Using Classical Planners for Tasks with Continuous Actions in Robotics

Stuart Russell

Joint work with Siddharth Srivastava, Lorenzo Riano, Pieter Abbeel
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Real work done by
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Outline

• Can we apply classical planners to robotics problems?
  ▪ Challenges: continuous action arguments, geometric reasoning

• Main ideas:
  ▪ Symbolic references to continuous values
  ▪ Optimistic model with symbolic corrections from low-level geometric motion planner, followed by replanning

• Why does this idea work? Can it be generalized?
  ▪ Roughly analogous to theorem-proving with quantifier elimination
  ▪ Current algorithm complete under strong assumptions

• Will it work for real-world problems?
  ▪ Results on PR2 simulator, PR2
Combining Task and Motion Planners

• Discrete/classical planners:
  + Effective algorithms for combinatorial discrete spaces (e.g., automated heuristic generation)
  – Not directly applicable to continuous spaces

• Continuous/motion planners:
  + Effective algorithms for high-dimensional continuous space (e.g., PRM, RRT)
  – Not directly applicable to discrete spaces induced by contact changes (e.g., pickup/putdown)
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• Obvious solution:
  - Use task planner for discrete actions
  - Implement those actions using continuous planner
Discrete blocks-world PickUp

PickUp(block1):
  precondition  OnTable(block1) ∧ Empty(gripper)
  effect       Holding(block1) ∧
               ¬ OnTable(block1) ∧
               ¬ Empty(gripper)

Geometric locations of robot, hand, or object not considered
A Continuous Version of Blocks World

PickUp(b1, l1, l2, l3, p):

precondition
  - GripperAt(l1) ∧
  - Empty(gripper) ∧
  - IsGraspingPose(l2, b1) ∧
  - At(b1, l3) ∧
  - ∀b2 ¬ Obstructs(b2, p, l1, l2)

effect
  - Holding(b1) ∧
  - ¬ At(b1, l3) ∧
  - ¬ Empty(gripper) ∧
  - GripperAt(l2)
A Continuous Version of Blocks World

PickUp(b1, l1, l2, l3, p):

precondition
GripperAt(l1) \land
Empty(gripper) \land
IsGraspingPose(l2, b1) \land
At(b1, l3) \land
\forall b2 \neg \text{Obstructs(b2, p, l1, l2)}

effect
Holding(b1) \land
\neg \At(b1, l3) \land
\neg \Empty(gripper) \land
GripperAt(l2)

Oops: infinitely many facts, infinite branching factor
A Continuous Version of Blocks World

PickUp(b1, l1, l2, l3, p):

precondition
GripperAt(l1) ∧
Empty(gripper) ∧
IsGraspingPose(l2, b1) ∧
At(b1, l3) ∧
∀b2 ¬ Obstructs(b2, p, l1, l2)

effect
Holding(b1) ∧
¬ At(b1, l3) ∧
¬ Empty(gripper) ∧
GripperAt(l2)

Oops: infinitely many facts, infinite branching factor

Solution: discretization
Discretization

- 10 points each in x, y
- Precompute
  - IsGraspingPose(l, b)
  - Obstructs(b, p, l1, l2)
- 5 objects = 50,000 facts
Discretization

- 10 points each in x, y
- Precompute
  - $\text{IsGraspingPose}(l, b)$
  - $\text{Obstructs}(b, p, l_1, l_2)$
- 5 objects = 50,000 facts

7DOF arm + 4DOF base/torso + 80 objects $\approx 10^{14}$ facts
Creating input...
Our approach

• PDDL planner uses “location references”
  ▪ Number of references depends on number of objects and on discrete plan size – no discretization
  ▪ Low-level motion planner interprets these references

• Low-level infeasibility is re-expressed as new PDDL facts about obstructions
  ▪ Expressed using location references

• PDDL planner replans with new information
A SIMPLE EXAMPLE
Discrete state: GripperAt(initLoc), At(block1, block1_loc), At(block2, block2_loc)

• High level intuitive plan:
  ▪ pick block1 after going to its grasping pose
Discrete state: GripperAt(initLoc), At(block1, block1_loc), At(block2, block2_loc)

• High level intuitive plan:
  - pick block1 after going to its grasping pose

1. Low level instantiates a grasping pose for block 1 independent of other block
2. Low level searches for a motion plan to reach grasping pose; finds no collision-free solution
Discrete state += “block2 obstructs grasping pose for block1 in path from initial location”

- High level intuitive plan:
  - pick block1 after going to its grasping pose

“block2 obstructs grasping pose for block1 from initial location”

1. Low level instantiates a grasping pose for block 1 independent of other block
2. Low level searchers for a motion plan to reach grasping pose; finds no collision-free solution
3. Reports obstruction to high level
Discrete state += “block2 obstructs grasping pose for block1 in path from initial location”

- **High level intuitive plan:**
  - pick block1 after going to its grasping pose
  - pick block2 after going to its grasping pose
  - release block2 in after going to release pose for free area
  - pick block1 after going to its grasping pose

1. Low level instantiates a grasping pose for block 1 independent of other block
2. Low level searchers for a motion plan to reach grasping pose; finds no collision-free solution
3. Reports obstruction to high level
4. **High level updates state, replans**
Discrete state diff: GripperAt “grasping pose for block2”, Holding(block2)

- High level intuitive plan:
  - pick block1 after going to its grasping pose
  - pick block2 after going to its grasping pose
  - release block2 in after going to release pose for free area
  - pick block1 after going to its grasping pose
Discrete state diff: At(block2, FreeArea), Empty(gripper)

• High level intuitive plan:
  ▪ pick block1 after going to its grasping pose
  ▪ pick block2 after going to its grasping pose
  ▪ release block2 in after going to release pose for free area
  ▪ pick block1 after going to its grasping pose
Discrete state diff: GripperAt “grasping pose for 1”, Holding(block1)

- High level intuitive plan:
  - pick block1 after going to its grasping pose
  - pick block2 after going to its grasping pose
  - release block2 in after going to release pose for free area
  - pick block1 after going to its grasping pose

Goal Reached!
SAME EXAMPLE IN FORMAL SYNTAX
Discrete state += Obstructs(block2, initLoc, gp(block1), path(initLoc, gp(block1)))

- High level intuitive plan:
  - PickUp(block1, initLoc, gp(block1), loc(block1), path(initLoc, gp(block1)))
  - REPLAN
    - PickUp(block2, initLoc, gp(block2), loc(block2), path(initLoc, gp(block2)))
    - PutDown(gp(block2), free_area, rp(free_area), path(gp(block2), rp(free_area)))
    - PickUp(block1, rp(free_area), gp(block1), loc(block1), path(rp(free_area), gp(block1)))
High level intuitive plan:

- `PickUp(block1, initLoc, gp(block1), loc(block1), path(initLoc, gp(block1)))`
- `PickUp(block2, initLoc, gp(block2), loc(block2), path(initLoc, gp(block2)))`
- `PutDown(gp(block2), free_area, rp(free_area), path(gp(block2), rp(free_area)))`
- `PickUp(block1, rp(free_area), gp(block1), loc(block1), path(rp(free_area), gp(block1)))`

Discrete state diffs: `GripperAt(gp(block1))`, `Empty(gripper)`, `Holding(block1)`

Goal Reached!
WHY DOES IT WORK??
Actions with Continuous Arguments

• Effect axioms for actions like “grasp” have the form
  \( \forall x \forall y (p(x,y) \Rightarrow q(x) \land r(x,g(y))) \)
  where \( p \) is the precondition, \( q \) is the post-condition
  \( x \): object, \( y \): continuous arguments

• In order to apply the action to achieve \( q(x) \), need to find some \( y \) (from infinitely many) satisfying \( p(x,y) \)

• Treat low-level motion planner as an unknown function \( f() \) s.t. \( p(x, f(x)) \) holds

• Planner can assume facts: \( p(x, f(x)) \) for each \( x \)
  • Treat “\( f(x) \)” like any other object in the world
Overall Approach

1. PDDL Problem Formulation
2. Classical Planner
   - Discrete Plan
     - Sampling based interpreter
6. Plan with reference terms
   - Low level executor
5. Success
4. Failed precons of unsuccessful action
3. Update State
Sufficient Conditions for Guaranteed Solutions

• Standard limitations of replanning:
  ▪ Initial PDDL model is incorrect, but algorithm may act anyway
  ▪ Can fail with dead ends and infinite loops
• BUT the model does improve with every non-executable action
• Theorem: Algorithm is sound and complete provided:
  ▪ Low level sampling terminates, succeeds when possible
  ▪ Problem has no dead ends
  ▪ Negative geometric preconditions can be deleted but not added
  ▪ Positive geometric preconditions can be added but not deleted
• For details, see paper or ask Siddharth
RESULTS ON A PR2 SIMULATOR
Experiments

• Used OpenRave for simulation, IK and grasp computation

• Scenario 1: pick and place with obstructions
  ▪ Many (50, 65, 80) randomly placed objects
  ▪ 3 tests (50, 65, 80 objects), 10 runs each
  ▪ Used FF planner (optimality not a concern)

• Scenario 2: setting a dinner table
  ▪ 2 cups, 2 mugs, 2 plates to be placed at predefined locations
  ▪ Tray available to carry multiple objects
  ▪ Stability constraints for item stacking not known a priori
  ▪ Used FD anytime planner with timeout
Cluttered Table, 50 Objects
Results

• Cluttered table, averages over 10 runs:

<table>
<thead>
<tr>
<th>#Objects</th>
<th>Time(s)</th>
<th>#Replan</th>
<th># Obstrns</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>139</td>
<td>2.1</td>
<td>1.8</td>
</tr>
<tr>
<td>65</td>
<td>228</td>
<td>2.6</td>
<td>2.0</td>
</tr>
<tr>
<td>80</td>
<td>602</td>
<td>2.3</td>
<td>2.6</td>
</tr>
</tbody>
</table>

- Most of the time spent in low level planning*

• Dinner table: planning + execution time ~230s
  - Most of the time was spent in high level planning
Simulations
Non-simulations
Conclusions

• A method for using classical planners with motion planners in a modular fashion
  ▪ Avoiding exponential discretization complexity
  ▪ Solution based on naming just the discrete-plan-relevant locations with uninterpreted functions
  ▪ Execution errors must be observable and expressible as new PDDL facts

• Still works with no internal low-level model
• Alternative algorithmic approaches could yield stronger guarantees given a low-level simulator