Multi-agent deep reinforcement learning in mobile robotics

Comité de suivi de 1ère année

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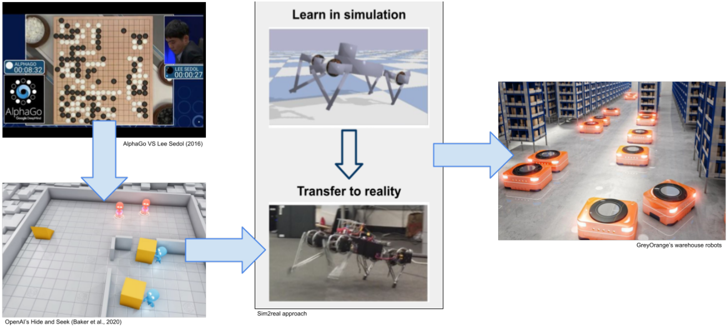
OR

Building a path to apply multi-agent deep reinforcement learning to mobile robotics



Our goal:

Perform a task in the real world with a multi-robot system.

⇒ The environment is partially observable.
⇒ We need to:

- be able to interpret our agents' strategy,
- interact with them.

Our proposed path:

1) Emergent communication

⇩

2) Learning an existing language

⇩

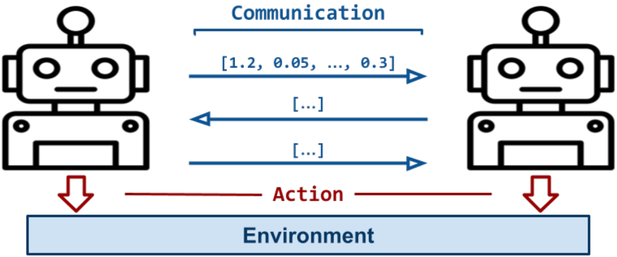
3) Multi-agent credit assignment

⇩

4) Macro-actions as a sim2real approach

Context:

- Partial observability prevents agents from having crucial information about the environment.



Proposed approach:

- Agents can overcome this issue by communicating their local observations.

Context:

- Need to *interact with our agents* and *understand their actions*.
- Emergent languages are very difficult to interpret (Lazaridou and Baroni, 2020).
- A discrete language is a way to understand the world and construct logical thoughts (Vygotsky, 1934).

Proposed approach:

- Learn a pre-defined language made of discrete tokens.

Type	Token
Entities	AGENT PACKAGE
Locations	NORTH SOUTH EAST WEST DELIVERY_AREA
Verbs	GOING_TO NEED_HELP PUSH

Possible tokens used in a language designed for a delivery task.

Context:

- The global reward does not necessarily reflect the quality of each agent's actions.
- The effect of communication must be accounted for in the quality of an agent's policy.

Proposed approach:

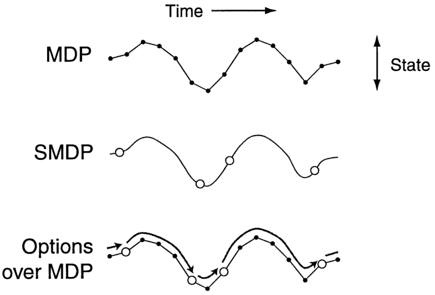
- Explore credit assignment methods in MADRL.
- Find ways to include communication in this process.

Context:

- DRL is difficult to perform in the real world.
- *Reality gap*: set of all differences between simulation and reality.

Proposed approach:

- Use macro-actions as a simulation-to-reality (sim2real) tool.
- On the macro level, the reality gap is thinner.



Macro-actions (or options) as defined by Sutton et al. (1999).

What has been done this year:

1) Literature review
2) Creating a simulated environment
3) Training methods from the literature

1) Literature review

Value-based methods:

$$V_\pi(s_t) = E_\pi[G_t | s_t]$$

$$Q_\pi(a_t | s_t) = E_\pi[G_t | a_t, s_t]$$

- **Deep Q-Network (DQN)** (Mnih et al., 2013, 2015)
- Prioritized Experience Replay (Schaul et al., 2016)
- Double DQN (van Hasselt et al., 2016)
- Dueling DQN (Wang et al., 2016)
- Noisy DQN (Fortunato et al., 2017)
- Recurrent DQN (Kapturowski et al., 2018)

Policy-based methods:

$$\pi(s) = a$$

- **Deep Deterministic Policy Gradient (DDPG)** (Lillicrap et al., 2015)
- Trust Region Policy Gradient (TRPO) (Schulman et al., 2015)
- **Proximal Policy Optimisation (PPO)** (Schulman et al., 2017)
- Twin Delayed DDPG (TD3) (Fujimoto et al., 2018)
- **Soft Acotr-Critic (SAC)** (Haarnoja et al., 2018)

Model-based methods:

Predicting the next states of the environment.
Use that for planning.

- **AlphaGo** (Silver et al., 2016)
- AlphaZero (Silver et al., 2017)
- World Models, (Ha and Schmidhuber, 2018)
- MuZero (Schrittwieser et al., 2019)
- PlaNet (Hafner et al., 2018)
- Dreamer (Hafner et al., 2019)

Centralised training, decentralised execution (CTDE):

- **Multi-agent DDPG (MADDPG)** (Lowe et al., 2017)

Independent learning:

- Independent DQN (Tampuu et al., 2017)
- Independent PPO (Schroeder de Witt et al., 2020)

Centralised execution:

- Deep Coordination Graphs (Böhmer et al., 2020)

Multi-agent Credit Assignment:

Dividing the reward given to the MAS, to match each agent's actions.

- Wonderful Life Q-function (WLQ) and Aristocrat Utility (Nguyen et al., 2018)
- **COMA** (Foerster et al., 2018)

Value factorisation:

$$\underset{\mathbf{u}}{\operatorname{argmax}}\, Q_{tot}(\boldsymbol{\tau}, \mathbf{u}) = \begin{pmatrix} \operatorname{argmax}_{u^1} Q_1(\tau^1, u^1) \\ \dots \\ \operatorname{argmax}_{u^n} Q_n(\tau^n, u^n) \end{pmatrix}$$

$$Q_{tot}(\boldsymbol{\tau}, \mathbf{u}) = f \begin{pmatrix} Q_1(\tau^1, u^1) \\ \dots \\ Q_n(\tau^n, u^n) \end{pmatrix}$$

- **Value-Decomposition Networks (VDN)** (Sunehag et al., 2018)
- **QMIX** (Rashid et al., 2018)
- Qtran (Son et al., 2019)
- Multiagent Variational Exploration (MAVEN) (Mahajan et al., 2019)
- Weighted QMIX (Rashid et al., 2020)
- QPLEX (Wang et al., 2021)

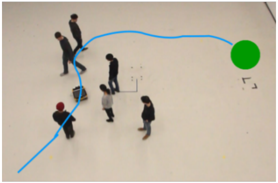
Literature review

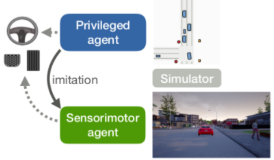
Learning in mobile robotics (1/3)

Navigation using DRL:

- Navigation from pixel input (Zhu et al., 2017; Kahn et al., 2018).
- Planning with other agents (humans and robots) in the environment (Everett et al., 2018, 2021).
- Application on aerial vehicles (Zhang et al., 2016),
- and autonomous vehicles (Shalev-Schwartz et al., 2016; Chen et al., 2020).

Zhu et al., 2017


Everett et al., 2021



Chen et al., 2020

Sim2real:

- Object manipulation through domain randomisation (Tobin et al., 2017; Peng et al., 2018; Andrychowicz et al., 2020).
- Navigation in mobile robotics (Tai et al., 2017; Kang et al., 2019).

Tobin et al., 2017

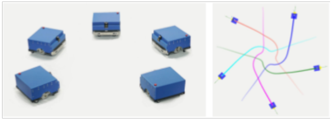

Andrychowicz et al., 2020


Kang et al., 2019

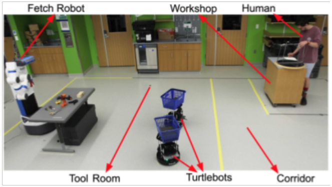
Multi-robot systems:

- Navigation with collision avoidance (Chen et al., 2017; Long et al., 2018; Semnani et al., 2020).
- Tool delivery (Xiao et al., 2020).
- Information gathering (Queralta et al., 2020).

Chen et al., 2017



Long et al., 2018



Xiao et al., 2020

Centralised communication network:

- **CommNet** (Sukhbaatar et al., 2016)
- BiCNet (Peng et al., 2017)
- IC3Net (Singh et al., 2019)
- **Targeted Multi-agent Communication (TarMAC)** (Das et al., 2019)

Decentralised execution:

- **DIAL** (Foerster et al., 2016)
- Emergent grounded compositional language (Mordatch and Abbeel, 2018)
- Attentional Communication (Jiang and Lu, 2018)

Communication in value factorisation:

- Variance based control (Zhang et al., 2019)
- Communication minimisation (Wang et al., 2020)
- Temporal message control (Zhang et al. ,2020)

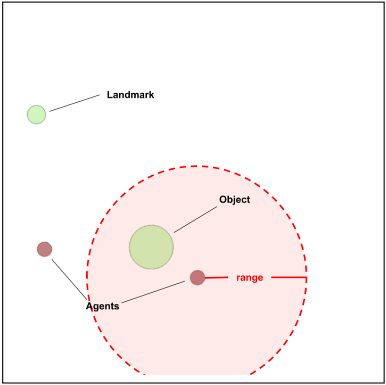
Issues with emergent communication:

- Adds a layer of complexity to the learning process.
- Difficult to measure the efficiency of the learnt language (Lowe et al., 2019).
- Difficult, if not impossible, to interpret (Kottur et al., 2017; Lazaridou and Baroni, 2020)

2) Creating a simulated environment

Multiagent Particle Environment:

- 2D
- Physics-based
- Used in the literature (Lowe et al., 2017; Mordatch and Abbeel, 2018; Jiang and Lu, 2018; Wang et al., 2020)



Coop Push Scenario:

- Agents (weight=0,4kg)
- Movable object (weight=10kg)
- Unmovable landmark
- **Goal:** Move the object on the landmark
- 100 steps maximum per episode
- Partially observable

Observations:

- Own position and velocity
- Position and velocity of agents and objects in observation range
- Position of landmarks in observation range

Actions:

- Discrete: Up/Down/Left/Right/Do nothing
- or Continuous: $[dx, dy], (dx, dy) \in [-1, 1]^2$

Reward:

$$R^t_{dist\_reward} = -dist(object, landmark)^2 - \frac{1}{n_{agent}} \sum_{k=1}^{n_{agent}} dist(agent_k, object) + \rho,$$

with ρ the collision penalty, fixed at -10.

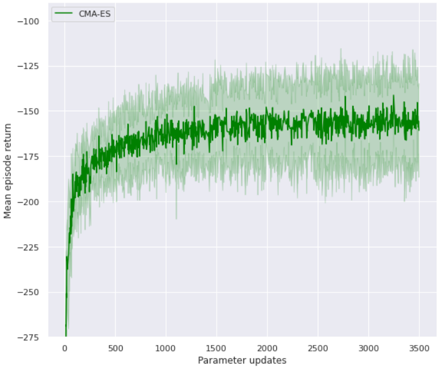
3) Training baselines from the literature

Training baselines from the literature

Chosen models

Model	Paper	Type	Action space
MADDPG	Lowe et al., 2017	Policy-based	Discrete or Continuous
QMIX	Lowe et al., 2017	Value factorisation	Discrete
CMA-ES	Hansen and Ostermeier, 2001	Evolutionary strategy	Discrete or Continuous

Scenario: 2 agents, dist_reward, fully observable



MADDPG: num_episodes=300K, num_updates=150K, lr=0,005, actions=continuous

QMIX: num_episodes=300K, num_updates=150K, lr=0.0005, actions=discrete

CMA-ES: pop_size=18, num_evals=3500, number of episodes per eval = 8, actions=continuous

Future steps

Period	Task
January-February	Find a working reward
February-March	Develop and train emergent communication
March-April	Review Language-Augmented RL
April-June	Develop a system for learning an existing language
June-August	Train agents with existing language
July-October	Publish
September-December	Explore further with credit assignment and macro-actions

One year from now

- Working reward
- A language to teach to artificial agents
- A system for teaching this language
- Proofs that communication improves the agents' performance
- One publication in a conference (NIPS, IROS, CoRL...)

Research

- Meeting every 2 weeks with Jae Yun Jun
- Meeting every 2 months with the whole team

Teaching (100 hours/year)

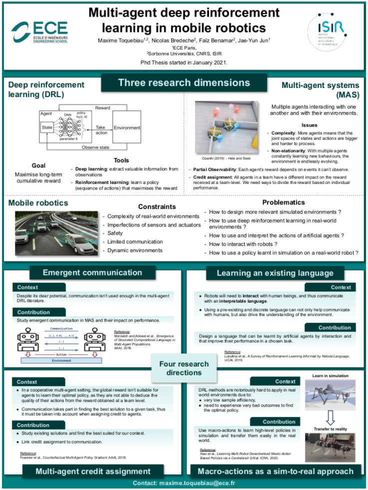
- Programming in C and Python, 1st year ECE students

Presenting my work

- Presentations to students and other researchers
- Poster for the careers fair

Mentoring students in the research minor

- Research project on meta reinforcement learning



Training plan

Technical formation				
Name of the course	**Number of hours**	**Place**	**Course followed**	**Dates**
Robotique Mobile	36	Sorbonne Universités	Yes	12/10/2021 - 03/01/2022
Non-technical formation				
Name of the course	**Number of hours**	**Place**	**Course followed**	**Dates**
Optimiser mes 3 ans de thèse	3	Online		
Scientific writing	12	Online	Yes	20 and 27/05/2021
Anglais - Faire une communication orale	12			

Thank you for your attention.