

AMIRKABIR WINTER SCHOOL
Minimalism in Robotics:
From Sensing to Filtering to Planning
PART 5: PLANNING IN INFORMATION SPACES

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March 5, 2012

Overview of Topics

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

1. An I-space view of planning, starting with temporal filters
2. General planning issues
3. Maze searching
4. Visibility-based pursuit-evasion
5. Shadow information spaces
6. Gap navigation trees
7. Landmark-based navigation
8. Bug algorithms
9. Sensorless manipulation
10. Wild bodies

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

From filters to planning

Using Filters For Planning

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Let \mathcal{I} be any I-space.

Assume a filter

$$l_k = \phi(l_{k-1}, u_{k-1}, y_k)$$

is given.

Let $G \subset \mathcal{I}$ be a *goal region*.

Starting from l_0 , what sequence of actions u_1, u_2, \dots , will lead to some future I-state $l_k \in G$?

Using Filters For Planning

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

The future may be unpredictable.

Introduce an *I-state dependent* plan:

$$\pi : \mathcal{I} \rightarrow U$$

Using a filter ϕ , the execution of a plan can be expressed as

$$l_k = \phi(l_{k-1}, y_k, \pi(l_{k-1}))$$

The I-space \mathcal{I} is just a sort of “C-space” that is being explored.

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

General issues

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

The following issues arise repeatedly in planning:

1. **Predictability**
2. **Reachability**
3. **Optimality**
4. **Computability**

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Are the effects of actions predictable in the I-space \mathcal{I} ?

If **yes**, then a *path* through the I-space is obtained.

Example: Sensorless manipulation

Example: Visibility-based pursuit evasion

By analogy to path planning in C-space:

1. Combinatorial planning in I-space
 2. Sampling-based planing in I-space
-

If **no**, then information feedback is critical

It is like feedback planning (or control) in C-space, but instead over I-space

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Reachability:

Is the goal region $G \subset \mathcal{I}$ even reachable from the initial I-state?

Do there even exist actions that will take us to G ?

Does there exist a plan that can reach G ?

With unpredictability, is G *guaranteed* to be reached, over all possible disturbances?

A more basic question is whether the goal can even be adequately expressed in \mathcal{I} .

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Perhaps many plans can reach G

What criteria should be formulated to compare plans?

Which plans are the best, or optimal with respect to criteria?

Do optimal plans even exist?

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Given a description of the problem, can an algorithm be determined that automatically computes a useful plan?

Sometimes a clever human designs the plan (e.g. bug algorithms)

What is the algorithmic complexity of computing a solution plan?

What is the implementation difficulty of computing a solution plan?

Important Generic Examples

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

State feedback: I-space is $\mathcal{I} = X$ and plan is $\pi : X \rightarrow U$

Open loop: $\mathcal{I} = \mathbb{N}$ and $\pi : \mathbb{N} \rightarrow U$

π can be written as (u_1, u_2, u_3, \dots)

Sensor feedback: $\mathcal{I} = Y$ and $\pi : Y \rightarrow U$

History feedback $\mathcal{I} = \mathcal{I}_{hist}$ and $\pi : \mathcal{I}_{hist} \rightarrow U$

Recall the previous filters over these 4 I-spaces.

Now we move from *passive* to *active*.

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Based on the task, an overall approach that leads to planning:

1. Design the system, which includes the environment, bodies, and sensors.

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Based on the task, an overall approach that leads to planning:

1. Design the system, which includes the environment, bodies, and sensors.
2. Define the models, which provide the state space X , the sensor mapping h , and the state transition function f .

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

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From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

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4. Take the desired goal, expressed over X , and convert it into an expression over \mathcal{I} .

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

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4. Take the desired goal, expressed over X , and convert it into an expression over \mathcal{I} .
5. Compute a plan π over \mathcal{I} that achieves the goal in terms of \mathcal{I} .

Really, all steps should be considered together.

Might have to backtrack.

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Visibility-based pursuit evasion

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

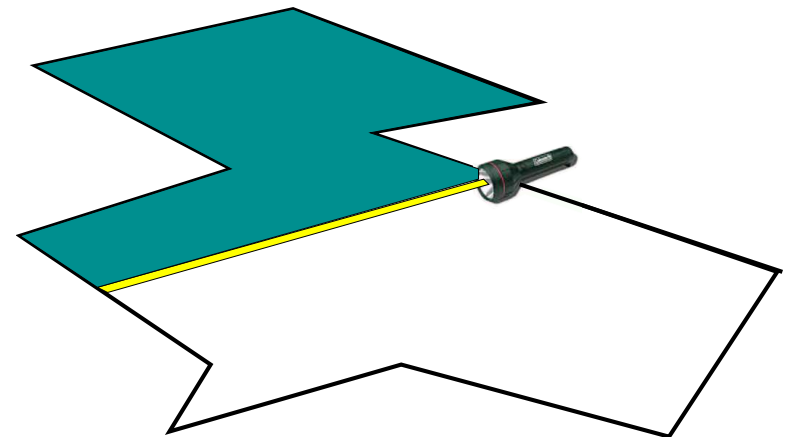
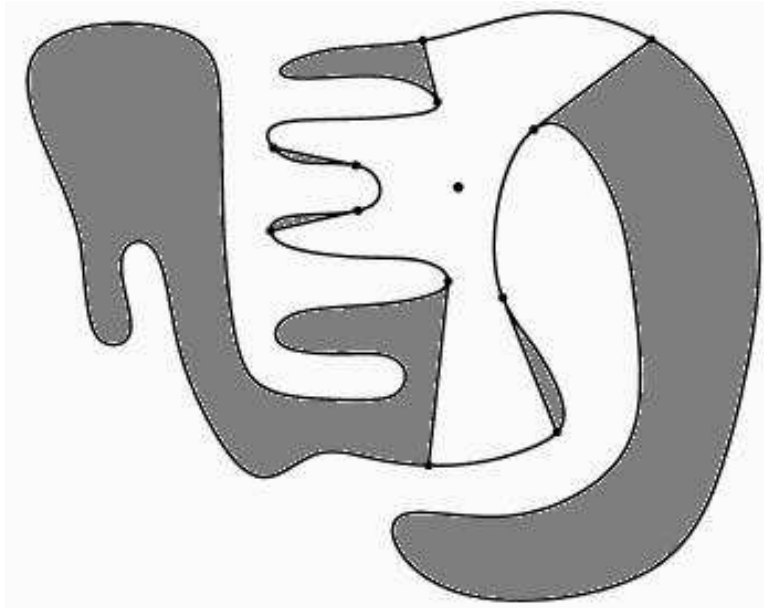
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- A 2D environment, possibly curved
- Unpredictable point “evaders” move with unbounded speed
- Point “pursuers” use visibility sensors to find all evaders



When Does a Solution Exist?

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

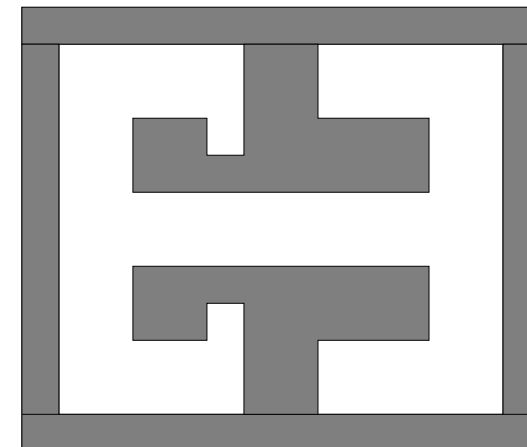
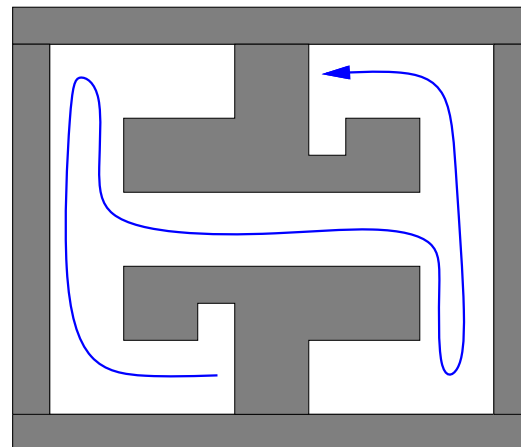
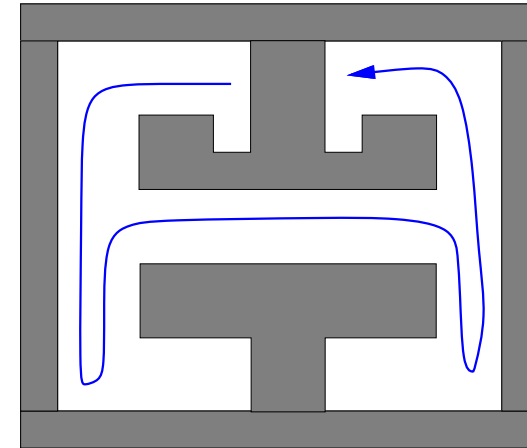
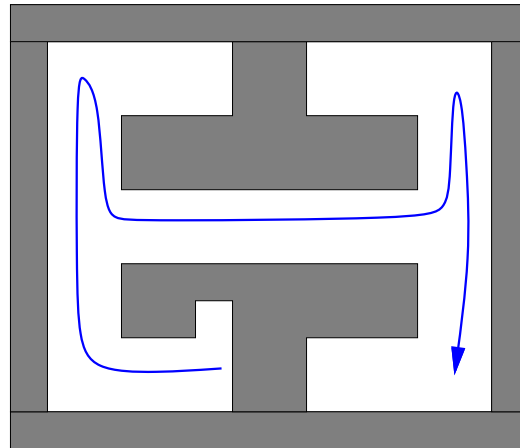
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Bug algorithms

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Try to solve using one pursuer with 360° vision:



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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

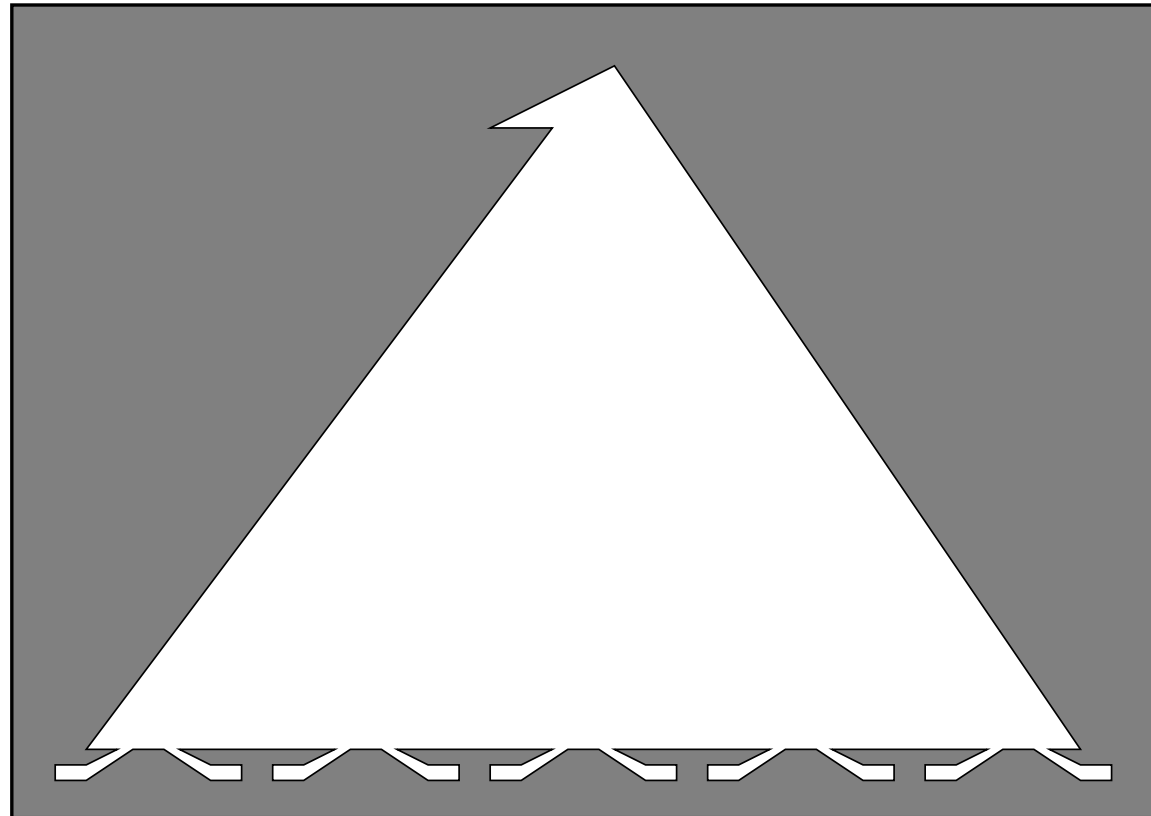
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Bug algorithms

Sensorless manipulation

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You might have to revisit the same place many times...



$\Omega(n)$ recontaminations

A Cell Decomposition

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General issues

Visibility-based pursuit evasion

Maze searching

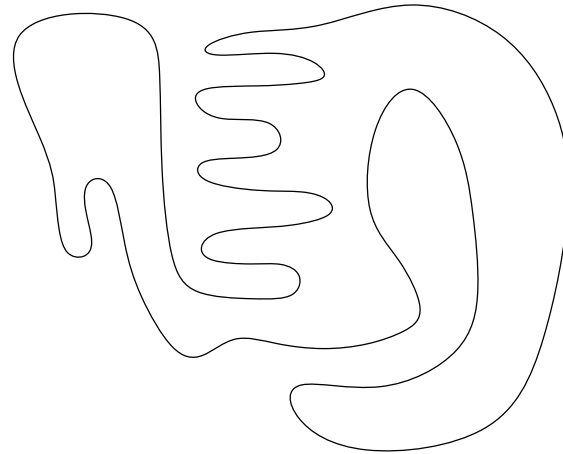
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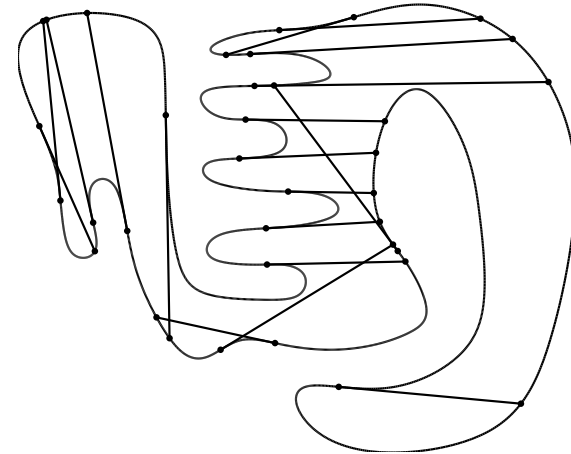
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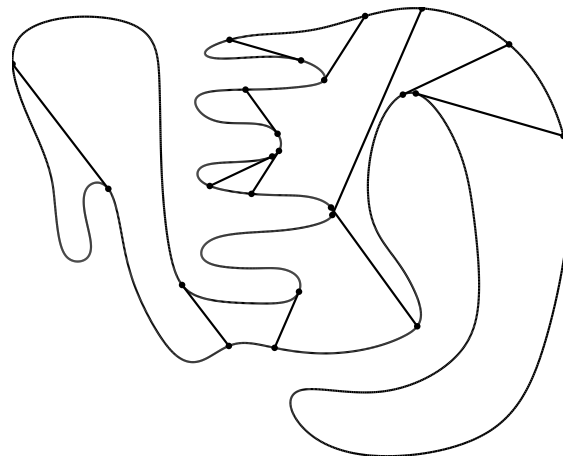
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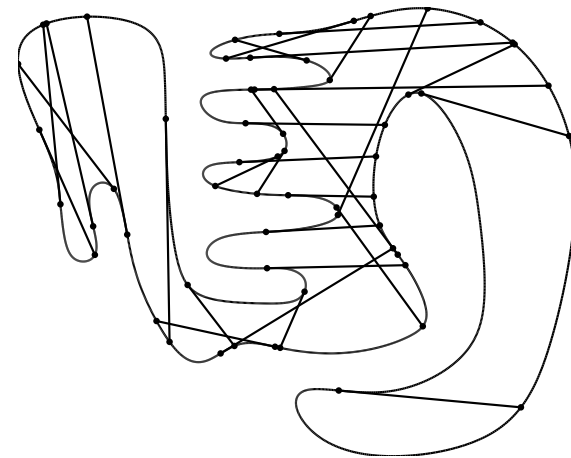
Environment



Inflections



Bitangents



Cell Decomposition

The Information Space

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

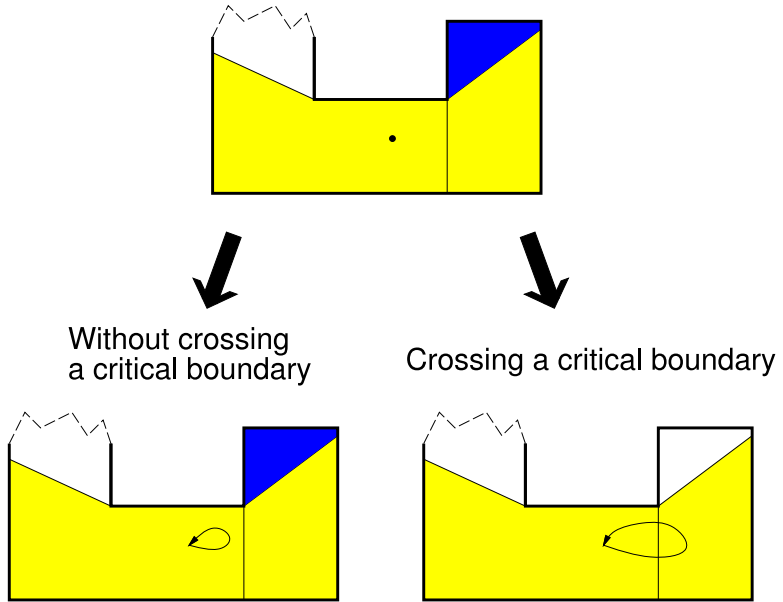
Identify all unique situations that can occur:

An information state is identified by (x, S) in which

x = *the position of the pursuer*

S = *set of possible evader positions*

The set of all information states forms an information space.



Many closed-path motions retain the same information state.

Systematic Graph Search

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

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- Let $G(V, E)$ be the dual of the cell decomposition
- For each $v \in V$, there are finitely many information classes
- Form a directed information state graph, $G_I(V_I, E_I)$
- Each $v \in V_I$ is an information class
- Each $e \in E_I$ indicates a transition between information classes (crossing an inflection or bitangent)

For each information class, label each shadow component with “1” for *contaminated* or “0” for *clear*.

Search G_I from a state in which

All labels are “1”

to a state in which

All labels are “0”

NP Hardness of Multiple Pursuers

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

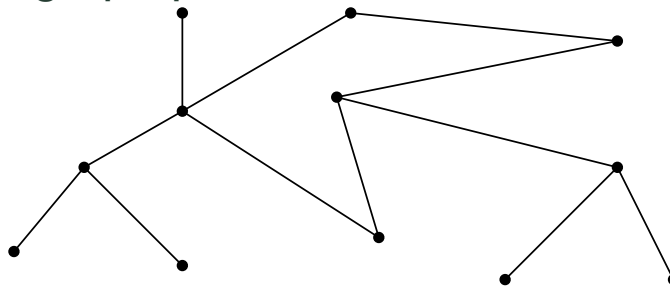
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Bug algorithms

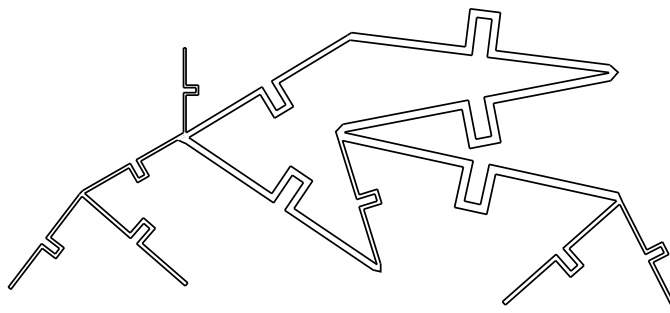
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Pursuit-evasion planar graph problem:



A geometric equivalent:



Results:

Deciding whether a simple polygon can be searched by k pursuers is NP hard.

$\Omega(\lg n + \sqrt{h})$ pursuers needed for some polygons

$\Omega(\lg n)$ Pursuers for Simple Polygon

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General issues

Visibility-based pursuit evasion

Maze searching

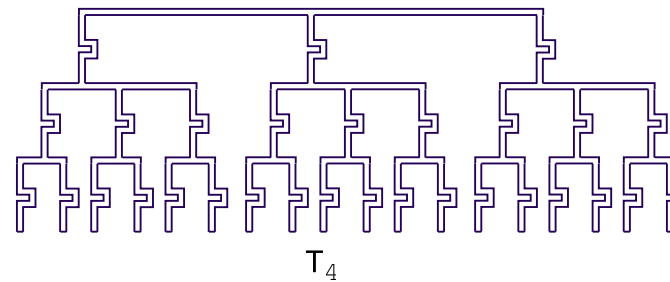
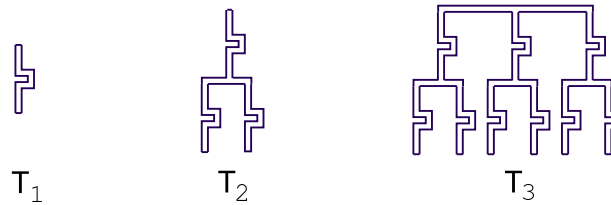
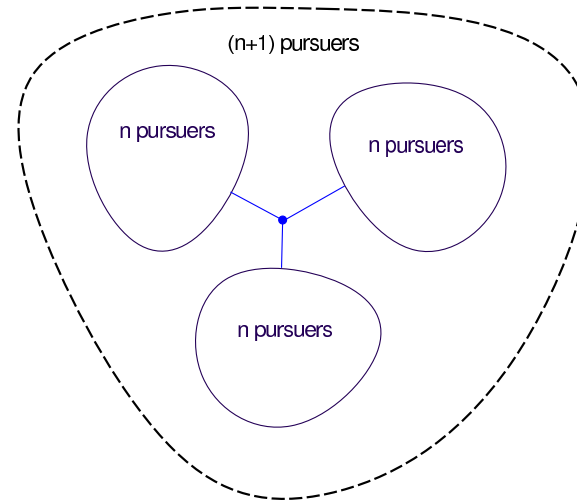
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Bug algorithms

Sensorless manipulation

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This sequence requires $\Omega(\lg n)$ pursuers.

Pursuit-Evasion Results with Perfect Models

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- Constructing and searching equivalence classes in the information space
- A complete algorithm for 360° visibility
- A complete algorithm for 1 pursuer with 1 flashlight
- A complete algorithm for 2 pursuers with 1 flashlight each

All of these assume perfect mapping, control, and localization.

Alternative pursuit-evasion approaches:

- Using the gap sensor (Sachs, Rajko, LaValle, IJRR 2004)
- Using a wall-following robot (Katsev, Tovar, Yershova, Ghrist, LaValle, IEEE Trans. Robotics, 2011)

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

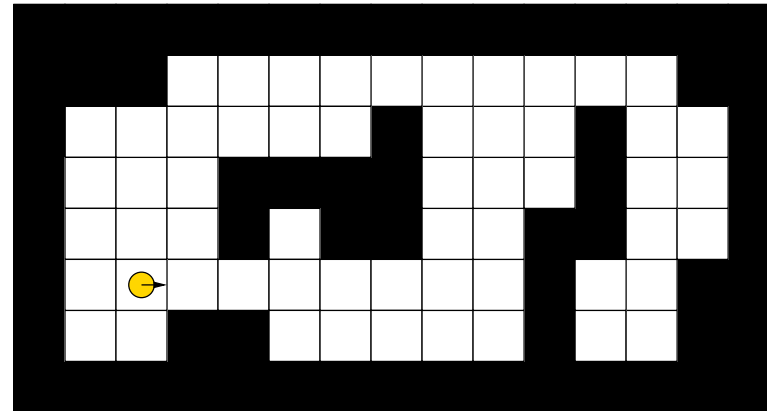
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Maze searching



Each $E \in \mathcal{E}$ is a bounded set of white tiles.

$$X \subset \mathbb{Z} \times \mathbb{Z} \times D \times \mathcal{E}$$

Actions: 1) Rotate 90 degrees CCW; 2) Move forward one tile.

Task: Make a plan that systematically searches all white tiles.
For example, find a hidden treasure.

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Maze Searching: Simple Mapping

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

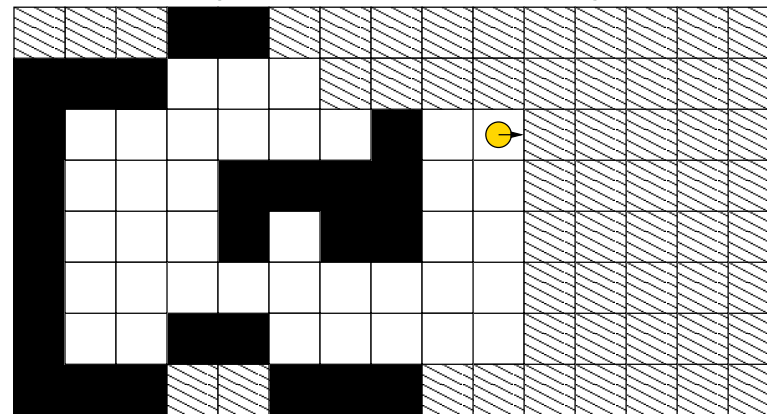
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Controlling Wild Bodies

Could try $\mathcal{I} = \text{pow}(\mathbb{Z} \times \mathbb{Z} \times D \times E)$.

Too large!

Instead, maintain I-states B (known black tiles) and W (known white tiles).



All other tiles assumed “unknown”.

I-space \mathcal{I} is all ways to partition $\mathbb{Z} \times \mathbb{Z}$ into connected “white”, “black”, and “unknown” tiles.

Linear space required for an I-state (filter memory).

Maze Searching: Blum and Kozen 1978

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General issues

Visibility-based pursuit evasion

Maze searching

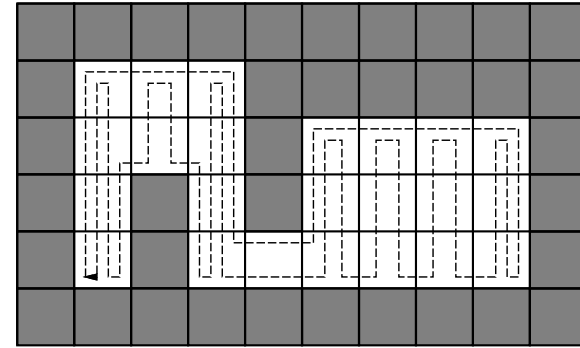
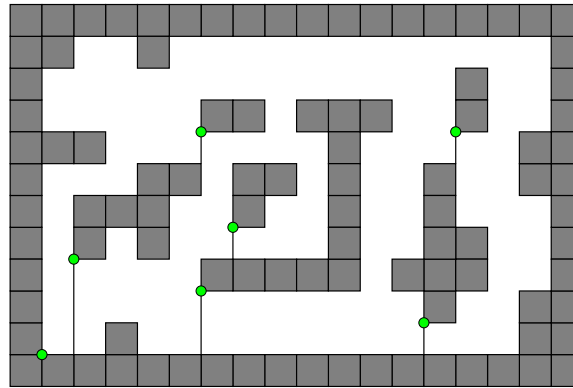
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Bug algorithms

Sensorless manipulation

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I-state: Latitude (integer) and orientation (two bits)

Only logarithmic space required: Not enough for a “map”.

They found an I-space that is much smaller than the set of all maps.

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Gap navigation trees

Make Gap Navigation Trees Active

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

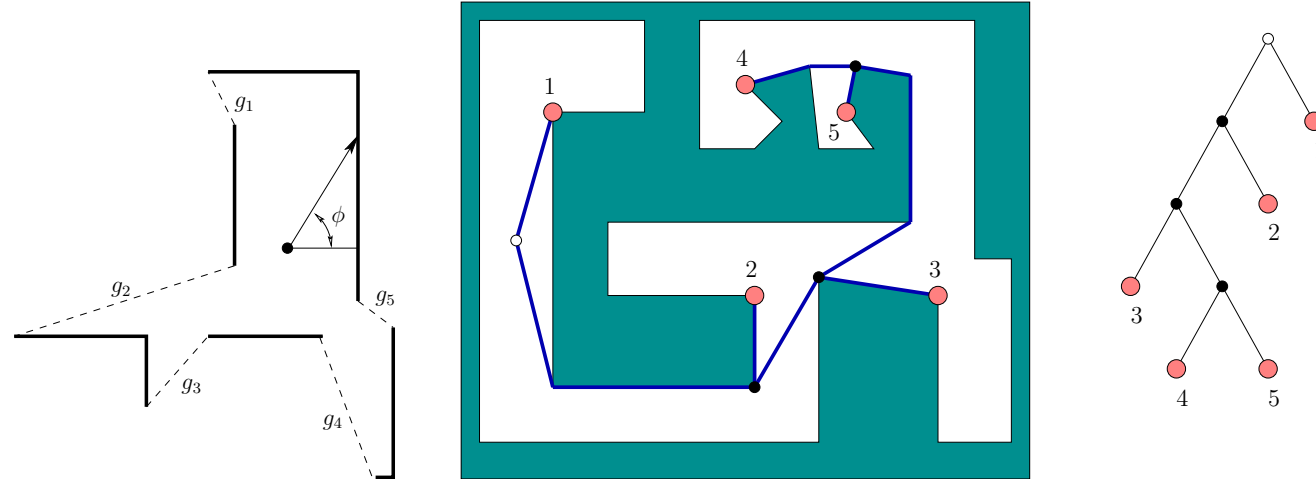
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Bug algorithms

Sensorless manipulation

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For gap navigation trees, two active tasks:

1. Full exploration of the environment
2. Distance-optimal navigation to retrieve objects

Tovar, Murrieta, LaValle, *IEEE Trans. Robotics*, 2007.

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

A gap-chasing action is introduced:

Move the robot toward a gap g until a critical event occurs.

One of two events must occur:

1. The gap g splits into two gaps g' and g'' .
2. The gap g disappears.

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

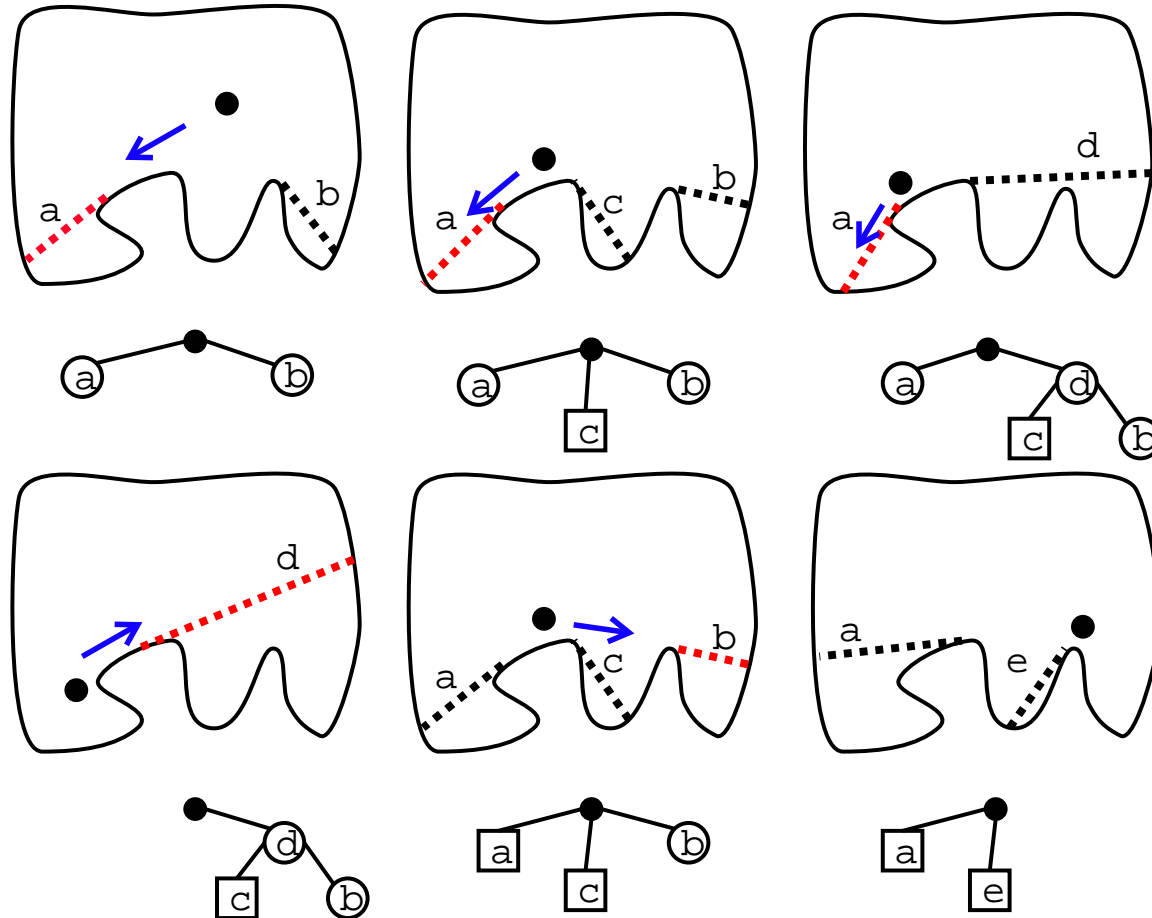
If a gap ever appears, mark it as *primitive*.

This is an extension to the filter I-state.

1. Mark all gaps in the initial tree as *non-primitive*.
2. Let $k = 1$.
3. Chase any gap g that is a non-primitive leaf.
4. If g *disappears*, then go to Step 6.
5. If g *splits*, then chase one of its children.
6. Unless all leaves are primitive, increment k and go to Step 3.

At the end, all leaves are primitive and the environment has been fully explored.

Chase every non-primitive leaf:



Eventually, all leaves become primitive.

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

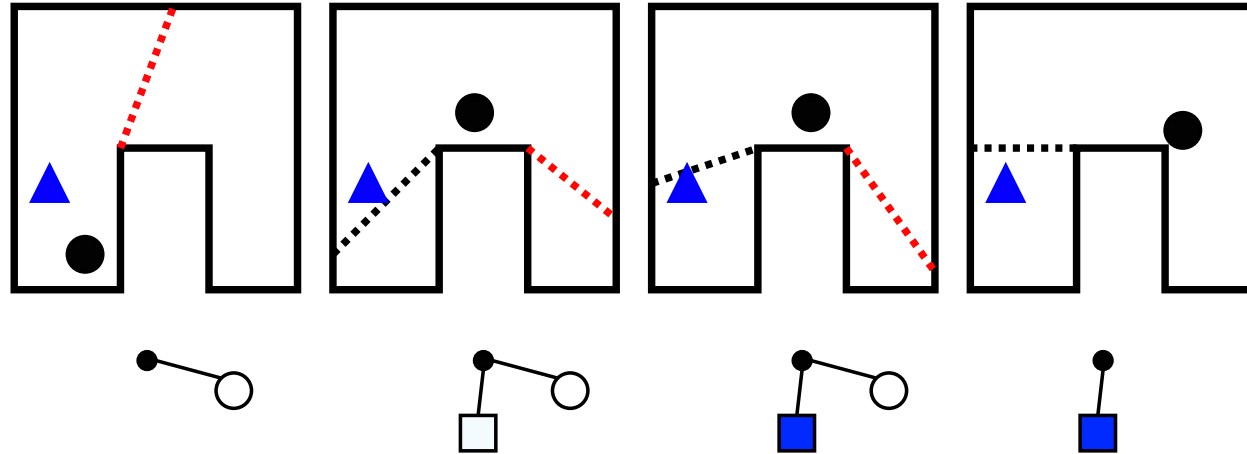
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Controlling Wild Bodies

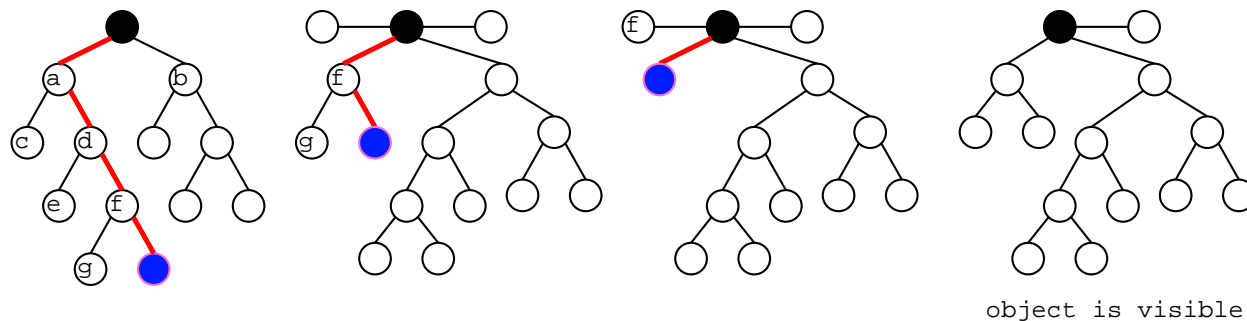
Optimal Object Retrieval

- From filters to planning
- General issues
- Visibility-based pursuit evasion
- Maze searching
- Gap navigation trees
- Learning convex hulls of landmarks
- Bug algorithms
- Sensorless manipulation
- Controlling Wild Bodies

There are no coordinates.



Objects hide behind gaps.



Chase the appropriate sequence of gaps.

Possible Current States

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General issues

Visibility-based pursuit evasion

Maze searching

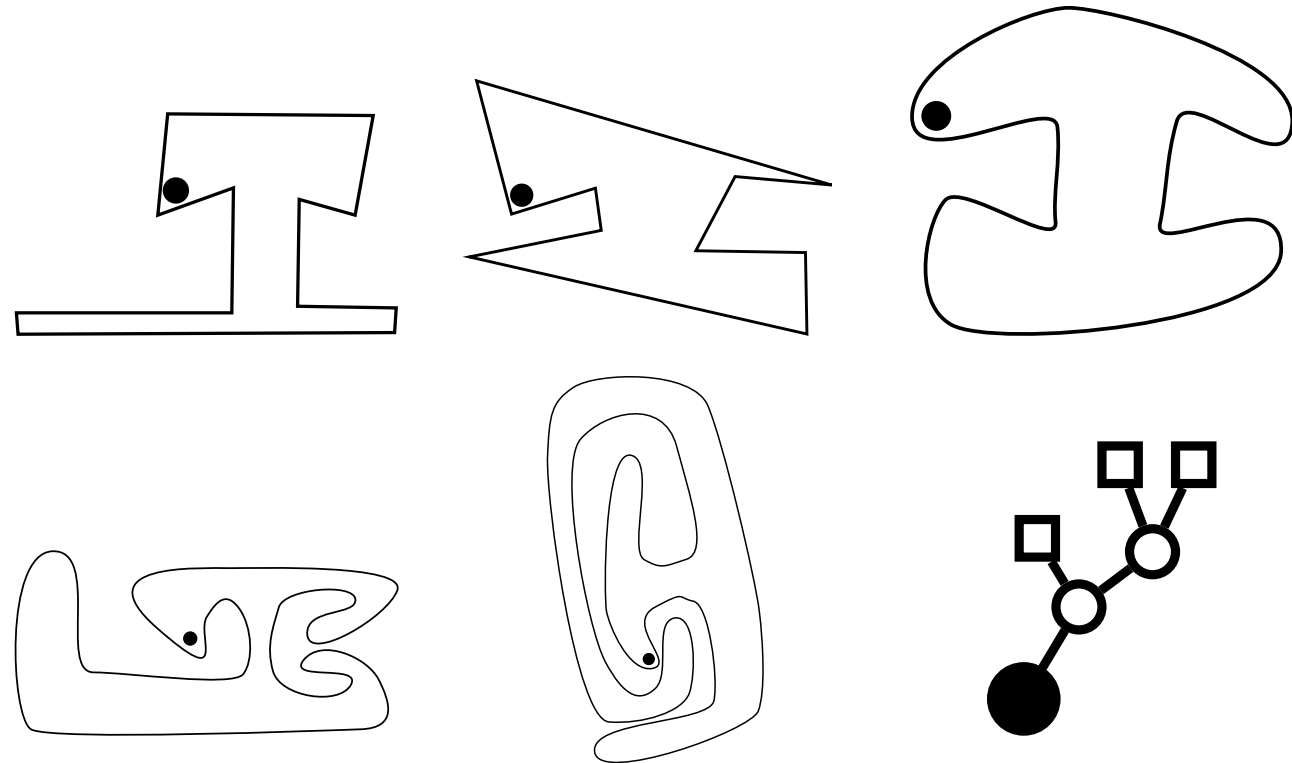
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Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Many configuration-environment pairs have the same tree.

The robot does not have to distinguish!

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

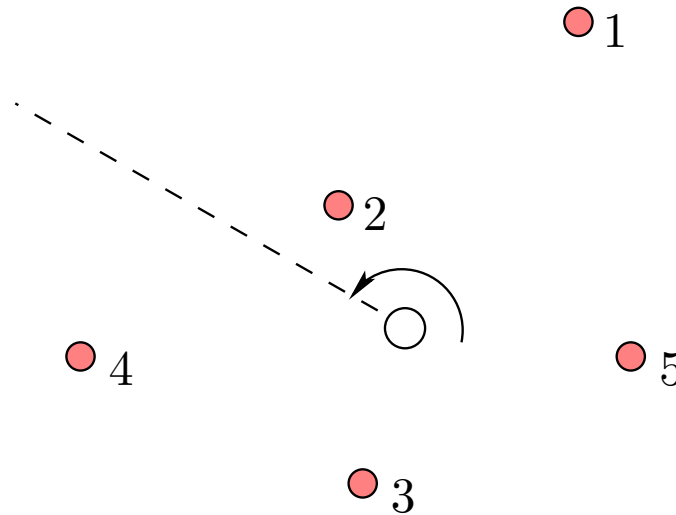
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Recall: Cyclic Permutation Sensor

Relation: “is to the left of in counterclockwise order”



Observation: $y = (1, 2, 4, 3, 5)$

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Making an Active Version

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

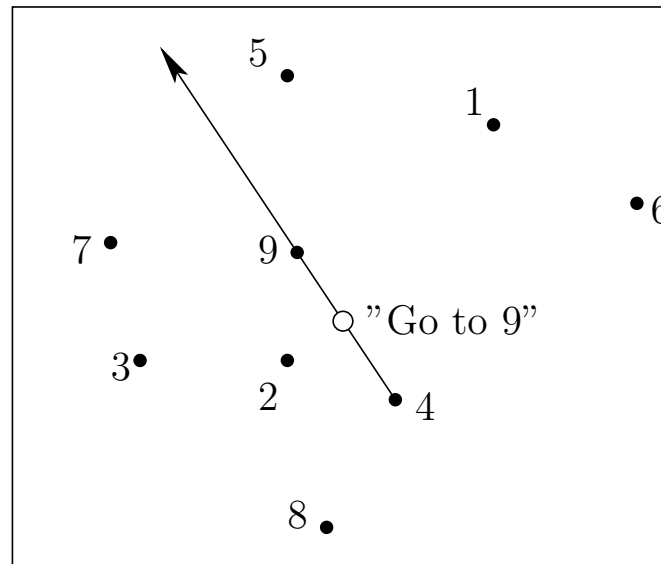
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Sensorless manipulation

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Tovar, Freda, LaValle, 2007.

- Landmark locations are unknown
- Introduce action: “Go to landmark i ”
- Can notice which landmarks are “to the left” of the path.



Sense that $(6, 1, 5)$ is to the right of $(7, 2, 3, 8)$.

Learning the Arrangement

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

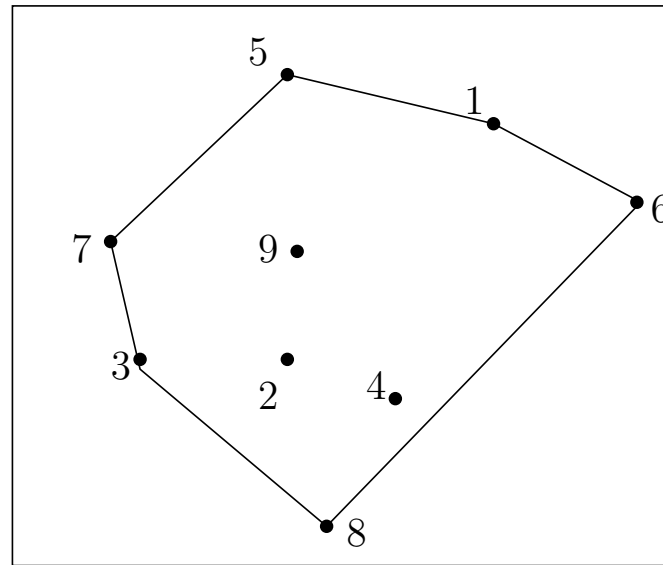
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Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



By visiting all pairs, the filter can learn:

- For any subset $L' \subset L$ of landmarks, which others in L lie in the convex hull of L' .
- Equivalently, the robot learns the dual arrangement, order types, oriented matroid.
- The robot can navigation to any goal specified as a cyclic permutation.

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Bug algorithms

Recall Bug Algorithms

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

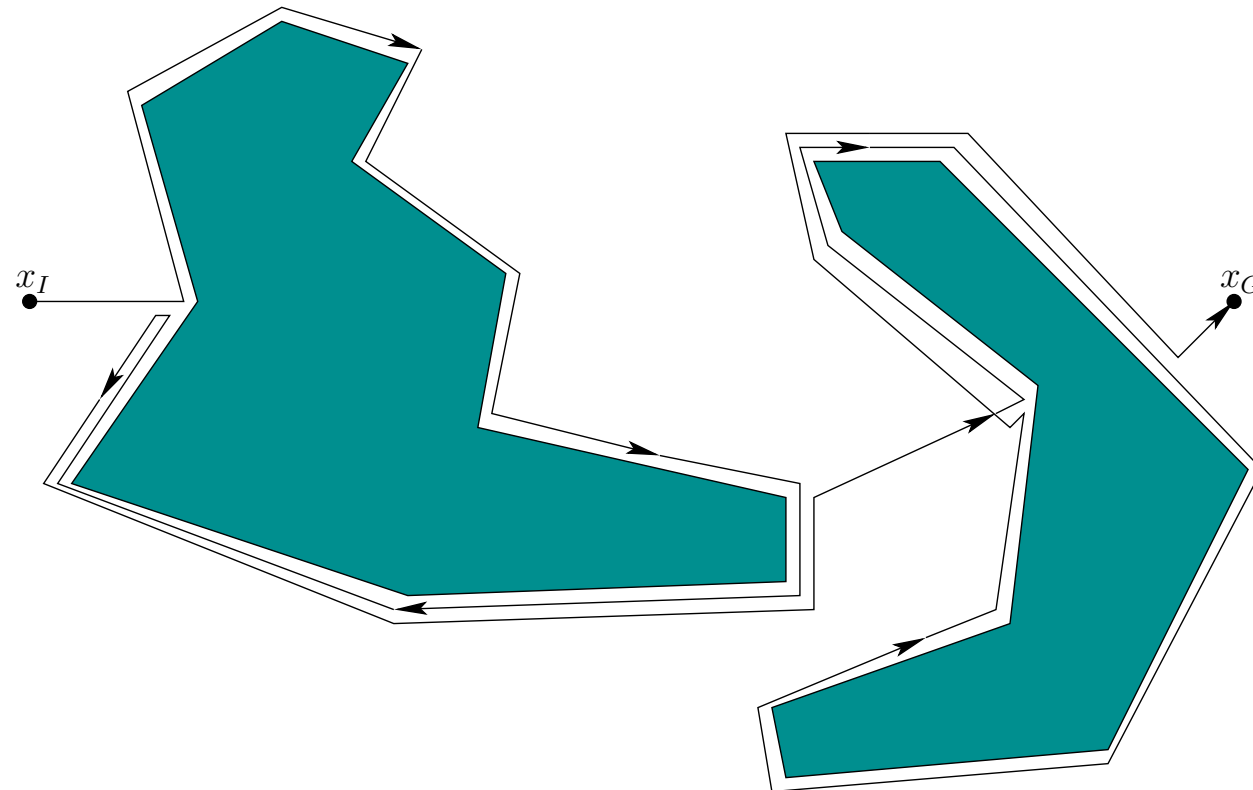
Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Navigate without being given an initial map E

Lumelsky, Stepanov, 1987; Kamon, Rivlin, Rimon, 1997; many others...

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Taylor, LaValle, ICRA 2009



- The plane contains unknown obstacles with piecewise analytic boundary.
- Each obstacle boundary has finite length.
- A *tower* sends a constant signal.
- Robot has very limited sensors.
- Command the robot so that it reaches the tower.

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

- **Boundary (or Contact) sensor:**

Indicate whether or not robot is on the boundary.

- **Tower alignment/gradient sensor:**

Indicate whether robot is facing the tower (or intensity gradient).

- **Transformed signal intensity sensor:**

Observe the value of $m(p - p_t)$.

Regarding m :

- m has only one local maximum, at the tower.
- The function m itself is not given.
- Level sets of m may be symmetric (circles) or asymmetric.

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

There are three possible actions:

u_{fwd} : Go straight until either ∂E is hit, tower is hit, or local intensity maximum detected.

u_{fol} : Follow ∂E until local maximum detected.

u_{ori} : Rotate until facing tower (or local gradient).

A Plan Designed by Humans

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Illustration of the Plan



Guaranteed to converge; upper bound on distance shown.

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

State space: $X \subset \mathbb{R}^2 \times S^1 \times \mathcal{E}$

I-space: $\mathcal{I} = Y^3 \subset \mathbb{R}^3$

I-state components:

1. Current observation
2. Observation when obstacle was last contacted
3. Observation just prior to application of u_{fwd}

Multiple Iterations in the Interior

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

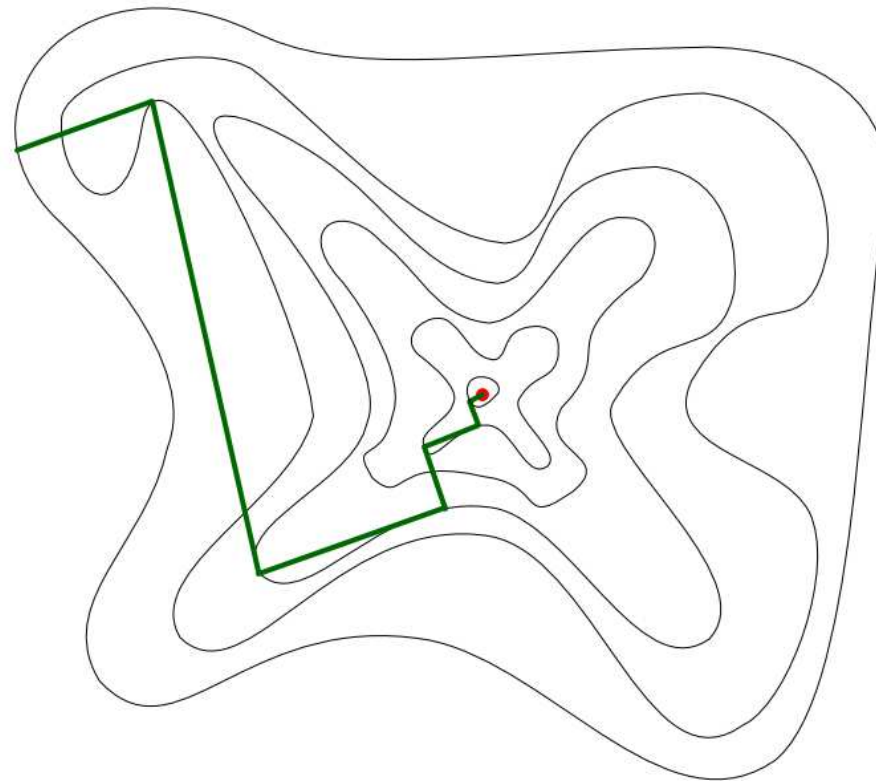
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Learning convex hulls of landmarks

Bug algorithms

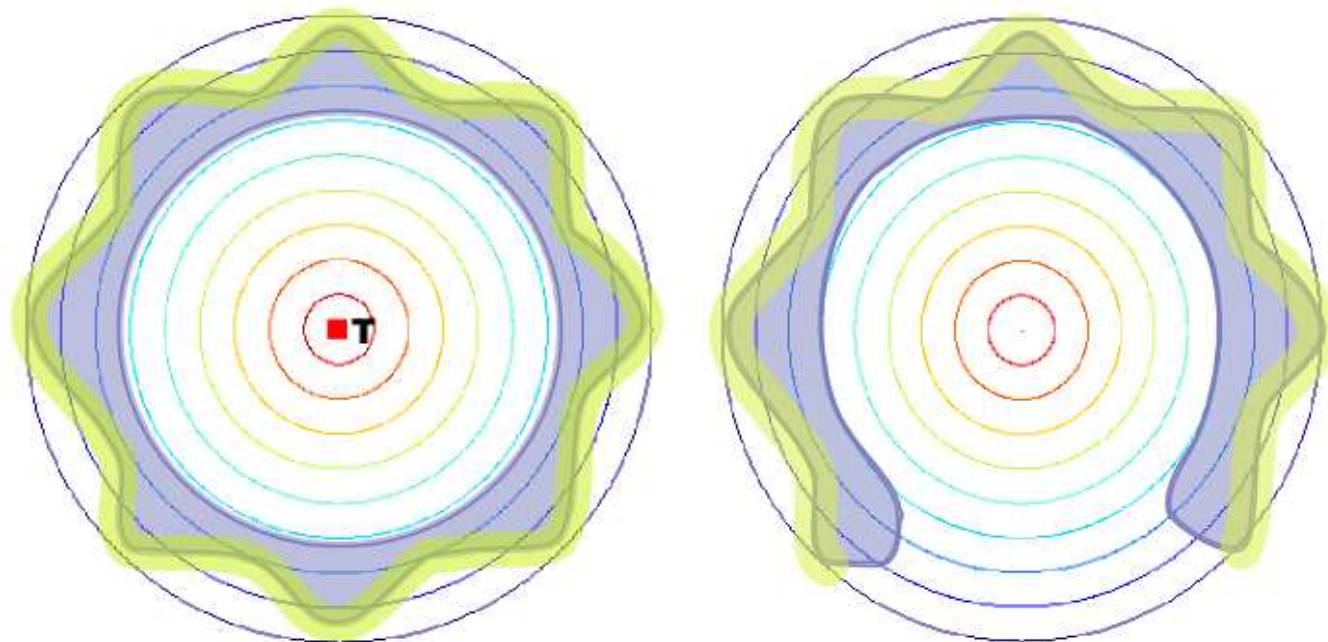
Sensorless manipulation

Controlling Wild Bodies



- Equivalent to Steepest Descent with Line Search.
- Result: Convergence is obtained, but distance bound depends on properties of m .

Proposition: Using its sensors and motion primitives, it is impossible for the robot to determine whether the tower is reachable, in other words whether $p_t \in E$.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Sensorless manipulation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

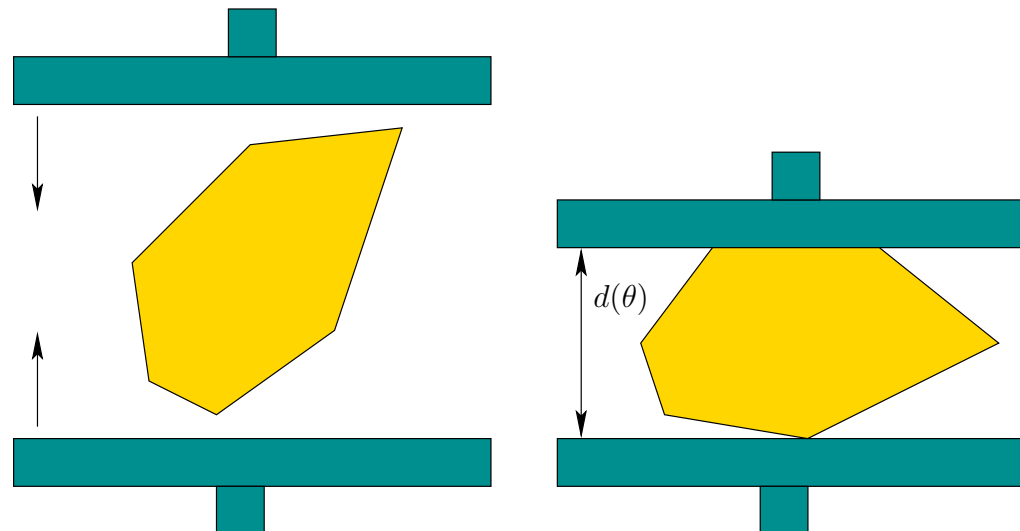
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Try to force parts into a known orientation



Mason, Goldberg, 1990

$$X = S^1 \quad \mathcal{I} = \text{pow}(X)$$

Plan: $\pi = (u_1, u_2, \dots, u_n)$

A sequence of squeeze operations

Sensorless Manipulation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

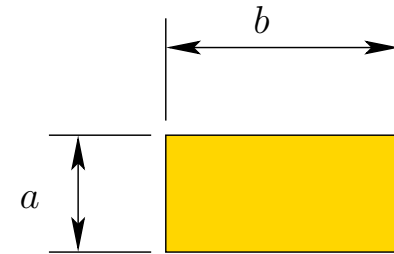
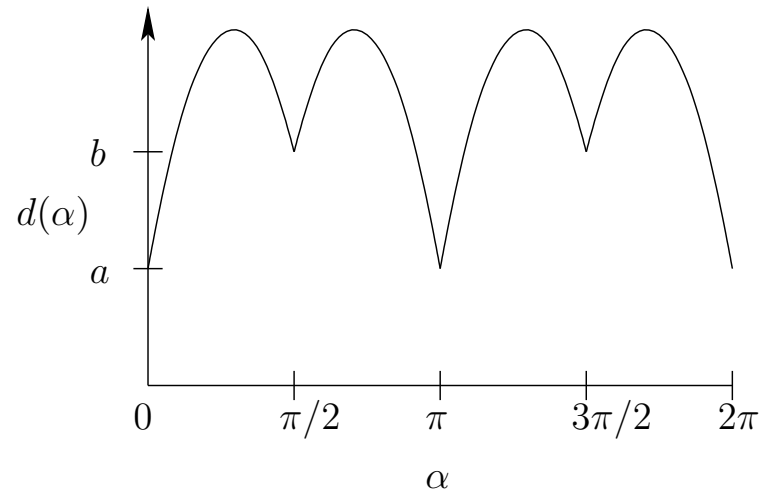
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Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Consider the “diameter” as a function of orientation.

Sensorless Manipulation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

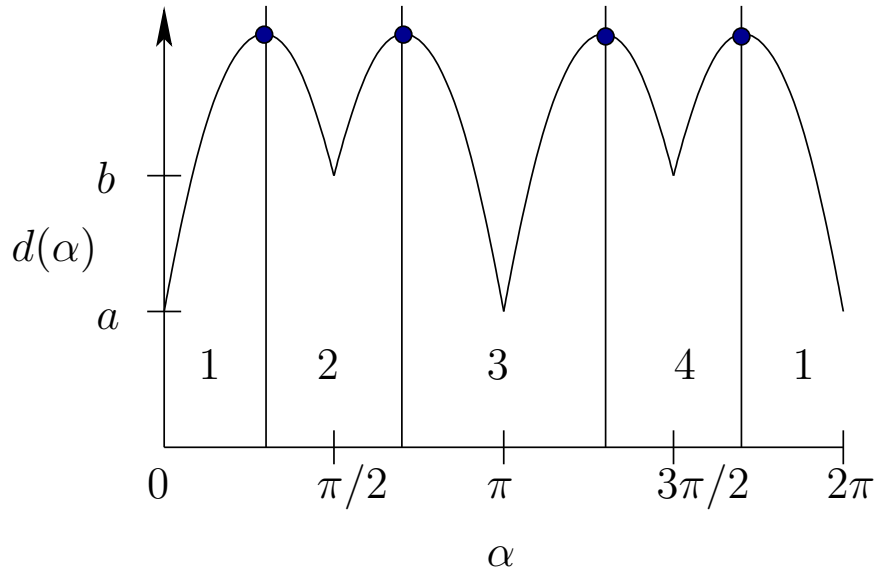
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Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



There are four regions of attraction.

This causes a funneling effect when actions are applied.

Sensorless Manipulation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

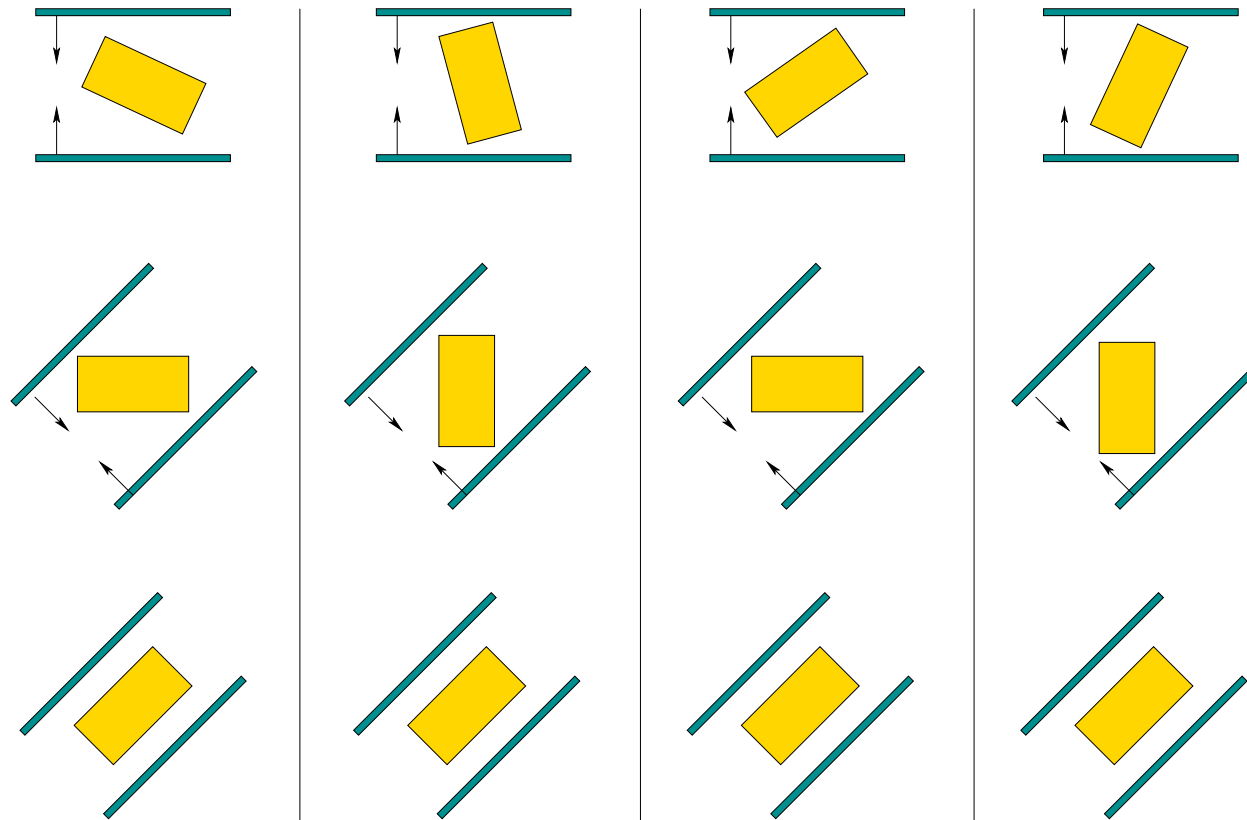
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Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



A computed plan that applies two squeeze actions

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

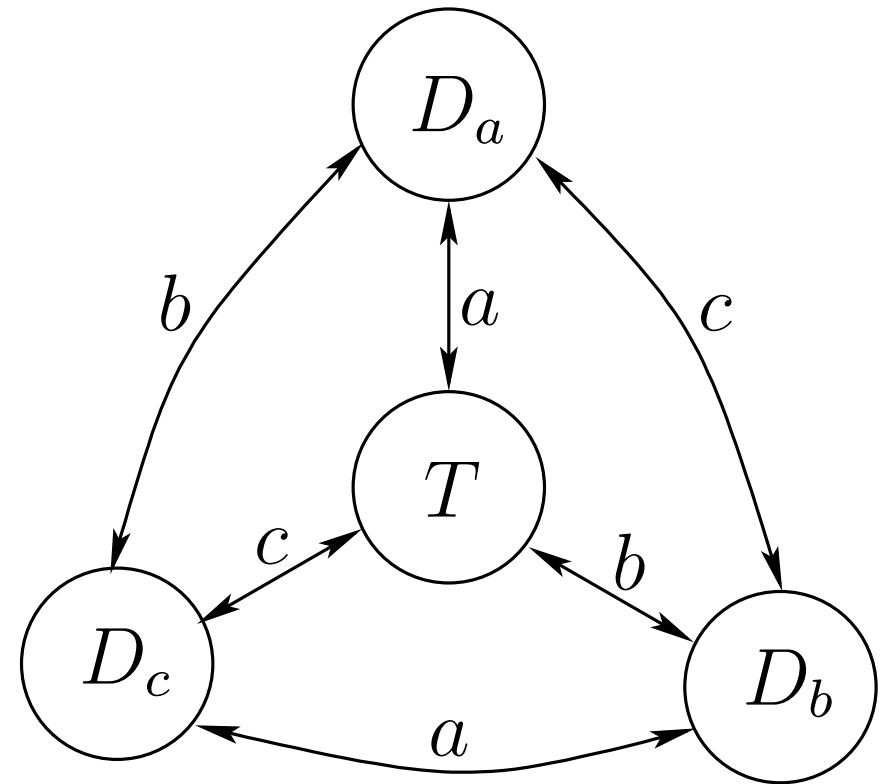
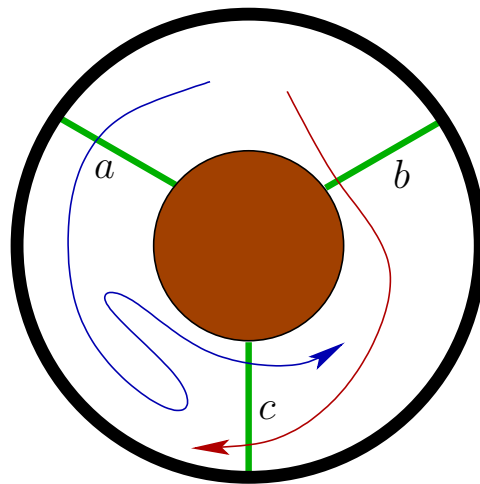
Sensorless manipulation

Controlling Wild Bodies

Controlling Wild Bodies

Recall: Two-Bit Filter

Recall the simple filter that determines whether two bodies are in the same region.



- From filters to planning
- General issues
- Visibility-based pursuit evasion
- Maze searching
- Gap navigation trees
- Learning convex hulls of landmarks
- Bug algorithms
- Sensorless manipulation
- Controlling Wild Bodies

Recall: Visibility-Based Pursuit-Evasion

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

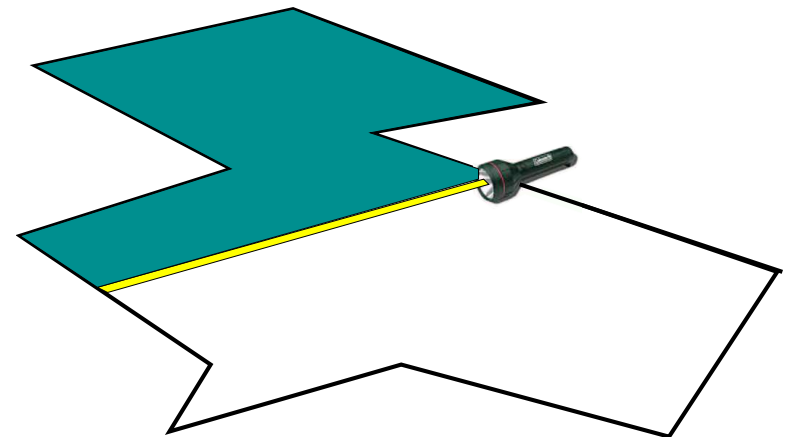
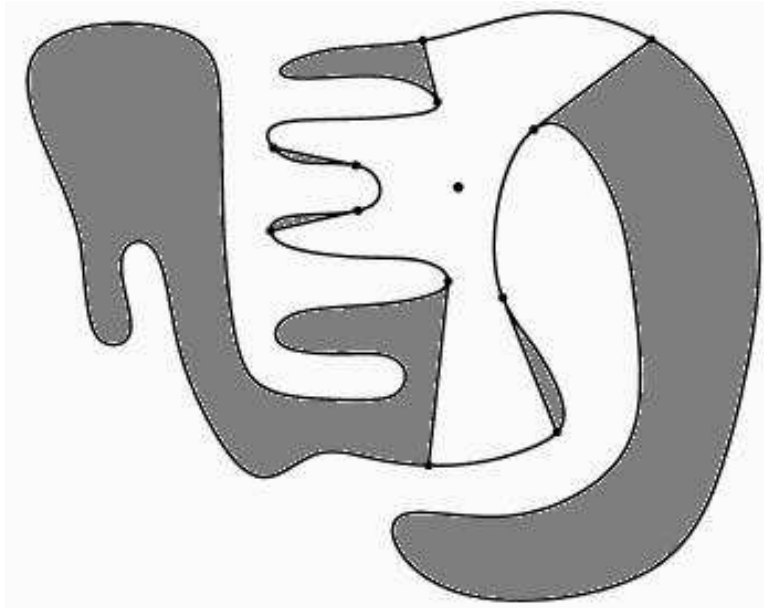
Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- A 2D environment, possibly curved
- Unpredictable point “evaders” move with unbounded speed
- Point “pursuers” use visibility sensors to find all evaders



Recall: Shadow Information Spaces

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

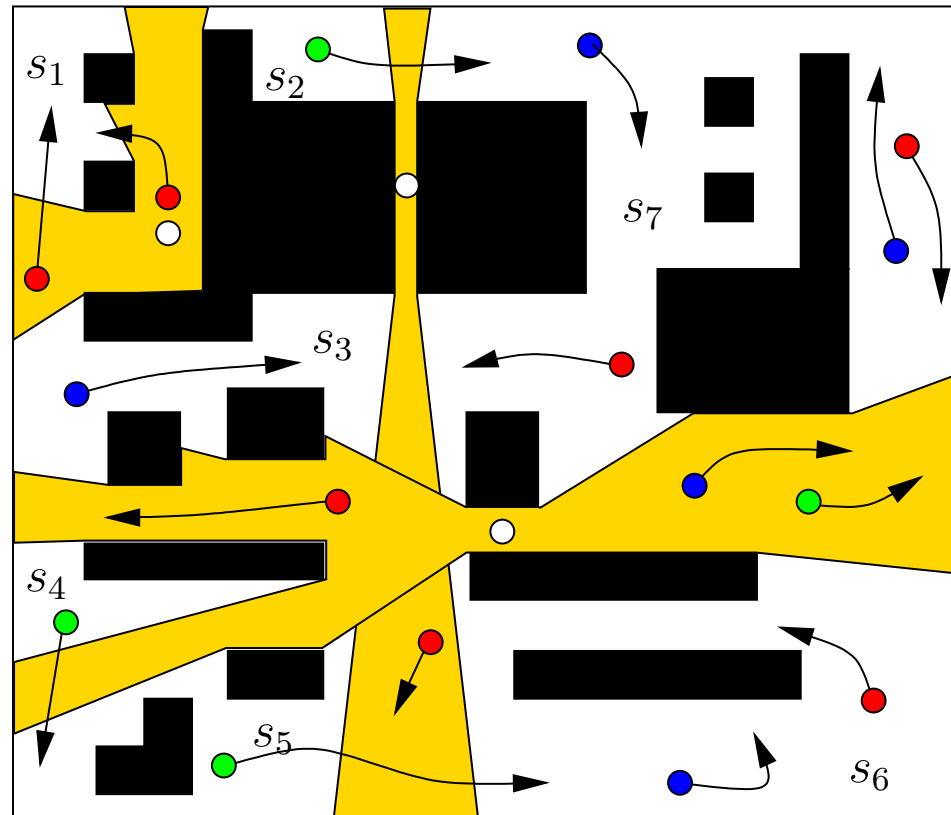
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Keep track of bodies out of view—in the shadows.

How many are there? What kinds of bodies are there?

From Filtering to Actuation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- Key exploited property in filters: **Motion continuity**

From Filtering to Actuation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- Key exploited property in filters: **Motion continuity**
- Bring in **actuation**, but continue with minimalism, reduced I-spaces
- Passive → Avoid state estimation
Active → **Avoid system identification**

- What is the new key property?

From Filtering to Actuation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- Key exploited property in filters: **Motion continuity**
- Bring in **actuation**, but continue with minimalism, reduced I-spaces
- Passive → Avoid state estimation
Active → **Avoid system identification**

- What is the new key property? **Wildness**

Our Simple Robot

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- No map is given in advance

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- No map is given in advance
- No position estimation is available

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- No map is given in advance
- No position estimation is available
- No system identification has been performed

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- No map is given in advance
- No position estimation is available
- No system identification has been performed
- No sensors, inside or outside of the robot

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- No map is given in advance
- No position estimation is available
- No system identification has been performed
- No sensors, inside or outside of the robot
- No computer or any other digital devices

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- No map is given in advance
- No position estimation is available
- No system identification has been performed
- No sensors, inside or outside of the robot
- No computer or any other digital devices
- Only one motor, oscillating at 2Hz

A Weasel Ball

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

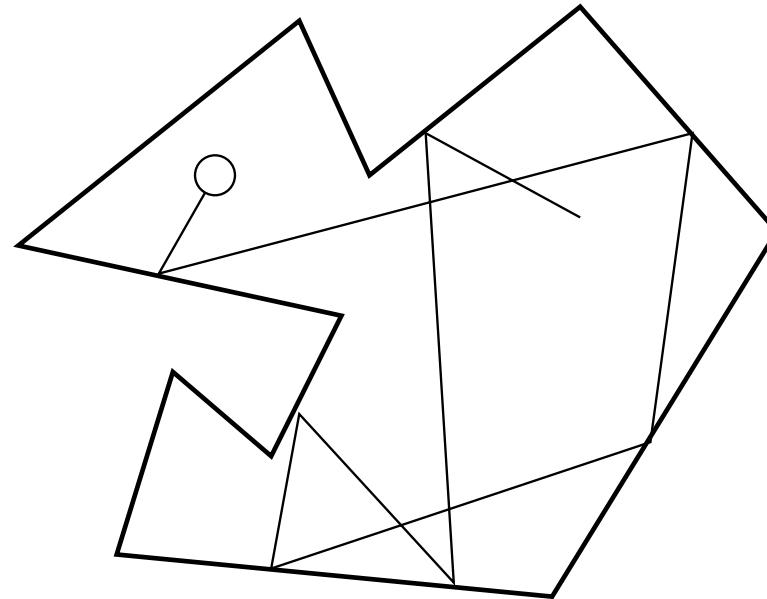
Controlling Wild Bodies



An old, popular toy (costs about \$4)

Wildness Condition

We say that a body is *wild* in a region $R \subseteq \mathbb{R}^2$ if it moves on a trajectory that causes it to repeatedly strike every open interval in ∂R (the boundary of R), with non-zero, non-tangential velocities.



Somewhat informal

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Interesting, But How to Control?

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- It is far from stable
- Almost impossible to predict
- Dynamical system modeling or identification is difficult

Interesting, But How to Control?

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- It is far from stable
- Almost impossible to predict
- Dynamical system modeling or identification is difficult

Hmm...the situation is similar for humans.

Manipulating Humans with Gentle Guidance

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



How to clear out the breakfast area after 9:30am?

Other Examples

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Also: bug traps

Some Related Research

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- Tray tilting, Mason, Erdmann, 1988
- Virtual fences for herding cows, Butler, Corke, Peterson, Rus, 2004.
- Manipulation by vibration, Canny, Reznick, 1998; Vose, Lynch, 2011
- Building evacuation, Chalmet, Francis, Saunders, *Fire Technology*, 1982.

Regions and Gates

From filters to planning

General issues

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Maze searching

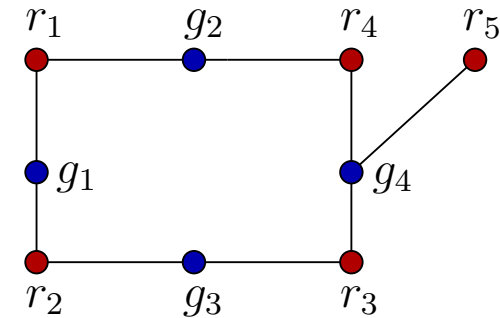
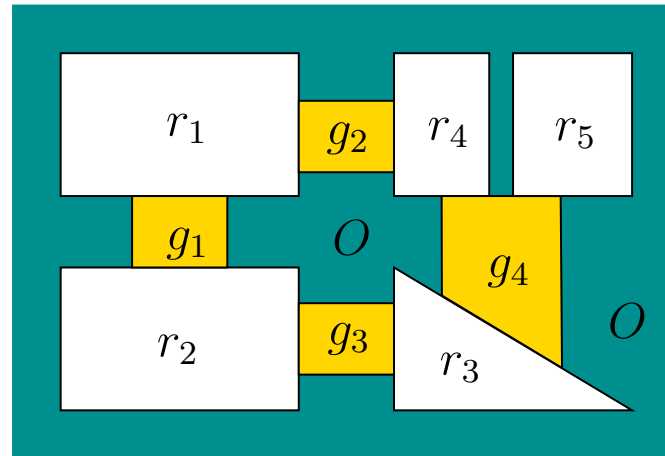
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



The plane \mathbb{R}^2 is partitioned into:

1) *obstacle* set, 2) finite set of *regions*, 3) finite set of *gates*.

A bipartite graph represents the connectivity.

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General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

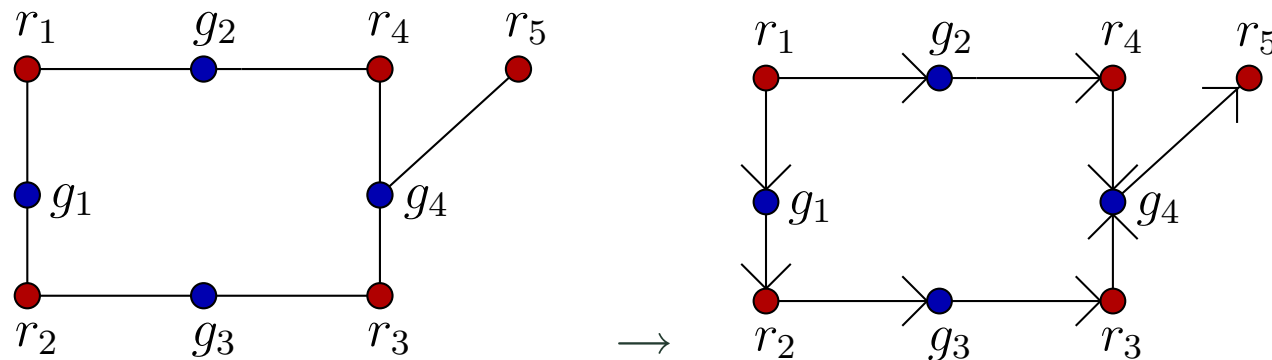
Sensorless manipulation

Controlling Wild Bodies

- Design some “wild” bodies
- Place bodies into regions
- Design gates to control them at the region level

Imagine an unusual hybrid system

A discrete flow across regions can be obtained



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

- **Static gates:** The gates are fixed in advance and allow one-way motions from region to region.
- **Pliant gates:** The gates have internal modes that affect how bodies are permitted to transition between regions and the modes may passively change via contact with bodies.
- **Controllable gates:** Based on information states, the gate modes are externally changed during execution.
- **Virtual gates:** Based on robot sensing, and never represent true physical obstructions.

Engineering a Static Gate

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

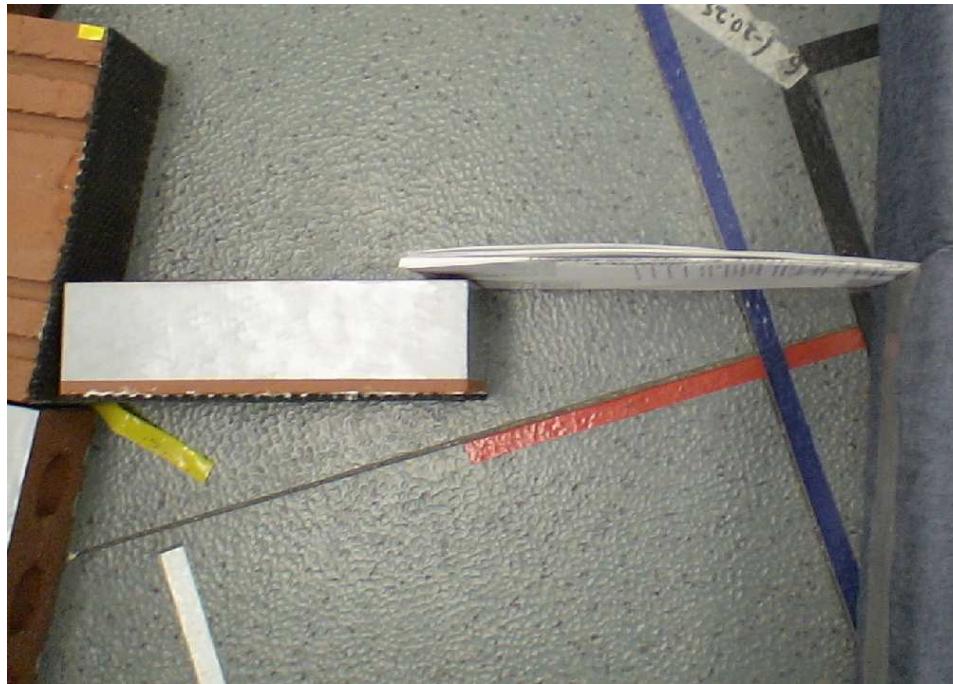
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Strips of paper, wedged between bricks

A Navigation Task

From filters to planning

General issues

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Maze searching

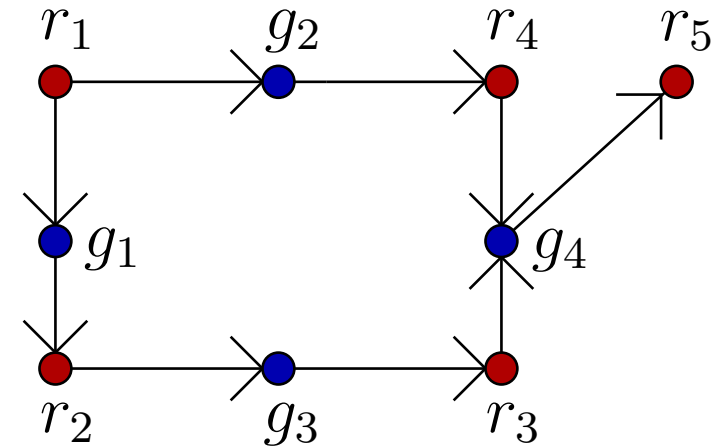
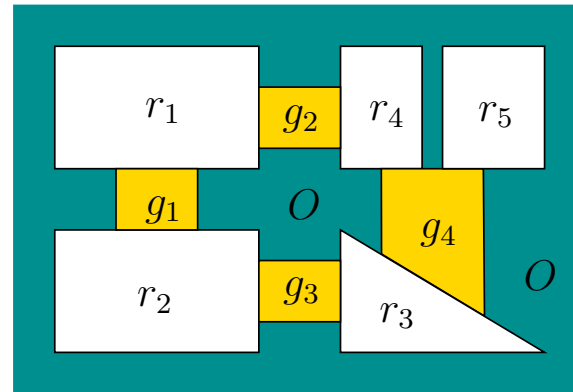
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Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Compute a discrete flow to the goal region (BFS, Dijkstra).

Related work: Sequential composition of funnels, Lozano-Perez, Mason, Taylor, 1984; Mason, Goldberg, 1990; Burridge, Rizzi, Koditschek, 1999; Conner, Rizzi, Choset, 2003.

Static Gates: Single-Body Navigation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

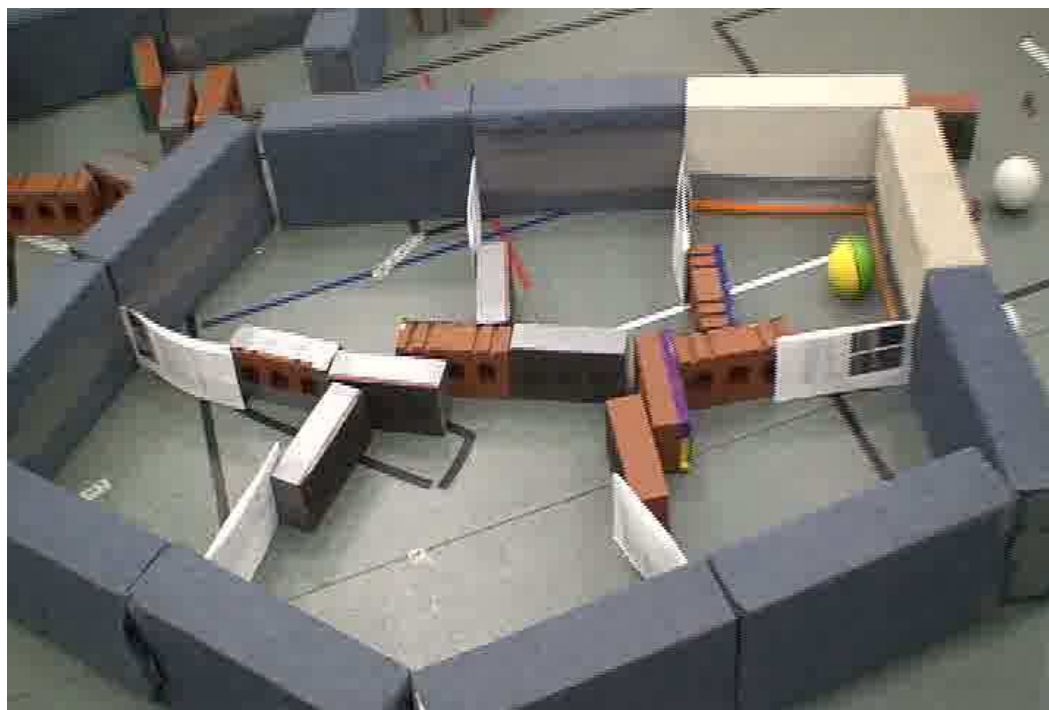
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Goal: Flow to lower left region.

Static Gates: Multi-Body Navigation

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

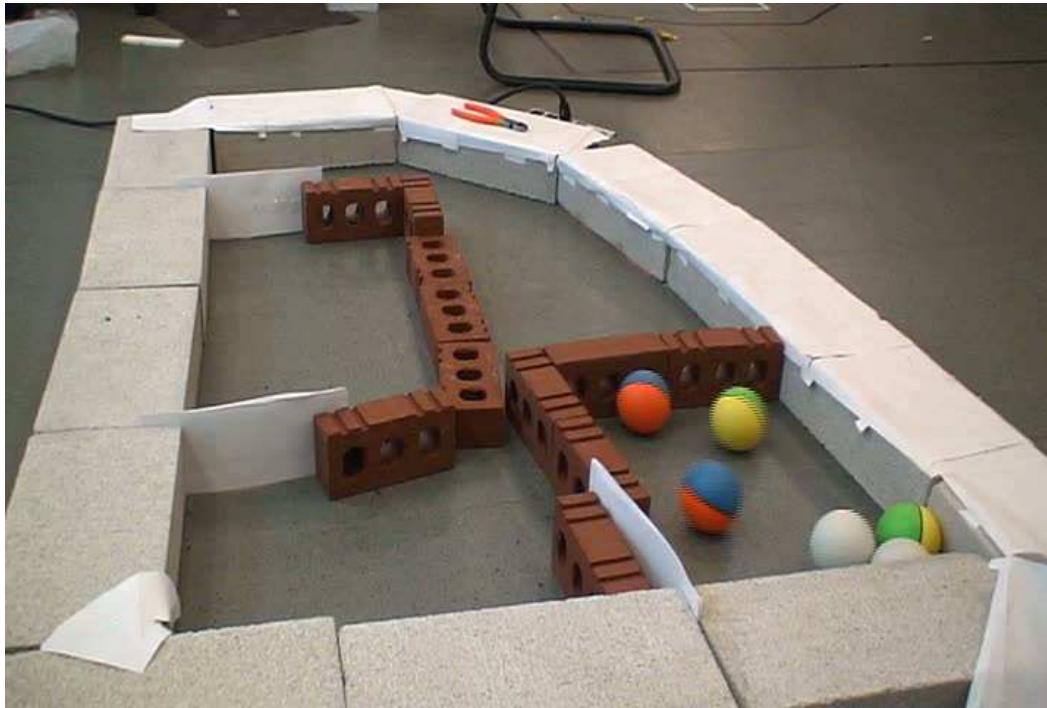
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Six balls must flow to the upper right region.

Static Gates: Navigation with Hexbug Nanos

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

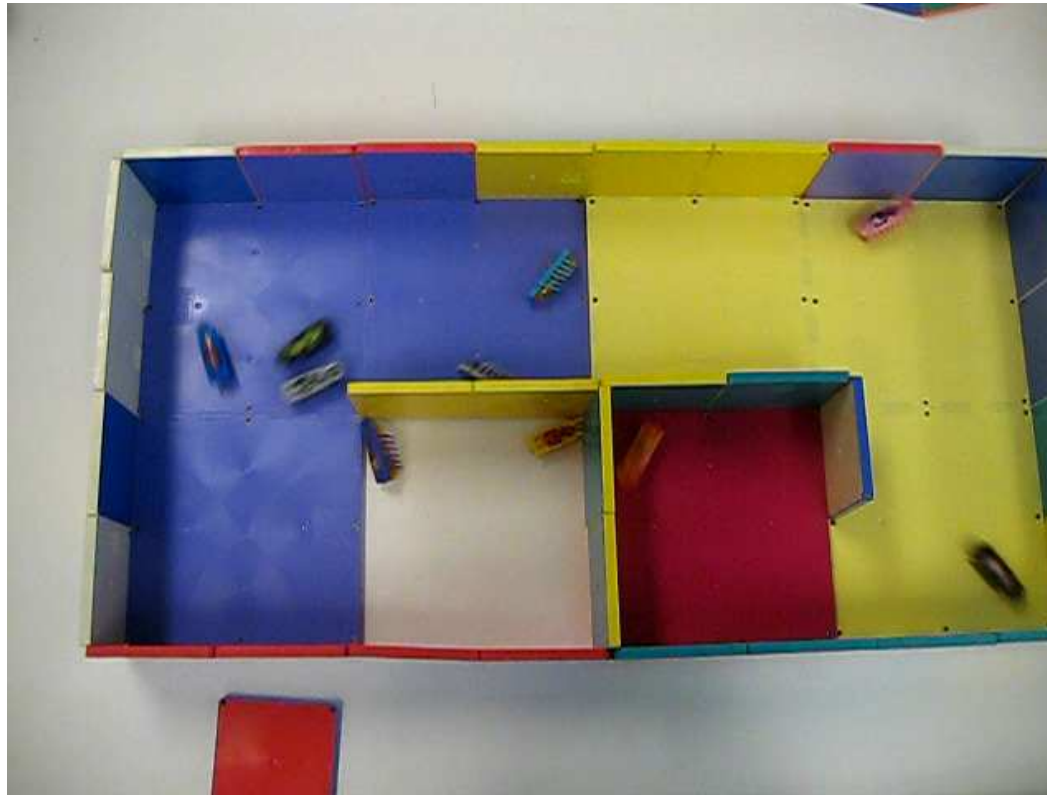
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Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Controlling 10 Hexbug Nanos.

Static Gates: Single-Body Patrolling

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Repeatedly travel a route through all regions.

Static Gates: Multi-Body Patrolling

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

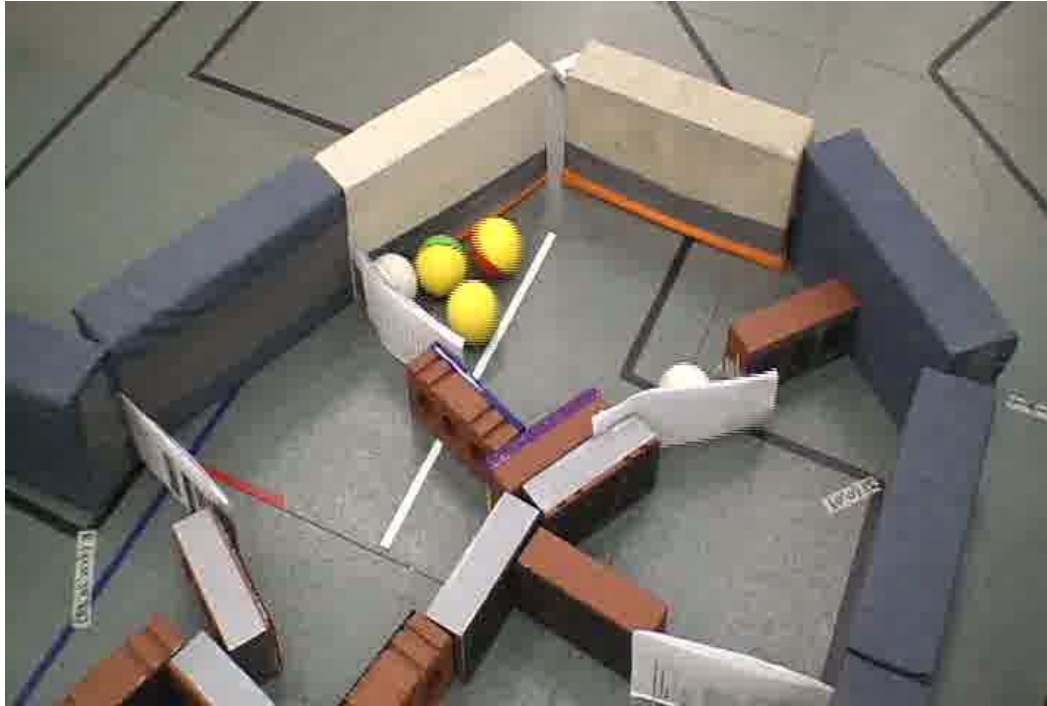
Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Send all bodies on patrol, asynchronously.

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



A tale of 50 weaselballs...

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

A pliant gate g has a finite set $M(g)$ of *modes*.

A body coming from region r into a gate g in mode m induces a *mode transition*:

$$m' = f(m, r)$$

Mode transitions are caused by the bodies while they traverse gates.

A Simple Pliant Gate Design

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

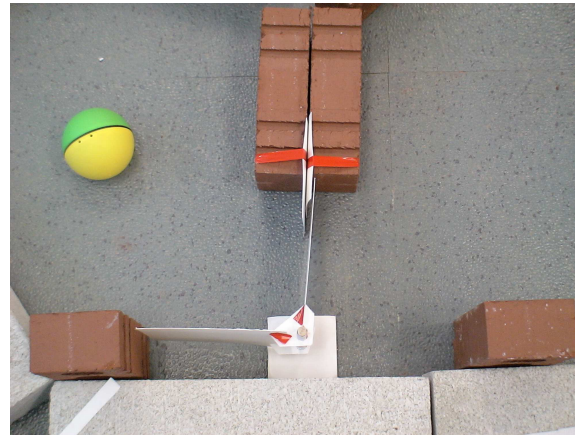
Gap navigation trees

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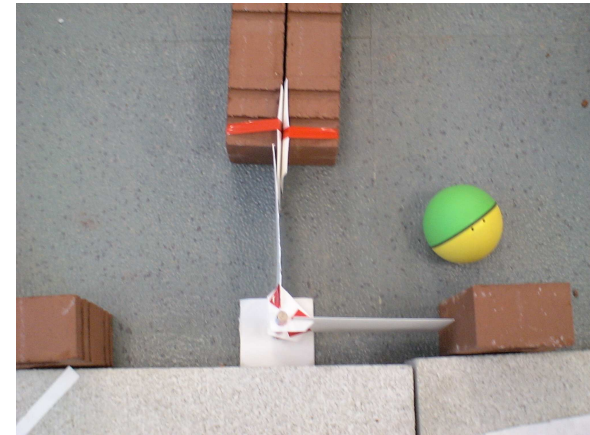
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Controlling Wild Bodies



Left to right



Right to left

A two-mode pliant gate that maintains region counts.

Pliant Gates: Two-Way Revolving Door

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Keeping the number of balls roughly constant in each region.

Pliant Gates: Four-Way Revolving Door

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Now suppose that the mode can be externally set by actuators.

Example modes $M(g)$ per gate g :

1. Block all passage
2. Allow left to right passage only
3. Allow right to left passage only
4. Allow bidirectional passage

Let M be the Cartesian product of all mode sets.

Key issue: What *information* is used to set $m \in M$?

Some Possible Control Laws

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

For some time interval $T = [0, t]$:

$$\pi : T \rightarrow M$$

Time feedback

For sensor with observation space Y :

$$\pi : Y \rightarrow M$$

Sensor feedback

More generally, for any information space \mathcal{I} , we have:

$$\pi : \mathcal{I} \rightarrow M$$

Sensor Feedback and Tilting Ramps

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

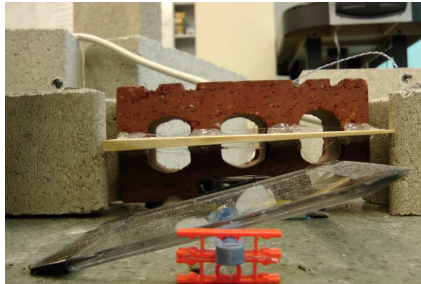
Learning convex hulls of landmarks

Bug algorithms

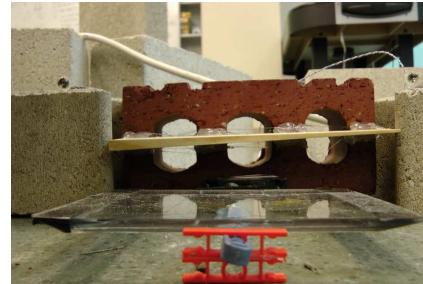
Sensorless manipulation

Controlling Wild Bodies

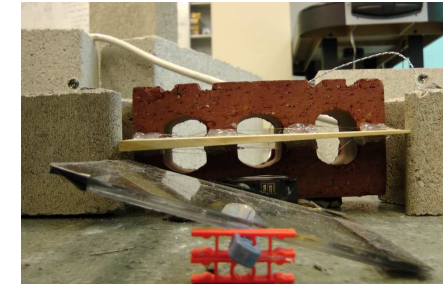
Tilting ramp:



L to R

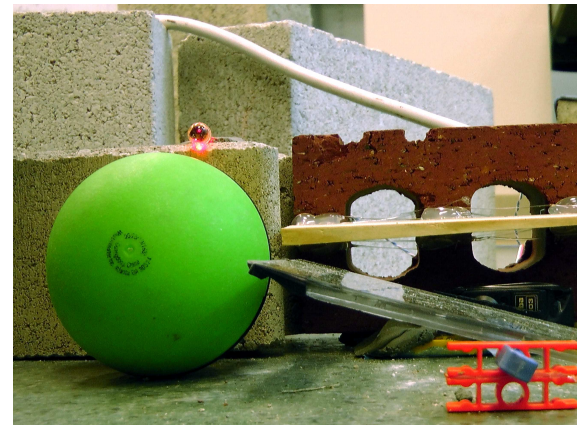
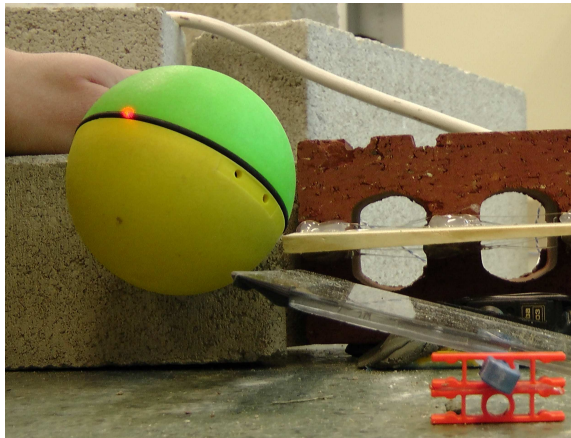


Blocked



R to L

Sensor beam feedback:



What Kinds of Tasks Can We Solve?

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Consider Linear Temporal Logic (LTL):

- Navigation: $\diamond \pi_1$
- Sequencing: $\diamond(\pi_1 \wedge \diamond(\pi_2 \wedge \diamond(\pi_3 \wedge \dots \diamond \pi_k) \dots))$
- Coverage: $\diamond \pi_1 \wedge \diamond \pi_2 \wedge \dots \wedge \diamond \pi_k$
- Avoiding regions: $\neg(\pi_1 \vee \pi_2 \dots \vee \pi_k) \mathcal{U} \pi_{final}$
- Patrolling: $\square(\diamond \pi_1 \wedge \diamond \pi_2 \wedge \dots \wedge \diamond \pi_k)$.

Examples are from Kress-Gazit, Fainekos, Pappas, 2005.

RSS 2011: From LTL to weaselball implementations.

What Kinds of Tasks Can We Solve?

From filters to planning

General issues

Visibility-based pursuit
evasion

Maze searching

Gap navigation trees

Learning convex hulls of
landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Approach:

1. Express the task in some logic
2. Convert into a solution in terms of region sequences
3. Implement using controllable gates and sensor feedback

Controlling Distributions of Bodies

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

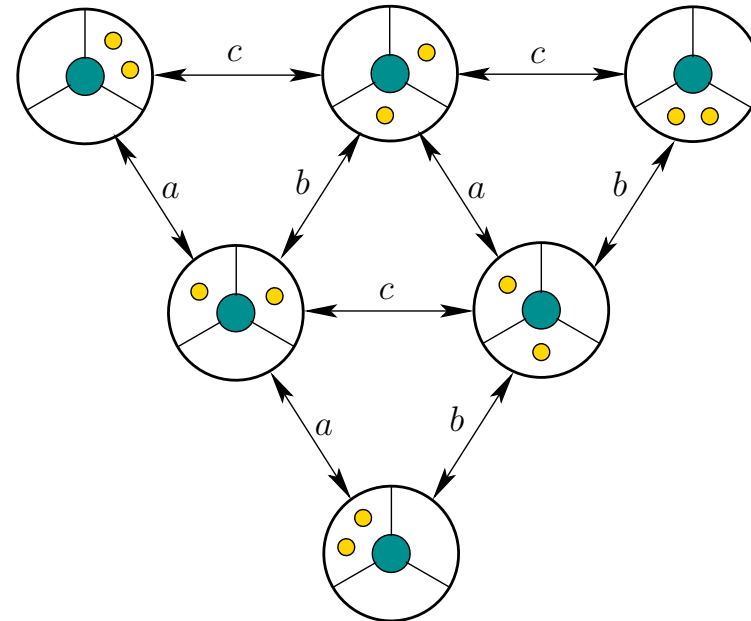
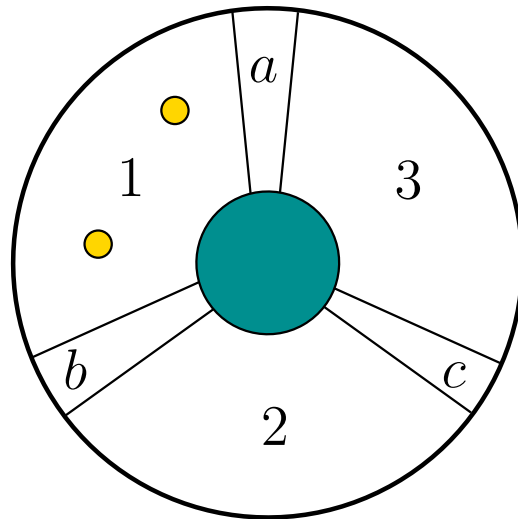
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Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



- Imagine indistinguishable balls in boxes.
- There is a natural transition graph.
- Express tasks using logic, and convert to sequences of distributions.

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

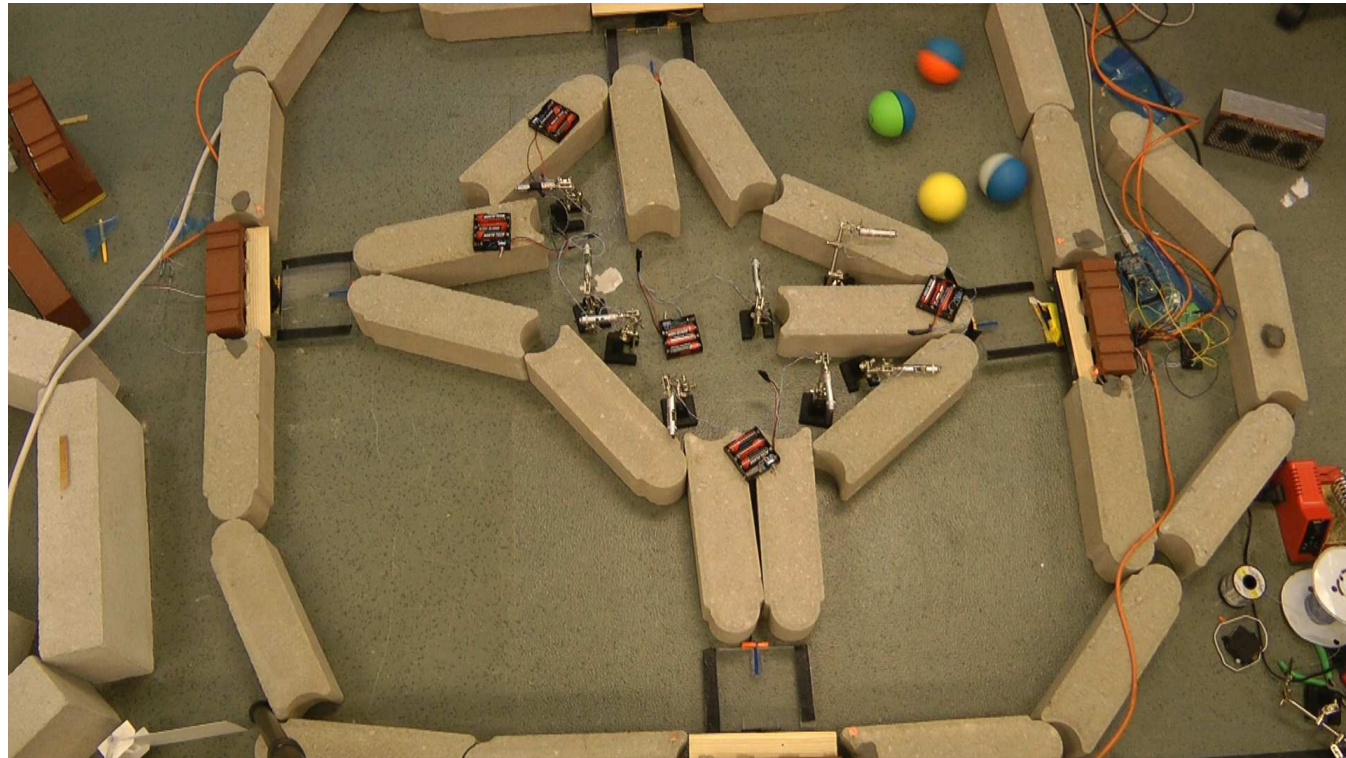
[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Splitting Video:



Merging Video

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

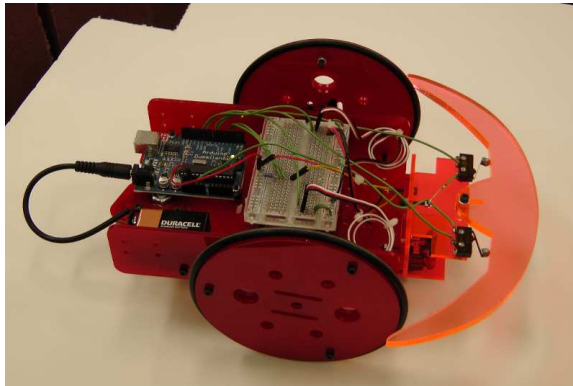
Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



A cheap color sensor detects a virtual gate crossing.



Communication allows simulation of a physical-gate system.

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

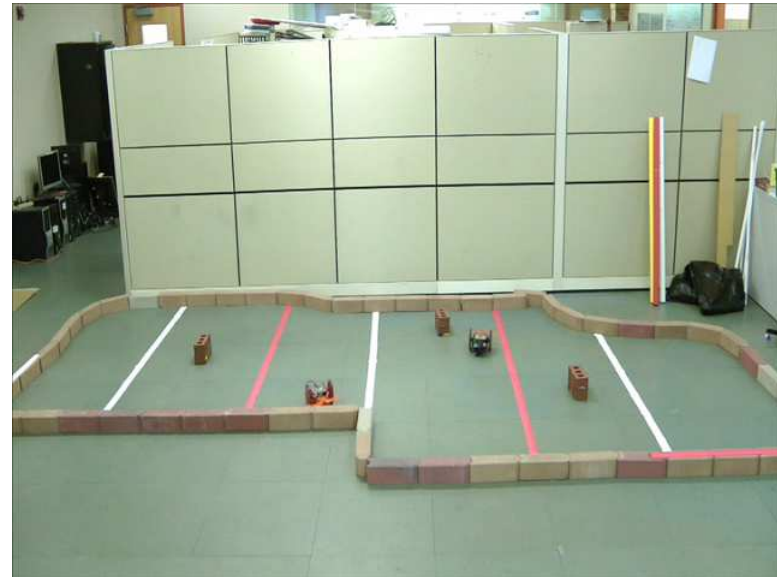
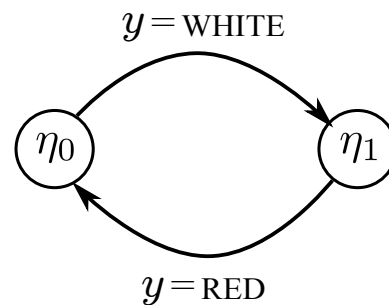
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Controlling Wild Bodies

A simple information-feedback plan: $\pi : \mathcal{I} \rightarrow M$

η_0 : White open, red closed

η_1 : White closed, red open



From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

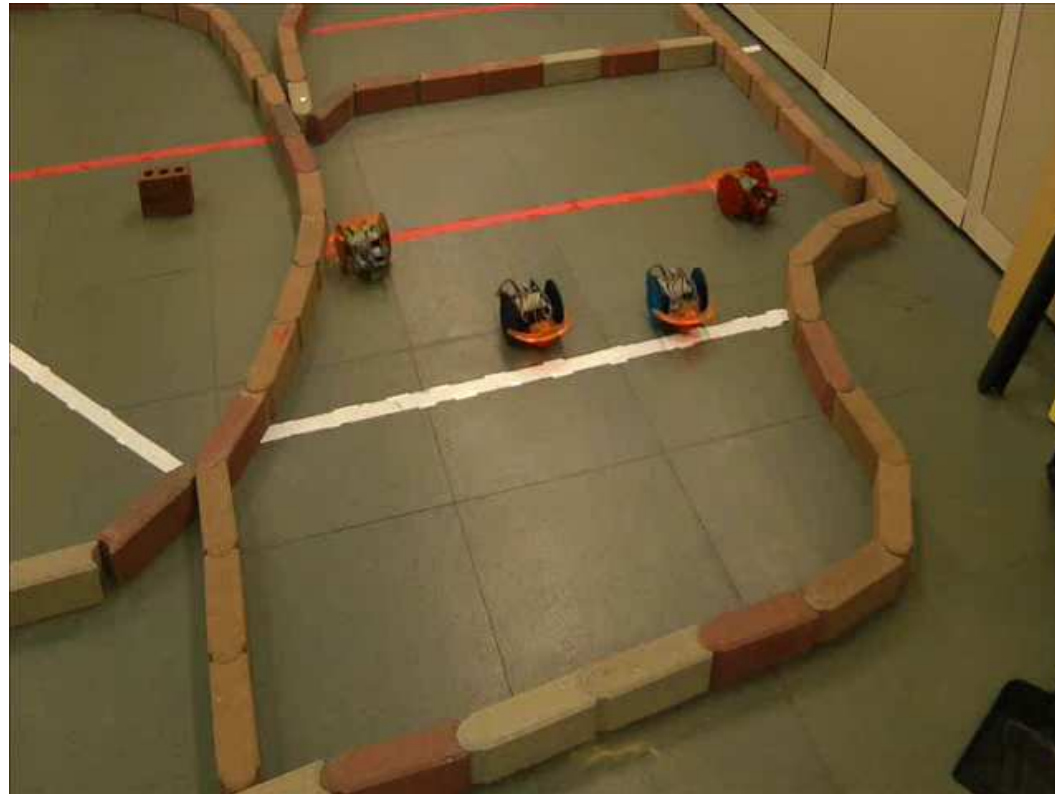
Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Separation into classes



Each robot can treat the boundaries (red and white) differently.

Information Feedback Using a Combinatorial Filter

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

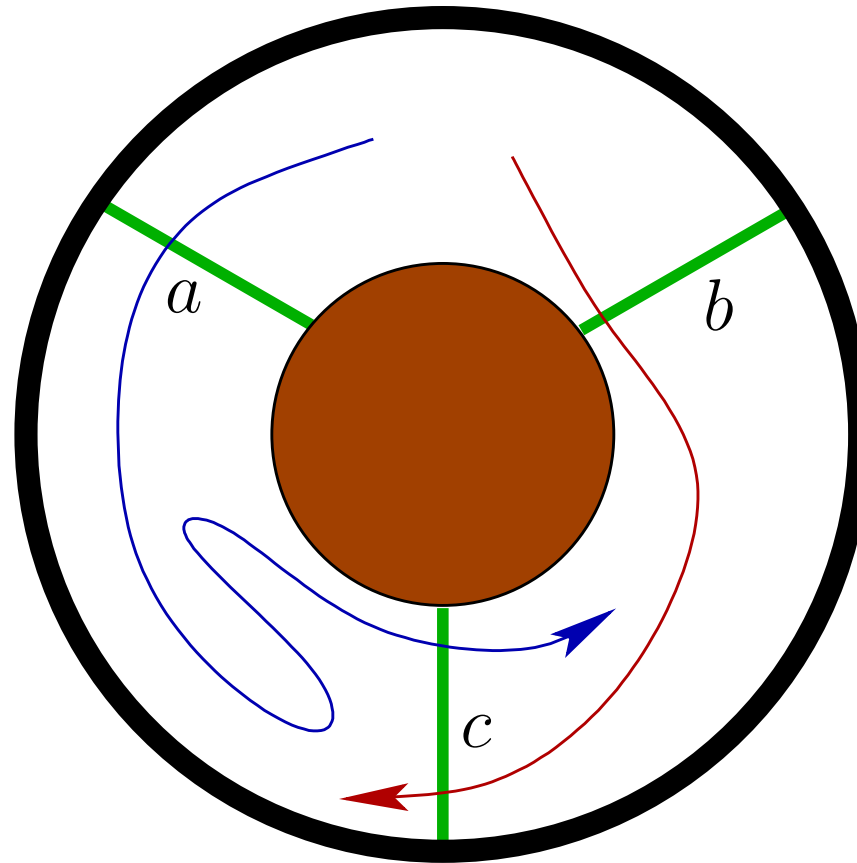
Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

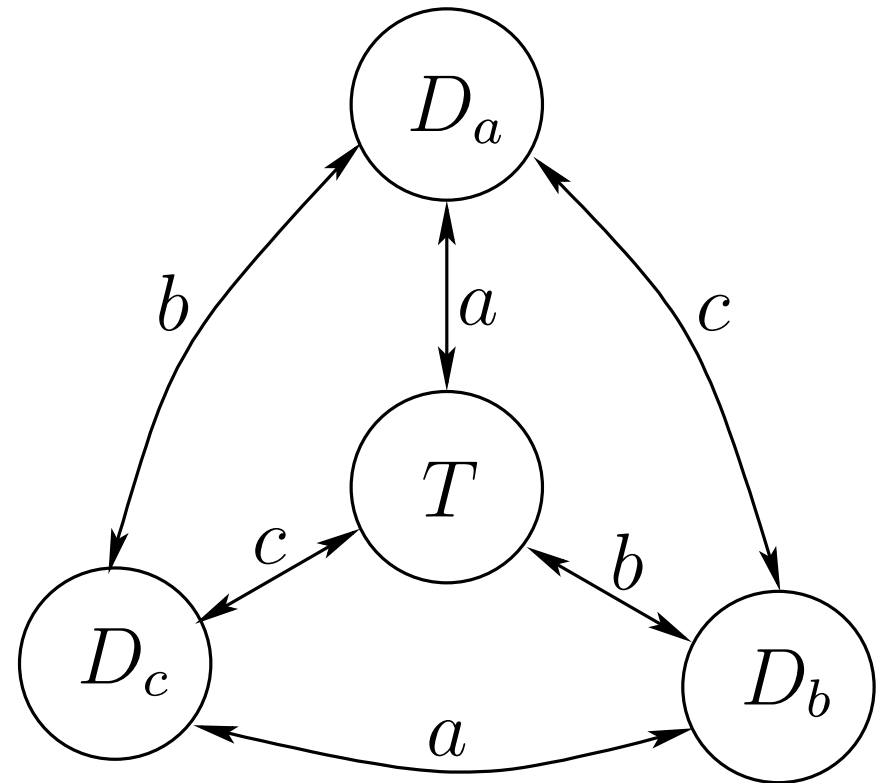
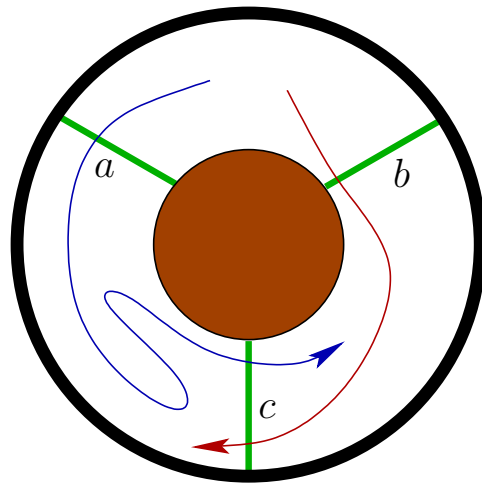


History I-state: $abbacbacabababcbbba$

Question: Are the bodies in the **same** room?

Living in a Tiny Information Space

This two-bit machine can read strings of any length and correctly report the answer.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

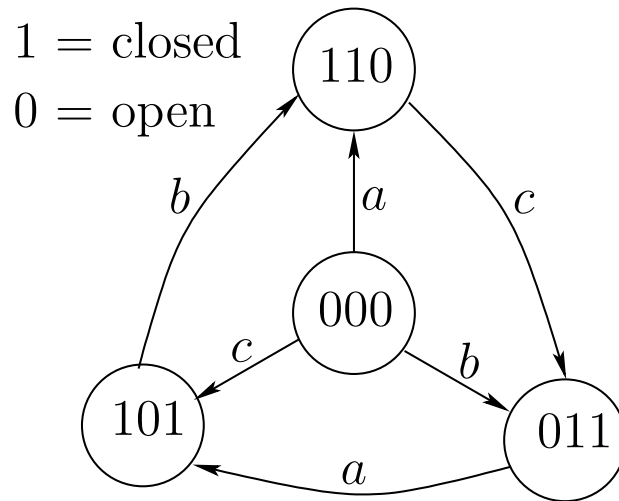
[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Three-Room Patrolling



Information space: $\mathcal{I} = \{T, D_a, D_b, D_c\}$

Information feedback plan: $\pi : \mathcal{I} \rightarrow M$

Communication is needed between the robots.

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Theoretical Design and Analysis

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

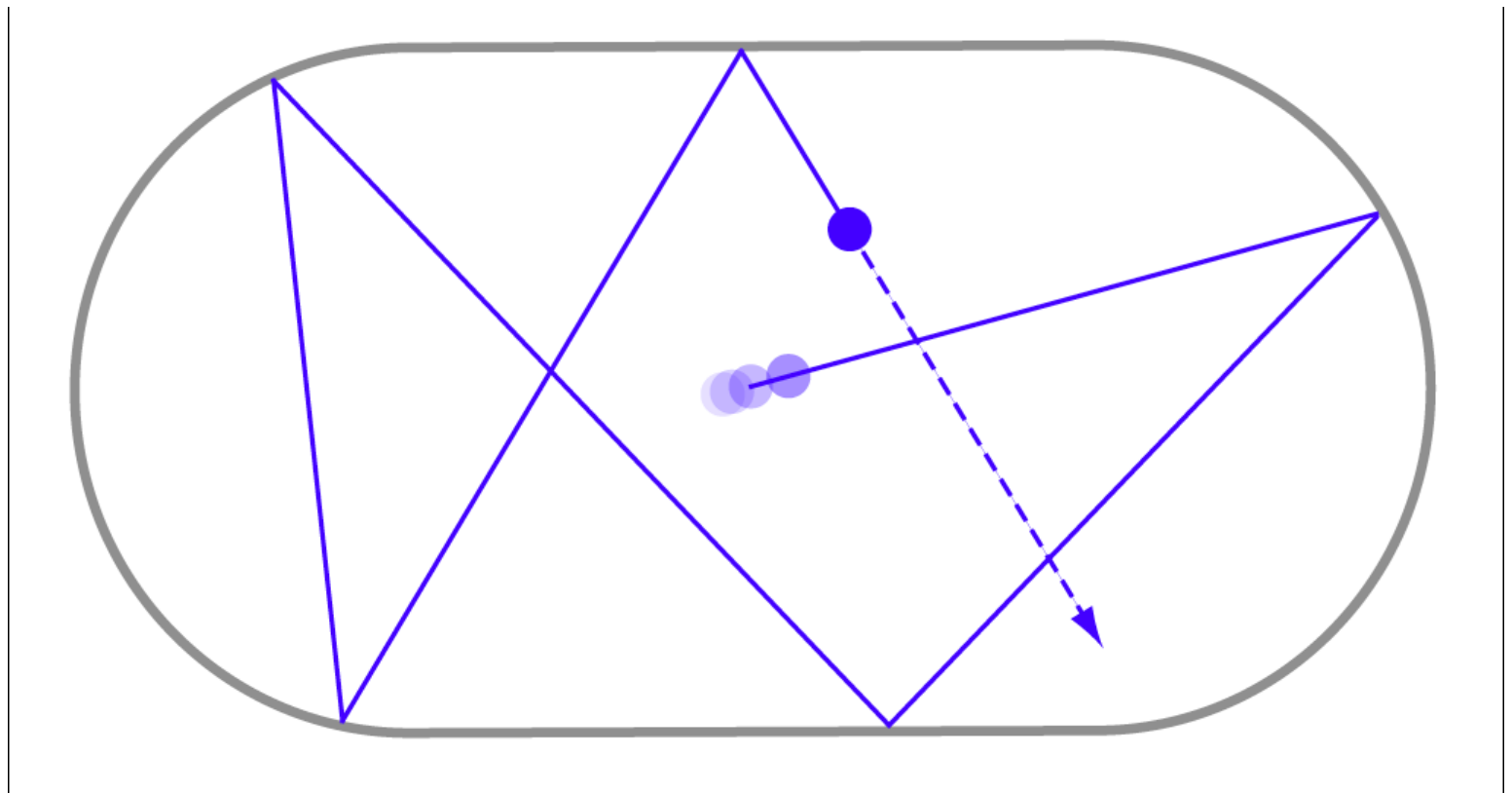
Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- Connections to results in mathematics
- Performance analysis
- Designing better motions
- Optimal searching for the gate

History: Poincare, Hadamard, Artin, Sinai, Bunimovich, ...



Bunimovich stadium

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

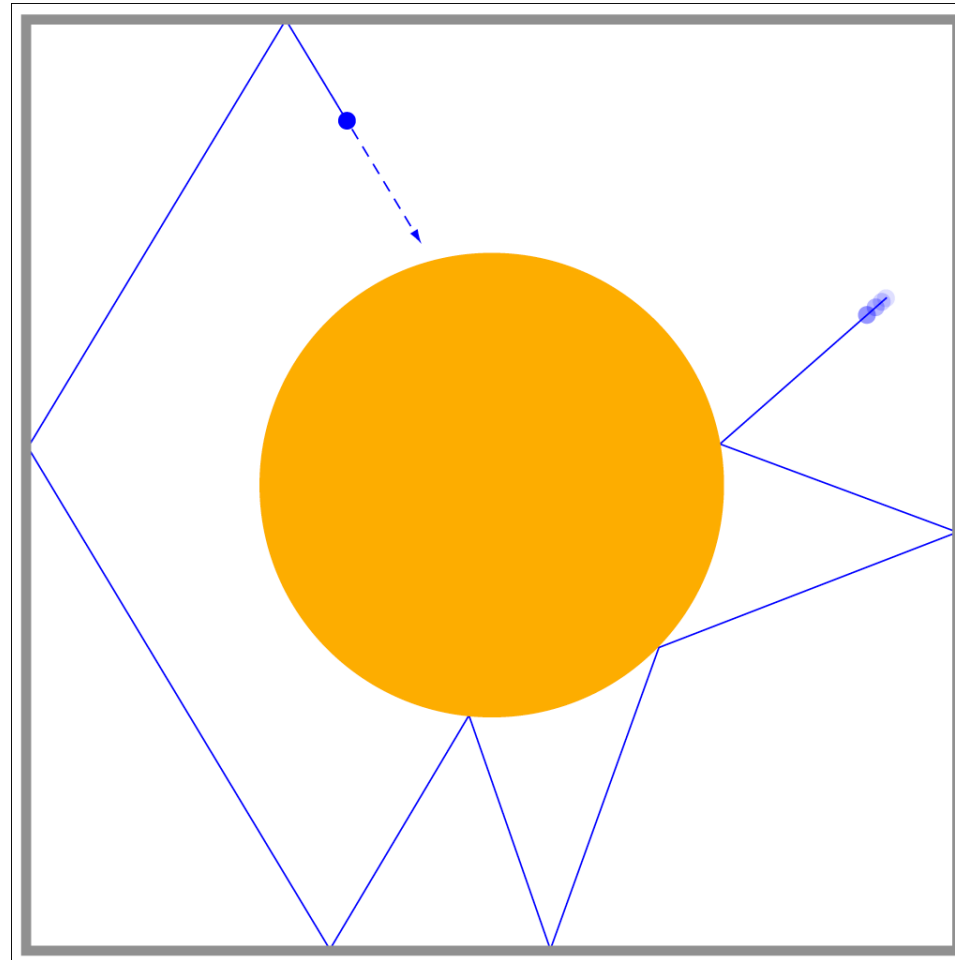
Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



Sinai billiard

Ergodic Dynamics: Definition

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

First, a *measure-preserving dynamical system* is a four-tuple (X, \mathcal{B}, μ, T) for which: 1) X is a set, 2) \mathcal{B} is a σ -algebra over X , 3) $\mu : \mathcal{B} \rightarrow [0, 1]$ is a measure, and 4) $T : X \rightarrow X$ is a measurable transformation that preserves measure (each $A \in \mathcal{B}$ satisfies $\mu(T^{-1}A) = \mu(A)$).

A measurable set $A \in \mathcal{B}$ is called T -invariant mod 0 if $\mu(T^{-1}(A) \triangle A) = 0$, in which \triangle denotes the symmetric difference. Note that if this is true then A is T^n -invariant mod 0 for all n .

T is *ergodic* if for every T -invariant mod 0 measurable set A , we have $\mu(A) = 1$ or $\mu(A) = 0$.

Intuition: You can't find a region (connected or not) that traps it.

Ergodic Dynamics: Intuitive Definition

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

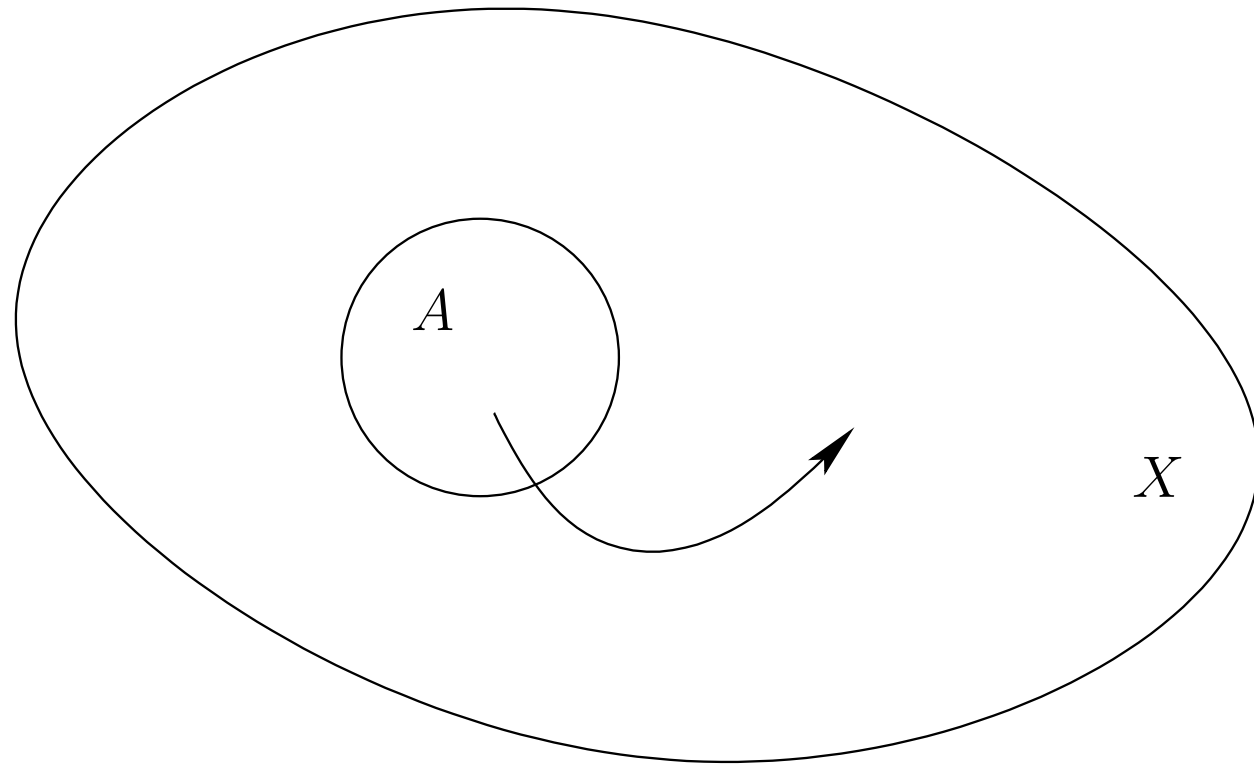
[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

The system is a *measure-preserving transformation* $T : X \rightarrow X$ on a state space X .



You can't find a region A (connected or not) that traps the system, unless A or its complement has measure zero.

Ergodic Dynamics: Example

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

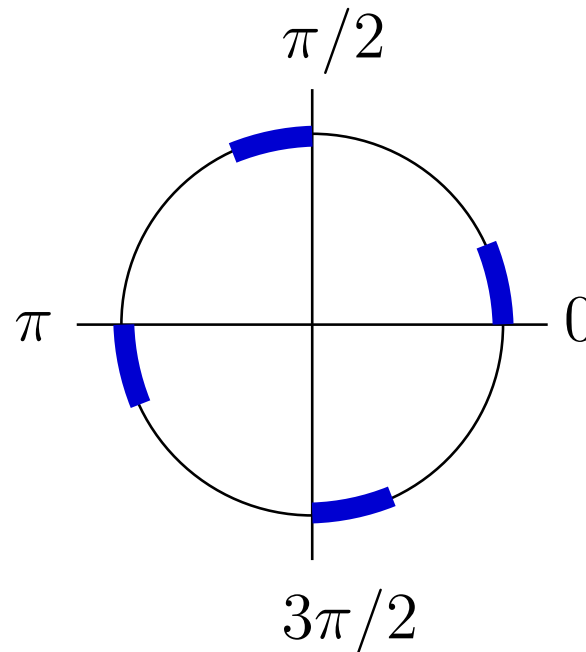
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Let T be a planar rotation by angle θ .

$$X = S^1$$

If θ/π is irrational, then T is ergodic; otherwise, it is not.

Example: $\theta = \pi/2$



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Let f be any μ -integrable function.

Time average:

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=0}^{n-1} f(T^k x)$$

Space average:

$$\frac{1}{\mu(X)} \int f d\mu$$

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

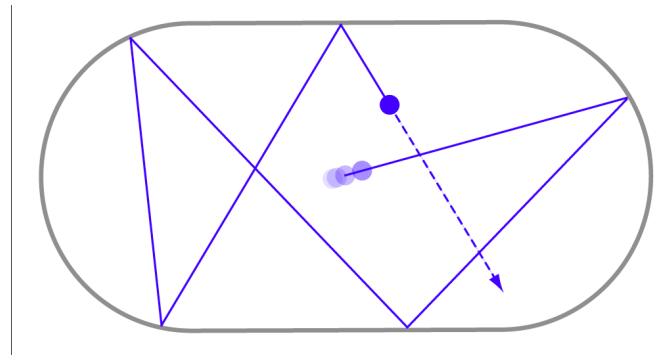
Birkhoff (1931): If T is ergodic, then the time and space averages are the same (almost everywhere).

Example:

Take any $A \subseteq X$

Let $f(x) = 1$ if $x \in A$ and $f(x) = 0$ otherwise.

In this case, Birkoff's theorem states that the frequency of visits to A is equal to $\mu(A)$.



Ergodicity in Polygons

[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Kerckhoff, Masur, Smillie, 1986: For almost all polygons and almost all initial conditions, the billiard trajectory is ergodic.



What Is Different About Our Problems?

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- We do not care about *measure-preserving* maps.
- There are many alternative ways to *bounce*.
- Classical ergodicity may be *overkill*.

This is ergodic almost everywhere, but not measure-preserving:

$$f : x \mapsto 2x \pmod{1}$$

Here, $f : [0, 1] \rightarrow [0, 1]$

Bouncing Strategies

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

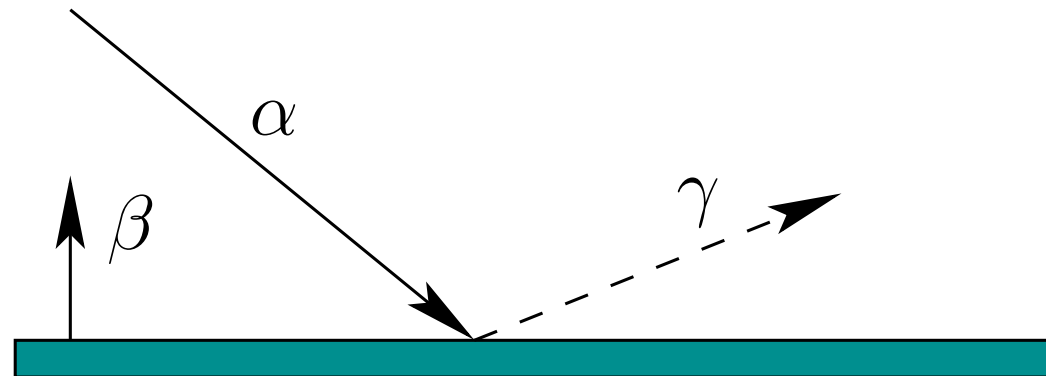
Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies



$$\gamma = h(\alpha, \beta)$$

Fundamental question: What sensors are needed?

Alternative: Select γ randomly (or with $p(\gamma|\alpha, \beta)$)

Weaker Than Ergodic

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

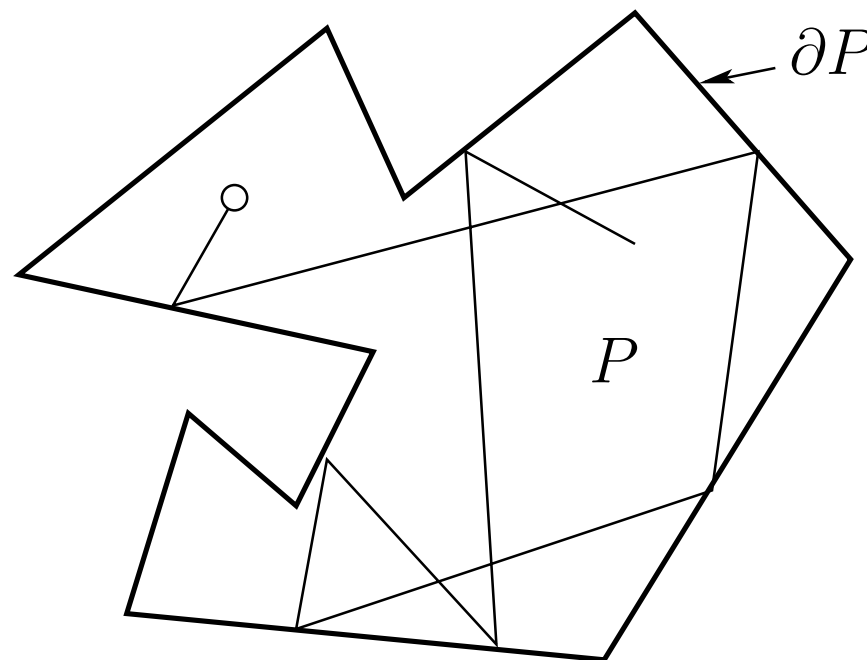
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Sensorless manipulation

Controlling Wild Bodies

Let $C \subseteq X$. Let $\tilde{x} : [0, \infty) \rightarrow X$ be a trajectory.

\tilde{x} is called *topologically transitive with respect to C* if for every open set $O \subset C$, there exists a time $t > 0$ for which $\tilde{x}(t) \in O$.

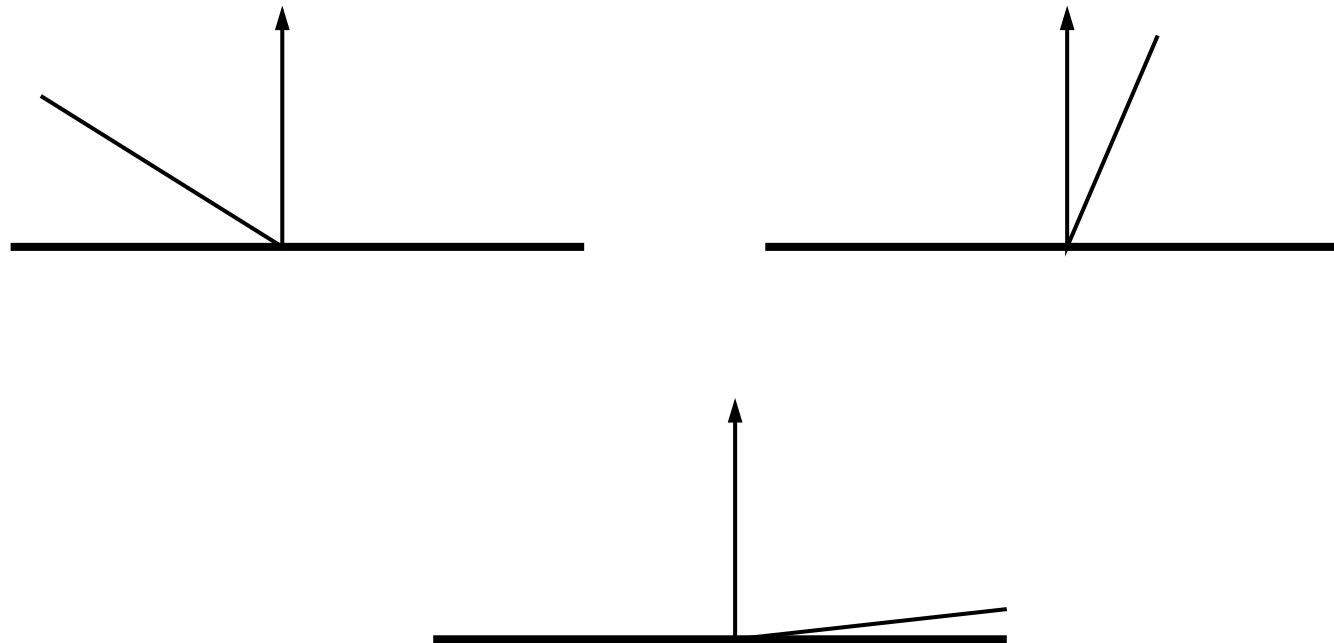


Suppose $X \subset \mathbb{R}^3$, in which $(x, y) \in P$ and $\theta \in S^1$.

Possibilities: $C = X$, $C = \partial P \times (0, \pi)$, or $C = \partial P$

Normal Bounce

Angle of incoming body not relevant to trajectory after impact.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

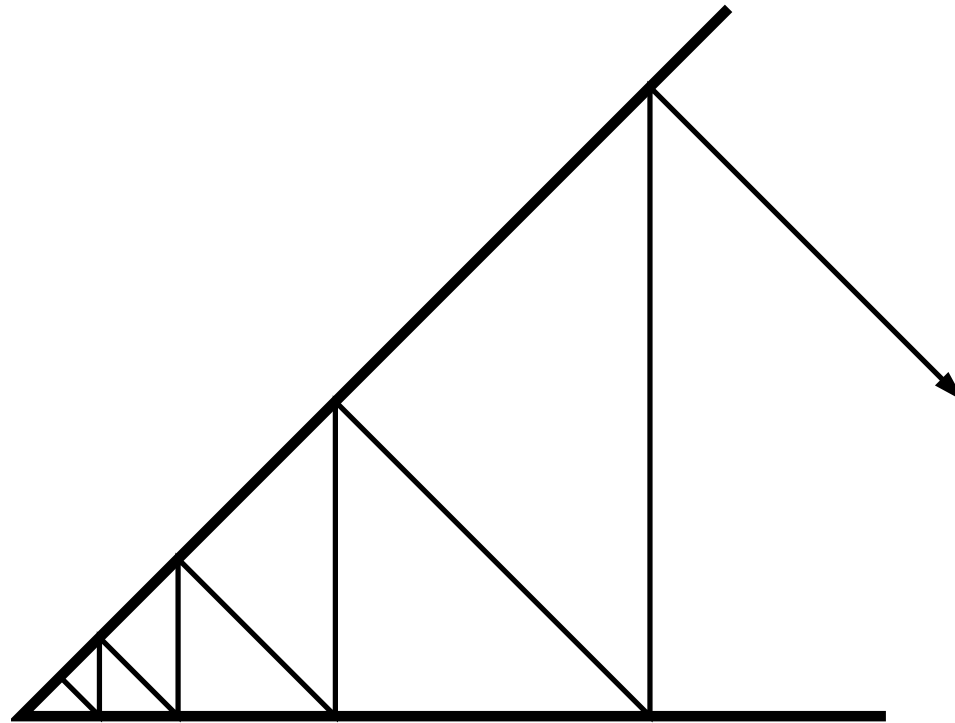
[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Bodies tend to move away from corners.



From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

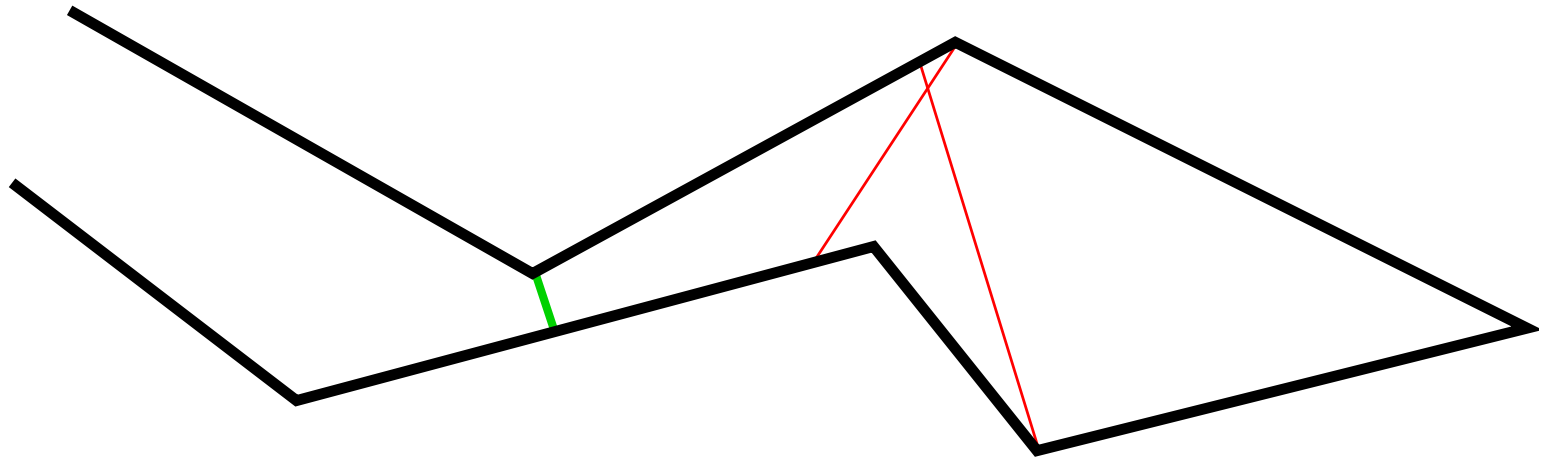
Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

Nothing to the right of the green line will deflect a body back over the green line.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

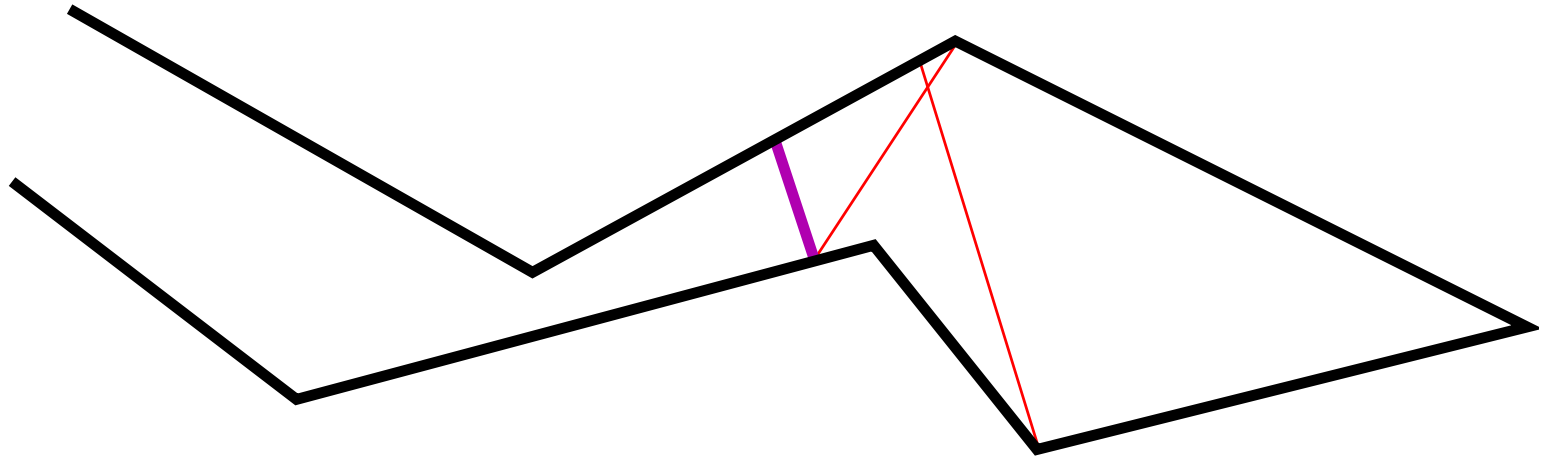
[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Nothing to the right of the purple line will deflect the body over the green line.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

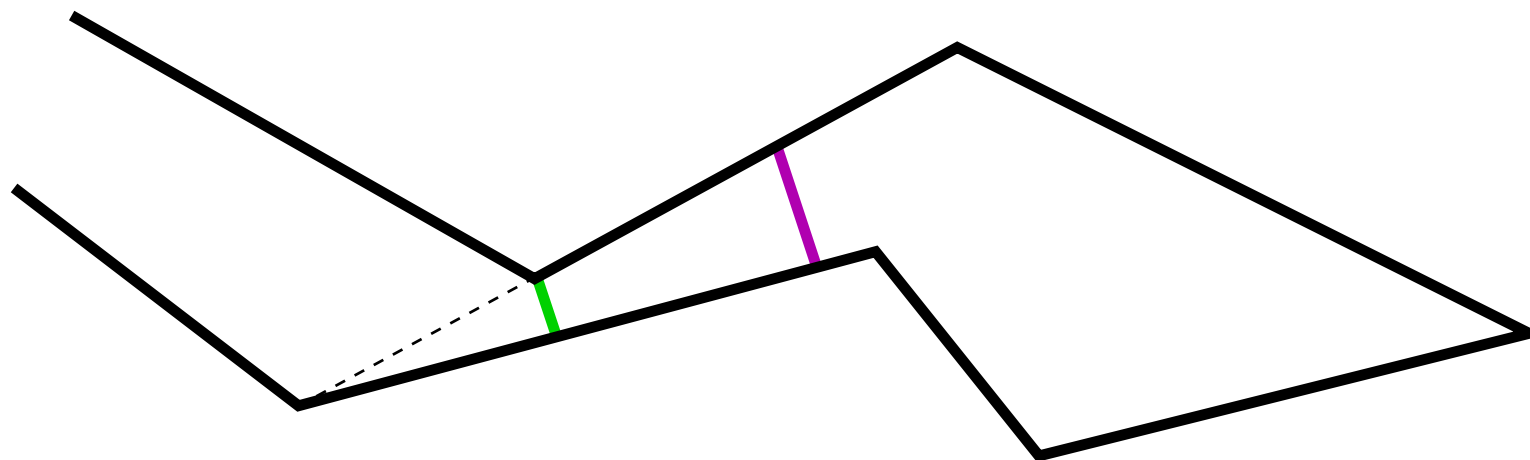
Learning convex hulls of landmarks

Bug algorithms

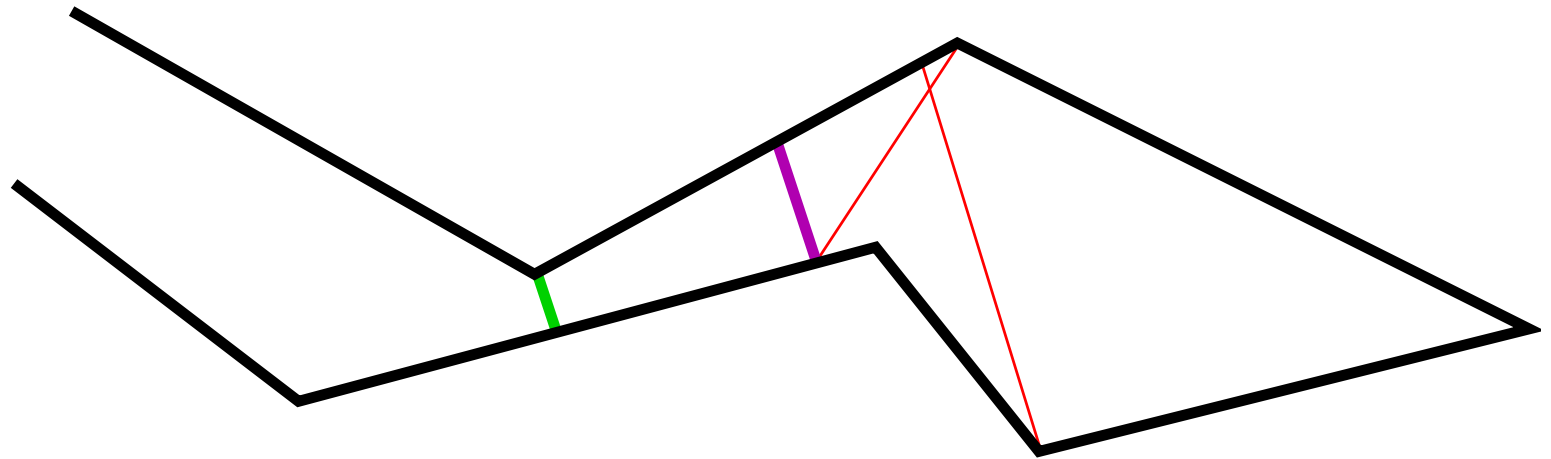
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Controlling Wild Bodies

When the body crosses the green line, it moves toward the purple line, away from the “corner”.



The green and purple lines denote the boundaries of a basin of attraction.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

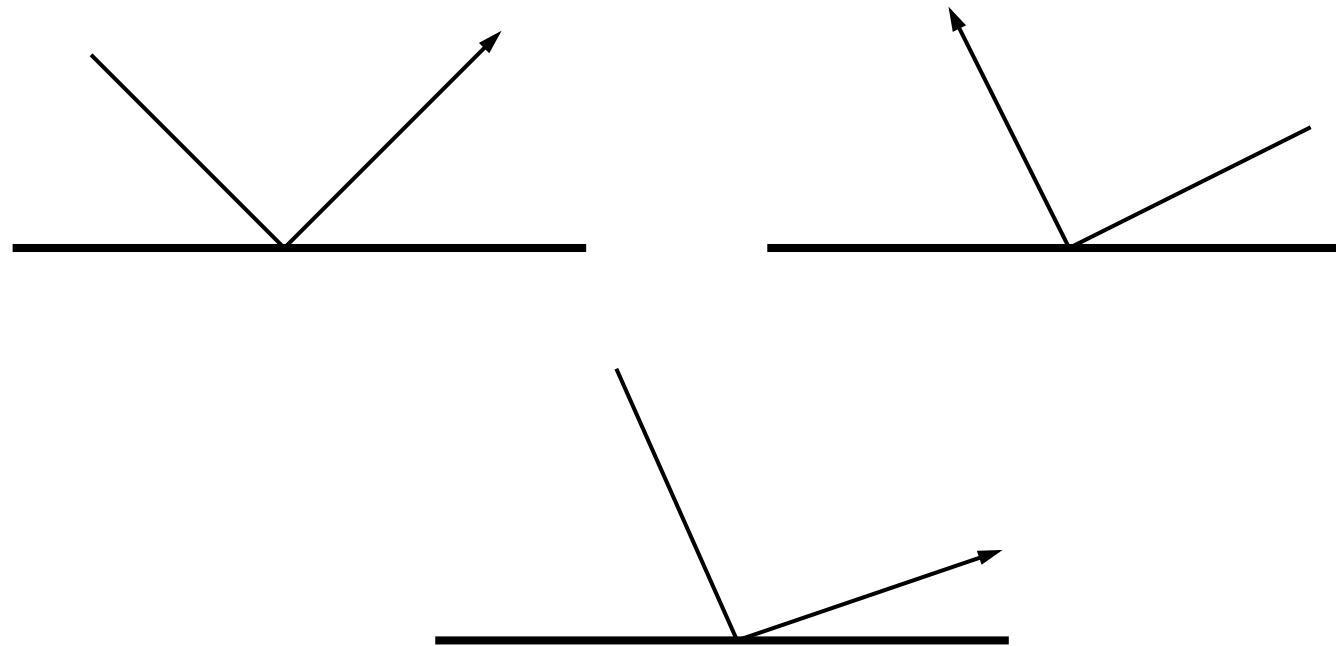
[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Right Angle Bounce

Body always reflects at a right angle, regardless of trajectory relative to wall.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

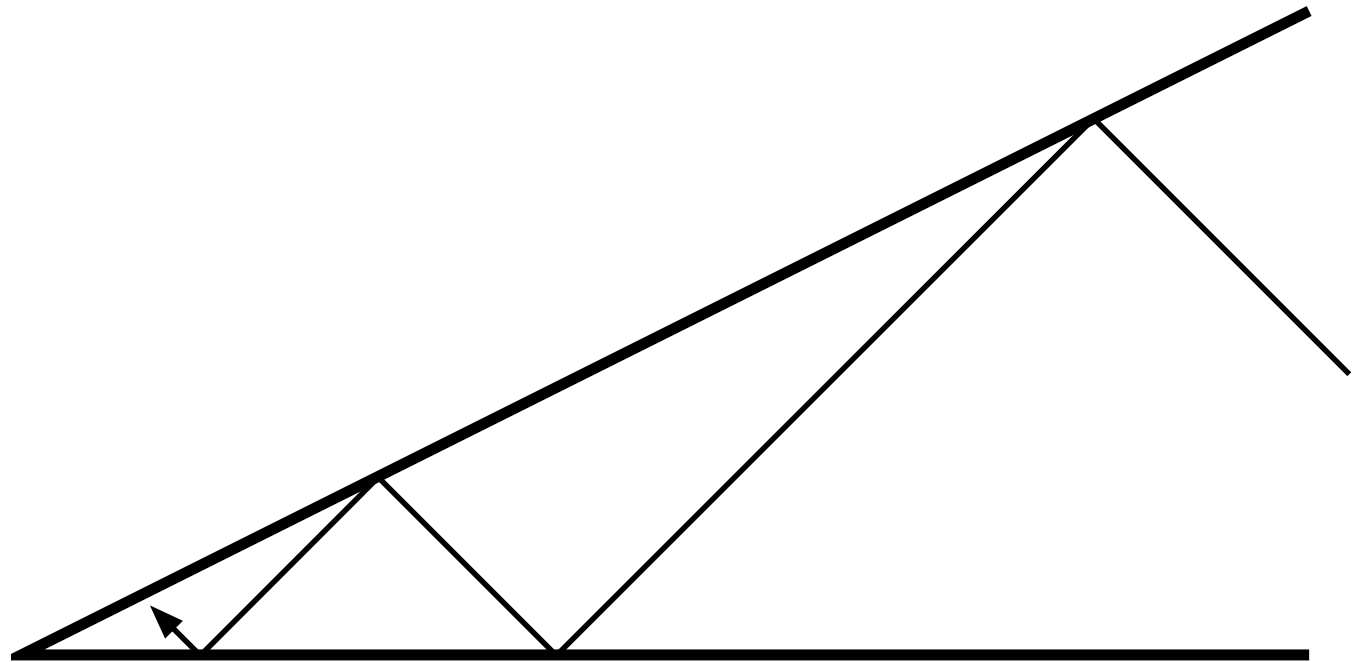
[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

Right Angle Behavior

Right angle bouncing is attracted to corners.



[From filters to planning](#)

[General issues](#)

[Visibility-based pursuit evasion](#)

[Maze searching](#)

[Gap navigation trees](#)

[Learning convex hulls of landmarks](#)

[Bug algorithms](#)

[Sensorless manipulation](#)

[Controlling Wild Bodies](#)

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

The general paradigm:

- Let the bodies “run wild”, rather than stabilizing.
- Use physical or virtual gates to gently guide them.
- Use as little sensing and communication as possible.

Challenges:

- Designing more systems of bodies and gates
- Characterizing the space of tasks that can be solved
- Development and analysis of simple bouncing primitives

From filters to planning

General issues

Visibility-based pursuit evasion

Maze searching

Gap navigation trees

Learning convex hulls of landmarks

Bug algorithms

Sensorless manipulation

Controlling Wild Bodies

- Use filters to make I-space transitions
- Plan directly in the I-space
- General planning issues
- Need to design virtual sensors, filters, and planning around a task
- Several examples were shown

Although several examples of nice reduced-complexity I-spaces have been found, we have barely scratched the surface...