Proactive Planning and Execution Strategies with Multiple Hypotheses

Jorrit T'Hooft





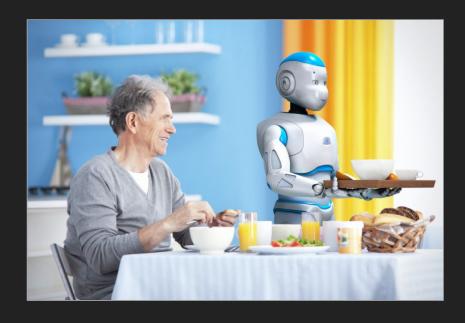




Complex Missions

- Human Assistance
- Search & Rescue
- Surveillance
- Dangerous Work





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Complex Environments

- Dynamic
- Unstructured
- Open
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- Search & Rescue
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Complex Environments

- Dynamic
- Unstructured
- Open
- Partially Observable
- ► Impossible to precompute a plan for each possible situation.
- Service robots need to plan and manage their actions online!





Triggers replanning to adapt the plan during execution.

1. M. Ghallab, D. Nau, and P. Traverso, "The actor's view of automated planning and acting: A position paper", Artificial Intelligence, vol. 208, pp. 1–17, 2014.

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Planning & Execution Strategy

The way of interleaving the planning, selection and execution of actions.

When to call which deliberative function, with which parameters.¹

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To ensure the integrity of the system and/or its environment when no valid plan is available.

Such default behavior can be precomputed or obtained by fast (sub-optimal) planning.²





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Reactivity

The robot must be able to adapt its behavior fast enough when unexpected events occur.

• Constraints on the software architecture.³





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Two Existing Strategies



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^{4.} B. Marthi, "Robust navigation execution by planning in belief space", in RSS 2012.

Two Existing Strategies

Plan-Replan^{1,2}

Only replans when strictly necessary.

► Triggers replanning only when no valid plan is available (only when default behavior is executed).



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Continuous Planning^{3,4}

Tries to avoid the situation where no valid plan is available, by integrating observed changes.

► Triggers replanning continuously during execution, with the freshest information available, to continuously update the plan.



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Extends *Continuous Planning* with the following concepts:

Proactive Planning¹

Anticipating situations by searching for solutions in a proactive manner.

Generating multiple solution-plans by proactive planning for multiple hypotheses (which can correspond to predictable future situations).

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Hypotheses

A collection of information in order to generate a corresponding type of solution-plan.

Such as:

- Constraints on the search space.
- A particular configuration or initialization ...

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Using One or Multiple Planners

Select the appropriate planner(s) to solve for each hypothesis.

A planner can be more suited than another:

- Ability to deal with uncertainties.
- Solving duration.
- Optimality guarentees ...

Solving a hypothesis with different planners to obtain different plans for the same constraints.



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Tackling (some) Uncertainties with Multiple Hypotheses

Generate hypotheses on-the-fly taking into account only appropriate uncertainties.

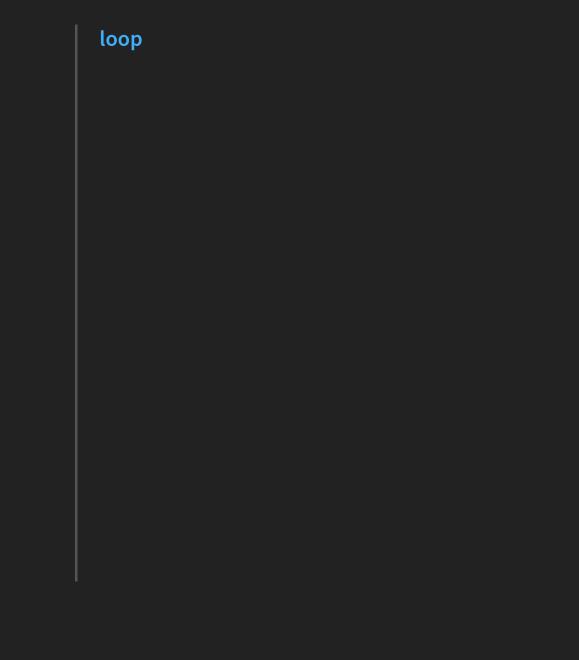
To speed up the search: take into account only a subset of the uncertainties.

To discard the need of modeling the uncertainties: solve for possible future situations separately.

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High-level algorithm:



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	loop
update context	update current goal, current state, planning results (if any)

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High-level algorithm:

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nage actions execute most appropriate action	<pre>if no action executing then select most appropriate action to execute; launch selected action else verify if the executing action is still the most appropriate if a more appropriate action is available then stop the executing of current action; launch new most appropriate</pre>
age planning plan for appropriate hypothesis with appropriate planner	<pre>if currently planning then if the hypothesis for which we are planning is still appropriate then continue planning else stop the corresponding algorithm if currently not planning then if hypothesis left to explore then h ← select hypothesis to plan for; select planning algorithm for h create planning algorithm input for h; launch the planner for h</pre>

te action;

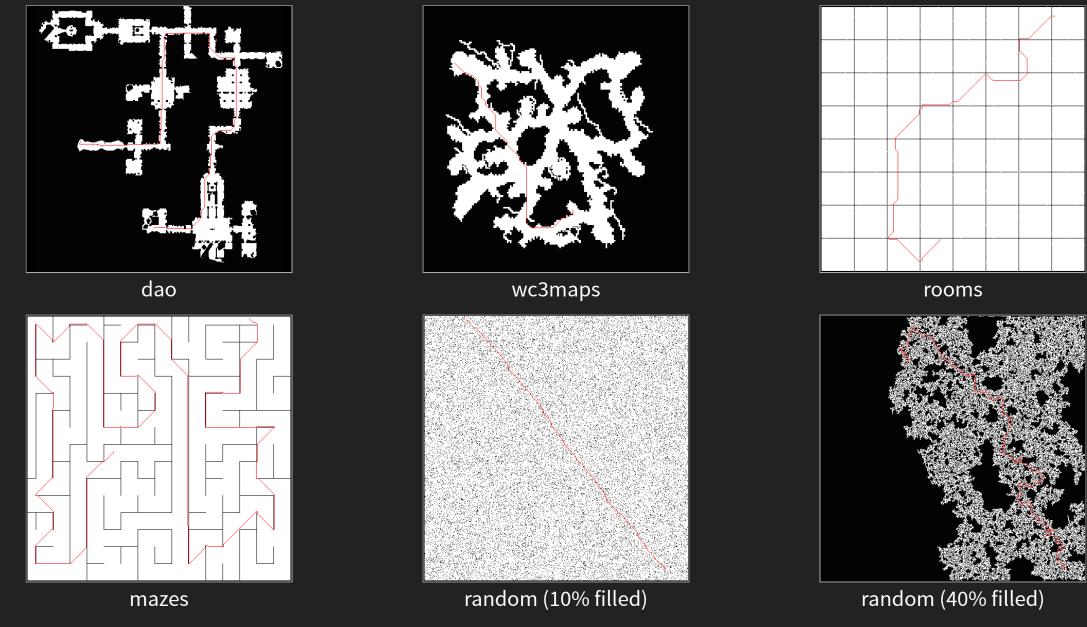


Tests – Autonomous Navigation in Dynamic Environments

Environments from grid-based path planning benchmarks¹

1. N. Sturtevant, "Benchmarks for Grid-Based Pathfinding," Transactions on Computational Intelligence and AI in Games, 2012.

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Actions

8 "normal" actions 1 "default" action



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2 Planners A^{*1} D* Lite²

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Dynamic obstacles

Invalidating the followed path with probability $P_{obstacle} \in \{0.2, 0.5, 0.8\}$

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Invalidating the followed path with probability $P_{obstacle} \in \{0.2, 0.5, 0.8\}$

Minimum duration of the "default" actions: 2 cases

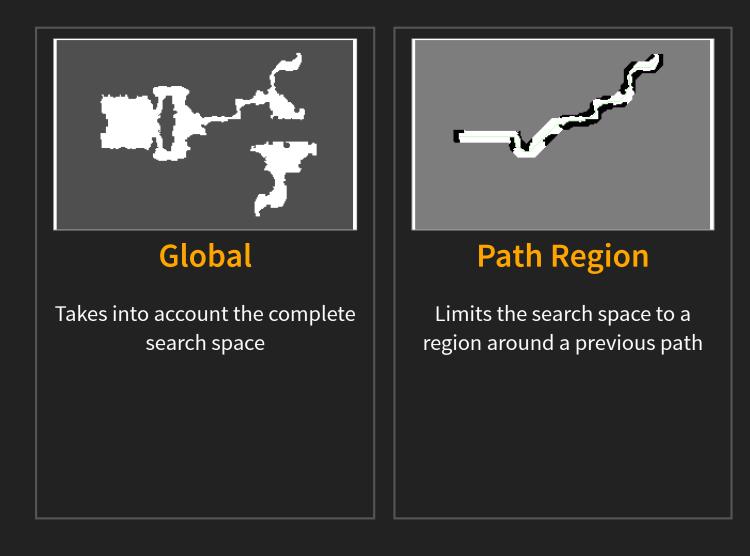
A: No minimum duration ⇒ The duration of a default action equals the (re)planning duration B: Minimum duration of 0.5s

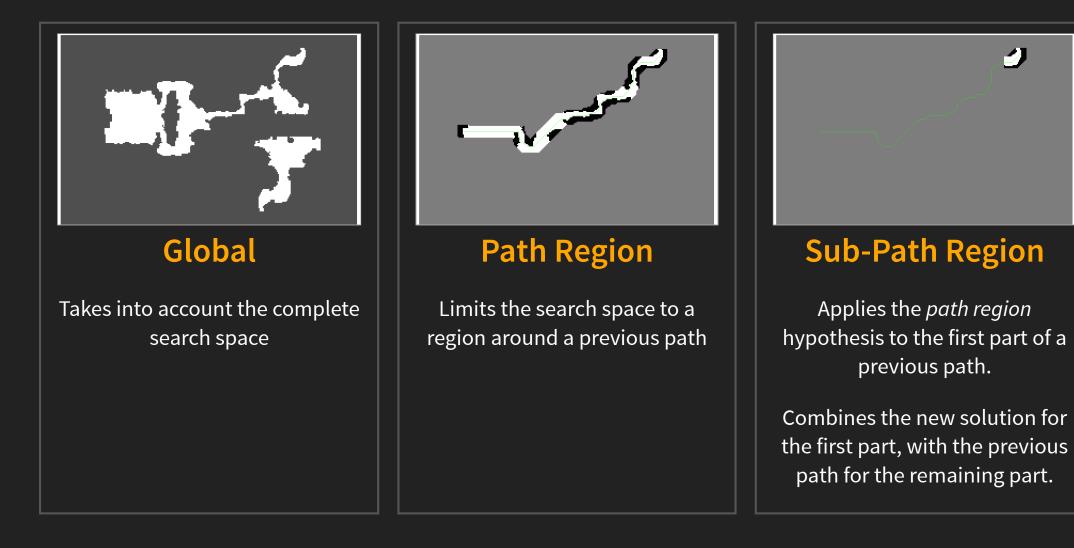


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Tested Instantiations



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Plan-Replan

PR-A

1 global hypothesis / A* planner

PR-D

1 global hypothesis / D* Lite planner

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Plan-Replan

PR-A

1 global hypothesis / A* planner

PR-D

1 global hypothesis / D* Lite planner

Continuous Planning

CP-D

1 global hypothesis / D* Lite planner

Tested Instantiations

Plan-Replan

PR-A

1 global hypothesis / A* planner

PR-D

1 global hypothesis / D* Lite planner

Continuous Planning

CP-D

1 global hypothesis / D* Lite planner

Continuous Proactive Planning with Multiple (10) Hypotheses CPP-1

1 global hypothesis / D* Lite planner

9 sub-path region hypotheses with different sub-goals / A* planner

CPP-2

1 global hypothesis / D* Lite planner

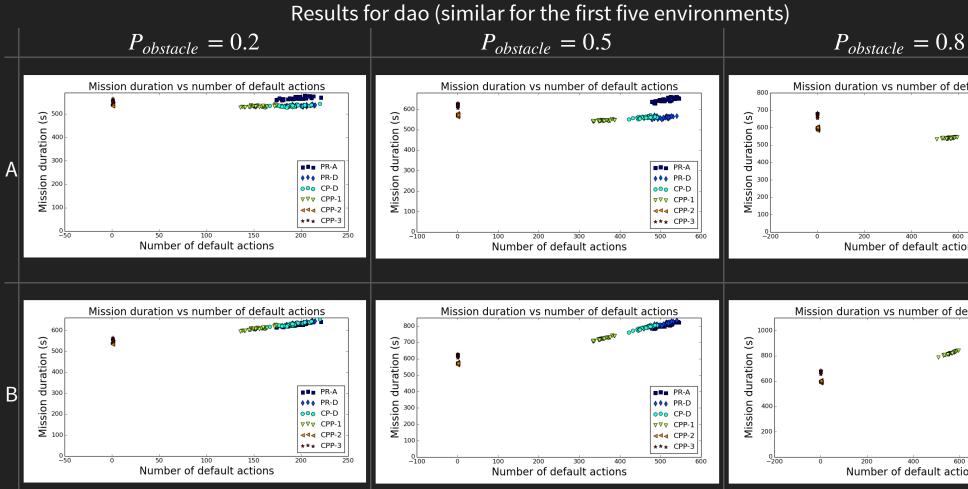
9 sub-path region hypotheses with different sub-goals + obstacle prediction / A* planner

CPP-3

1 global hypothesis / D* Lite planner

9 global hypotheses with obstacle prediction / D* Lite planner





Dynamic obstacles

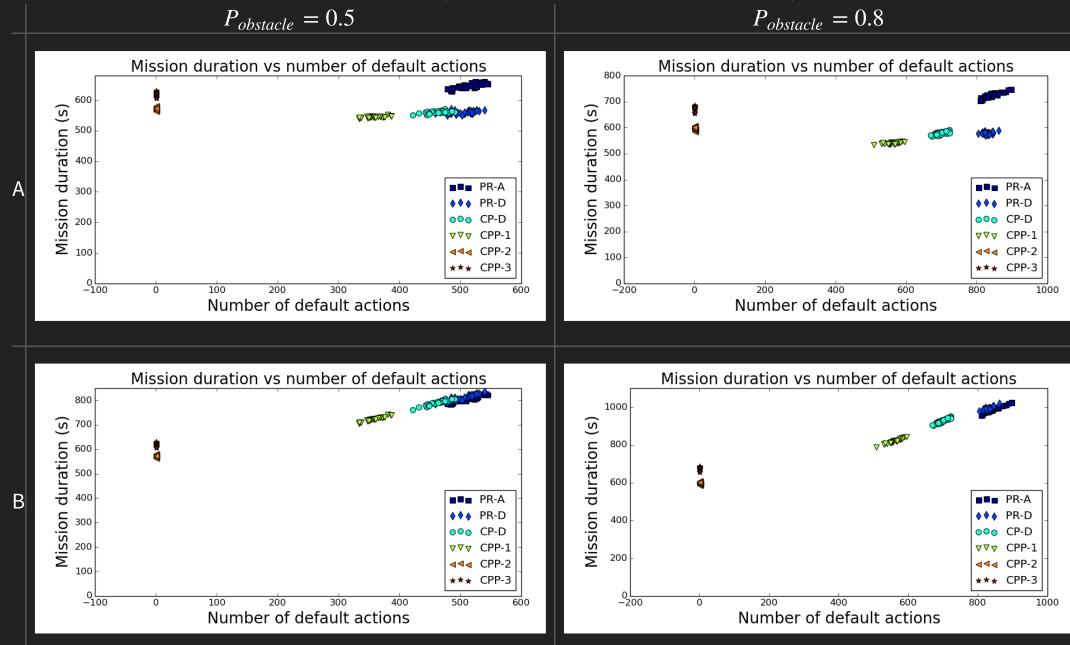
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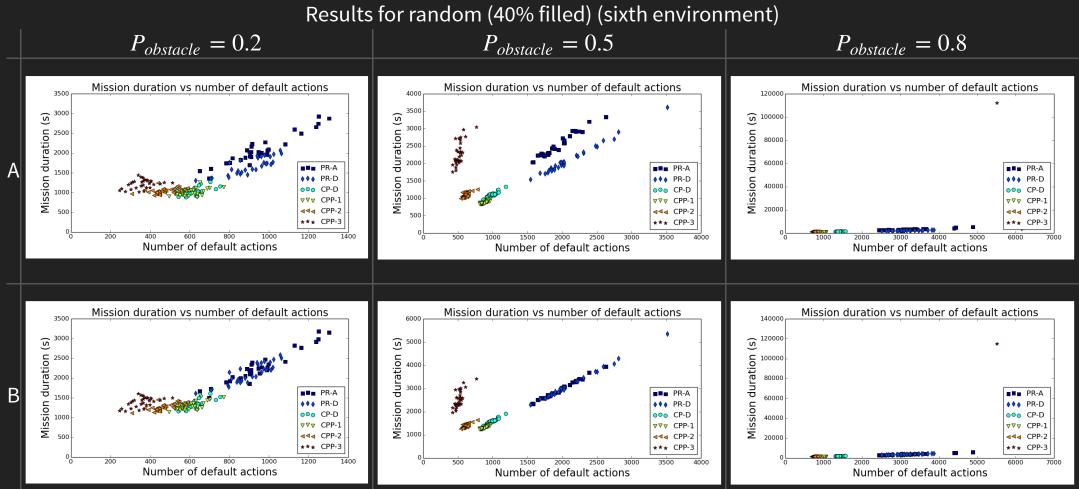
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	PR-D CP-D CPP-1	-
	PR-D CP-D CPP-1 CPP-2 CPP-3	



Results for dao (similar for the first five environments)



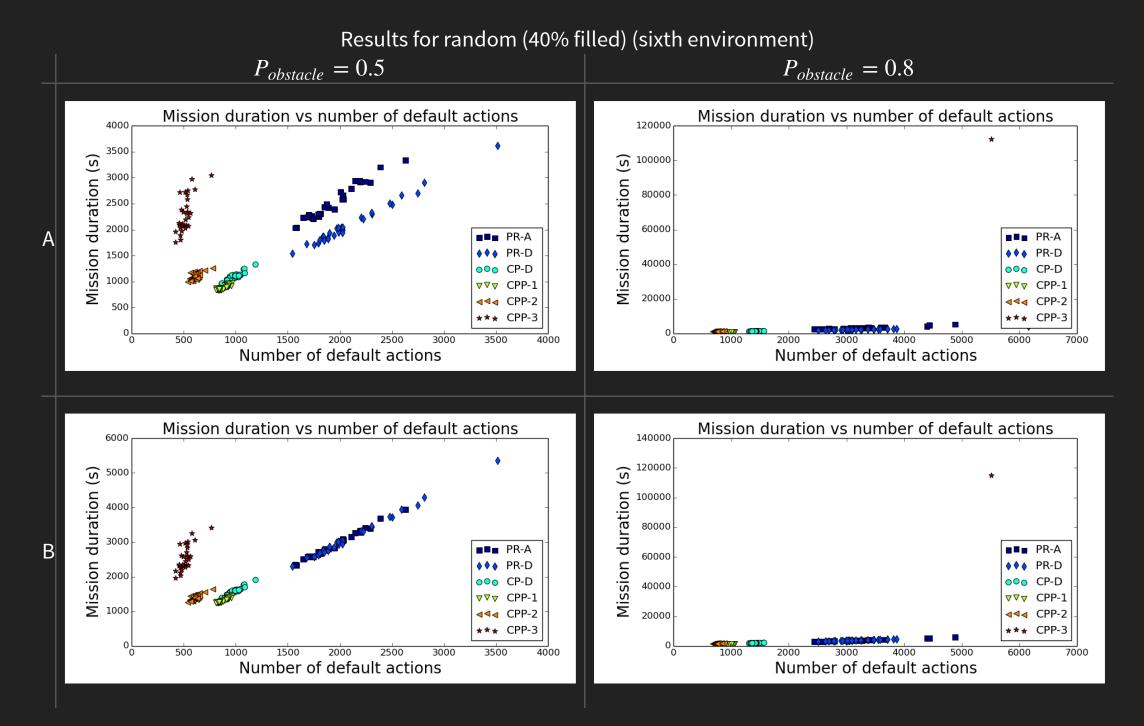




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9 additional hypotheses for generating multiple solution-plans

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The most appropriate:

- D* Lite for adapting the previous plan (the goal remains the same)
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Tackling uncertainties with multiple hypotheses

Planning for some possible futures separately



Conclusion from the Tests

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Proactive planning with multiple hypotheses may be able to improve the performances compared to commonly used strategies.

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But the hypotheses to plan for and the actions to execute must be selected carefully, otherwise unexpected behavior may appear.

(CPP-3 for the tests)

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► The multiple hypotheses paradigm needs enough semantic information to be efficient.





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Therefore, we are investigating tools for acquiring, storing and managing semantic information, such as RoboSherlock¹, KnowRob² and CRAM³.

^{1.} Michael Beetz et al. "RoboSherlock : Unstructured Information Processing for Robot Perception", in ICRA 2015

^{2.} Moritz Tenorth et Michael Beetz. "Representations for robot knowledge in the KnowRob framework", in Artificial Intelligence 2015

^{3.} Michael Beetz, Lorenz Mösenlechner et Moritz Tenorth. "CRAM—A Cognitive Robot Abstract Machine for everyday manipulation in human environments", in IROS 2010