Learned Collision Avoidance Policy for Distributed Multi-Robot Navigation in Warehouses

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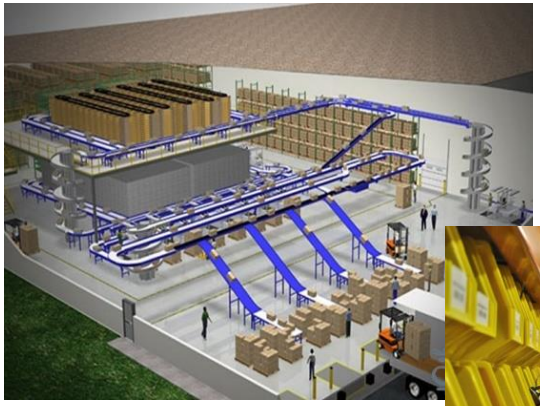
dorabot


Problems we try to solve

Different choices for warehouse automation

Number of Items Per Goods Type

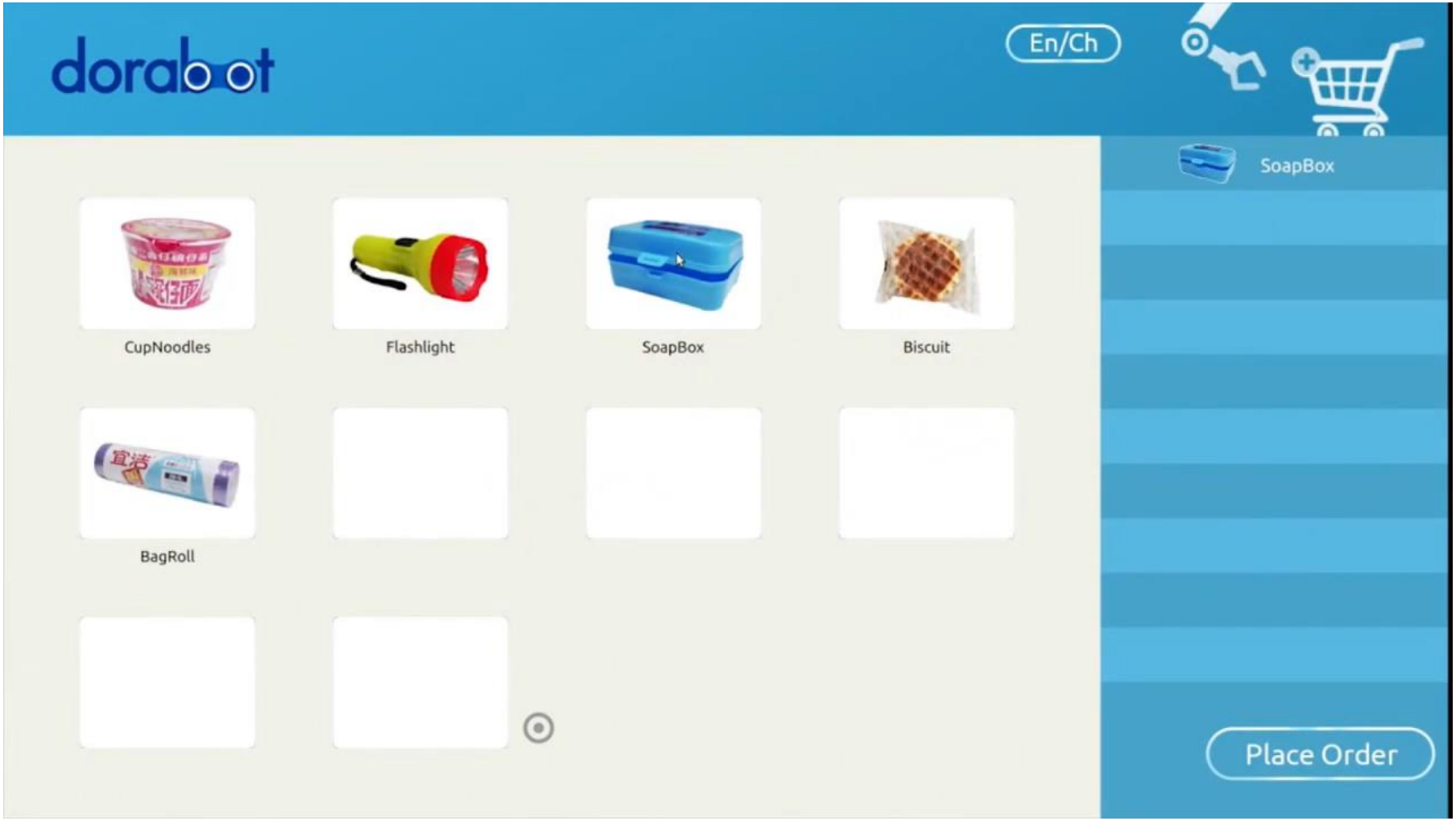


Number of Goods Types

Autonomous agents

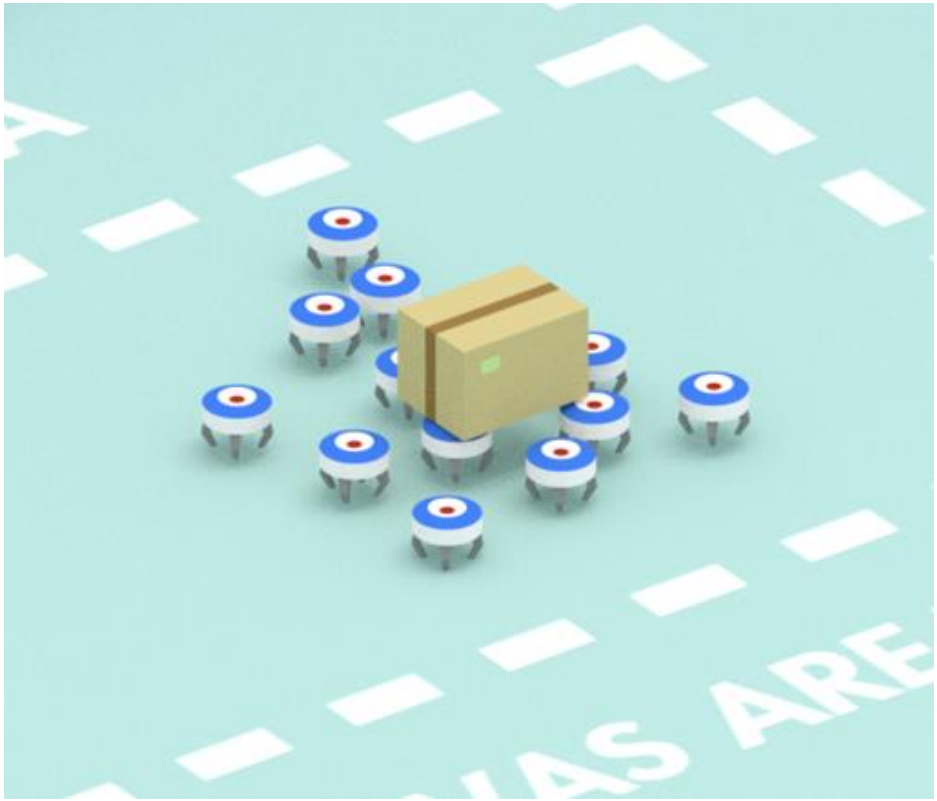
Autonomous agents

Overview


doraboot
En/Ch
SoapBox
CupNoodles
Flashlight
SoapBox
Biscuit
BagRoll
Place Order

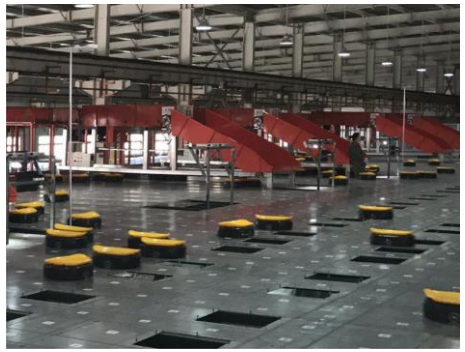
Multi-agent navigation challenge

- How to enable a **large number** agents **efficiently** work **together** in a warehouse?



Centralized solutions

- Using barcode tracks
- Centralized or distributed task / goal assignments
- Mostly centralized path planning for all agents



Kiva

Similar systems: Geek+, HKVISION, etc.

Significant changes to the scenario ☹

Not energy efficient ☹

A centralized scheduler ☹

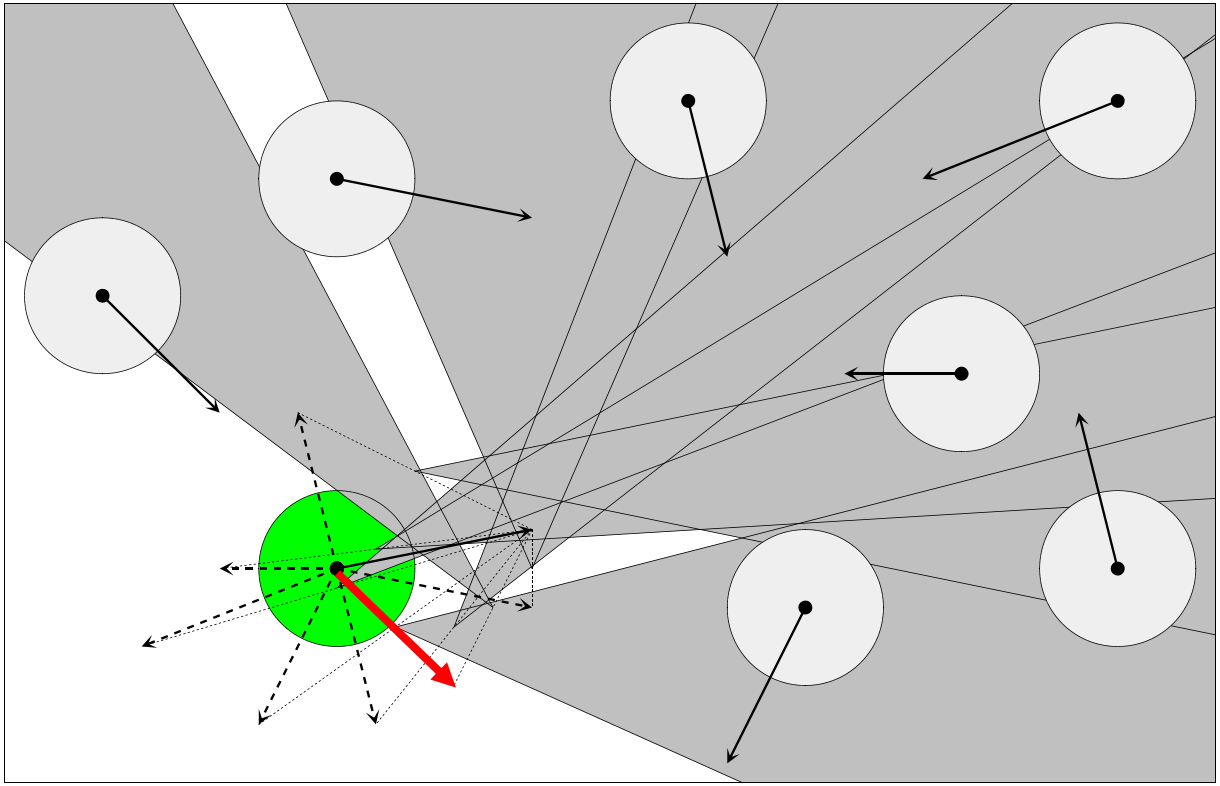
Not space efficient ☹

Robot alone; no human co-workers ☹

Optimal navigation plans ☺

Distributed solutions

- Many methods are based on reciprocal velocity obstacles (RVO) [Jur van den Berg, 2008]



Inputs:

1. An agent's velocity and preferred velocity (aiming at the goal)
2. All neighboring agents' velocities and positions

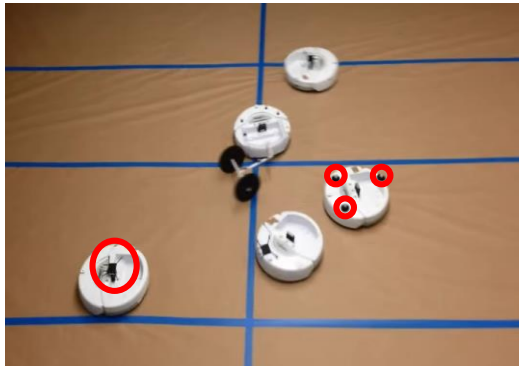
Output:

The agent's new velocity, outside the union of RVOs and closest to the preferred velocity

Distributed solutions X

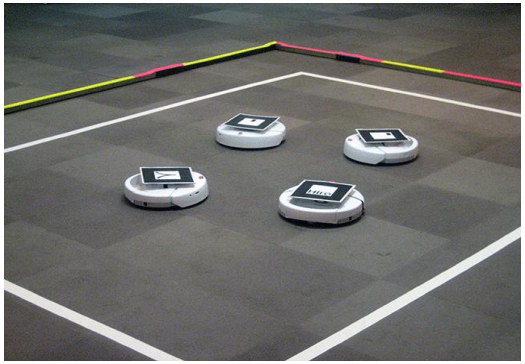
CALU: Collision Avoidance with Localization Uncertainty
Claes et al. 2012

Need inter-robot communication ☹



Generalized Reciprocal Collision Avoidance
Daman Bareiss and Jur van den Berg, 2015

Need overhead motion capture system ☹



The Hybrid Reciprocal Velocity Obstacle
Jamie Snape et al. 2011

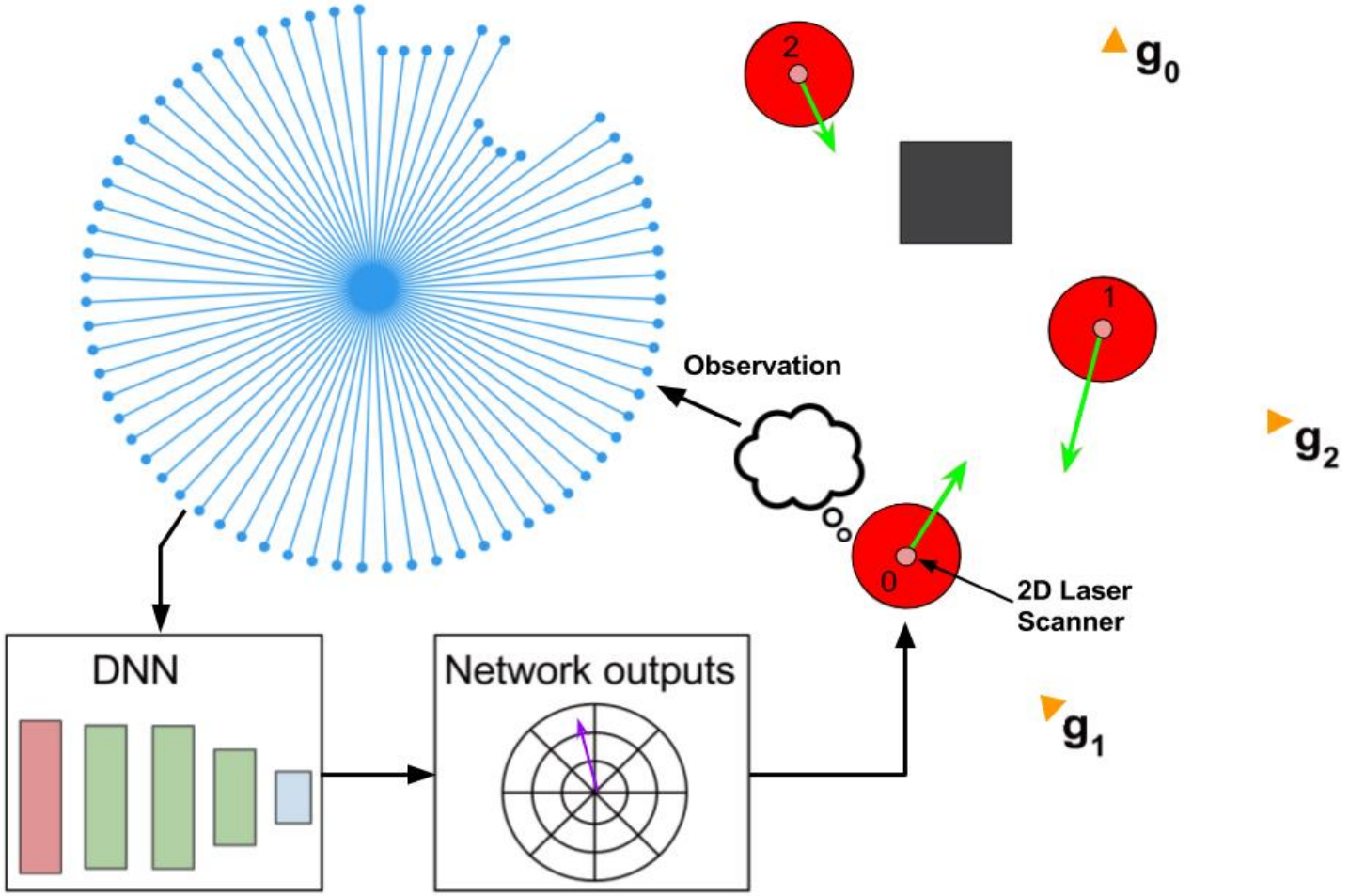
Need overhead motion capture system & AR markers ☹

Other problems of RVO

- Parameter tuning is rather difficult ☹☹☹
  - Different parameters → different behaviors
  - Many parameters; no clear guidance about tuning
- Agent-level planning/navigation algorithm ☹☹☹
  - First need the pipeline of segmentation, recognition and tracking to identify nearby agents or moving obstacles
  - Difficult to be robust
- Suboptimal policies due to partial information ☹
- No way to fine-tune the navigation policy for a specific scenario or application ☹☹☹

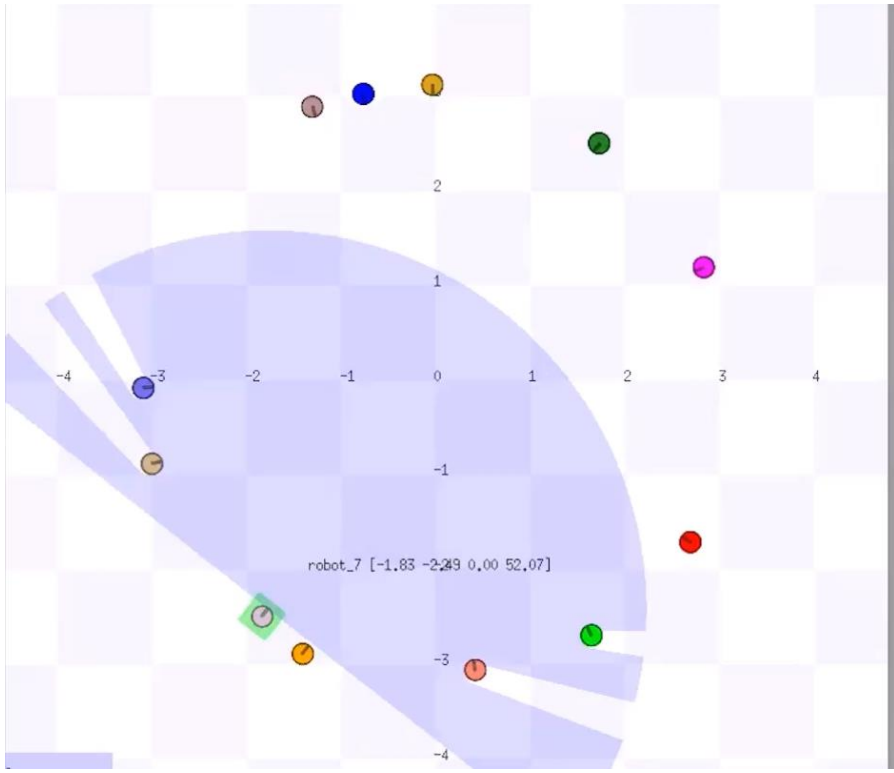
Completely distributed navigation system “seems” to be possible

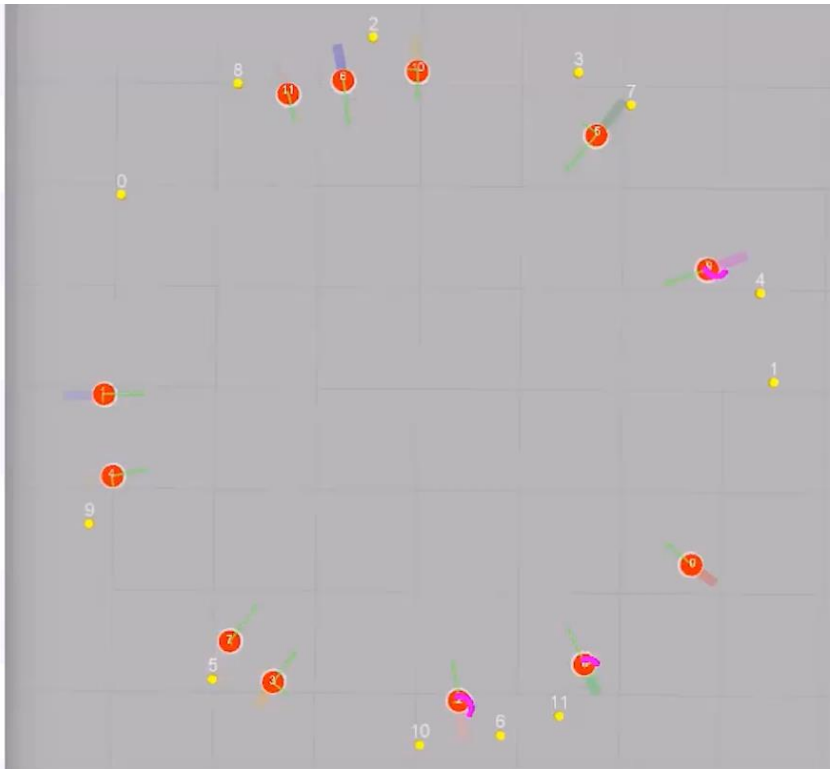
Robots navigate as humans



Decision making based on sensor measurements

- Using raw LIDAR/camera data; avoid troubles for segmentation, recognition, and tracking

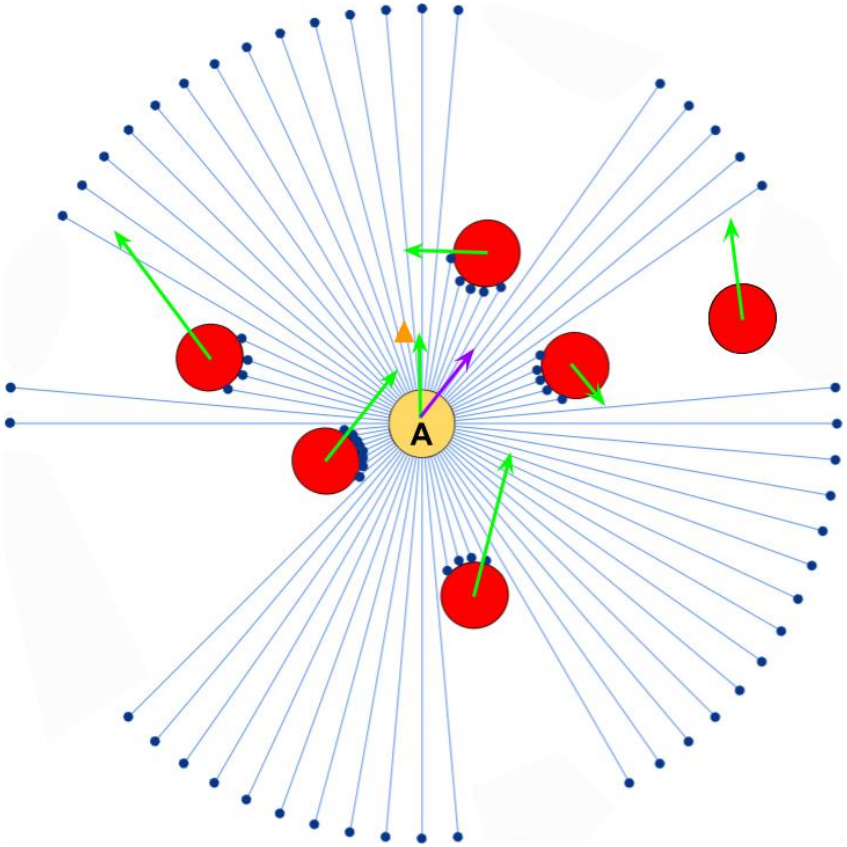




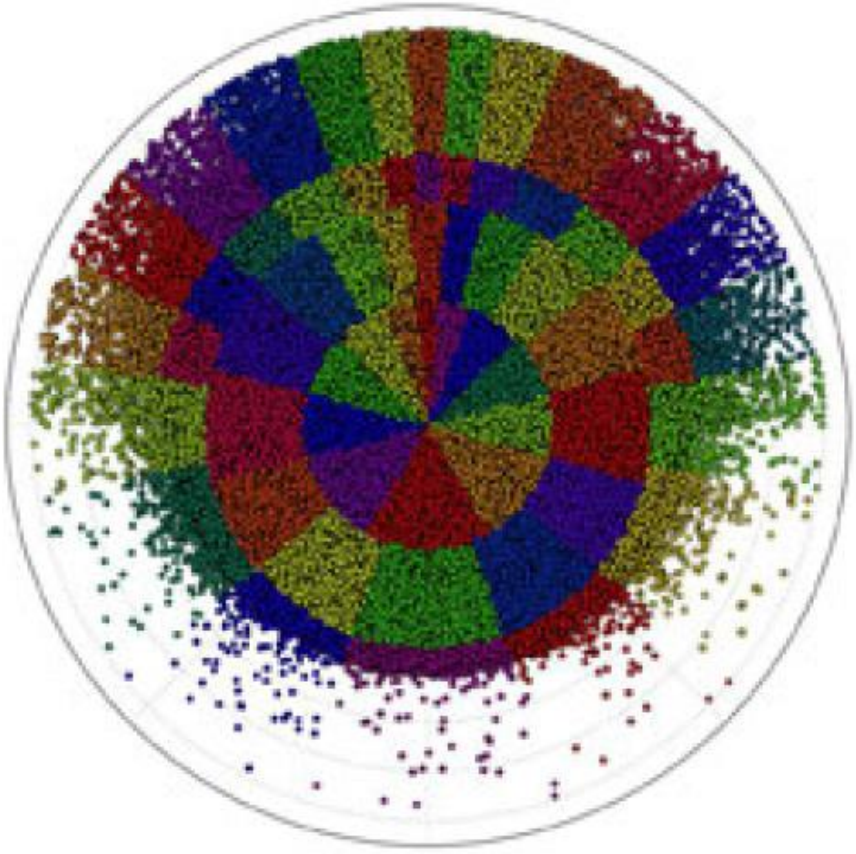
Training data

- Given an agent
  - Randomly sample its velocity and preferred velocity
  - Randomly sample a set of agents in its neighborhood
  - Velocities and goals of these agents are also randomly sampled
- Get the LIDAR data (with additional noise added)
- Select the agent's new velocity by running RVO simulator for one time step
  - Try a set of different RVO parameters
  - Remove RVO failure cases
  - Augment data using symmetries

Training data



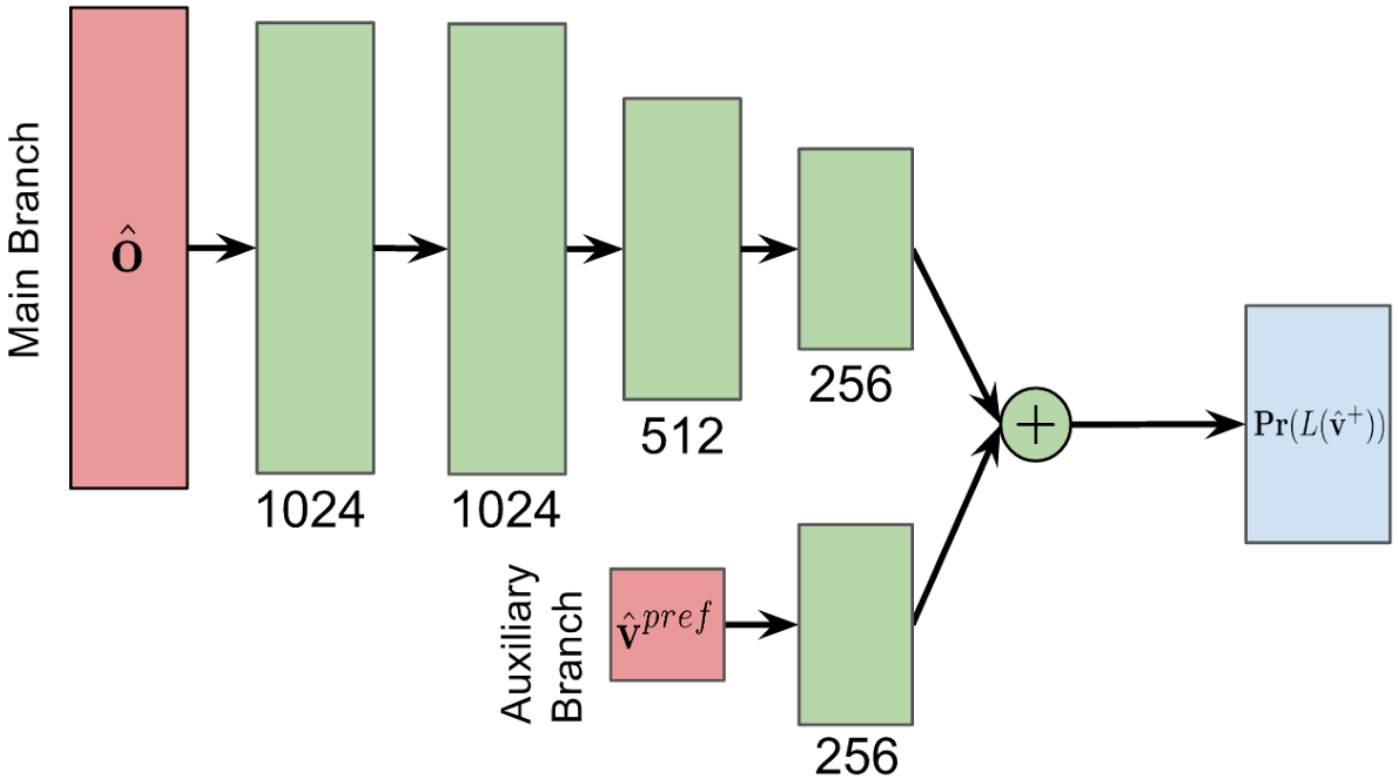
A sampled data and the RVO result



Quantization setting for velocities

Supervised learning

- Given sensor measurements & preferred velocities
- Output a reactive velocity for collision avoidance



Differences with RVO?

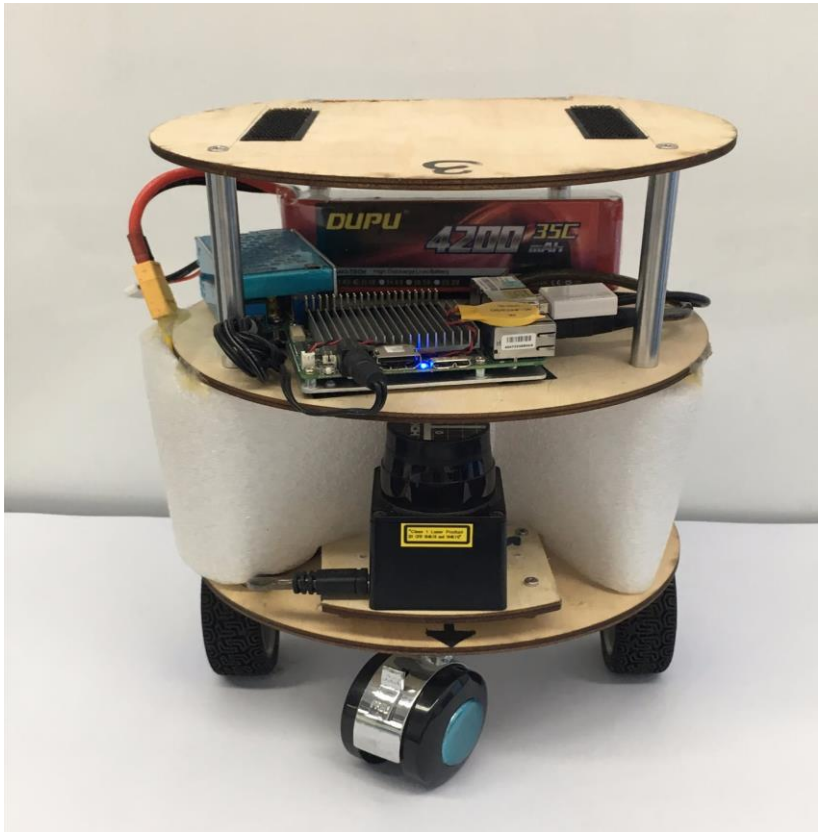
- Avoid the parameter tuning difficulty in RVO
  - Fuse RVO policies with different parameters
  - Data clearance removes bad behaviors of each policy
  - Combine different RVO policies' strengths
- From agent-level to sensor-level planning
  - The input to the controller is the sensor data
  - No need for complex vision pipelines
  - Easier to transfer to different robots and environments with obstacles
- Also benefit from the RVO's (correct) local collision avoidance heuristic

Experiments

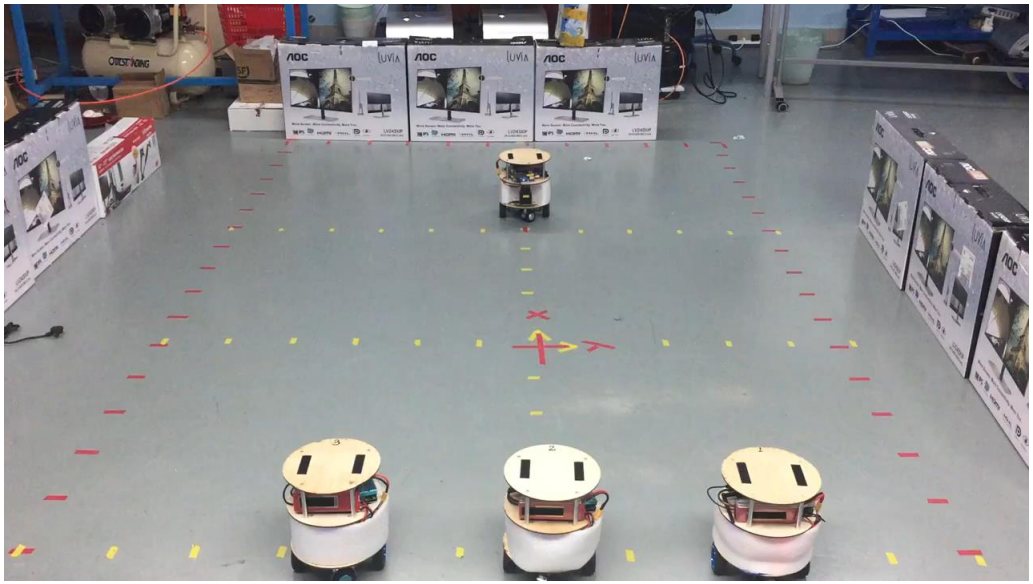
- Fully distributed and parallel system
- Non-holonomic robot dynamics
- Training data:
  - Scenarios without any static obstacles
  - Robots are of the same size
  - Only in simulation
- Test data
  - Scenarios with obstacles with different shapes
  - Robots with different size
  - Both simulation and real robots

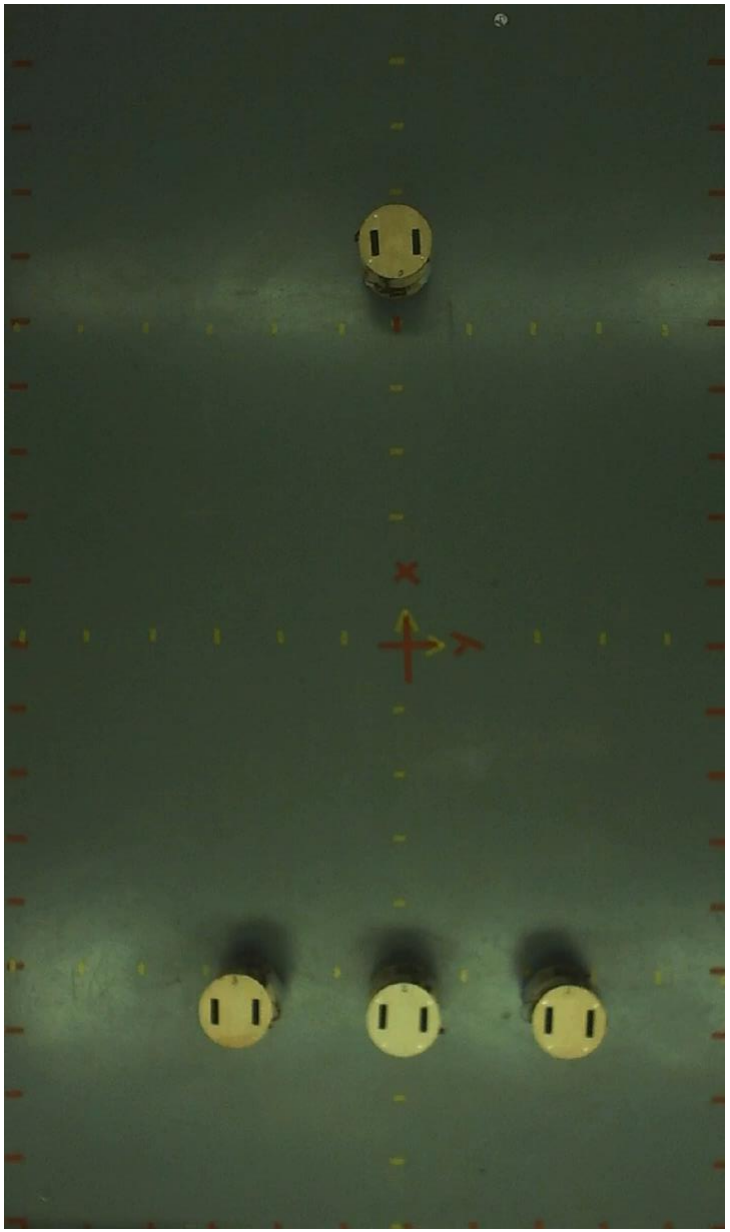
Experiment platform

- Differential driven robots
- 180-degree 2D laser scanner
- Each robot observes other robots via on-board 2D laser scanner.

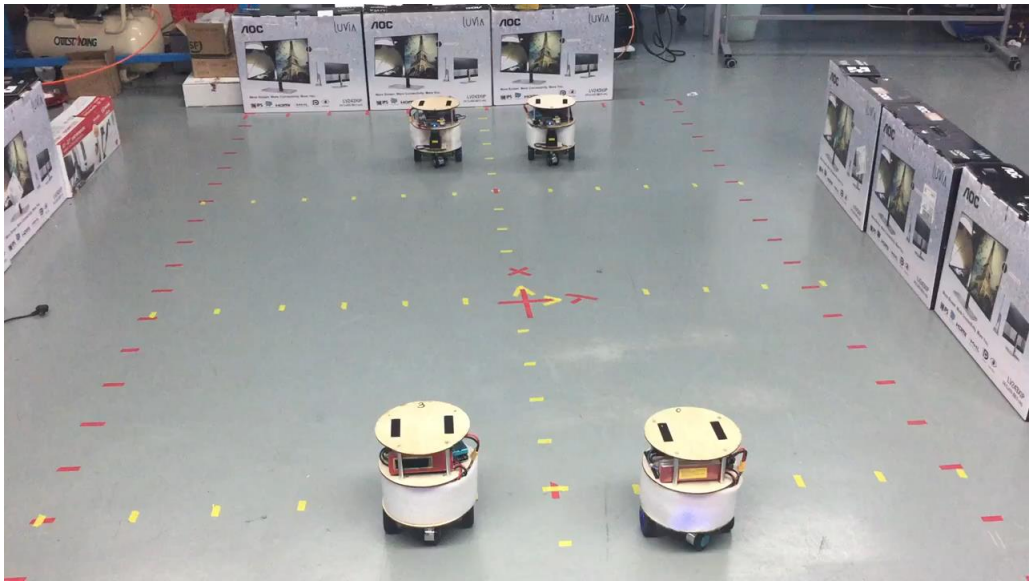


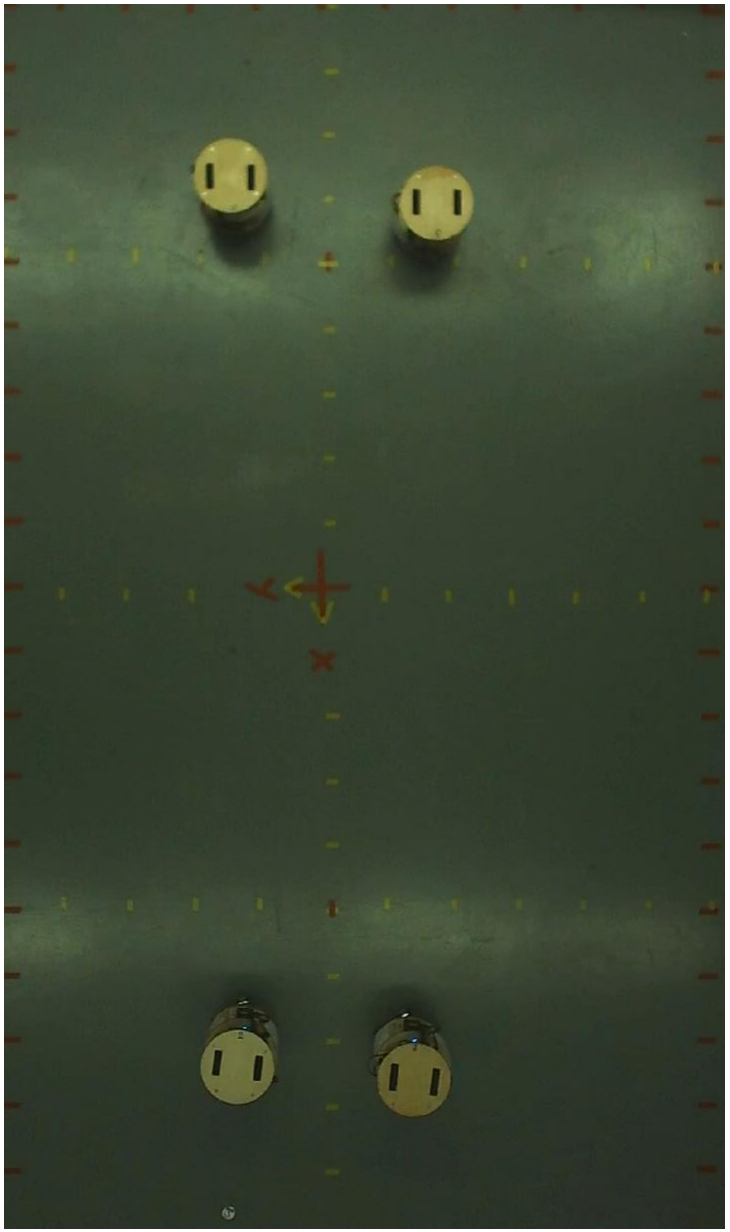
Real robots (1vs3)



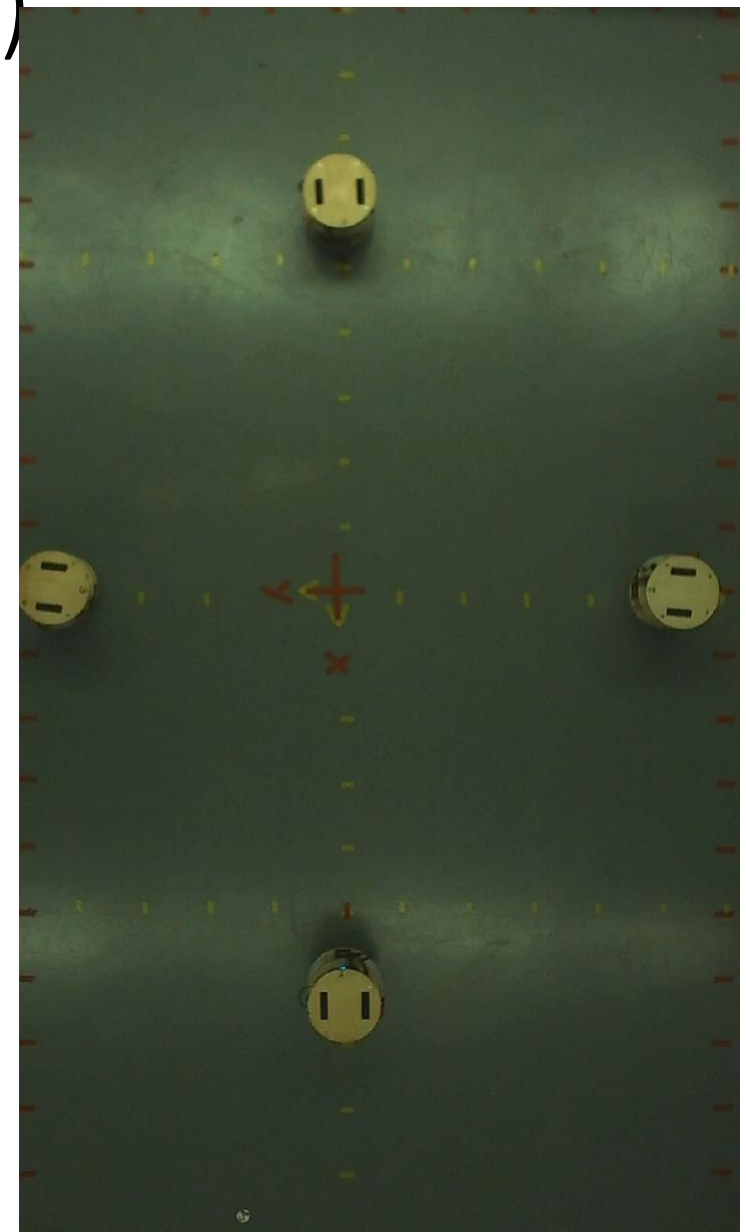


Real robots (2vs2)

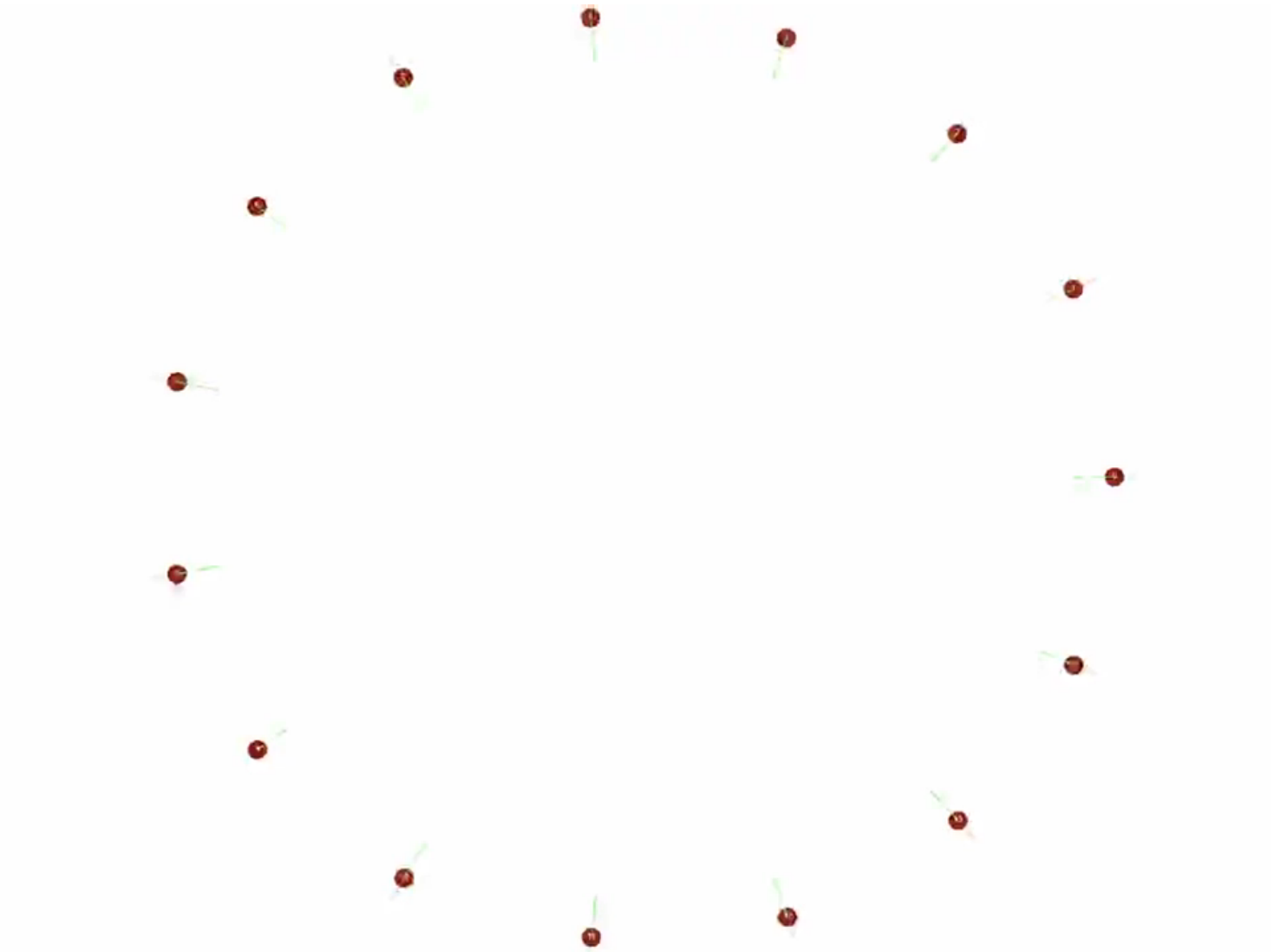




Real robots (4 circles)



Simulated robots

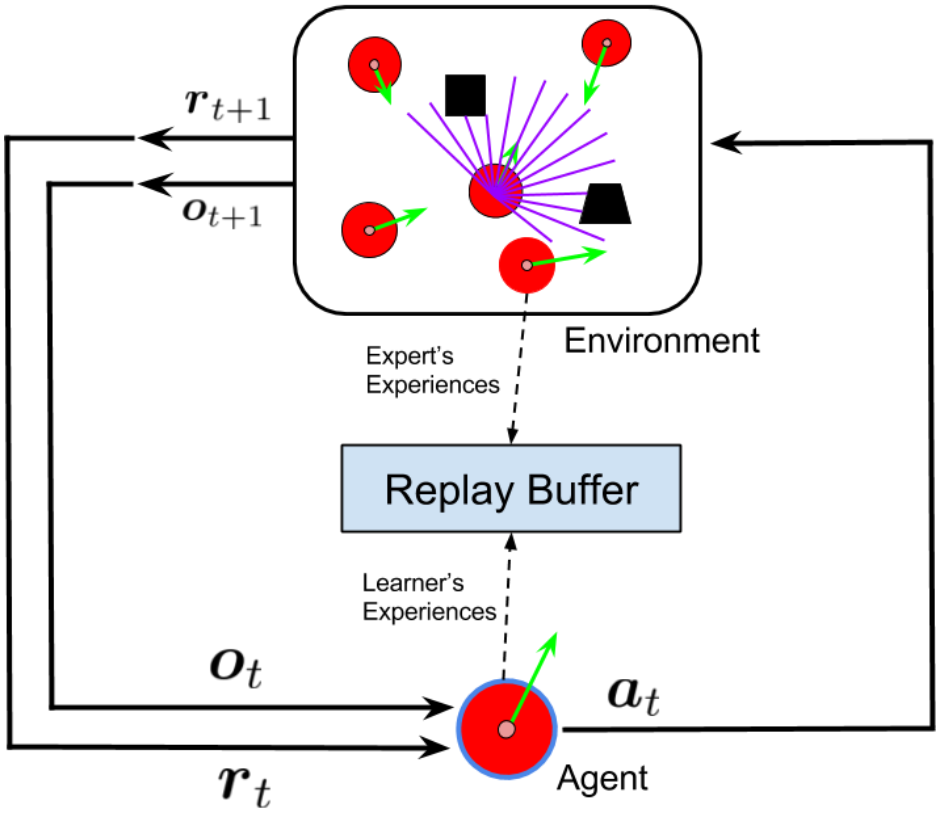


Pros and Cons

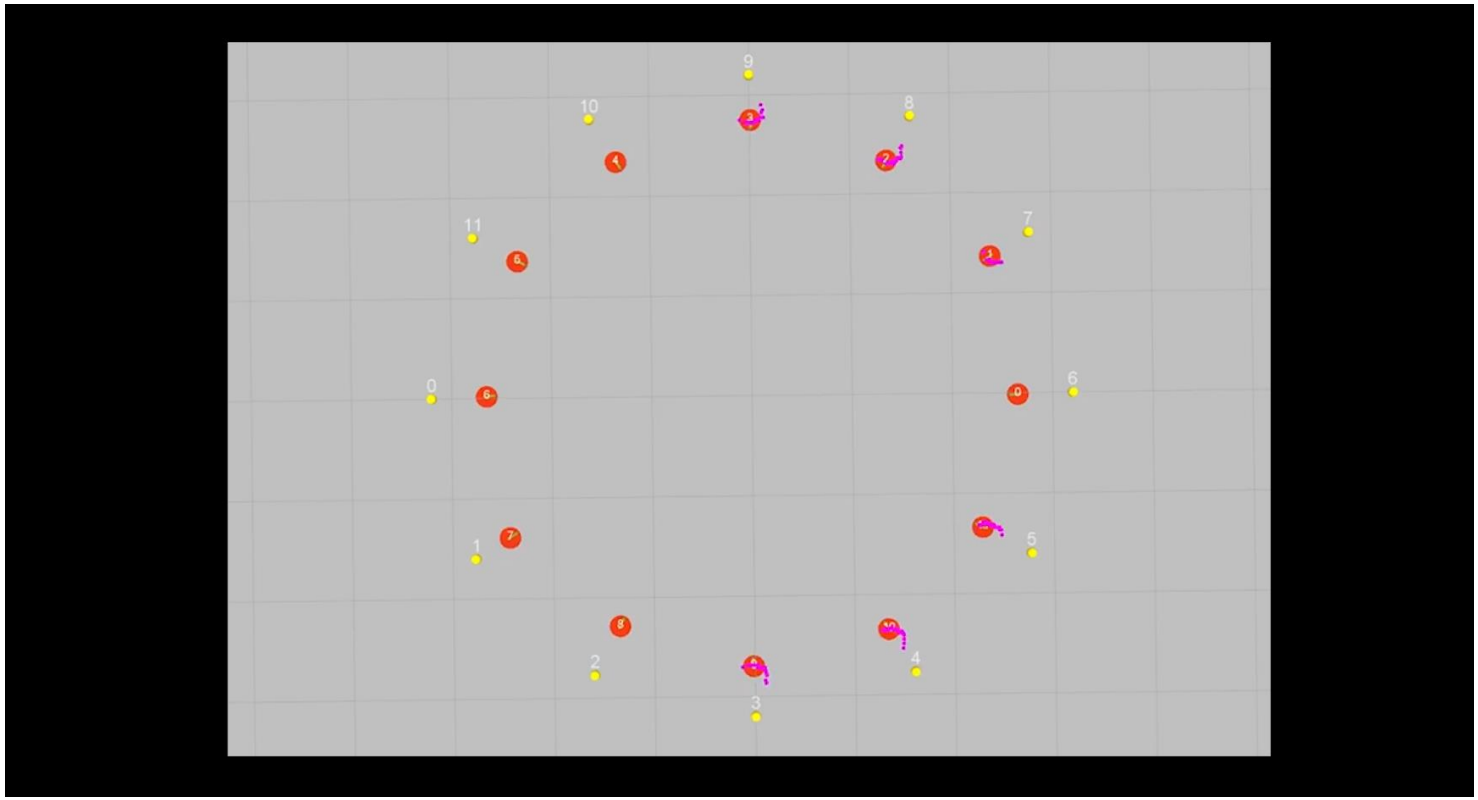
- Compared with RVO variants
  - No tedious parameter tuning ☺
  - Better generalization for static obstacles, robots with different shapes, and robots with complex dynamics ☺
- Compared with centralized methods
  - Better use of free spaces ☺
  - Better scalability ☺
  - But suboptimal ☹
- Solution: use reinforcement learning to improve trajectory quality for a given scenario/task

Optimize the navigation policy using reinforcement learning

- Given some initial policy π_0
- For k-th iteration
  - Select one agent s
  - All other agents use policy π_{k-1}
  - Agent s updates policy from π_{k-1} to π_k using DDPG [Lillicrap 2015]
  - Repeat until convergence

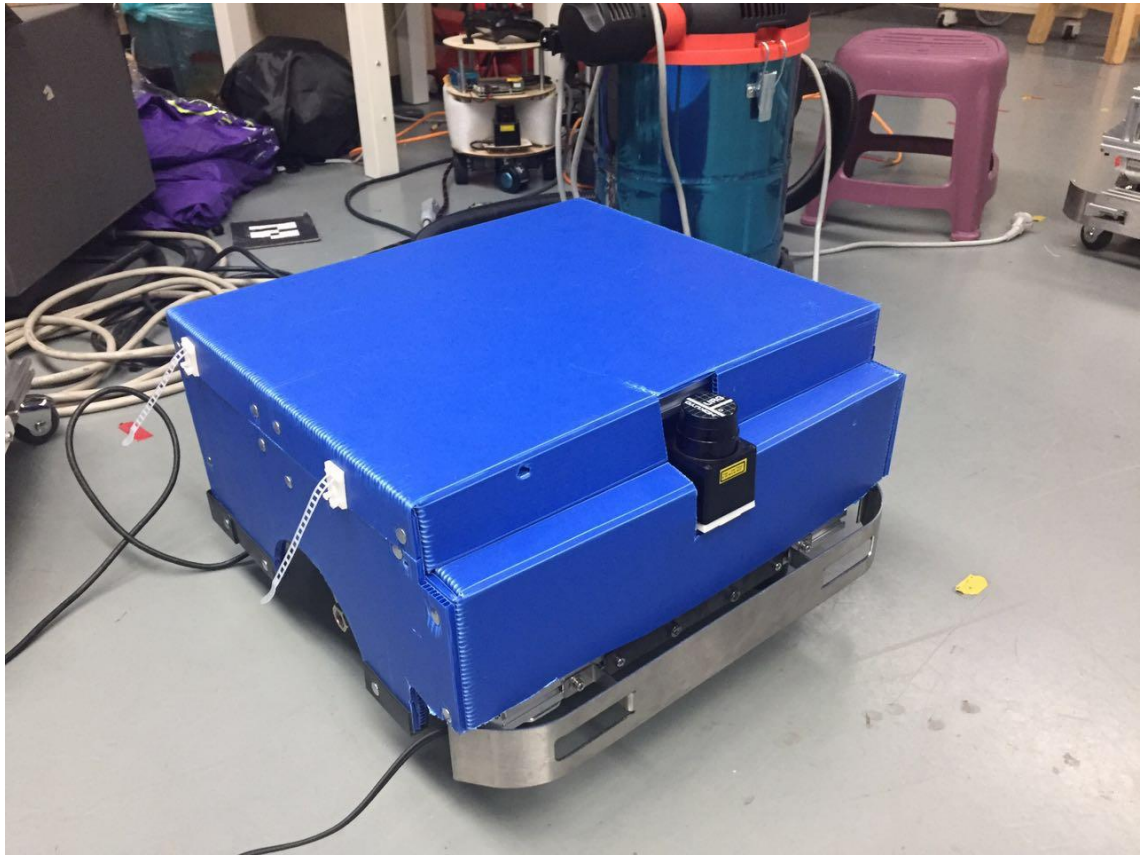


More natural and faster movements



Next step: robot platforms

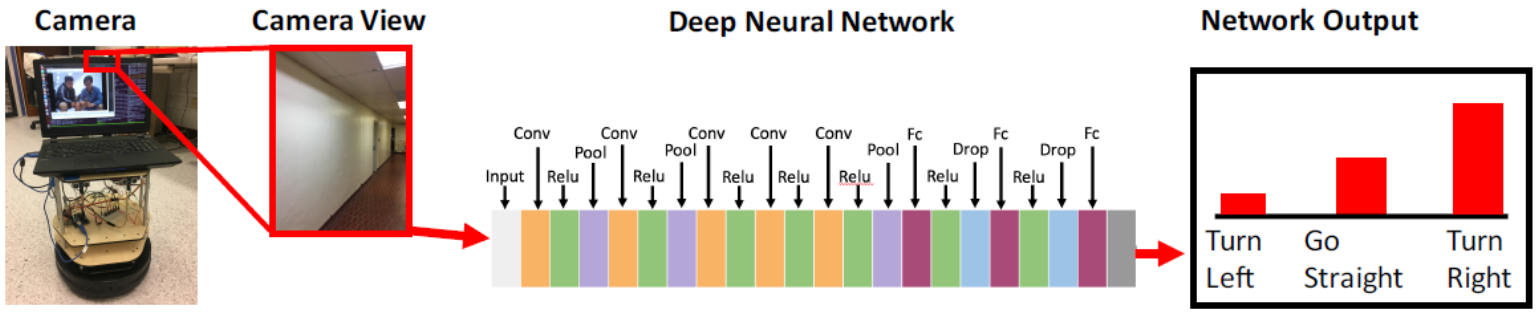
- 10 to 20



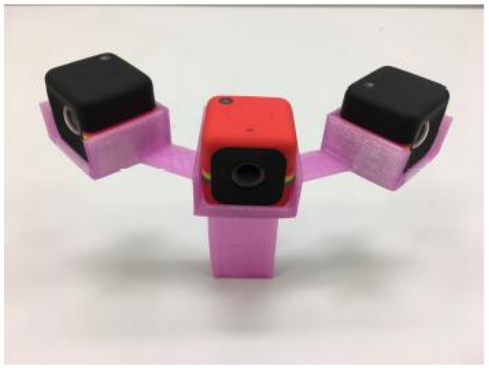
Next step: add human coworkers

- More difficult than multi-robot navigation or robot collision avoidance in static environments
- Human-human collision avoidance policy
- Human-robot & robot-human collision avoidance policy
- Human’s policies are different with robots and have higher variance

Navigation through human crowds



(a) Polaroid Cube+, motion cameras for video recording.



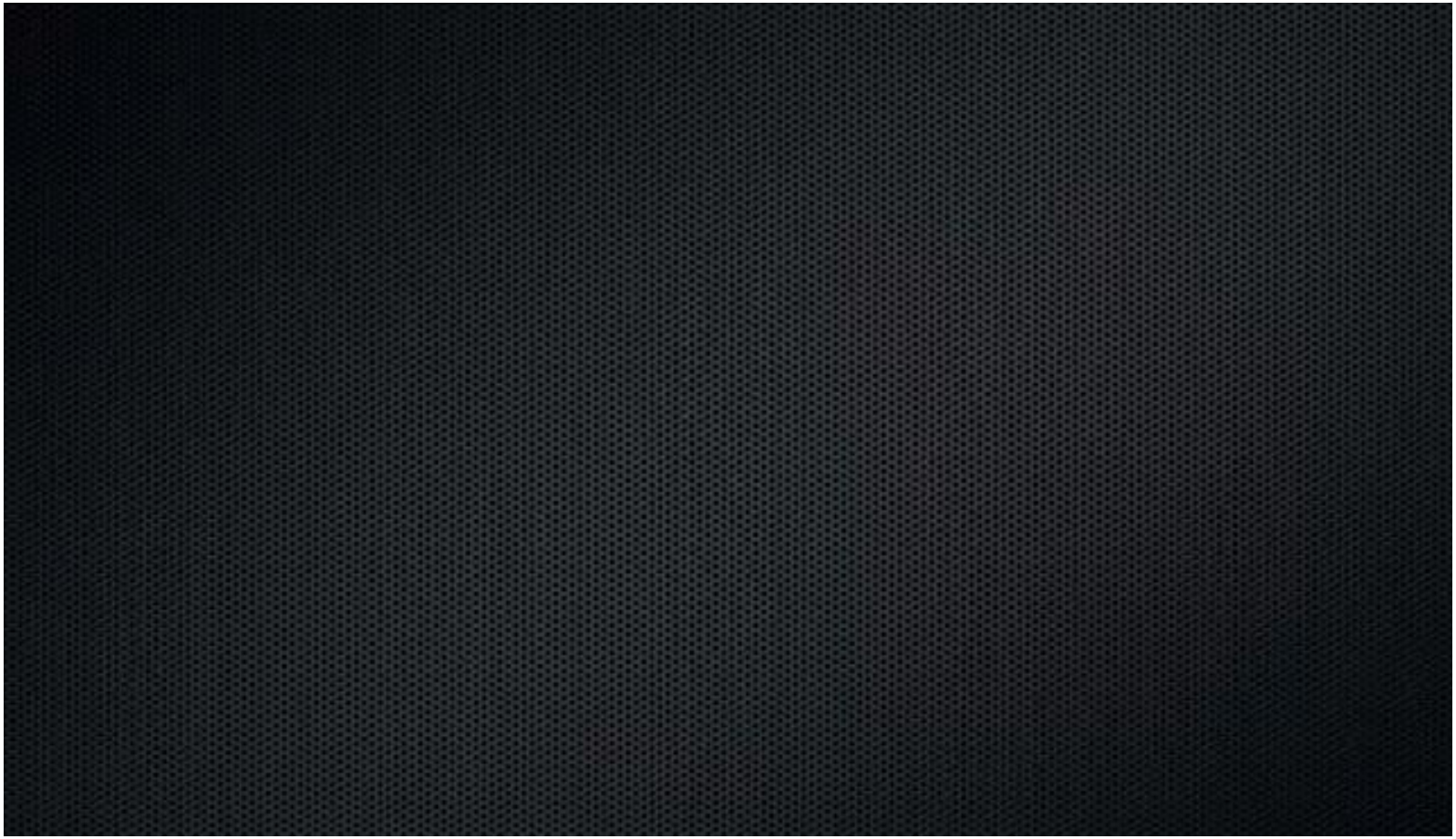
(b) Three cameras mounted on a 3D-printed holder

(c) DJI OSMO is used as a mechanical stabilizer

Data collection similar to [Giusti 2016]

Navigation through human crowds (preliminary result)

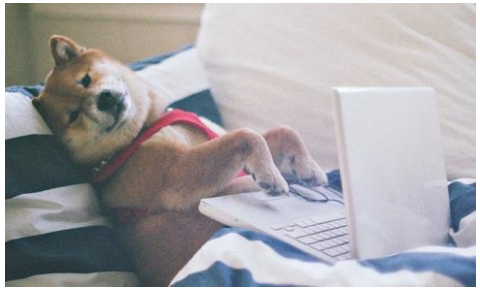
Fast Collision Avoidance



Conclusions

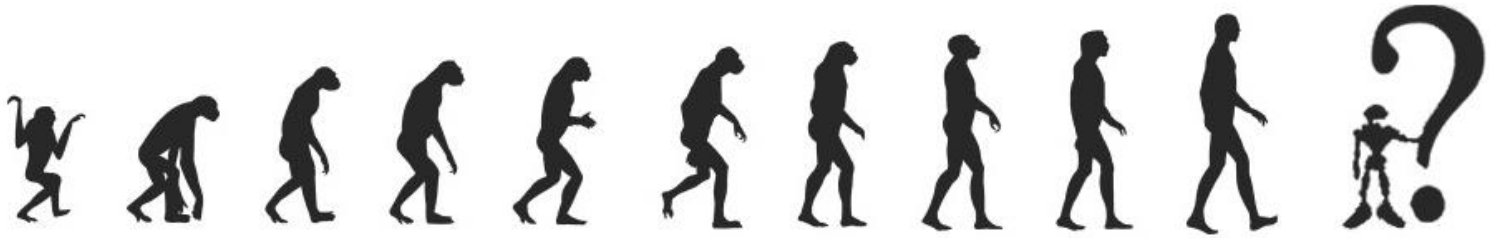
- Multi-robot navigation control for warehouses
- Distributed instead of centralized policy
- Sensor-level instead of agent-level planning
- Reinforcement learning to improve optimality
- Eventual goal: minimize the quality gap between distributed planning and centralized planning

Students wanted



- Perception for robotic manipulation
  - Tracking & reconstruction for manipulation
  - Bonus: background on slam / vision
- Advanced manipulation policies
  - Trajectory/task planning, deep reinforcement learning
  - Bonus: background on optimal control / deep learning
- Design of manipulation devices
  - Task-specific design &optimization of grippers & fixtures
  - Bonus: sensor fabrication / control / learning

Thanks



Recognition and tracking

- Would be useful for improving the distributed navigation policy for heterogonous robots or human-robot teaming
- Navigation policy can be used to help improve the vision task quality
- Vision task can be used to further improve navigation performance