



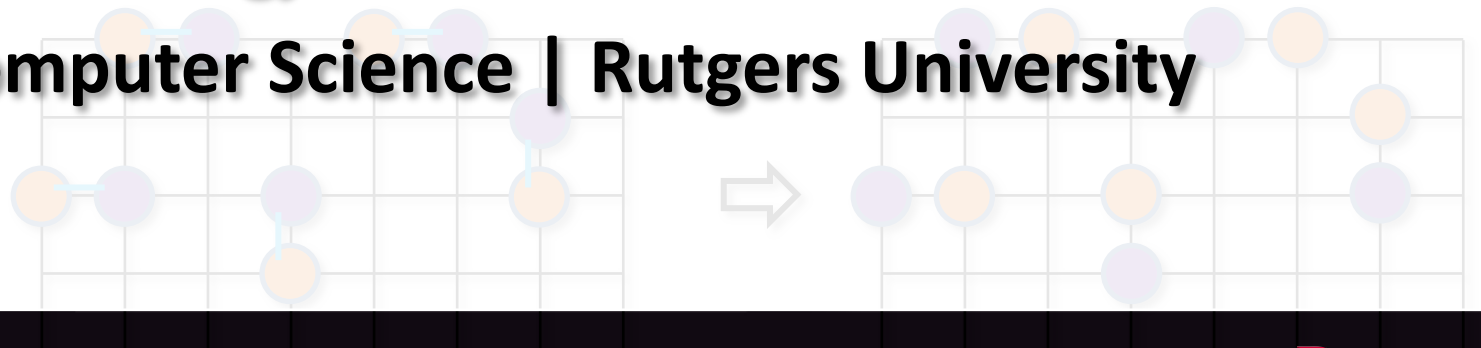
X_I

X_G

Optimal Multi-Robot Motion Planning: Theoretical Limits and Fast Algorithms

Jingjin Yu

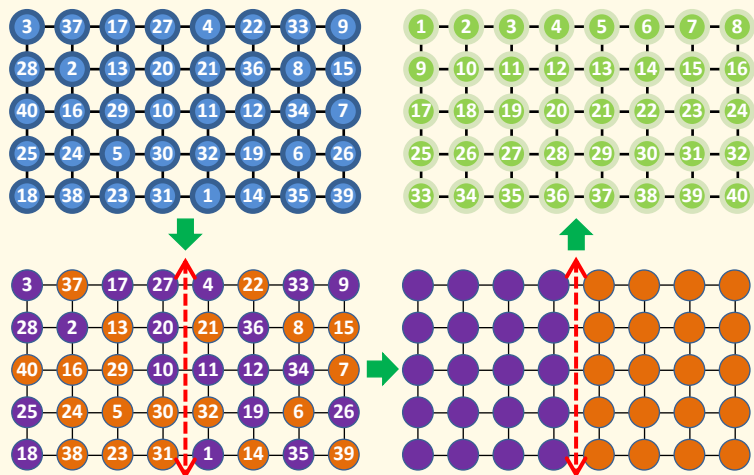
Department of Computer Science | Rutgers University



Highlights of Contributions

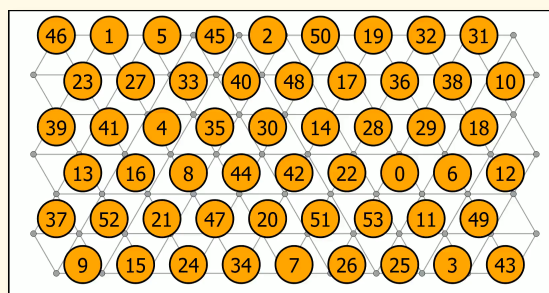


Theoretical Breakthroughs on Optimal Multi-Robot Motion Planning

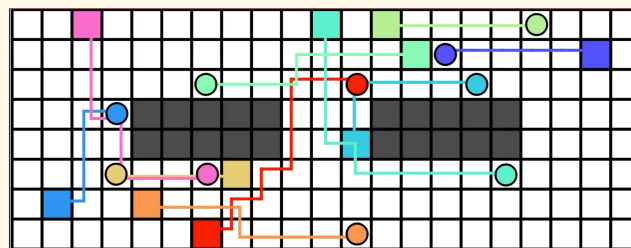


Polynomial time algorithm for constant factor multi-robot motion planning on grids under maximum density [RSS'18]

Effective and Principled Algorithms

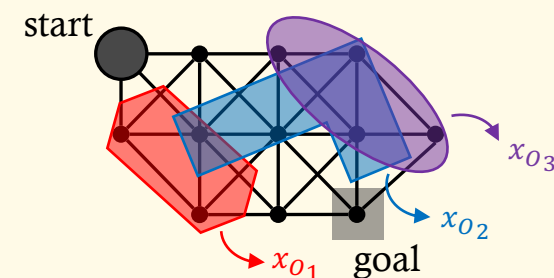


Fast algorithms for continuous, high density settings [WAFR'18]



Fast algorithms for dynamic settings [RA-L/ICRA'20]

General Methodology for Path-Based (Multi-Robot) Optimization



$$\sum_{v \in N(v^l)} x_{v^l, v} = \sum_{v \in N(v^g)} x_{v, v^g} = 1, \quad \sum_{v \in N(v^l)} x_{v, v^l} = \sum_{v \in N(v^g)} x_{v^g, v} = 0$$

$$\forall v_i \in V \setminus \{v^l, v^g\}, \quad \sum_{v_j \in N(v_i)} x_{v_i, v_j} = \sum_{v_j \in N(v_i)} x_{v_j, v_i} \leq 1$$

$$\forall O_k \in \mathcal{O}, Lx_{O_k} \geq \sum_{v_i \in O_k} \sum_{v_j \in N(v_i)} x_{v_i, v_j} + x_{v_j, v_i}$$

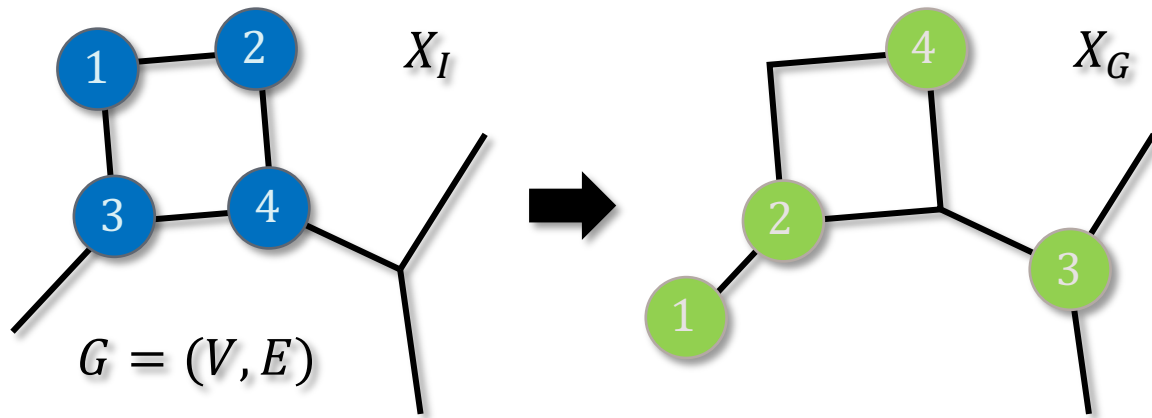
$$\text{Minimize } \sum_{O_k \in \mathcal{O}} x_{O_k}$$

[IROS'19, Best Student Paper Finalist, Best Application Paper Finalist]

Optimal Multi-Robot Motion Planning on Graphs



Optimal Multi-Robot Path and Motion Planning



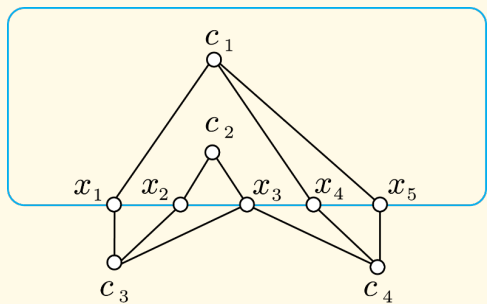
MPP: (G, X_I, X_G) , seek collision free $P = \{p_1, \dots, p_n\}$

- ⇒ Min max time (makespan): $\min_{P \in \mathcal{P}} \max_{p_i \in P} \text{time}(p_i)$
- ⇒ Min total time: $\min_{P \in \mathcal{P}} \sum_{p_i \in P} \text{time}(p_i)$
- ⇒
- ⇒ We seek (near-) optimal solutions (ideally, 1.x in practice)

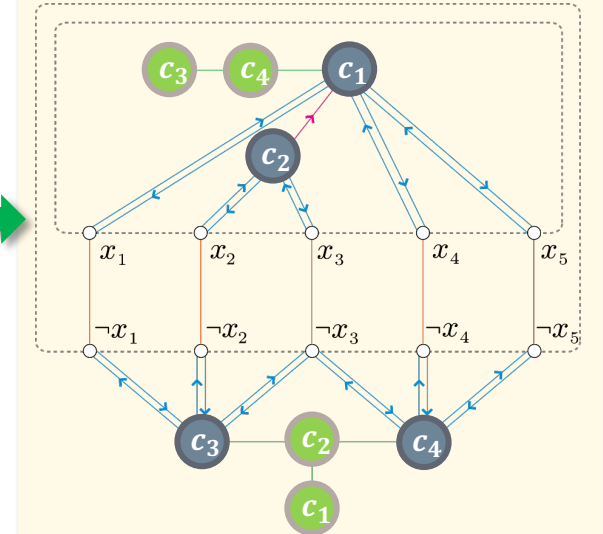
Computational Intractability

Planar Monotone 3-SAT

- $(x_1 \vee x_4 \vee x_5)$ c_1
- $\wedge (x_2 \vee x_3)$ c_2
- $\wedge (\neg x_1 \vee \neg x_2 \vee \neg x_3)$ c_3
- $\wedge (\neg x_3 \vee \neg x_4 \vee \neg x_5)$ c_4



Planar MPP

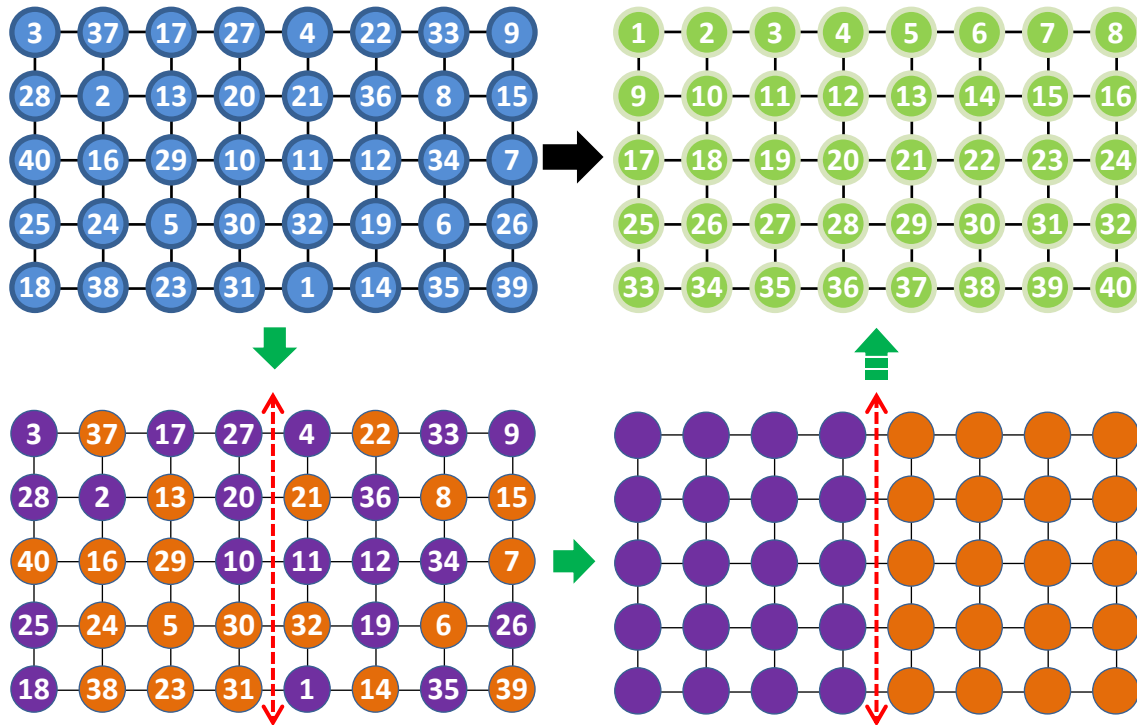


Theorem. Optimal Planar MPP is NP-hard for min makespan, min total time, min max distance, and min total distance objectives [RA-L' 16].

Polynomial Time $O(1)$ -Optimal Algorithm (1)

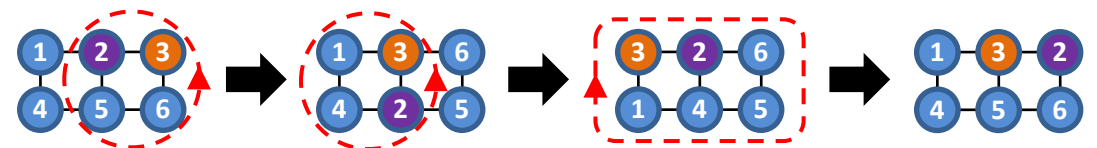


Divide-n-Conquer Approach for Exp. $O(1)$ -Optimal Solution

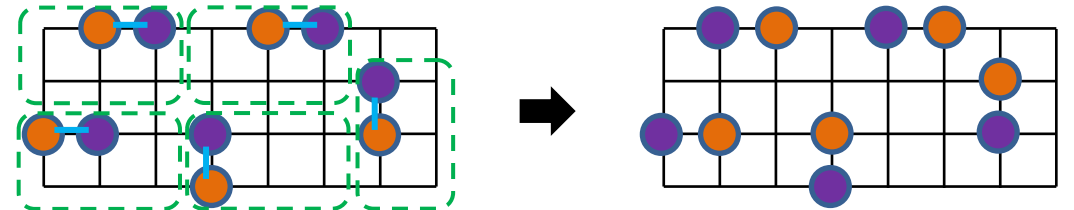


Treating a labeled problem as an unlabeled problem helps!

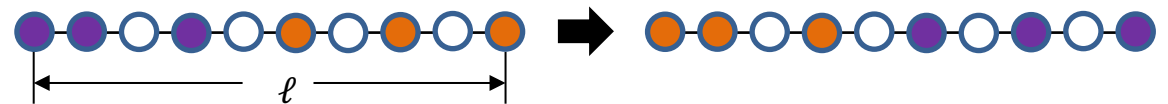
Motion Primitives



$O(1)$ -step "edge flip" within a 2×3 grid



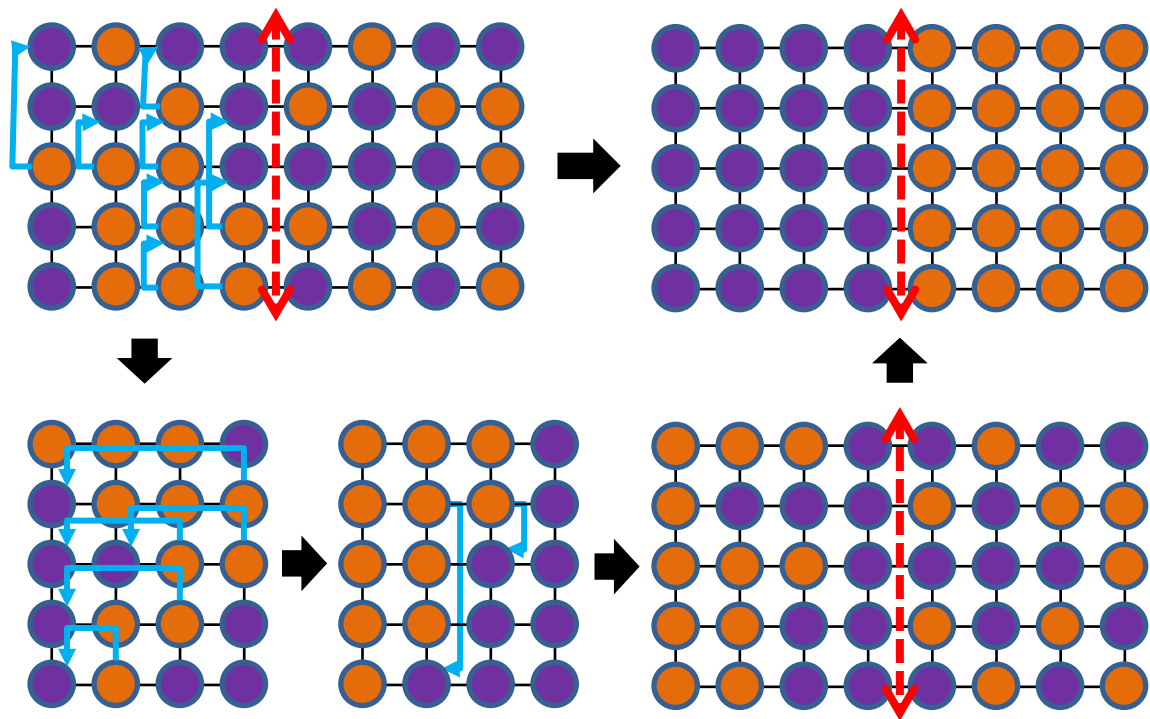
Multiple concurrent edge flips in **parallel** in $O(1)$ steps



Exchange two groups on an **embedded line** in $O(\ell)$ steps

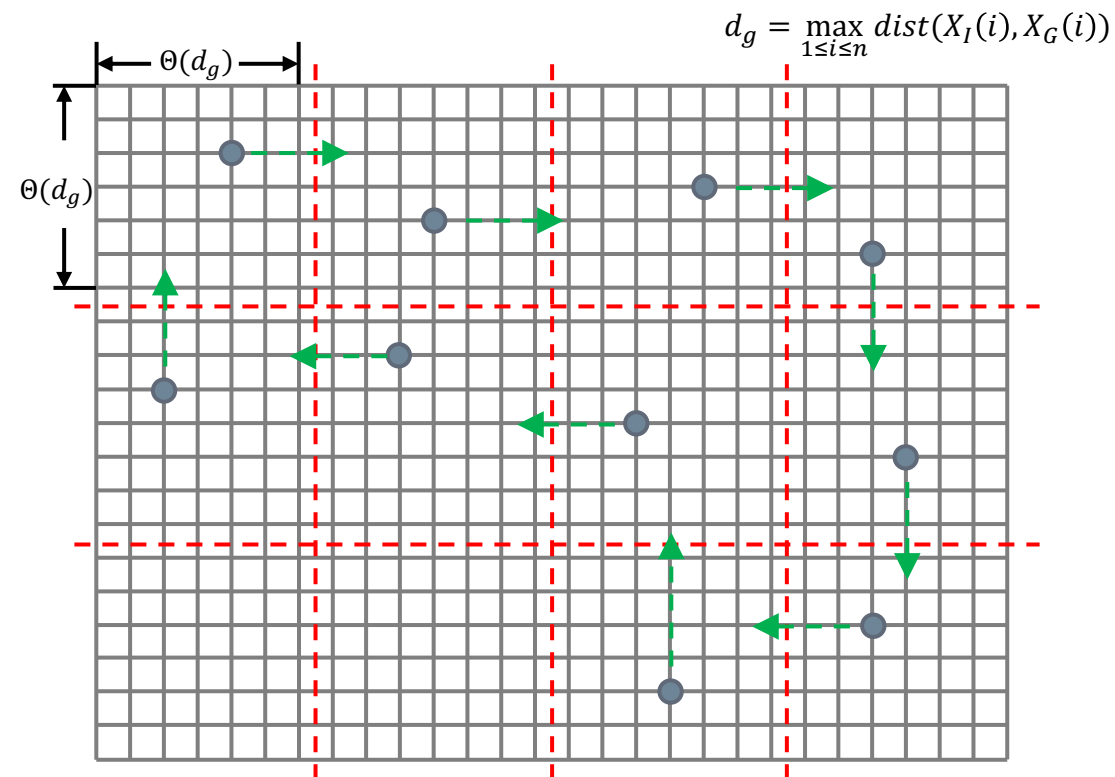
Polynomial Time $O(1)$ -Optimal Algorithm (2)

Split & Group via Multiple "Shuffles"



Split & Group (SaG) computes **expected** $O(1)$ -optimal sol.

Global Partition & Flow

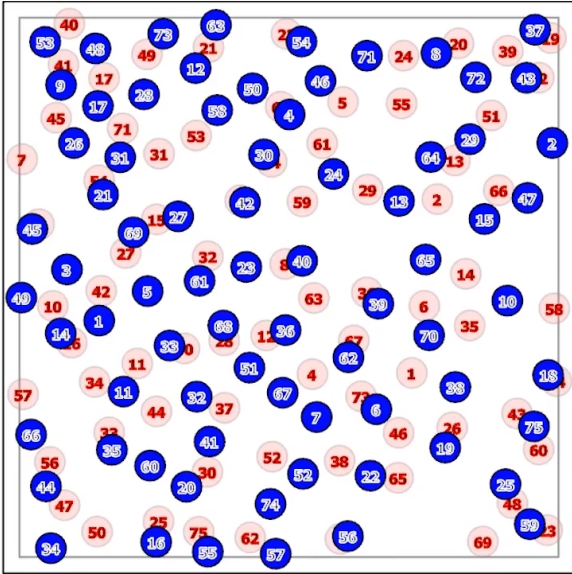


Applying global partition & flow yields $O(1)$ -optimal solution

Fast Algorithms for Dense Continuous Problems

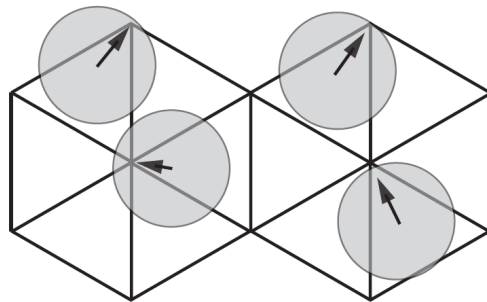


Prior Work on Continuous Multi-Robot Motion Planning

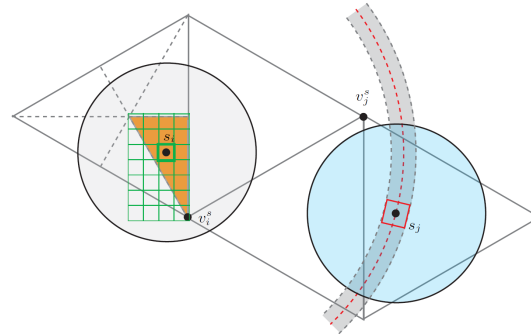


23% maximum density with provable optimality guarantee [ISRR'15]

New WAFR Work: Maximum Density of 51% with Completeness Guarantee

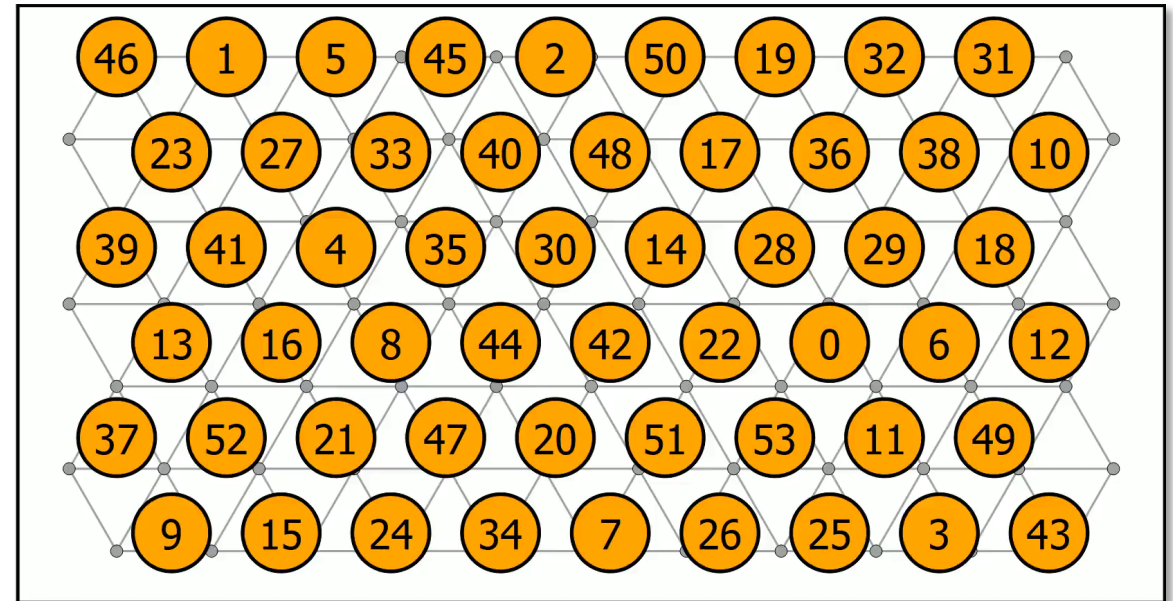


Novel discretization method



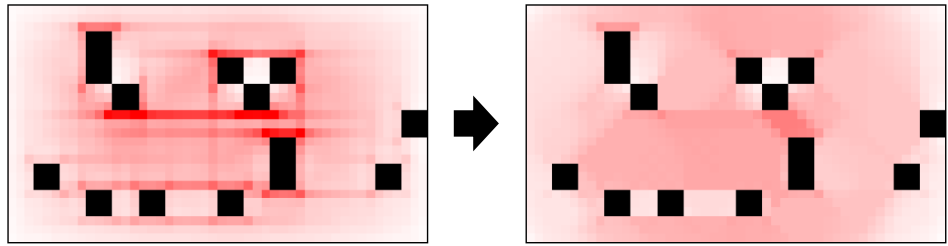
Computer assisted proof

- ▶ Opt. guarantee on discrete problem on triangular grid
- ▶ Completeness guarantee on continuous problem
- ▶ Fast computation for continuous problem
- ▶ All with highest supported density in the literature

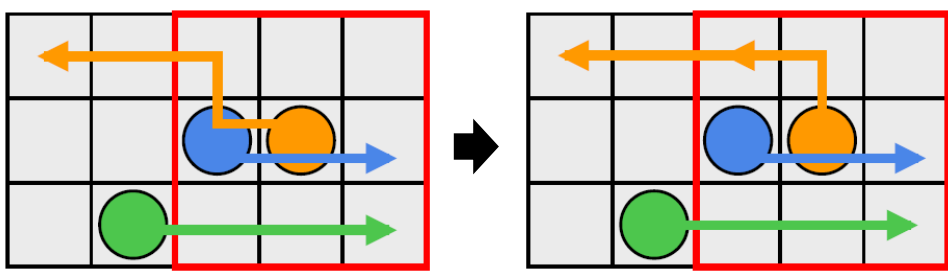


Fast Algorithms for Dynamic Re-Planning

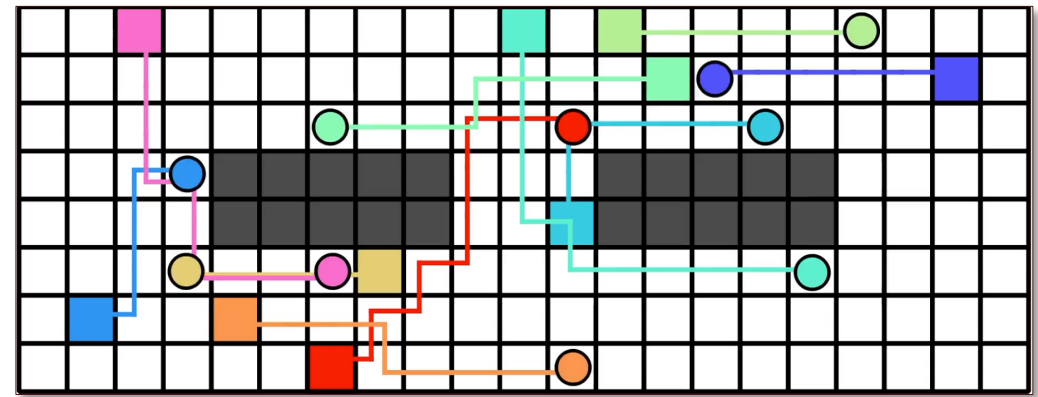
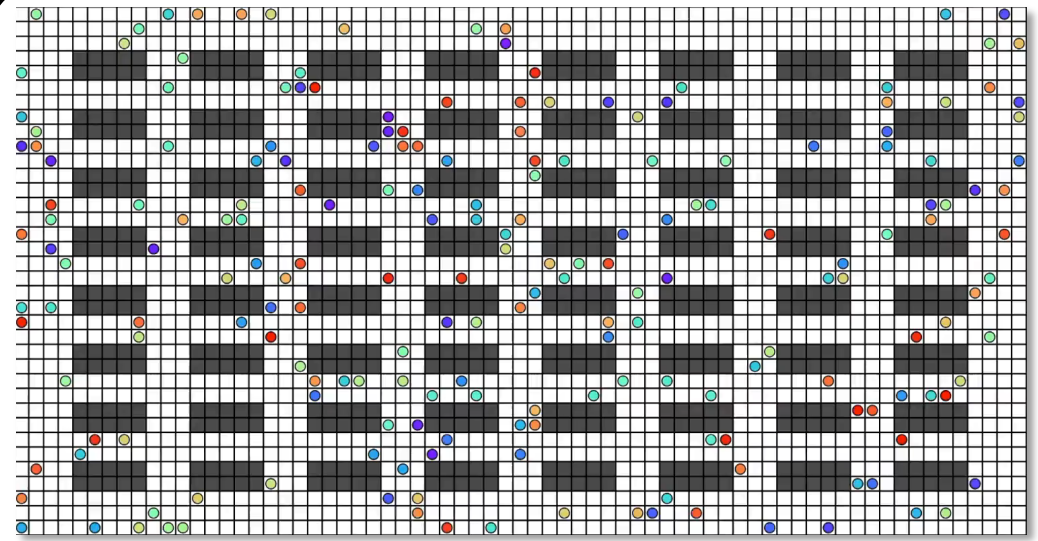
DDM: Multi-Robot Motion Planning w/ Path Diversification and Solution Database Lookup



Apply path diversification to reduce congestion



Using solution database to speed up local planning



Static settings:

- ▶ Fast
- Ex: 69 x 36 grid
- 200 robots
- Time: 0.1 s
- ▶ High quality
- 1.x optimal

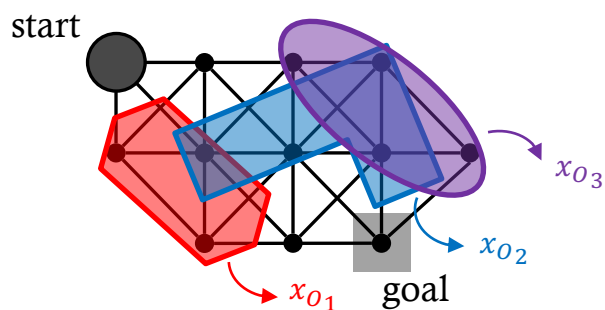
Dynamic settings:

- ▶ Fast replanning
- ▶ High throughput
- ▶ High quality

Methodology for Path-Based Multi-Robot Optimization

IROS'19, Best Application Paper Finalist, Best Student Paper Finalist

General IP Optimization Framework



$$\sum_{v \in N(v^I)} x_{v^I, v} = \sum_{v \in N(v^G)} x_{v, v^G} = 1$$

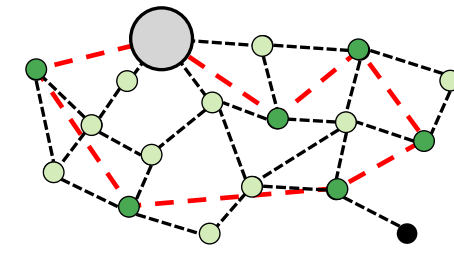
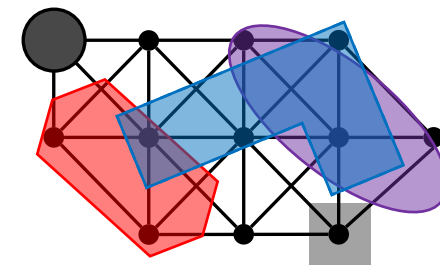
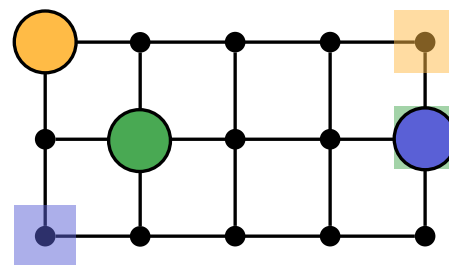
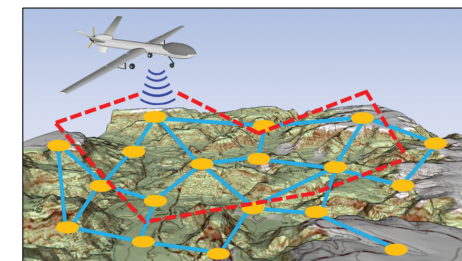
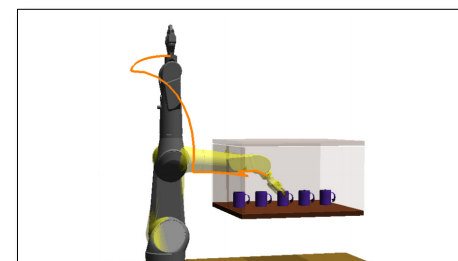
$$\sum_{v \in N(v^I)} x_{v, v^I} = \sum_{v \in N(v^G)} x_{v^G, v} = 0$$

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$$\text{Minimize } \sum_{O_k \in \mathcal{O}} x_{O_k}$$

Applications to Many Path-Based Optimization Problems in Robotics



Multi-robot motion planning

Minimum constraint removal

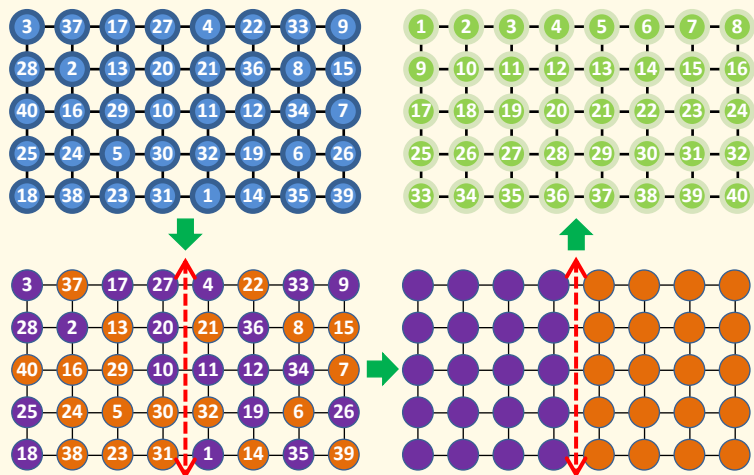
Reward collection problems

► A good first option for your path-based optimization problems – give it a try!

Highlights of Contributions

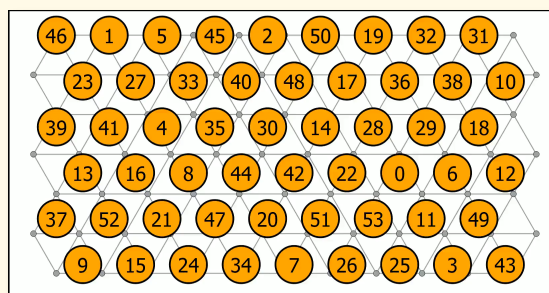


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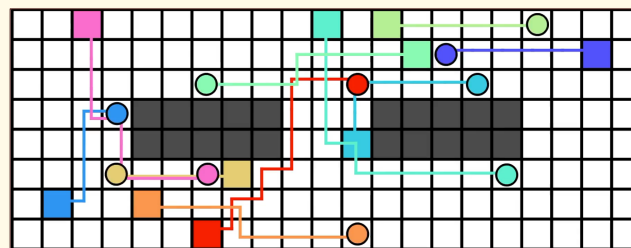


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Effective Algorithmic Solutions

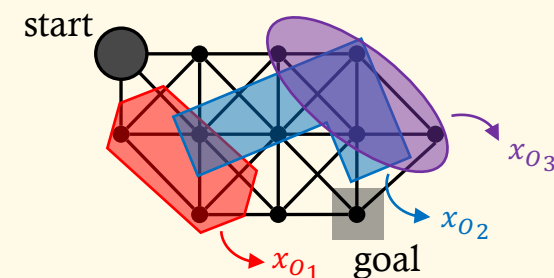


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