Cooperative Multi-Robot Navigation in Dynamic Environment with Deep Reinforcement Learning

Seminar on Artificial Intelligence II

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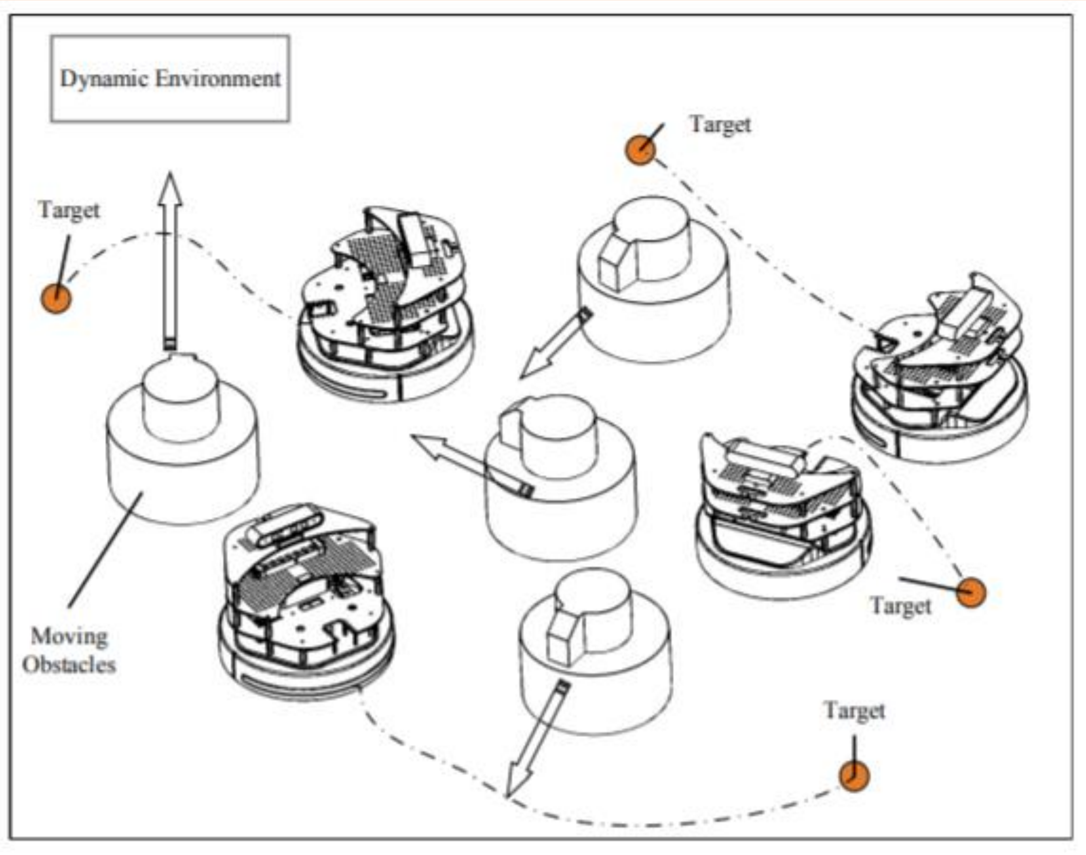
Outline

1. Introduction
2. Cooperation framework design
3. Deep reinforcement learning model
4. Target location allocation algorithm
5. How to solve the transfer to real world
6. Experiments

Multi-robot navigation problem

- N robots, M obstacles
  - Obstacles **move** as well
- Dynamic
- Partially observable
- **Multiple targets**
  - Robots can go to any target
  - Goal allocation
- Simulation and **Real World**
- Task: learn the **navigation policy**

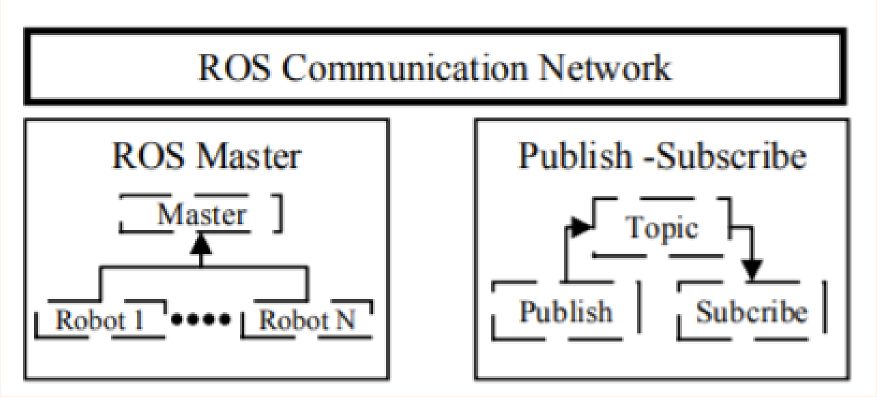


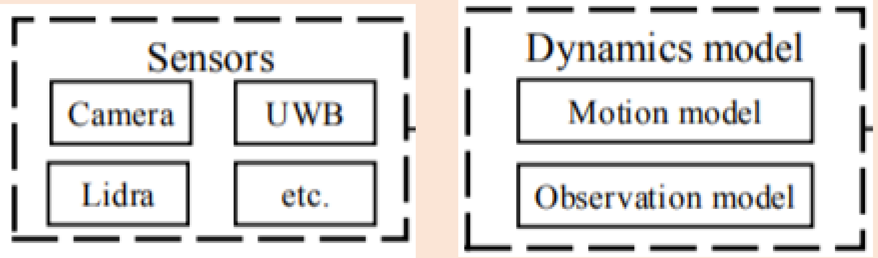
Challenges

- Efficient **target** location **allocation**
  - Allocate the goals fast
  - Reduce the total travel time
- Robot **cooperation**
  - How to combine the experience of all robots
- **Transfer** from **simulation** to **real world**
  - Noise in observations from sensors
  - Noise in motion when applying actions
  - The noise parameters differ across different scenarios (sensor type etc.)

System framework of multi-robot navigation

- They **share one neural network** and policy
  - The network is trained using input from all robots
- Agents communicate through ROS
  - They **share observations**
    - obstacle positions, their position,…
  - They **receive actions**
- Agents get information from **sensors**
- Agents have a **dynamics model**





Problem definition

- POMDP
- States
  - **Robot** states: $\boldsymbol{s}_r^t = \left[p_{rx}^t, p_{ry}^t, \theta_r^t, v_{rx}^t, v_{ry}^t\right]$ (position, orientation, velocity)
  - **Obstacle** states: $\boldsymbol{s}_o^t = \left[p_{ox}^t, p_{oy}^t, v_{ox}^t, v_{oy}^t, r_o^t\right]$ (position, velocity, radius)
  - **Target** positions: $\boldsymbol{s}_g = \left[p_{gx}, p_{gy}\right]$
- Actions: $\boldsymbol{a}^t = [v_t^t, v_r^t] \sim \pi\left(\boldsymbol{a}^t \middle| \boldsymbol{s}_r^t, \boldsymbol{s}_o^t, \boldsymbol{s}_g\right)$
- Objective:
  - **Minimize travel time** of all agents **to goals** while **avoiding collisions**

$$
\begin{aligned}
\underset{\pi_\theta}{\operatorname{argmin}} \quad & \mathbb{E}\left[T \middle| \pi_\theta, \mathbf{s}_{r,1:N}, \mathbf{s}_{o,1:M}, \mathbf{s}_{g,1:N}\right] \\
s.t. \quad & \forall i, j \in [1, N], k \in [1, M] \\
& d_{rr,i,j} > 2r_r \\
& d_{ro,i,k} > r_r + r_o \\
& d_{g,i} < d_{\min}
\end{aligned}
$$

RL quick overview

- Estimate v(s) or q(s,a) … average return from state s (starting with a)
  - $V(s) = \mathbb{E}[G_t \mid s_t = s] = \mathbb{E}[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \ldots \mid s_t = s]$
- Bellman equation
  - $V^\pi(s) = \sum_a \pi(s,a) \sum_{s'} P(s', r \mid s, a)(r + \gamma V^\pi(s'))$
- The equation is estimated, since we don't know the probability model
  - In POMDP, we even don't know the states
  - We also want to learn the policy π

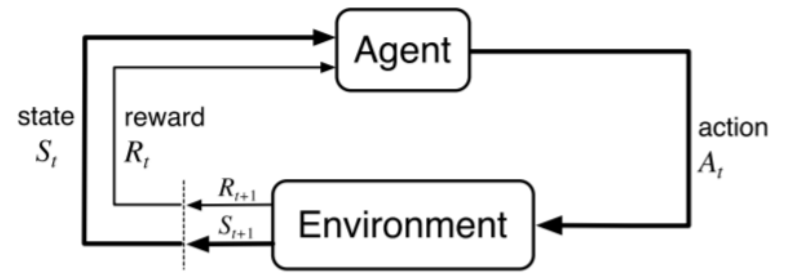


Figure 3.1 of "Reinforcement Learning: An Introduction, Second Edition".

1. Deep reinforcement learning framework

- **State** space: $\boldsymbol{s}^t = [\boldsymbol{s}_r^t, \tilde{\boldsymbol{s}}_r^t, \boldsymbol{s}_o^t, \boldsymbol{s}_g^t]$
  - Robot state, other robot states, obstacle state, *allocated* goal state
- **Action** space: $\boldsymbol{a}^t = [v_t^t, v_r^t]$
  - Velocities **clipped** to some range (hyperparameter)
  - The reason is limited obstacle detection speed
- **Reward** of robot *i*: $r_i^t = r_{g,i}^t + r_{c,i}^t$

$$r_{g,i}^t = \begin{cases} 5 & if d_g^t < 0.1 \\ 1 + d_g^t * 0.5 & if 0.1 < d_g^t < 0.4 \\ 10 * (d_g^{t-1} - d_g^t) & otherwise \end{cases}$$

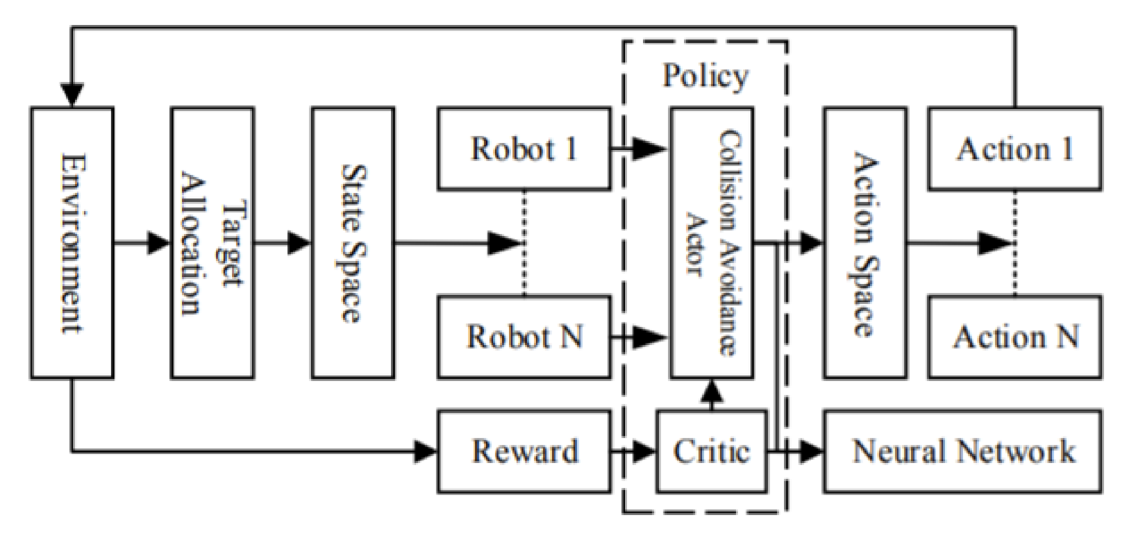
Goal reward

$$r_{c,i}^t = \begin{cases} -10 & if \quad d_{rr}^t < 2 * r_r \\ -10 & if \quad d_{ro}^t < r_r + r_o \\ 0 & otherwise \end{cases}$$

Collision avoidance reward

1. Deep reinforcement learning framework

- Model used – **PPO**
- Temporal-difference method
- Actor-critic – 2 dense networks
  - Actor – outputs **actions**
  - Critic – **estimates** the **value** function



- Predicted actions are **continuous**
  - Transitional and rotational velocities are modelled
  - Network outputs mean and standard deviation (Gaussian distribution)
  - The **action** is **sampled** from these distributions

2. Target location allocation

- *Why?* – While avoiding obstacles, the **closest target** may **change**
- For N robots and N targets, allocate targets such that the total **distance** is **minimal**
  - Allocation is a permutation of robots
- Presented algorithm – basically just **check all permutations** and select the best one
- Run only **after T_a steps**
  - T_a is a hyperparameter
  - Chosen according to no. of agents & computing power

3. Dynamics randomization

- Transfer from simulation to the real world
- Real sensors have noise that can be different for every device
- We want to **avoid retraining** the model on new data
- However, not retraining could lead to worse performance
- Solution: **add noise** during **training**
  - The noise stays the same during the episode
  - Uniformly selected from a predefined range
  - All noises are $N(0, \xi_i)$
  - At each step, we sample from it

- Noise in transitional velocity, ξ_1
- Noise in rotational velocity, ξ_2
- Noise in the position (coordinates) of robots, ξ_3
- Noise in position (coordinates) of obstacles, ξ_4
- Noise in the measurements of obstacles ξ_5
- Mass of robots m_r

Full training cycle

- Classic DRL setting
  - Simulate multiple episodes
- For every episode, **set dynamics**
- Train
  - Every few steps, **allocate goals**
  - Sample actions using the **actor**
  - Collect **next state**, **reward**
- After T steps, compute **losses**

Algorithm 2 Policy Training with PPO

```
Initialize neural network π_θ
for episode=1,2,... do
    Reset the environment with the initial state, s_init
    Sample the dynamics parameters λ from a range γ uniformly, λ ~ γ
    for robot i=1,2,... do
        Receive state s_i^t, select the goal position s_{g,i}^t
        Add noise, ŝ_i^t ~ s_i^t + [ξ_3, ξ_4, ξ_5]
        Sample action a_i^t ~ π_θ(a_i^t | ŝ_i^t)
        Add noise, â_i^t ~ a_i^t + [ξ_1, ξ_2]
        Publish â_i^t to robot i
        Collect state ŝ_i^t, reward r_i^t and a_i^t for T_i time steps
        Compute advantage estimates Â_i^1, ..., Â_i^T
    end for
    Optimize surrogate loss L^CLIP(θ) wrt θ, with Adam optimizer and learning rate l_a for K epochs
    θ_old ← θ
    Optimize value loss L^V(ψ) wrt ψ, with Adam optimizer and learning rate l_v for L epochs
    ψ_old ← ψ
end for
```

Related work

1. DRL models
    - Q-learning, DQN, A3C, DDPG, PPO
    - The difference is what they estimate (state/action-value function) and how
2. Multi-agent learning
    - MADDPG – shared critic, one actor per robot
    - SLCAP – similar approach, but PPO
    - GA3C-CADRL – one policy for all agents, asynchronous
    - These methods need preallocated targets
    - IDRL – allocates targets, but needs static obstacles

High hardware cost,
needs specific sensors

Asynchronous update
inefficient for
homogenous robots

3. Real world transfer – either retrain, or complicated dynamics model

Experiments

- Simulation
  - Gym-Gazebo env, Turtlebot robots
  - Obstacles – turtlebots that periodically change velocity
- Three models
  - 1. Without target allocation and dynamics
  - 2. With target allocation
  - 3. Full model
- Real world scenario
  - UWB, Kinect v2 – coordinates, obstacle pos.

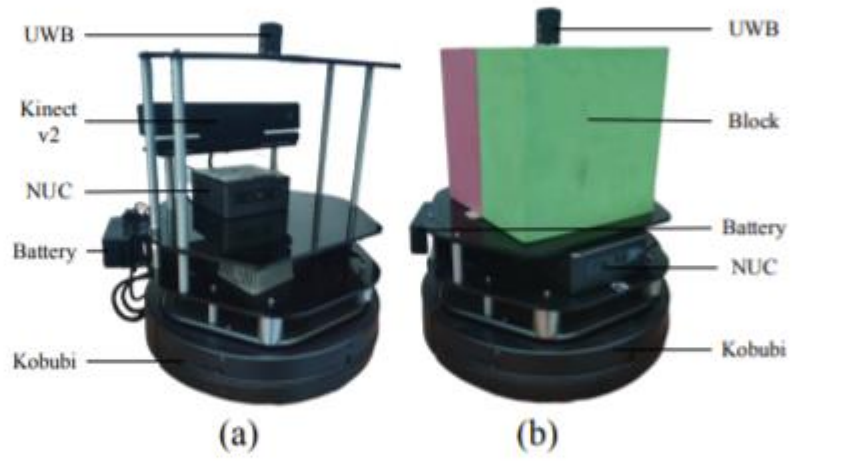


Fig. 5. Configuration of real robots and obstacles

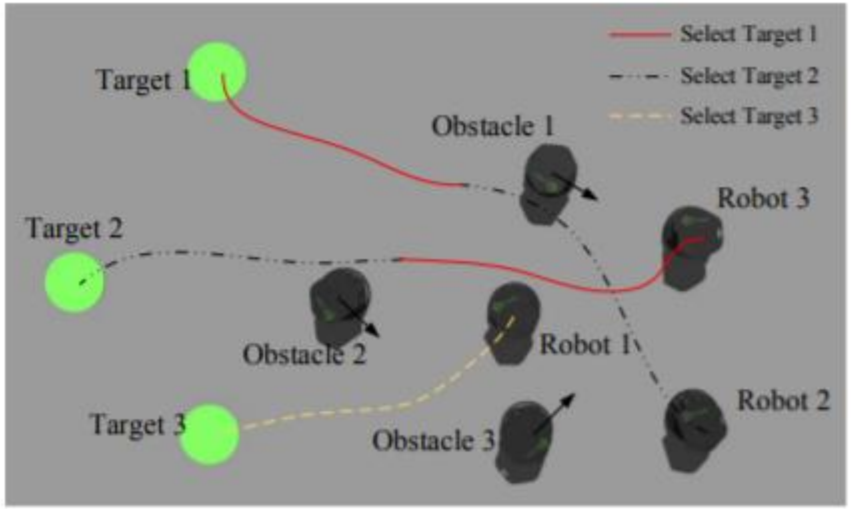
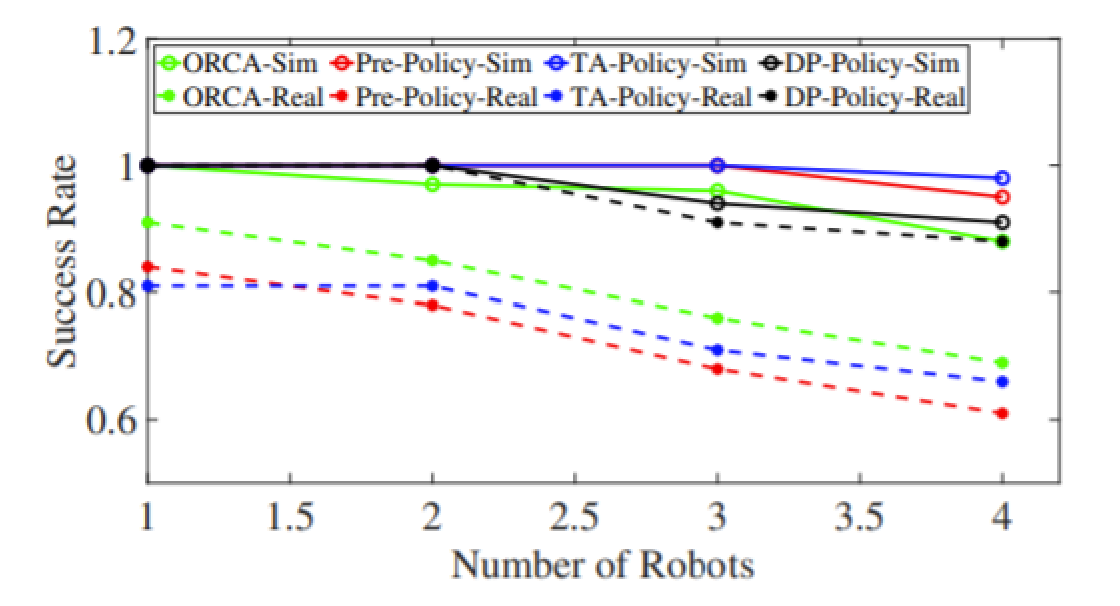
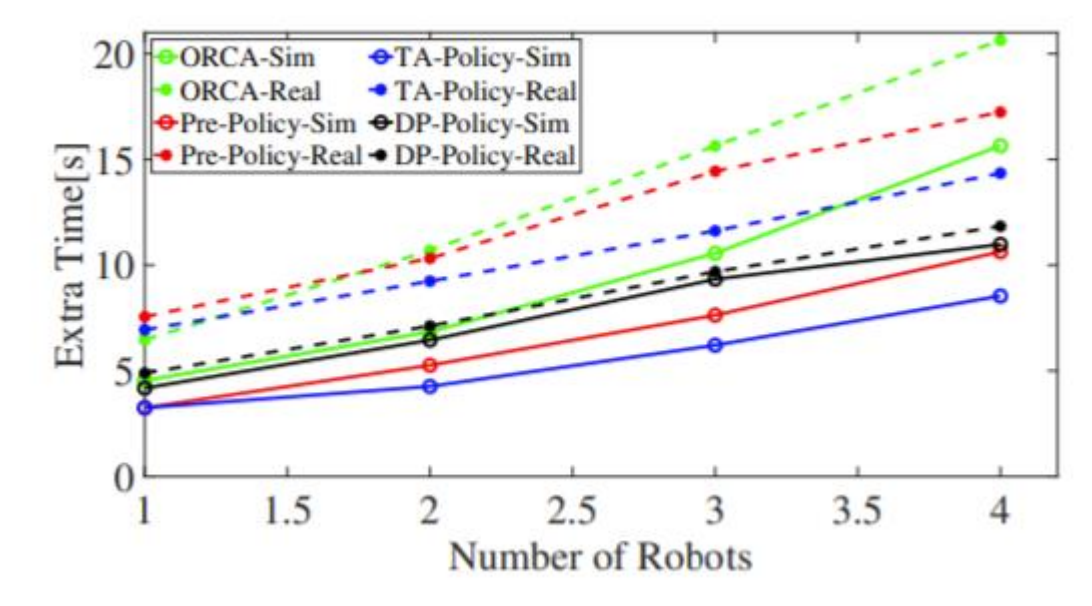


Fig. 4. Simulation scenario

Results

- Baseline – ORCA (computes “allowed” velocities as to not collide)
- Metrics
  - Success rate – # of bots that arrive to the goal
  - Extra time – (avg bot travel time - lower bound on travel)





Summary

- Introduced a **cooperative scheme** for multi-robot navigation
- Collision avoidance
- Closest **target** location **allocation**
- **Dynamics model** for real world transfer
- **Actor-critic** based neural network model
- Two experiments – simulation & real world

Thank you for your attention!

Image sources: the paper
DRL basics: Straka’s lectures

What I think about the paper

- The dynamics (noise) is nice
- Clearly written main results
- The model is not too complicated
- All steps could be easily used in other models and scenarios
- ~~The robots are cute~~

- The models with allocation/dynamics are trained longer
- Only one env/robot type, baseline model
- No confidence intervals in plots
- No code ☹
- The permutation allocation is lame