

Faster Motion Planning Using Learned Local Viability Models

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University of British Columbia

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Outline

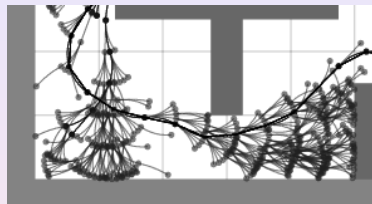
- 1 Introduction
 - Current planner weaknesses
 - Perception
 - Learning
- 2 Implementation
 - Planner augmentation
 - Viability model
- 3 Experiments
 - Problem specification
 - Results
 - Tree structure

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General observations

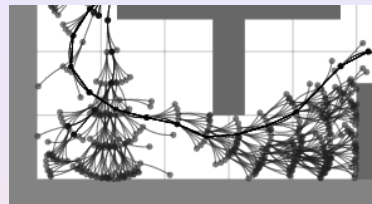
- differential constraint planners: room for improvement
- current planners:
 - do questionable explorations (e.g., try to drive into walls)
 - they keep doing this, repeatedly (i.e., “experience” not accumulated)
- underlying problems:
 - planners cannot “see”
 - planners do not learn (transferrable skills)



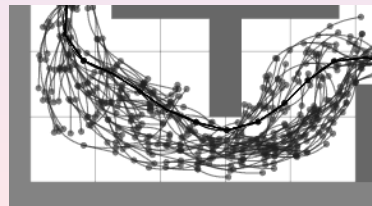
inefficient

Specific problems addressed

- we address these shortcomings
 - provide “sight”
 - avoid “questionable” exploration
- the point: greater efficiency, speed up of up to 10x



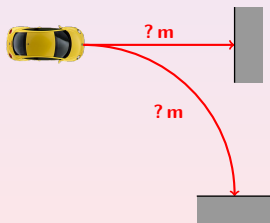
inefficient



better

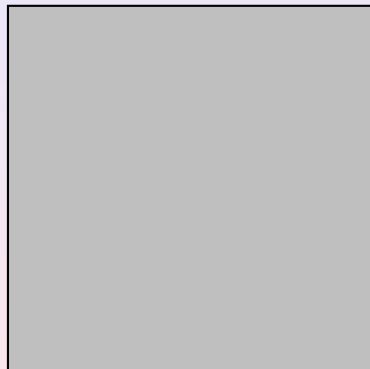
Adding “sight”

- “sight”
 - needed to anticipate and avoid traps, behave smarter
 - collision-check: only a tactile sense
 - need longer range, “perception at a distance”
- \Rightarrow augment agent with **virtual sensors**
 - measure *agent* \leftrightarrow *environment* distance along line or curve



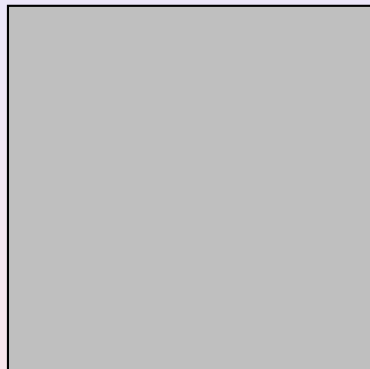
Learning smarter behaviour

- “questionable explorations” =
 - **nonviable** states
(Viability Theory: J.P.Aubin)
 - \mathcal{X}_{ric}
(J.Kuffner & S.LaValle)
 - **Inevitable Collision States** (ICS)
(T.Fraichard *et al.*)
- goal: learn these states, avoid them
i.e., **viability filtering**
- same solutions, less time & effort



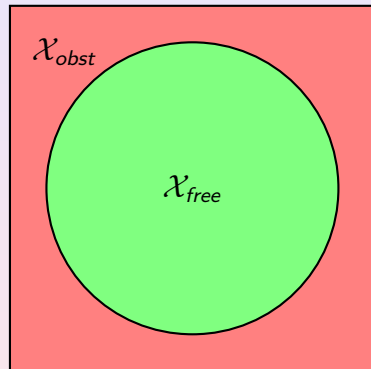
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 \mathcal{X} 

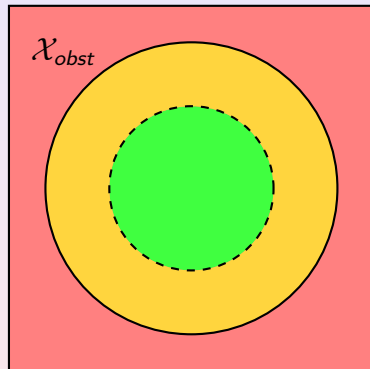
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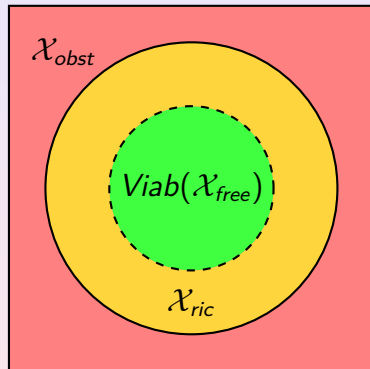
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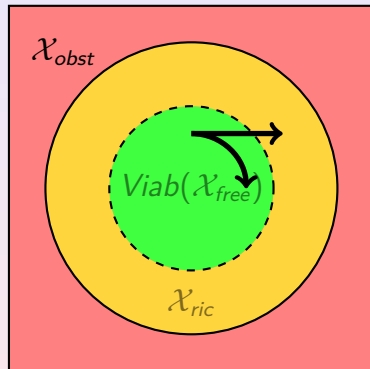
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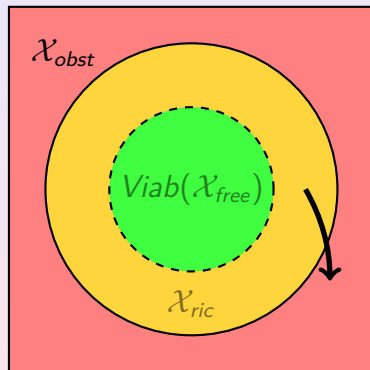
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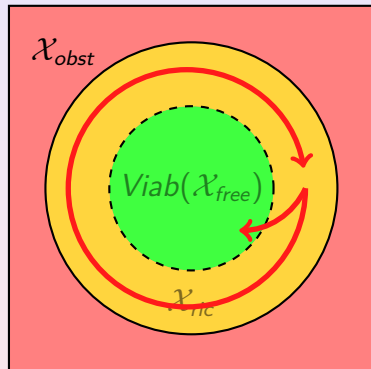
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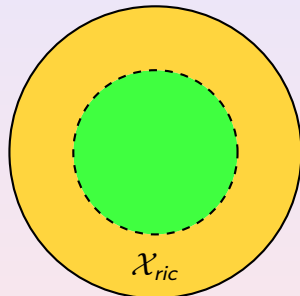
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impossible!

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Why viability filtering makes sense

basic observation from viability theory

- a nonviable state (e.g., $x_{nv} \in \mathcal{X}_{ric}$) cannot lead to a viable state
- if it did, x_{nv} would be viable, by definition

Thus

- if x_{goal} viable:
 - x_{nv} cannot lead to x_{goal}
 - $\Rightarrow x_{nv}$ **cannot be part of a solution**
 - \Rightarrow exploring x_{nv} = pointless, waste of effort
- if x_{goal} nonviable:
 - still partially helpful
 - automatically resolved when using two trees
(see paper)

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Adding “viability filtering” to a planner

Retrofitting a planner

Simple:

- 1 build or obtain a local viability model for agent
- 2 replace calls to `collision_check(x)` with `nonviable_check(x)`

Modeling viability

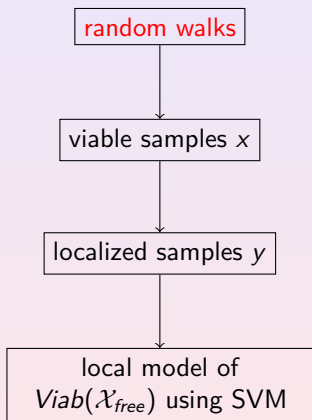
problem

- $Viab(K)$ usually not known ahead of time; where does $Viab(K)$ end and \mathcal{X}_{ric} start?

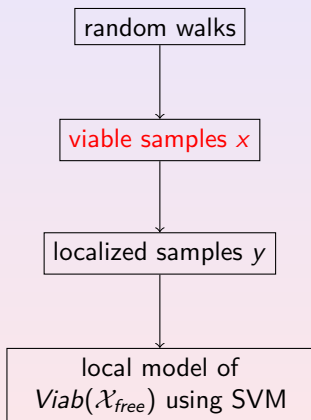
solution

- empirical data + simple heuristic \rightarrow approximate model
- prior solution trajectories: potential empirical data source
- model is local: parametrized by virtual sensors' output

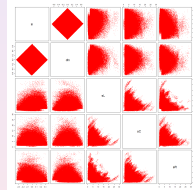
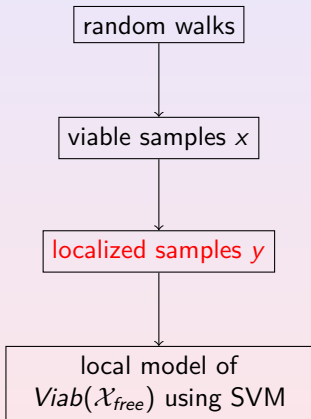
Our model building process



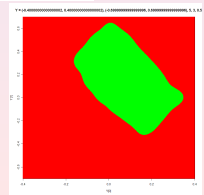
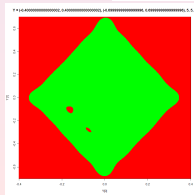
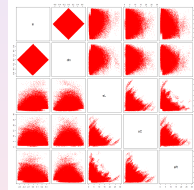
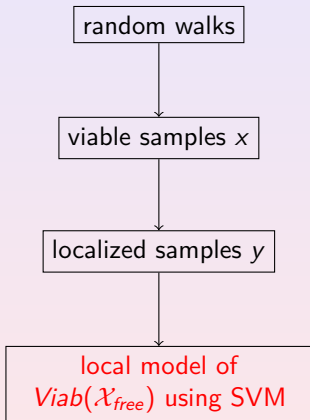
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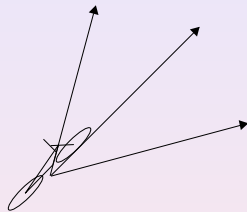
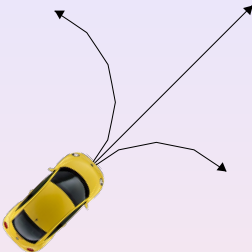
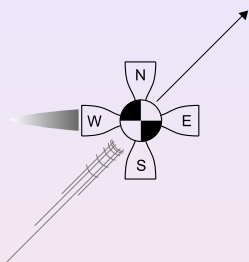
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Agents & sensors



inertial point

- one thruster always "on"
- sensor along velocity vector

car

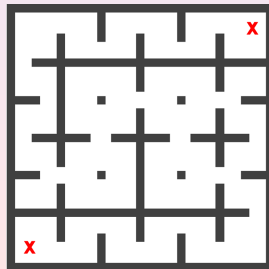
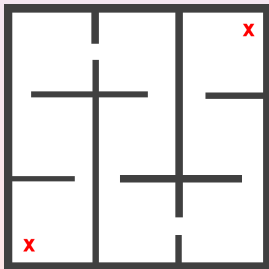
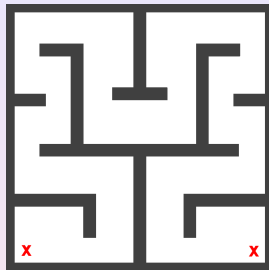
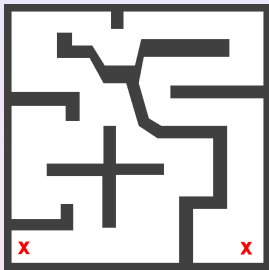
- minimum turning radius: large
- fixed forward velocity
- curved path sensors: max 180°

bike

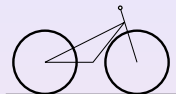
- fixed forward velocity
- steering for balance and navigation
- failure if lean exceeds 60°

Environments

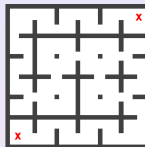
some environments tested



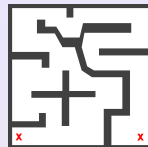
Sample results



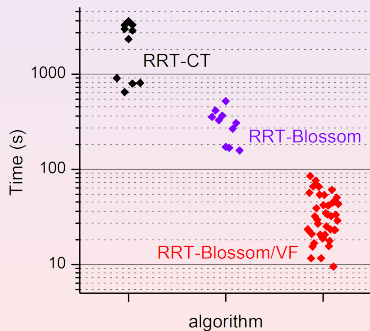
agent



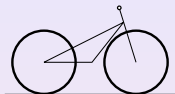
problem posed



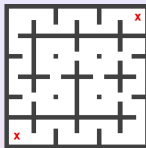
model trained on



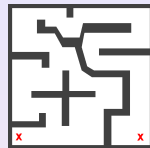
Sample results



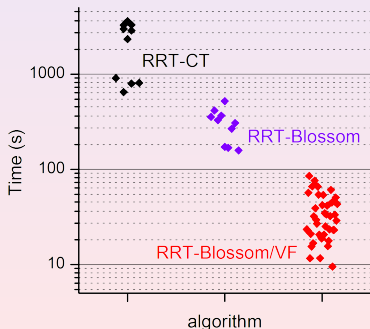
agent



problem posed



model trained on



problem	algo.	runtimes
	RRT-CT	371.5s
	RRT-Blossom	21.0s
	RRT-Blossom-VF	5.6s
	RRT-CT	209.9s
	RRT-Blossom	13.5s
	RRT-Blossom-VF	3.6s
	RRT-CT	2148.6s
	RRT-Blossom	305.7s
	RRT-Blossom-VF	34.3s

Effect of viability filtering on tree branches

without filtering

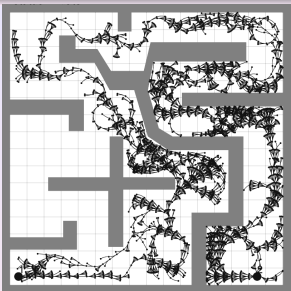


with filtering

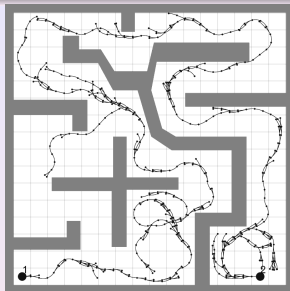


Tree structure comparison

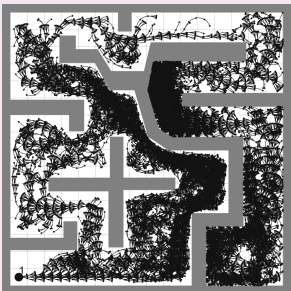
RRT-Blossom (plain)



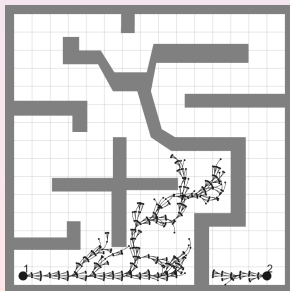
↓
RRT-Blossom (filtered)



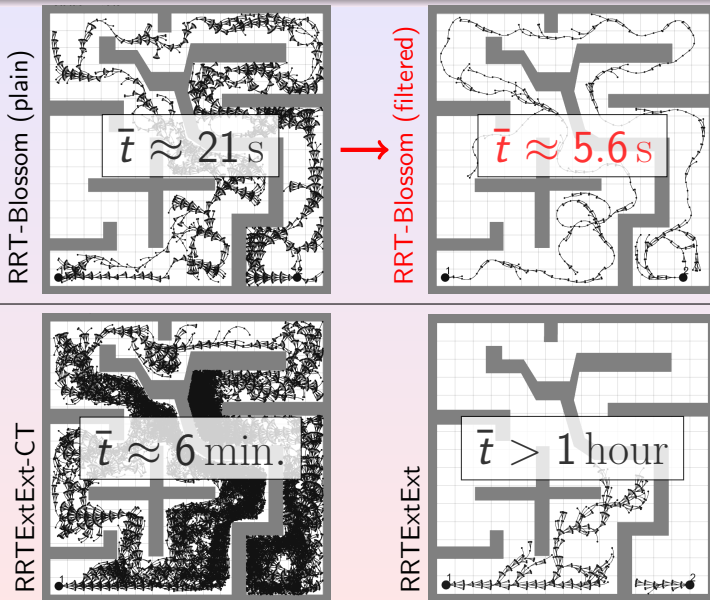
RRTExtExt-CT



RRTExtExt



Tree structure comparison



Summary

Key points:

- current planners do not “see”, nor “learn” transferrable lessons
- limit planner to $Viab(\mathcal{X}_{free})$: same solutions, significant speed-up (e.g., 4x–10x)
- good results despite heavily imperfect models

Additional information

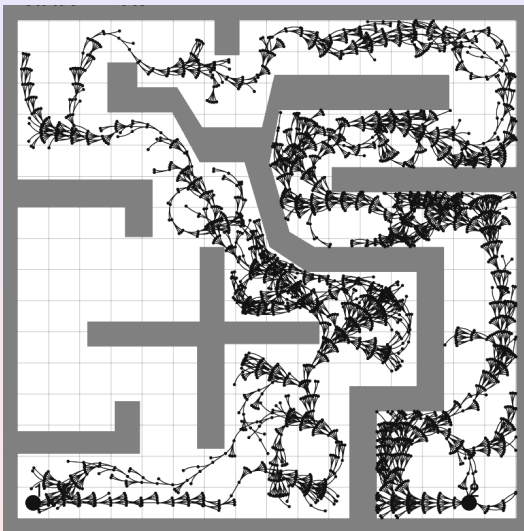
- <http://www.dgp.toronto.edu/~mac/research/viability-filtering/>

Appendix

- 4 Appendix
 - Tree structure (zoom)

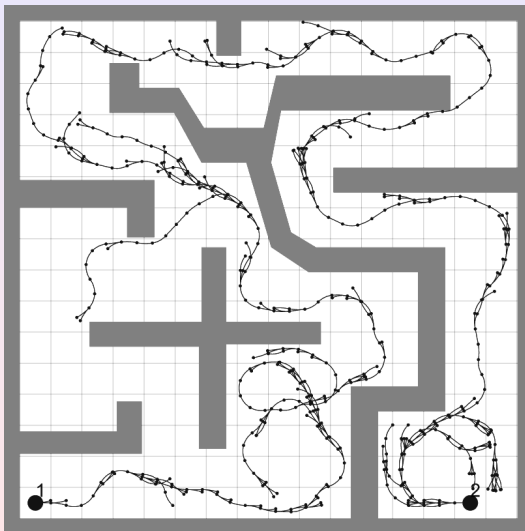
Tree structure comparison

RRT-Blossom (plain)



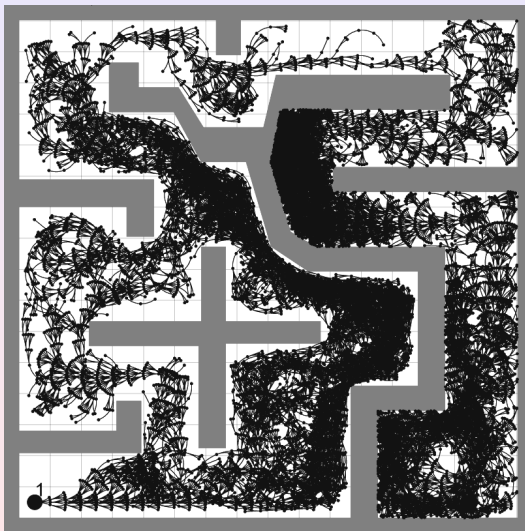
Tree structure comparison

RRT-Blossom (**viability-filtered**)



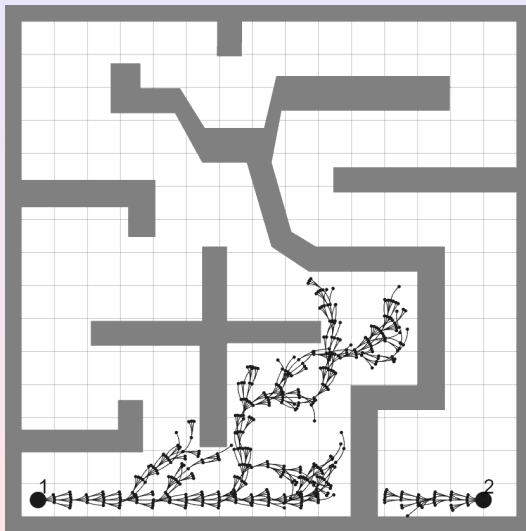
Tree structure comparison

RRT w/Collision Tendency (RRT-CT)

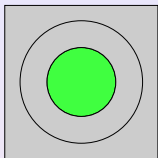


Tree structure comparison

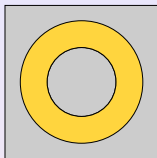
plain RRT (RRTEstExt)



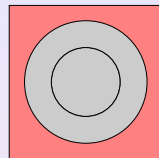
Viability vs. collision-checking



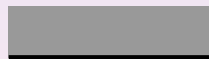
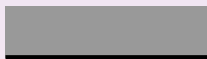
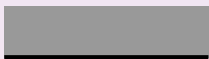
$$x \in \text{Viab}(\mathcal{X}_{\text{free}})$$



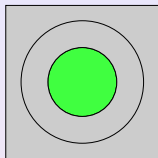
$$x \in \mathcal{X}_{\text{ric}}$$



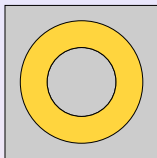
$$x \in \mathcal{X}_{\text{obst}}$$



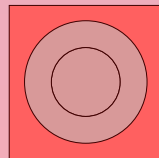
Viability vs. collision-checking



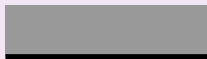
$$x \in \text{Viab}(\mathcal{X}_{\text{free}})$$



$$x \in \mathcal{X}_{\text{ric}}$$

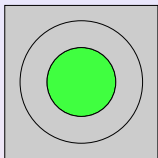


$$x \in \mathcal{X}_{\text{obst}}$$

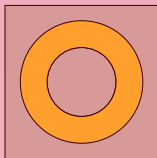


“collision filtering”

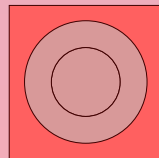
Viability vs. collision-checking



$$x \in \text{Viab}(\mathcal{X}_{\text{free}})$$



$$x \in \mathcal{X}_{\text{ric}}$$



$$x \in \mathcal{X}_{\text{obst}}$$



viability filtering