Cooperative Multi-agent RL for Factory Manipulation

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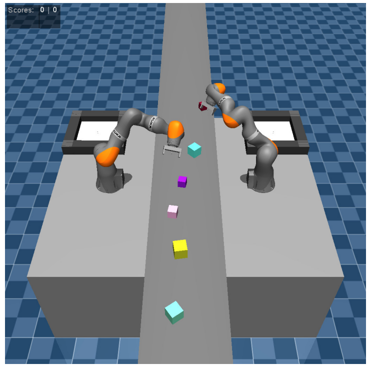
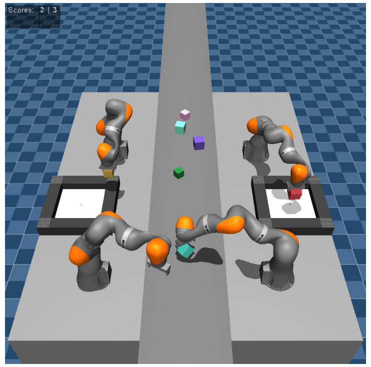




Big Picture

goal: *multiple robot arms cooperating to maximise efficiency in factory manipulation task*

- conventional pre-programming too inflexible and tedious
- multi-agent RL may find near-optimal behaviour

Given: The Environment

- even number of robot arms (8 DOF each)
- basket in reach for each arm
- conveyor belt with increasing speed transporting cubes
- score = number of cubes in baskets
- episode termination if either:
  - arm hits the environment (incl. other arms)
  - cube is missed by all arms

Given: IK Base Policy

- state machine working on *one target object at a time*
- different base policies *ignore each others' target objects*
- control calculated via *inverse kinematics (IK)*

(A) Continuous Control: Setting

action space: $[-1, 1]$ per joint and learnt arm to control joint state
observation space: joint and cube states

learning choices per arm:

- *full RL:* learn entire joint control RL from scratch (hard)
- *delta:* learn only deviation from IK base policy (simplication)
- *base*: execute IK base policy (baseline)

(A) Continuous Control: Reward Shaping

- problem: learning hard due to discrete, *highly sparse* reward
  $\Longrightarrow$ denser reward function needed
- desirable incentives:
  - I_0: reward *new cubes* put into bucket
  - I_1: reward approach of *gripper* to closest cube
  - I_2: reward approach of closest cube to *bucket*
- reward function: $r = r_0 + \omega_0 I_0 + \omega_1 I_1 + \omega_2 I_2$
  (base reward r_0 prevents learning to terminate episode)

(A) Continuous Control: Results

for 2 robot arms (simplest case):

- pure sparse reward: absolutely no learning, *random behaviour*
- progress-based reward ($r_0 = 0.4, \omega_0 = 1, \omega_2 = 0.2, \omega_3 = 0.4$)
  - successful *collision avoidance* due to implicit survival reward
  - BUT: *no gripping* at all (see screenshot (A) and videos)

test results averaged over 100 episodes

learning choice	avg episode score	avg episode length
full RL	$(0, 0)$	219.9
delta	$(0, 0)$	220.5
base	$(1.65, 1.17)$	208.8

(B) Discrete Control: Setting

action space: $\{\text{ON}, \text{OFF}\}$ per arm to toggle use of IK base policy
observation space: joint and cube states + *proposed IK control*

behaviour choices for case OFF:

- *pause:* freeze at the current position
- *retreat:* return to a safe default position
- *base:* continue executing IK policy

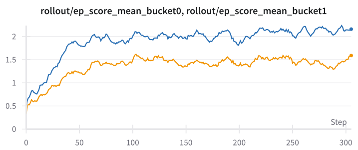
(B) Discrete Control: Results

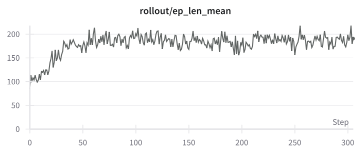
for case of 4 robot arms:

- *pure sparse score-based reward* suffices for effective learning!
- successful *dodging and gripping*! (see screenshot (B) and videos)
- pausing strategy manages to *improve upon baseline*!

test results averaged over 100 episodes

learning choice	avg episode score	avg episode length
pause	$(2.01, 1.5)$	173.04
retreat	$(0, 2.12)$	216.74
base	$(1.18, 1.16)$	119.74





Future Work

- modify setting s.t. discrete control decides *which cube to grab*
- introduce *auxiliary tasks* (grip, carry, release) & *curriculum learning*
  $\Longrightarrow$ requires careful design and much more computing resources