# **Search-based Motion Planning with Topology-based Heuristic Functions**

Maxim Likhachev Robotics Institute & NREC Search-based Planning Lab (SBPL) Carnegie Mellon University

Joint work with Sandip Aine, Victor Hwang, Venkatraman Narayanan, Siddharth Swaminathan



- Topology-based Heuristics
- Multi-Heuristic A\* to support the use of Topology-based Heuristics



• 3D  $(x, y, \Theta)$  path planning with full body collision checking







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• 4D  $(x, y, \Theta, v)$  path planning for a ground vehicle







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is there enough space for a turn within UGV's min. turning radius?









• 7D  $(q_1, q_2, ..., q_7)$  planning for a robotic arm







• 7D  $(q_1, q_2, ..., q_7)$  planning for a robotic arm



is there enough reach in the arm to go from this side?



Multiple Hypotheses = Multiple Low-D solutions THE ROBOTICS INSTITUTE

### • 3D $(x, y, \Theta)$ path planning with full body collision checking

each hypothesis is a solution to a low-dimensional projection of the problem: a shortest path within its own topological class









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More generally: we can often easily generate N arbitrary heuristic functions that estimate costs-to-goal

### Can we utilize a bunch of inadmissible heuristics simultaneously,

*leveraging their individual strengths while preserving guarantees on completeness and bounded sub-optimality?* 



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### **Can we utilize a bunch of inadmissible heuristics simultaneously**, leveraging their individual strengths while preserving guarantees on completeness and bounded sub-optimality?

## Combining multiple heuristics into one (e.g., taking max) is often inadequate

2D distance accountin



## - information is lost

- creates local minima
- requires all heuristics to be admissible



### Multi-Heuristic A\* (MHA\*) [Aine et al., IJRR'15]:

Heuristic search that does support multiple arbitrary heuristics with guarantees on completeness and bounded sub-optimality



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- We run N independent searches
- Hope one of them reaches goal





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Problems:

- Each search has its own local minima
- We do N times more work
- No completeness guarantees or bounds on solution quality







- We have N inadmissible heuristics
- We run N independent searches
- Hope one of them reaches goal
- Key Idea #1: Share information (g-values) between searches! Benefits:
- Searches help each other to circumvent local minima
- States are expanded at most once across ALL searches Remaining Problem:
- No completeness guarantees or bounds on solution quality





- We have N inadmissible heuristics
- We run N independent searches
- Hope one of them reaches goal
- Key Idea #1: Share information (g-values) between searches!
- Key Idea #2: Search with admissible heuristics controls expansions **Benefits**:
- Algorithm is complete and provides bounds on solution quality

![](_page_23_Figure_8.jpeg)

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![](_page_24_Figure_0.jpeg)

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![](_page_24_Picture_8.jpeg)

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![](_page_25_Figure_0.jpeg)

We have N inadmir Theorem 1: min. key of  $OPEN_0 \le w_1$ \*optimal solution cost We run N independent Hope one of them Theorem 2: min. key of  $OPEN_i \le w_2 * w_1 * optimal solution cost$ Key Idea #1: Share Key Idea #2: Search ansions Theorem 3: *The algorithm is complete* and the cost of the found solution is no more than **Benefits**:  $w_2 * w_1 * optimal solution cost$ Algorithm is complete and prove soution guality Theorem 4: *Each state is expanded at most twice*: at most once by one of the inadmissible searches

![](_page_25_Picture_4.jpeg)

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![](_page_26_Figure_0.jpeg)

- We have N inadmissible heuristics
- We run N independent searches
- Hope one of them reaches goal
- Key Idea #1: Share information (g-values) between searches!
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![](_page_26_Picture_7.jpeg)

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![](_page_27_Picture_0.jpeg)

![](_page_27_Picture_1.jpeg)

• Many planning problems in robotics have low-dimensional projects that can provide excellent estimates on cost-to-goal distances/heuristics

• Multiple topology-based heuristics correspond to different hypotheses on feasible solutions

• Multi-Heuristic A\* (MHA\*) can utilize multiple arbitrary heuristics with rigorous guarantees

![](_page_28_Picture_0.jpeg)

![](_page_28_Picture_1.jpeg)

• Applying to different planning domains including humanoid planning, mission planning, etc.

• Figuring out what topology classes to consider

• Dynamically instantiating new topology-based heuristics (e.g., Dynamic MHA\* [Islam et al., ICRA'15]

![](_page_29_Picture_0.jpeg)

- Students/postdocs who contributed:
  - Sandip Aine
  - Victor Hwang
  - Venkatraman Narayanan
  - Siddharth Swaminathan

- Funding:
  - ONR
  - ARL
  - NSF

Thanks