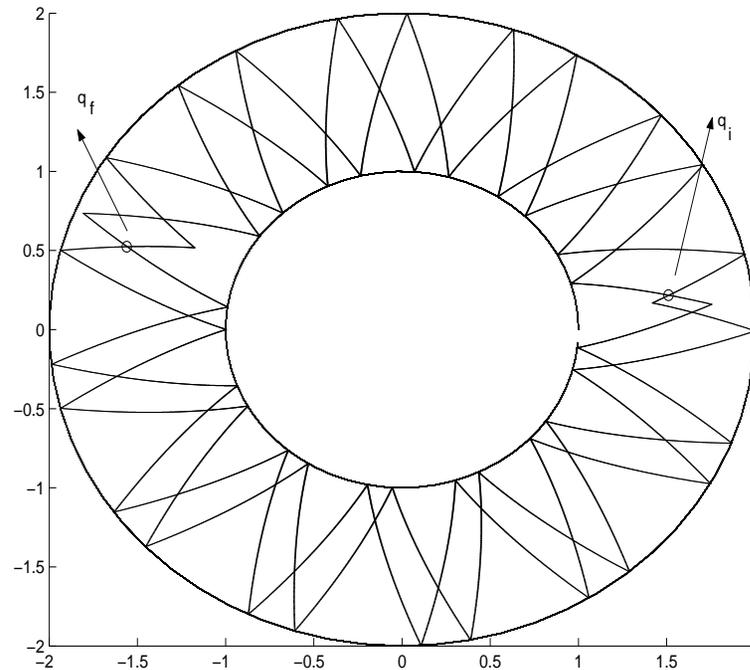
- **Optimality**

Theorem 2: Optimal paths between admissible configurations consist of path segments for which viewing angle ϕ is saturated (logarithmic spiral) and straight line segments.

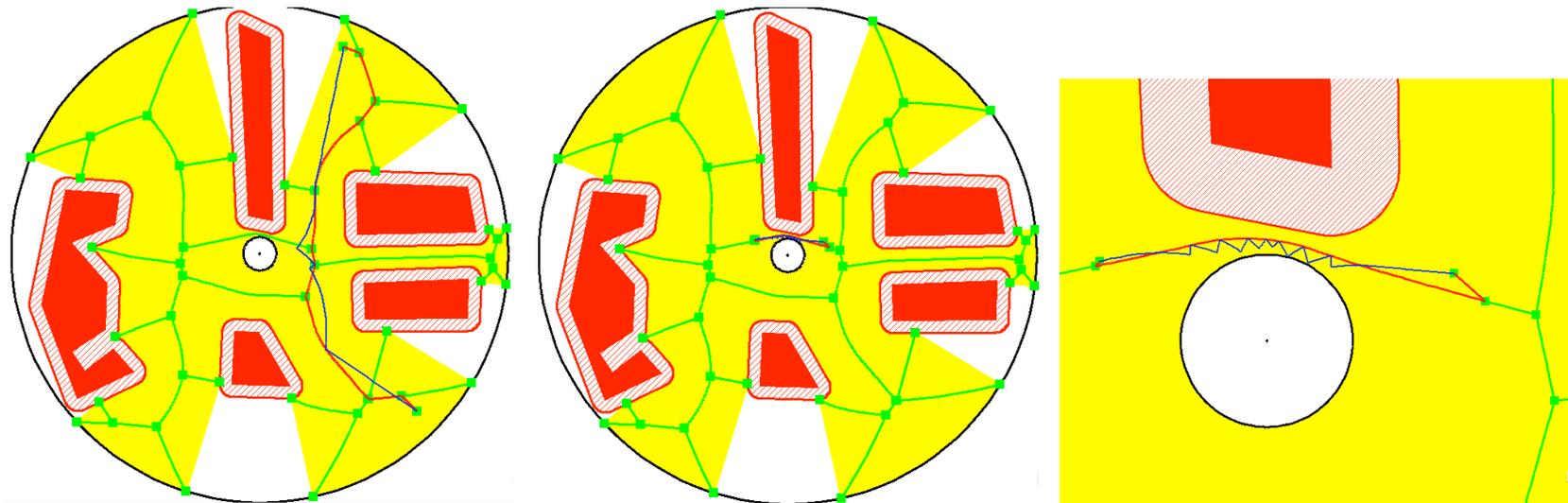
Controllability

- **Constructive proof of controllability**

Build a path by following appropriate set of S-curves.



Maintaining Visibility of a Landmark with Obstacles



(Left) Examples of a path computed by the recursive algorithm.
(Center) and (Right) Behavior of the planner in narrow passages: as expected, a solution may imply a quantity of maneuvers to finally reach the goal.

(Right) is a zoomed view of (Center).

Optimal Navigation II

- Formulation of the problem of tracking a static target with sensing constraints
- Proposed a constructive proof for the controllability of the system
- Proposed the nature of optimal paths.
- This work has been extended to the presence on obstacles, which generate both motion and visibility obstructions.
- In the case of obstacles the optimality is lost but the completeness is guaranteed.

Optimal Navigation II

- A Motion Planner for Maintaining Landmark Visibility with a Differential Drive Robot, J.-B. Hayet, C. Esteves and R. Murrieta-Cid, **Proc Workshop on the Algorithmic Foundations of Robotics, WAFR 2008, Guanajuato, México, G.S. Chirikjian et al Eds., STAR 57, pages 333-347, 2009.**
- Optimal Paths for Landmark-based Navigation by Nonholonomic Vehicles with Field-of-View Constraints, Sourabh Bhattacharya, Rafael Murrieta-Cid and Seth Hutchinson, **IEEE Transactions on Robotics, Vol 26, No.3, pages 47-59, February 2007.**
- Path Planning for a Differential Drive Robot: Minimal Length Paths - a Geometric Approach, S. Bhattacharya, R. Murrieta-Cid and S. Hutchinson, **IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 2793-2798, Sendai Japan, IROS 2004.**

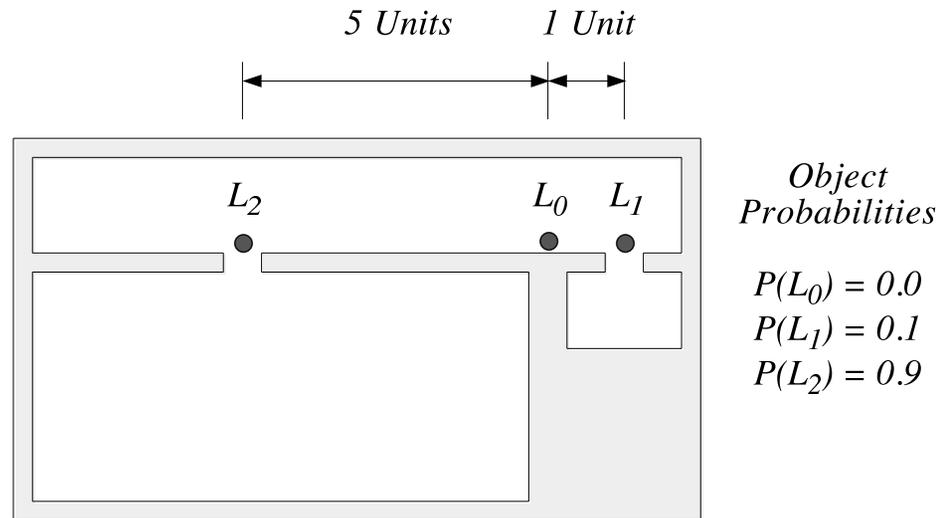
Object Finding

Problem Definition:

- Use one or more mobile robots to find an object as quickly as possible on average.
- robots move in a known environment.

Object Finding

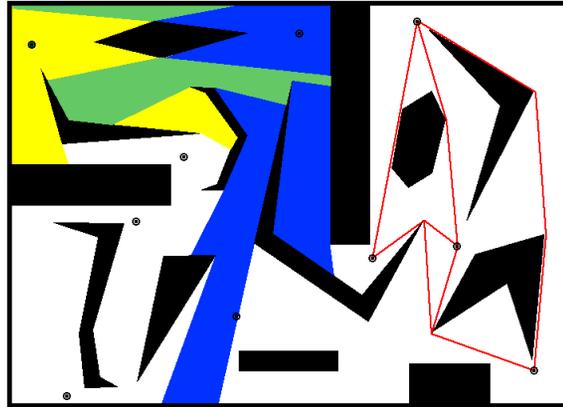
Expected Value vs. Worst Case:



- Route 1: $L_0 \rightarrow L_1 \rightarrow L_2$
 - $E[T|Route_1] = (0.1)(1) + (0.9)(7) = 6.4$
 - Worst case time = 7
- Route 2: $L_0 \rightarrow L_2 \rightarrow L_1$
 - $E[T|Route_2] = (0.9)(5) + (0.1)(11) = 5.6$
 - Worst case time = 11

Object Finding

Different Versions of the Problem:

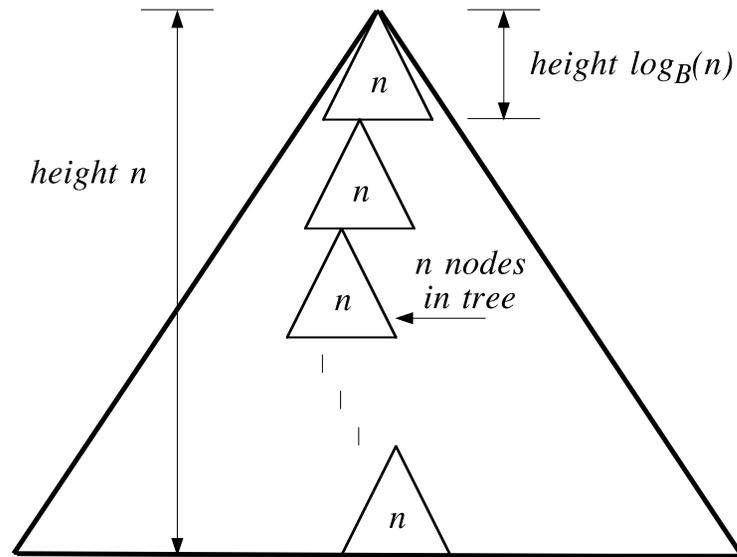


- Sensing at specific locations.
- Polygonal environment.

Result:

Theorem: Finding the route that minimizes the expected value of the time for finding the object is a NP-hard problem even for a point robot moving in a 2-D polygonal environment.

Object Finding



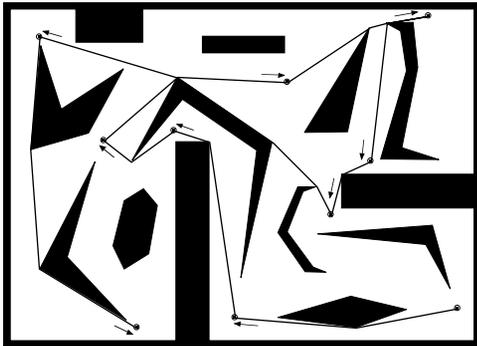
- Use a utility function to drive a greedy algorithm

$$U(L_j, L_k) = \frac{P(L_k)}{\text{Time}(L_j, L_k)}$$

- Locations with a high probability or that are close will be preferred.

Object Finding

Results

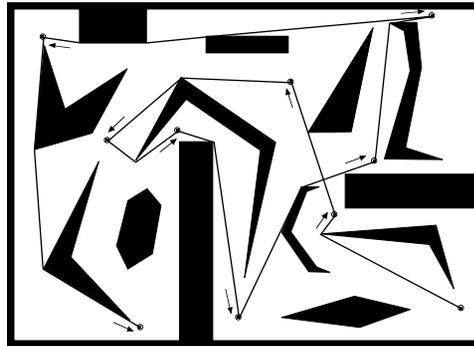


Optimal (Expect. Time)

Expected time: 943.21

Distance: 2783.20

Processing: 892.82 sec



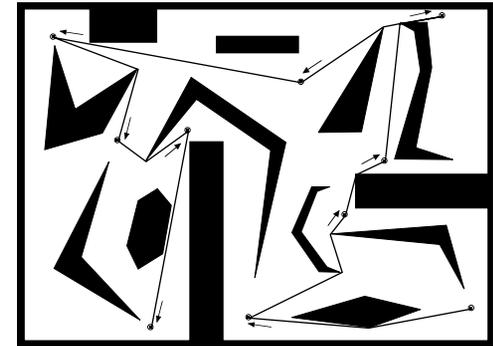
Heuristic Algorithm

Expected time: 982.21

Distance: 2970.43

Processing: 0.44 sec

(2000-fold improvement!)



Shortest Distance

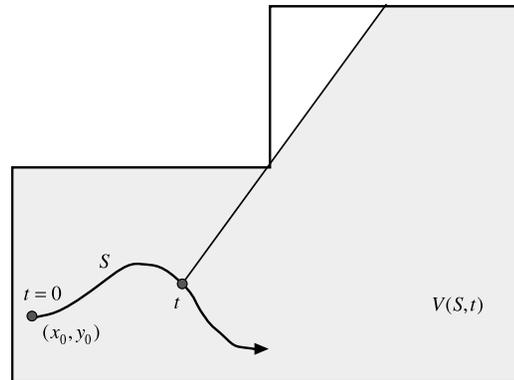
Expected time: 994.79

Distance: 2273.09

Processing: 488.87 sec

Object Finding

Different Versions of the Problem: Continuous sensing



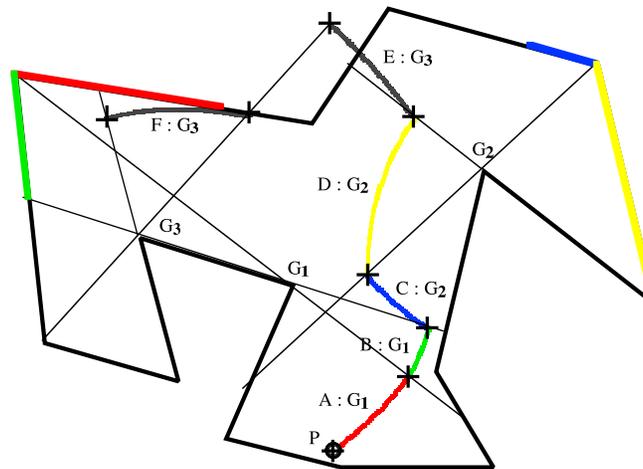
- Polygonal environment
- Robot senses the environment as it moves

$$S^* = \arg \inf_S \{E[T|S]\} = \inf_S \left\{ \int_0^\infty t \cdot f_{T|S}(t|S) dt \right\}.$$

Object Finding

Two-Layered Approach:

- Partition the environment into regions bounded by critical curves.



- Find an ordering of visiting these regions.
- Solve each region independently and concatenate the resulting sub-paths.

Calculus of Variations

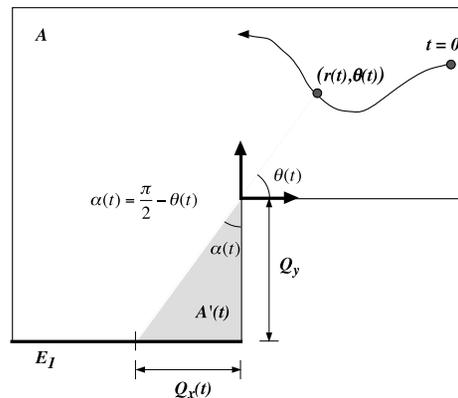
- Find stationary values of integrals of the form

$$I = \int_a^b F(x, y, y') dx$$

- Integral has a stationary value if and only if the Euler-Lagrange equation is satisfied

$$\frac{\partial F}{\partial y} - \frac{d}{dx} \left(\frac{\partial F}{\partial y'} \right) = 0$$

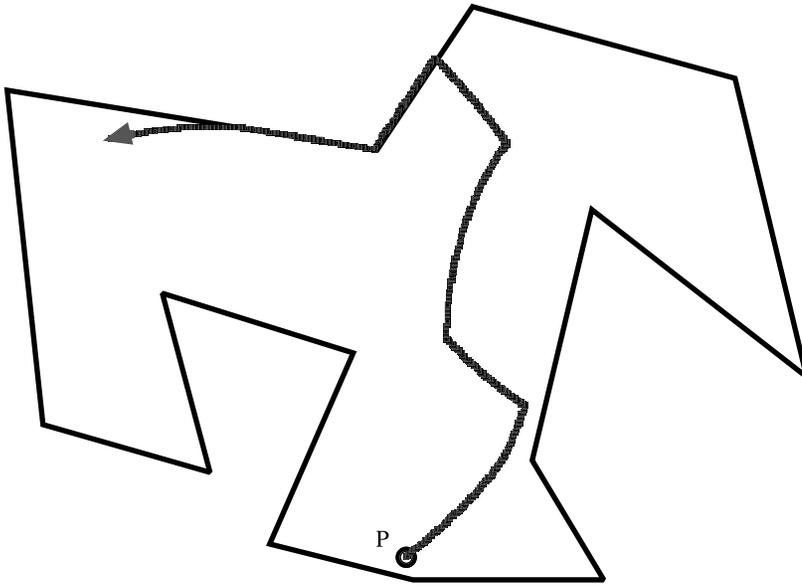
- Minimize unsewn area



- Second order non-linear differential equation

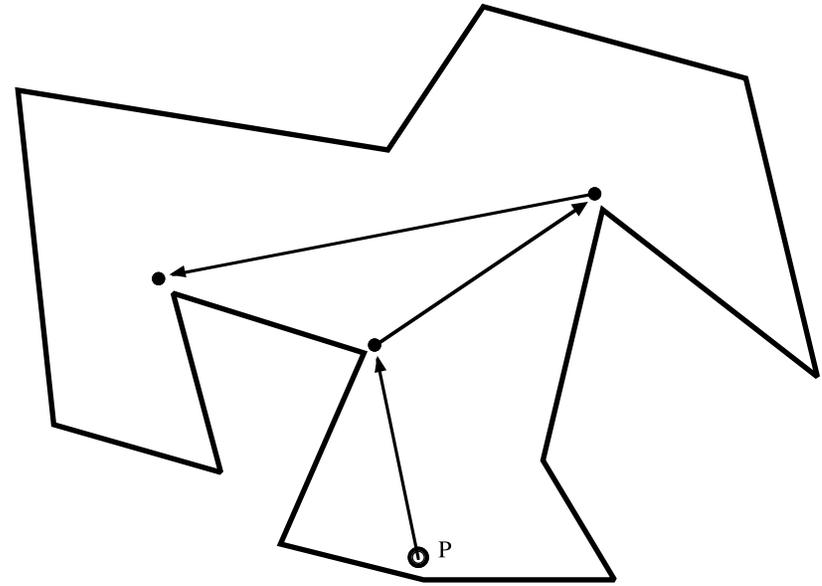
$$r'' = r + \frac{2r'^2}{r} + \frac{2}{\sin(2\theta)} \left(r' + \frac{r'^3}{r^2} \right)$$

Simulation Results



Locally Optimal

Expected time: 115.3

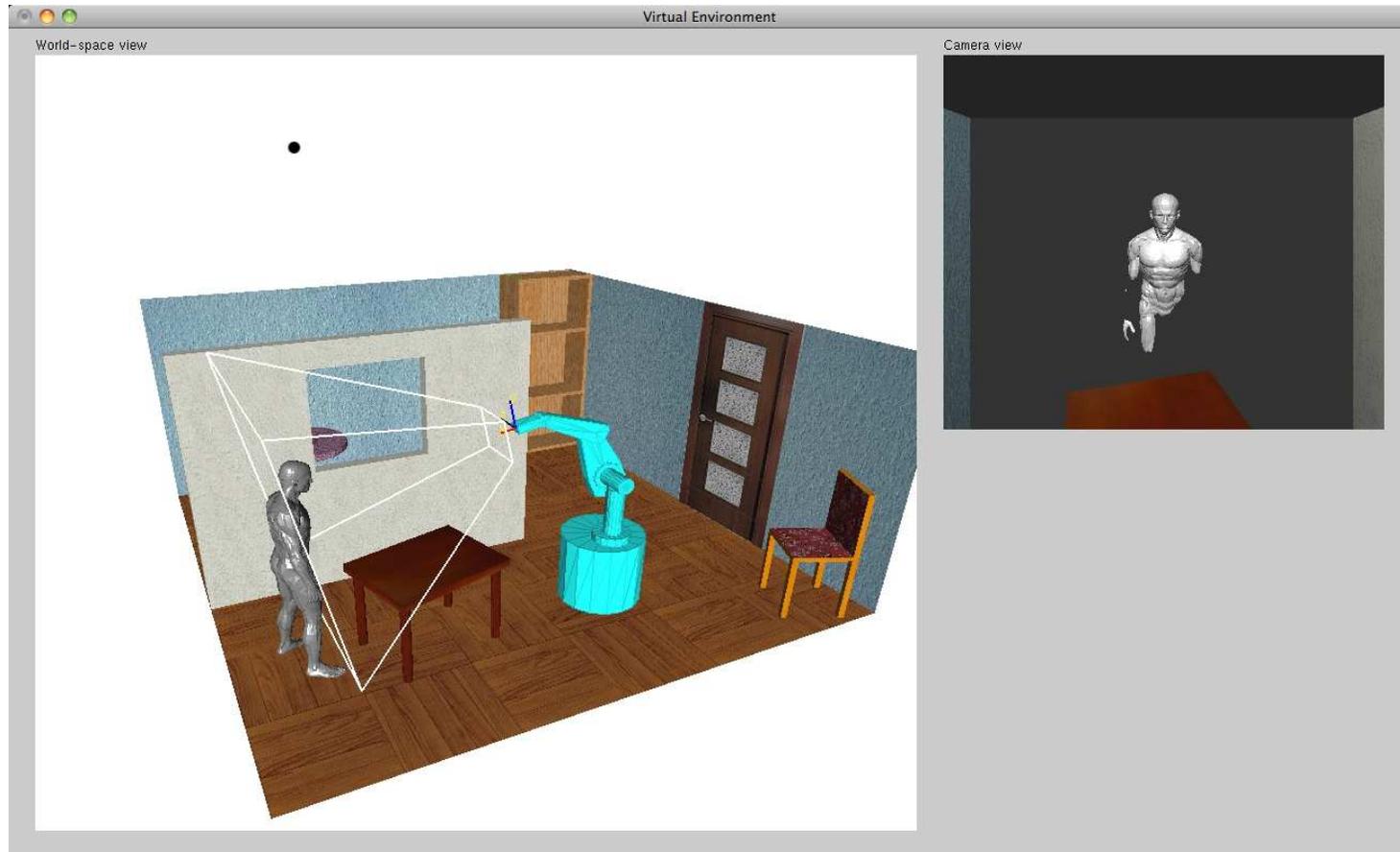


Straight Line

Expected time: 136.9

Object Finding

3-D environment and a mobile manipulator robot with limited sensing



Simulations and Experiments

Object Finding

- Repairing Plans for Object Finding in 3-D Environments, J. Espinoza and R. Murrieta-Cid, **Proc IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2011, pages 4528-4535, San Francisco California, USA, Sept 2011.**
- A Motion Planning Strategy for Finding an Object with a Mobile Manipulator in 3-D Environments, J. Espinoza, A. Sarmiento, R. Murrieta-Cid and S. Hutchinson, **Journal Advanced Robotics, pages 1627-1650, Vol 25 No 13-14, August 2011.**
- An Efficient Motion Strategy to Compute Expected-Time Locally Optimal Continuous Search Paths in Known Environments, A. Sarmiento, R. Murrieta-Cid and S. Hutchinson, **Journal of Advanced Robotics, Vol. 23, No 12-13, pages 1533-1560, October 2009.**
- A Sample-based Convex Cover for Rapidly Finding an Object in a 3-D environment, A. Sarmiento, R. Murrieta-Cid and S. Hutchinson, **Proc IEEE International Conference on Robotics and Automation, pages 3497-3502, Barcelona Spain, ICRA 2005.**

Pursuit-Evasion

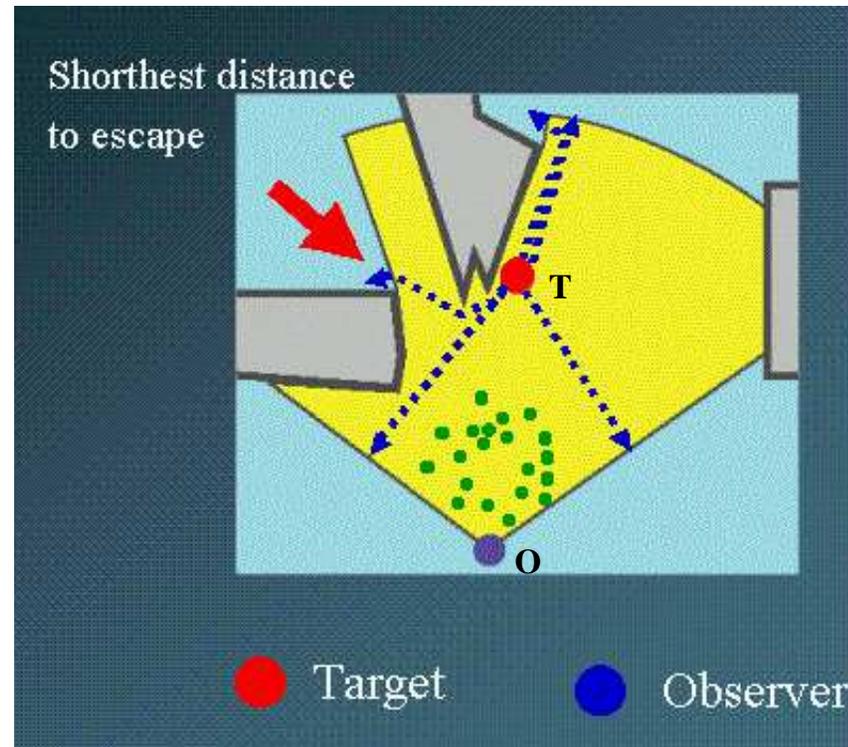
Problem definition:

- A mobile robot must maintain visibility of a moving evader.
- The geometry of the environment is known a priori.
- We are assuming a feedback control scheme where the instantaneous target velocity is measured or reported.
- The observer speed is bounded.
- **Antagonism:** Non-cooperative games.
- Decision problem: can the evader escape?
- Planning problem: the motion strategy.

Pursuit-Evasion

Sampling Based Motion Planning

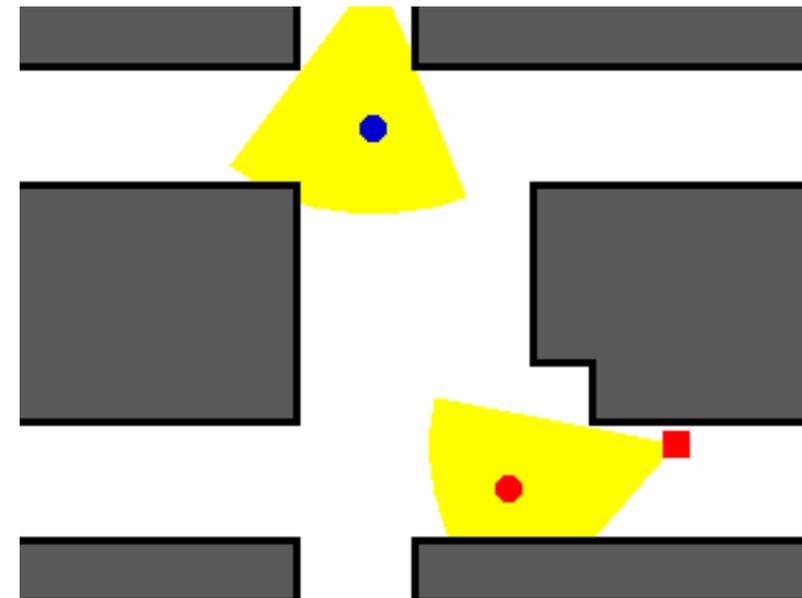
- The shortest distance to escape: Our algorithm computes a motion strategy by maximizing the *shortest distance to escape* —the shortest distance the target must move to escape an observer's visibility region.



Pursuit-Evasion



Experiments real robot:Controller
Experiments real robot:Planner and Controller



Simulation two-pursuers/two-evaders
Tracking People with mobile robots.

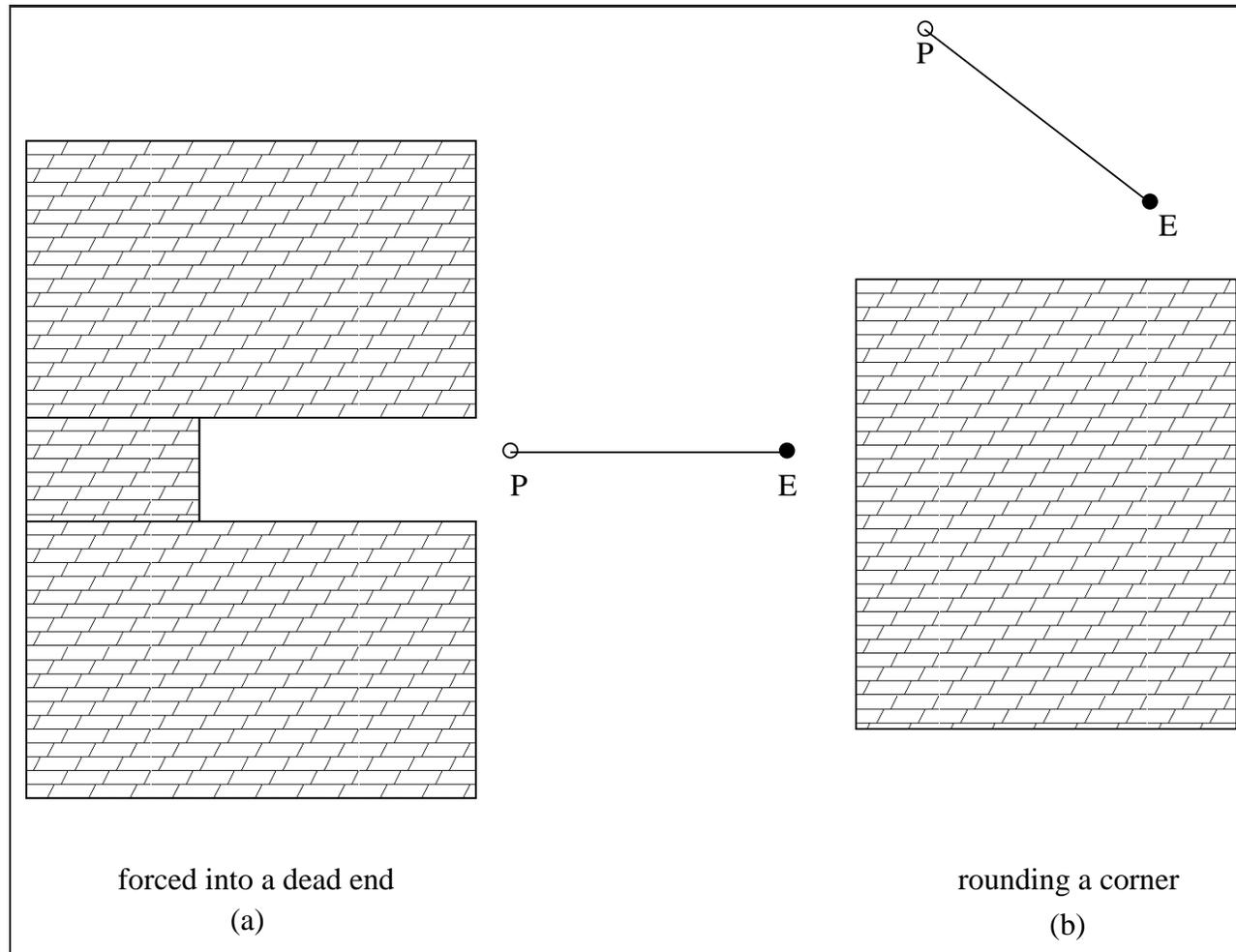
Pursuer with Finite Sensor Range

Deterministic approach:

- This problem is analogous to the path planning problem of moving a rod in the plane (Schwartz and Sharir).
- The end points of the rod represent the pursuer and evader.
- The rod represents the surveillance constraints.
- The evader controls the rod origin (x, y) and the pursuer controls the rod orientation θ .
- Violation of the visibility constraint corresponds to collision of the rod with an obstacle in the environment.

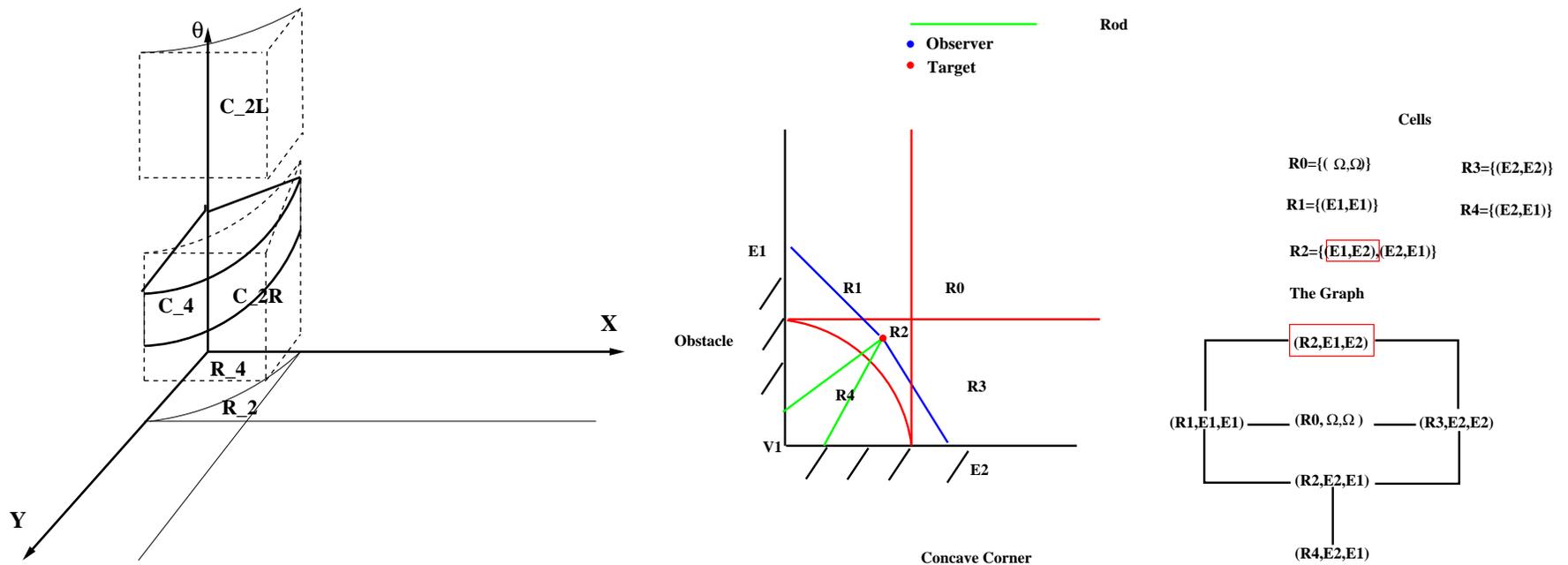
Key Idea: Capture the qualitative structure of the problem using a combinatoric representation.

The Basic Cases

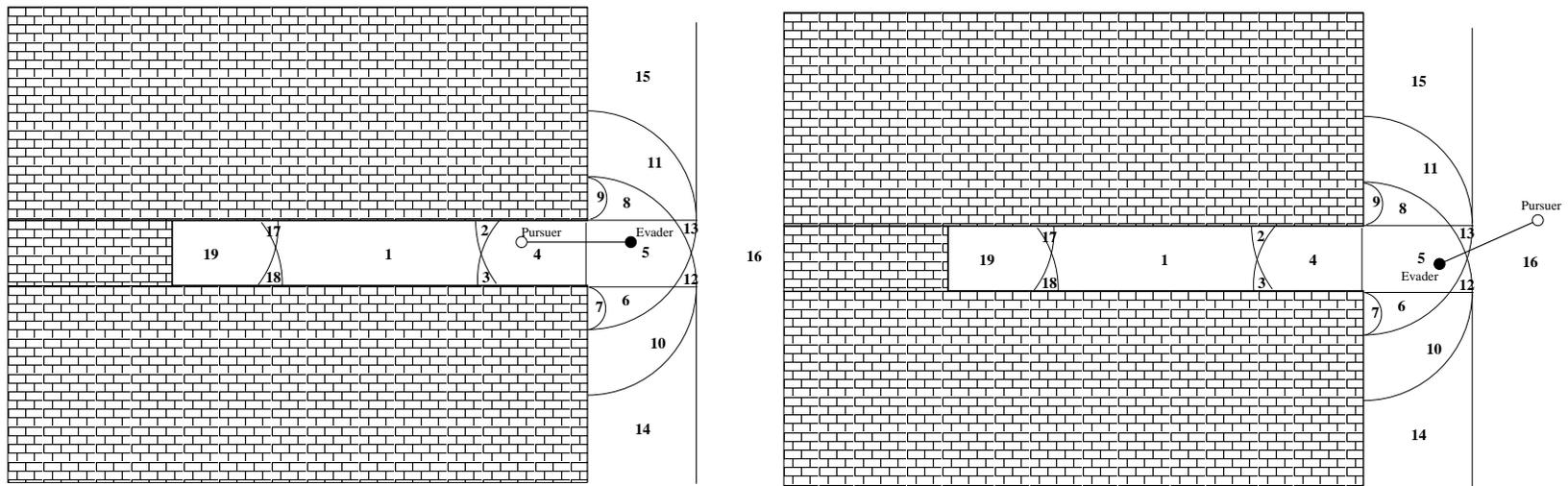


Cells in \mathcal{C}

- The configuration space for the rod, $\mathcal{Q} = SE(2) \times [L_{\min}, L_{\max}]$.
- Each non-critical region in the plane defines a cylinder in \mathcal{C} .

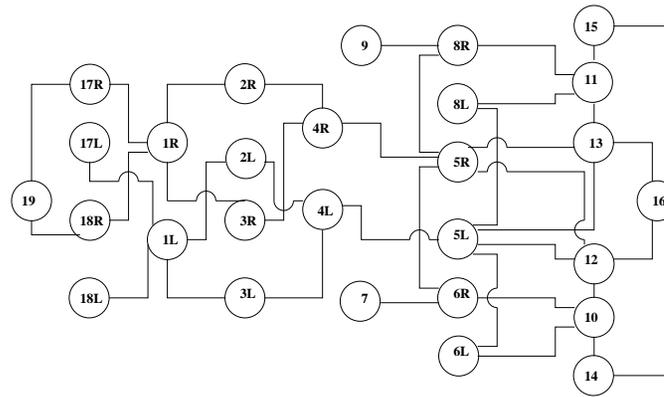


Cells in \mathcal{C}



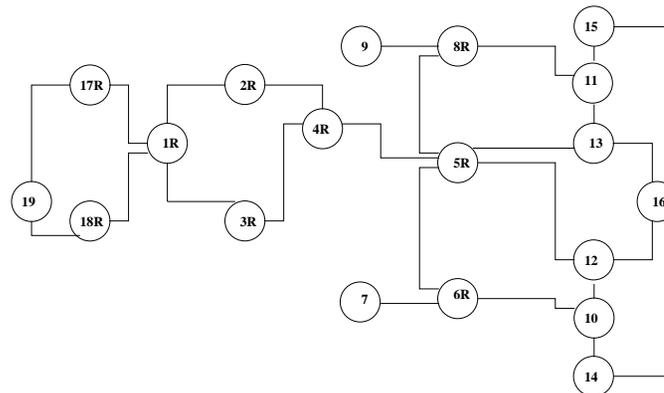
In the figure on the left, the rod's configuration is in cell κ_{5L} . In the figure on the right, the rod's configuration is in cell κ_{5R} .

The Reduced Connectivity Graph



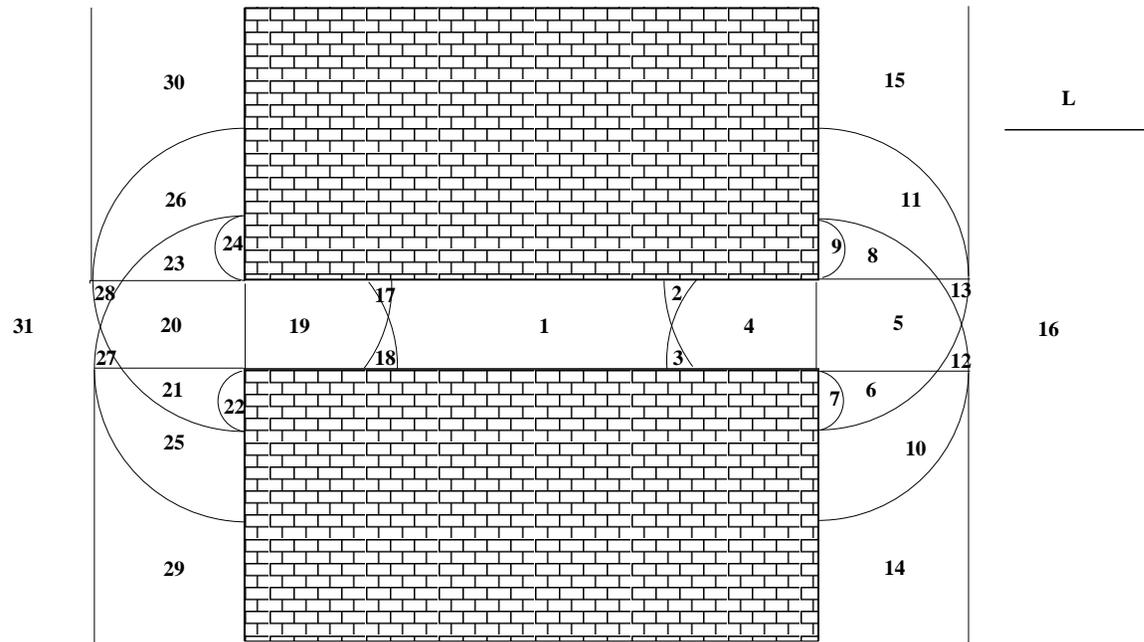
The complete connectivity graph for the simple corridor example.

- G is a non-directed graph whose nodes are all the C-space cells. There is an edge connecting any two nodes only if the corresponding cells are adjacent.

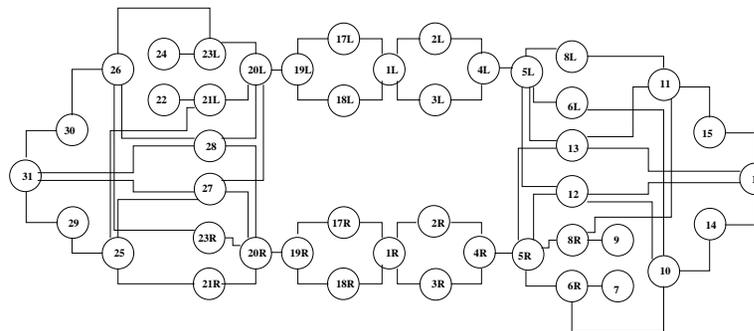


The reduced connectivity graph for the example

No Solution for the Pursuer



A simple workspace in which a corridor connects two large empty spaces



Connectivity graph for the example

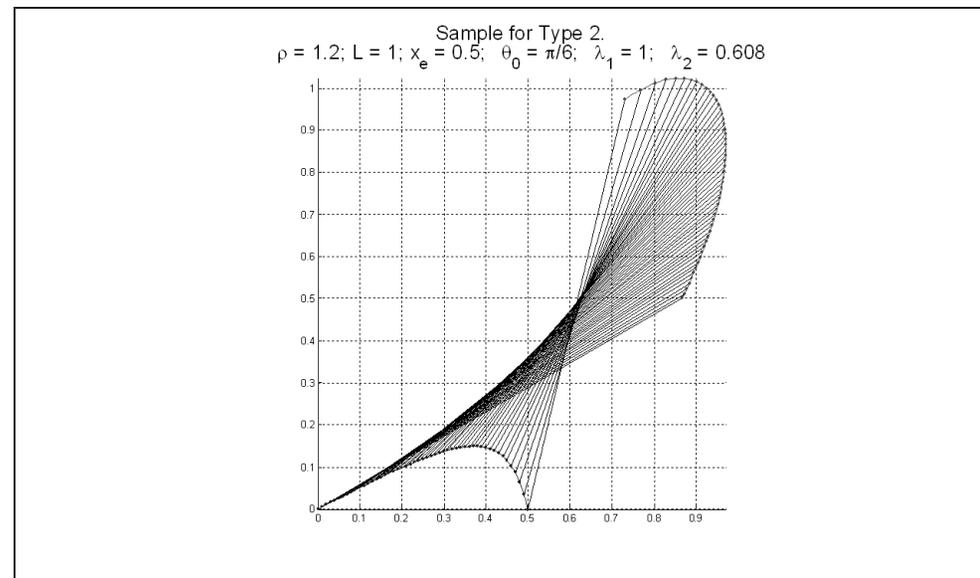
Bounded Speed: An Optimal Control Problem

- We use the *Pontryagin's Maximum Principle* [Basar et al. 2004] to solve the optimization problem and solve the resulting equations numerically using a shooting method.

$$u^* = \operatorname{argmin} \mathcal{H}(\zeta(x), \lambda(x), u(x), x)$$

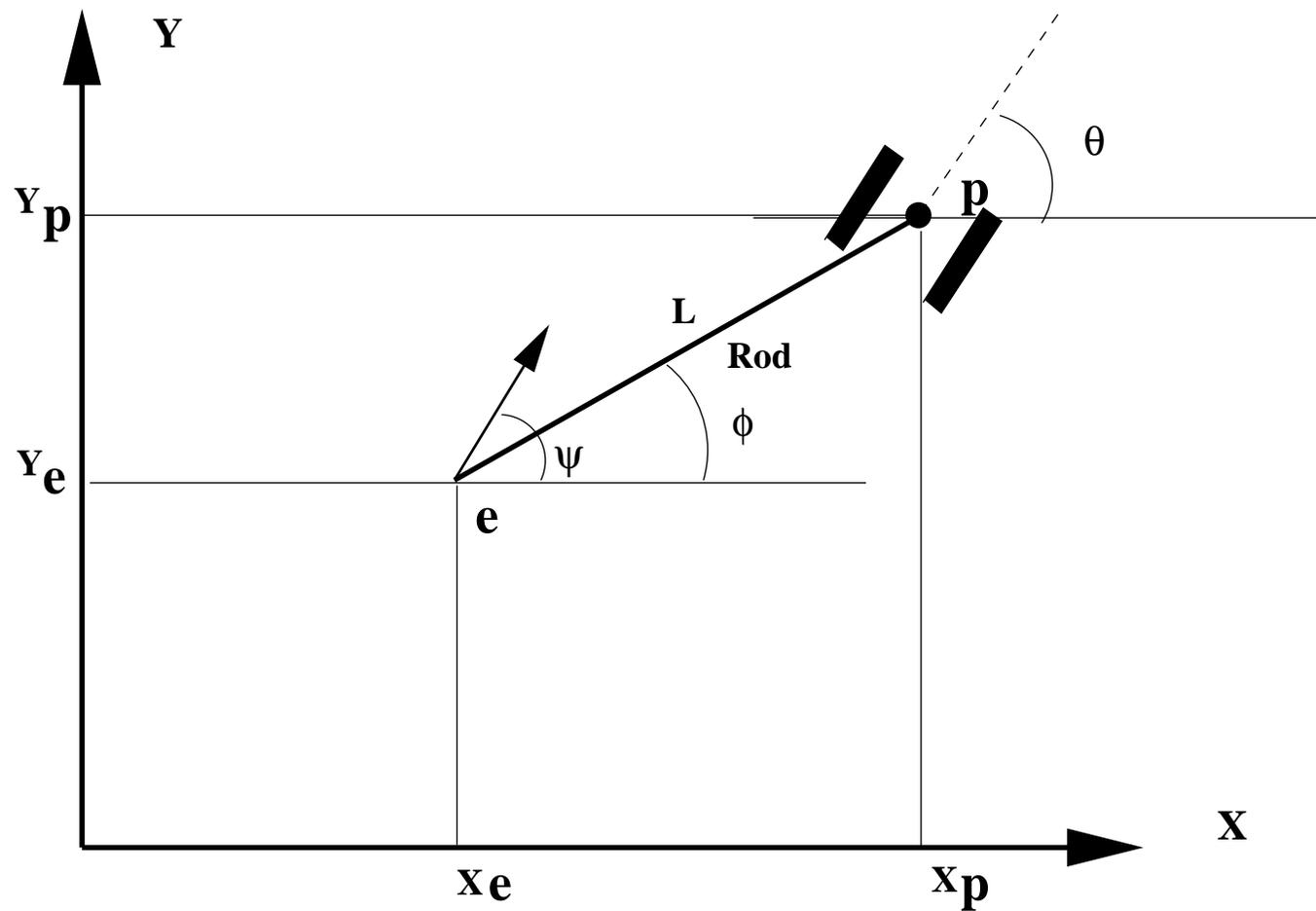
$$\mathcal{H} = l + \lambda^T f, \quad \dot{\lambda} = -\nabla_{\zeta} \mathcal{H}$$

Pursuer and evader paths



Pursuit-Evasion

Tracking an omnidirectional evader with a nonholonomic robot (DDR).



Pursuit-Evasion

Tracking an omnidirectional evader with a nonholonomic robot (DDR).

Main results

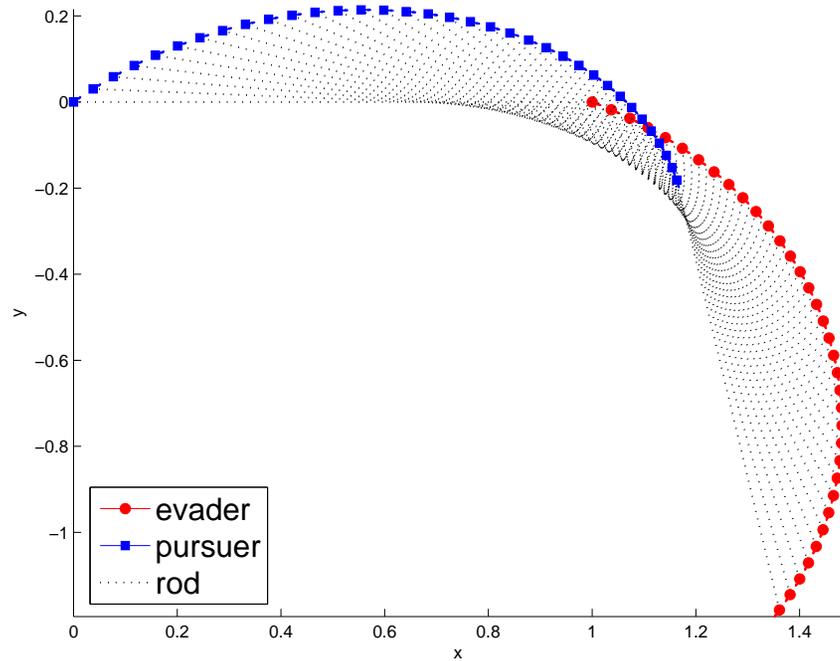
- **Theorem :**

$$M(V_e^{max}, V_p^{max}, \theta, \phi) = |\dot{\phi}(u_1^*, u_2^*)| - \frac{1}{b}(V_p^{max} - |u_3^{**}|)$$

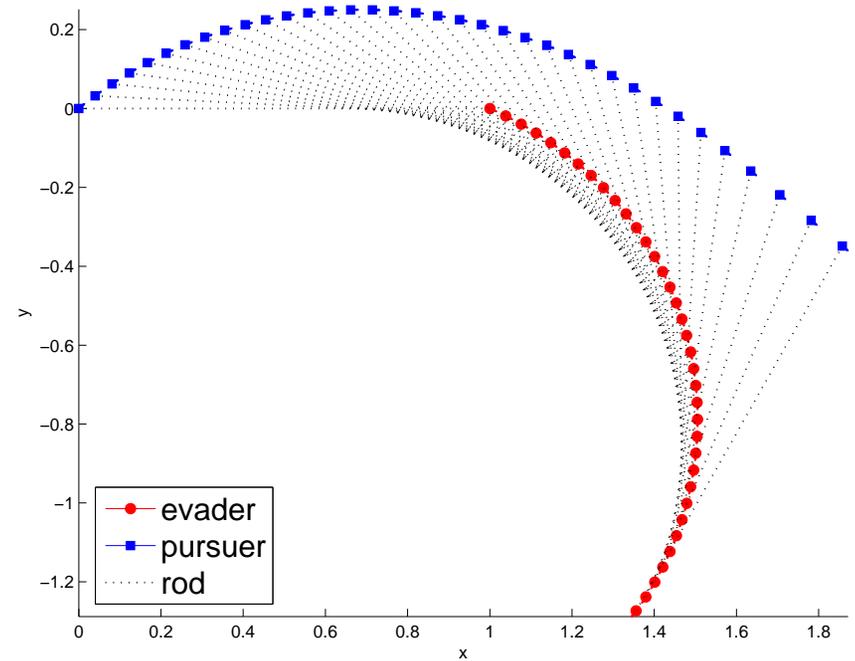
The manifold $M(V_e^{max}, V_p^{max}, \theta, \phi) = 0$ partitions the space spanned by $V_e^{max}, V_p^{max}, \theta, \phi$ into 2 regions, one in which the pursuer can maintain surveillance indefinitely, and another in which the evader can eventually escape.

If $M(V_e^{max}, V_p^{max}, \theta, \phi) > 0$ at the beginning of the game, then the evader eventually wins at some time $t > t_0$ if the strategy $(u_1, u_2) = (u_1^*, u_2^*)$ is applied at all times, regardless of the strategy applied by the pursuer. Otherwise, if at the beginning of the game $M(V_e^{max}, V_p^{max}, \theta, \phi) \leq 0$, the pursuer wins, if the strategy $(u_3, u_4) = (u_3^*, u_4^*)$ is applied at all times, regardless of the strategy applied by the evader.

Simulation Results



Pursuer wins
Optimal trajectories



Evader wins
Optimal trajectories

Pursuit-Evasion

- Tracking an Omnidirectional Evader with a Differential Drive Robot, R. Murrieta-Cid, U. Ruiz, J. L. Marroquin, J.-P. Laumond, and S. Hutchinson, **To appear in Journal Autonomous Robots, special issue on Search and Pursuit/Evasion with Mobile Robots.**
- Evader Surveillance under Incomplete Information, I. Becerra, R. Murrieta-Cid and R. Monroy, **IEEE International Conference on Robotics and Automation, pages 5511-5518, Anchorage USA, ICRA 2010.**
- A Complexity Result for the Pursuit-Evasion Game of Maintaining Visibility of a Moving Evader, R. Murrieta-Cid, R. Monroy, S. Hutchinson and J.-P. Laumond, **IEEE International Conference on Robotics and Automation, pages 2657-2664, Pasadena USA, ICRA 2008.**
- Surveillances Strategies for a Pursuer with Finite Sensor Range, Rafael Murrieta-Cid, Teja Muppirala, Alejandro Sarmiento, Sourabh Bhattacharya and Seth Hutchinson, **International Journal on Robotics Research, Vol. 26, No 3, pages 233-253, March 2007.**
- A Sampling-Based Motion Planning Approach to Maintain Visibility of Unpredictable Targets, Rafael Murrieta-Cid, Benjamín Tovar and Seth Hutchinson, **Journal Autonomous Robots, Vol. 19. No 3, pages 285-300, December 2005.**

General Conclusion and Future Work

- Sensor-based robotics raises various problems combining: computer vision, geometry, planning and control, ranging from theoretical to applied and experimental.
- Relations with art-gallery problems, but with moving guards.
- Important theoretical issues: Complexity, optimality, completeness, incomplete or imperfect information.
- Future work: Robustness, reactivity, dynamic constraints, information spaces.