Automatic Piloting of Drones by Reinforcement Learning

SENECHAL Morgan
M1 Big Data & Machine Learning | EFREI Paris

Mai 2024

Introduction

Unmanned aerial vehicles (UAVs) play a key role in varied applications such as search, rescue and surveillance. However, their autonomous navigation in unpredictable environments remains a major challenge. To overcome this difficulty, a new Deep Reinforcement Learning (DRL) algorithm, named Robust-DDPG, was developed. It uses an actor-critic approach to simultaneously manage speed, orientation and reduce collision risks, enabling efficient navigation in dynamic environments without prior mapping.

Prerequisites

Reinforcement learning (RL)

Motion control of a UAV is formalized via reinforcement learning, where the UAV learns optimal control policies by interacting with a dynamic environment characterized by changing conditions and unexpected events.

Drone kinematics

This equation describes the motion of a UAV in terms of its planar position and flight angles, while accounting for disturbances, as it makes coordinated turns at a constant altitude.

$$\frac{d}{dt}\begin{pmatrix} x_u \\ y_u \\ \psi_u \\ \phi_u \end{pmatrix} = \begin{pmatrix} v_u \cos\psi_u + \eta_x \\ v_u \sin\psi_u + \eta_y \\ -(g/v_u)\tan\phi_u + \eta_{\dot\psi} \\ f(\phi_u, a_\phi) \end{pmatrix}$$

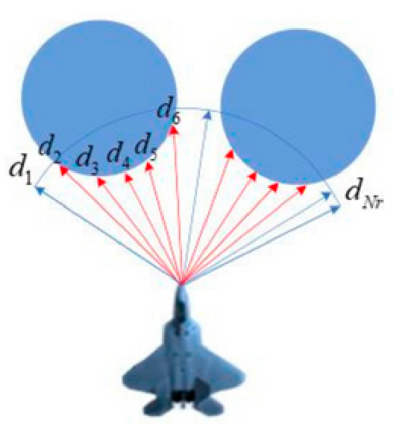
xu,yu: Cartesian planar position of the UAV
g: acceleration due to gravity.
ψu,ϕu: heading angle and roll angle
v_u: linear speed of the UAV.
ηix,ηiy,$\eta i\psi$: disturbance terms due to speed and rate of change of heading

$$\begin{cases} v_{u,t} = (1-\lambda_v)v_{u,t-1} + \lambda_v(1-a_{v,t})v_{u,max} \\ \phi_{u,t} = (1-\lambda_\phi)\phi_{u,t-1} + \lambda_\phi a_{\phi,t}\phi_{u,max} \end{cases}$$

$v u$,r: Speed control update
ϕu,r: Roll command update

Methods

State and Action



State(s): The state of the system is a vector of information that includes planar position (xu,yu), planar velocity (x'u,y'u), heading angles ψu and roll angles ϕu, as well as the distances di detected by the LiDAR for each ray Nr, which measure the relative distance to surrounding threats. Additionally, the state includes the target position (xT,yT), transmitted periodically to the UAV.

Action (a): The action is a vector that includes the collision probability av to control the UAV speed and the signal aϕ to control the roll angle. av varies between 0 and 1, where 1 represents the maximum collision probability, and aϕ varies between -1 and 1, where the values determine the direction and amount of roll.

Reward

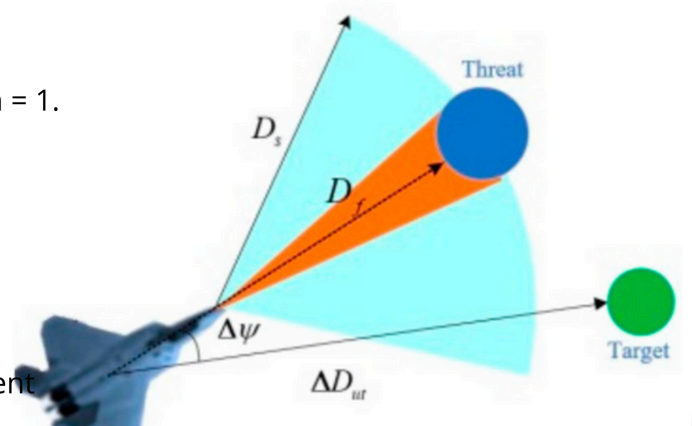
Reward function:

$$r(s,a) = \mu_1 r_A + \mu_2 r_B + \mu_3 r_C + \mu_4 r_I$$

μ1,μ2,μ3,μ4: weight the importance of the rewards: sum = 1.

$$r_A = D_{ut}^{pre} - D_{ut}^{cur}$$
$$r_B = (v_u / v_{u,max}) \times \cos\Delta\psi$$
$$r_C = -\Delta\psi/4$$
$$r_D = (v_u / v_{u,max}) \times (D_f / D_s - 1)$$

rA: approach towards the target
rB: speed towards the target taking into account alignment
rC: penalty for movement away from the target
rD: penalty for approaching potential threats



Future Rewards & Objective Function

Objective function ($J\pi$):

$$J_\pi = \mathbb{E}_{s_i\sim p, a_i\sim\pi}\left[\sum_{i=0}^{H} \gamma^i r(s_i, a_i)\right]$$

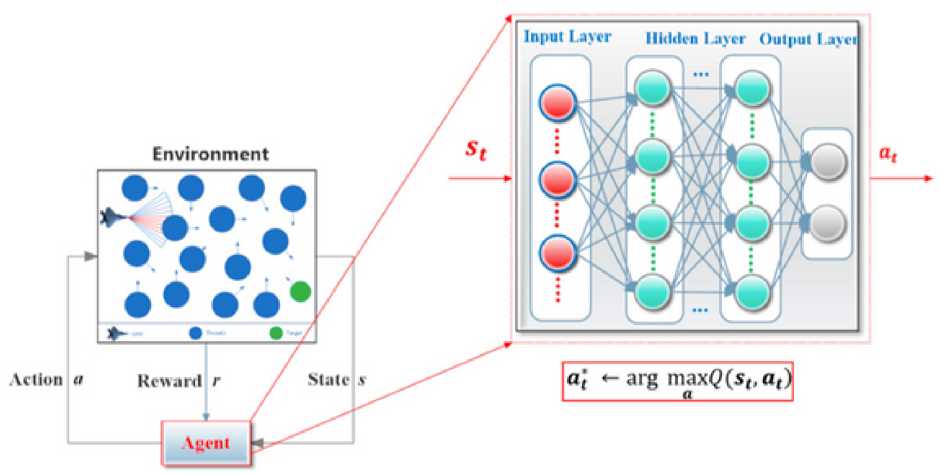
Policy π is optimized to maximize the weighted sum of future rewards over horizon H, with weighting given by a discount factor γ

$$= \mathbb{E}_{s_i\sim p, a_i\sim\pi}\left[\sum_{i=t}^{H} \gamma^{i-t} r(s_i, a_i) \middle| s_t, a_t\right]$$
$$= \mathbb{E}_{s_{t+1}\sim p}\left[r(s_t, a_t) + \gamma \mathbb{E}_{a_{t+1}\sim\pi}[Q_\pi(s_{t+1}, a_{t+1})]\right]$$

For a state-action pair (s,a), the Q-value is the measure of the quality of action a in state s under policy π. It is defined as the expected sum of future rewards discounted, starting with state s and action a and then following policy π.

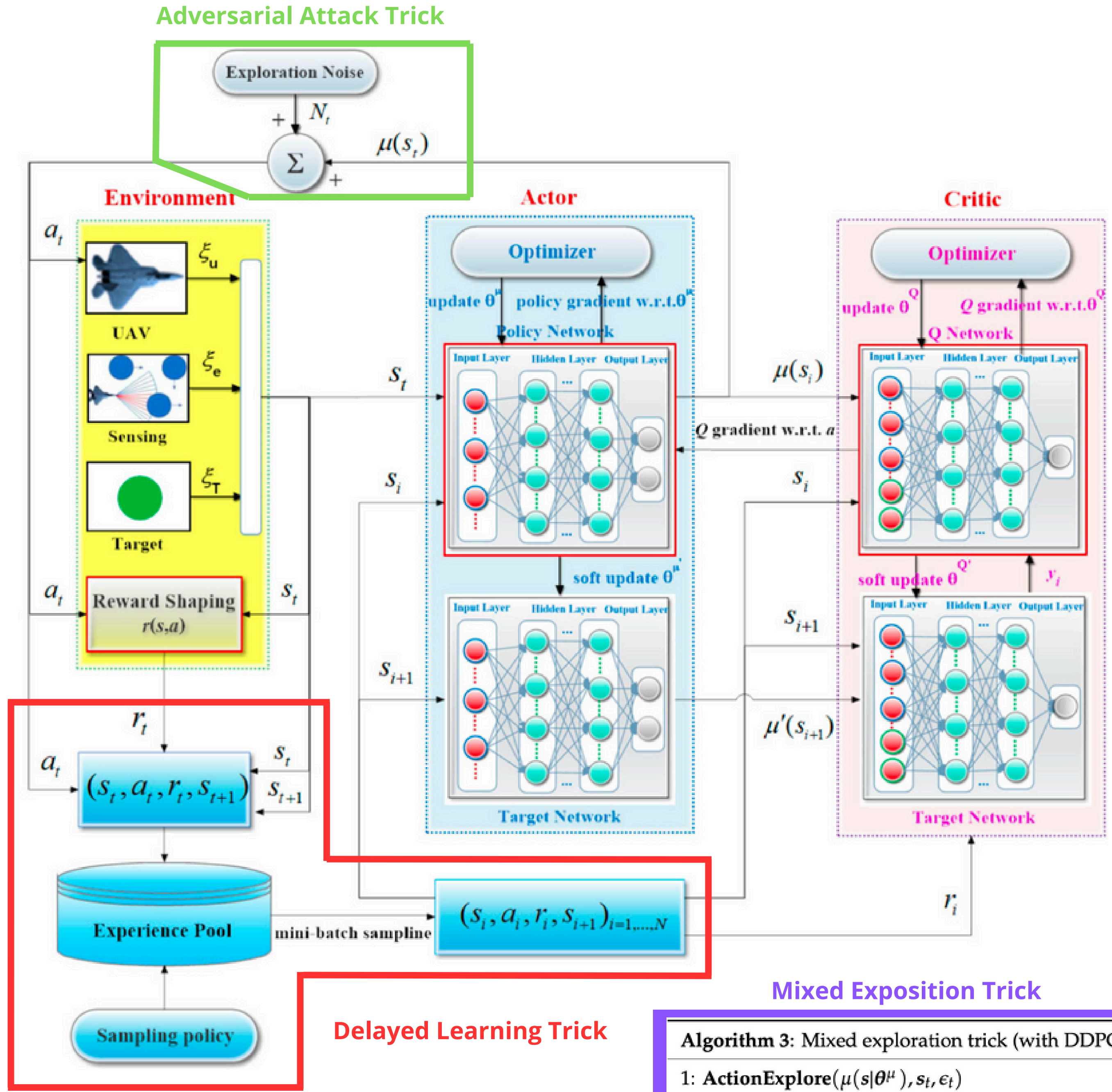
Using a Deep Neural Network:

Q-Value : $Q_\pi(s_t, a_t)$ $\quad a_t^* \leftarrow \mu(s_t|\theta^\mu)$



The optimal action at∗ is identified by maximizing the Q-value for a specific state. To approximately determine the best action, a deep neural network fθ(s) directly links a continuous state to its optimal action. The network is trained to estimate the parameters θ∗ guiding the control policy.

Robust Deep deterministic policy Gradient



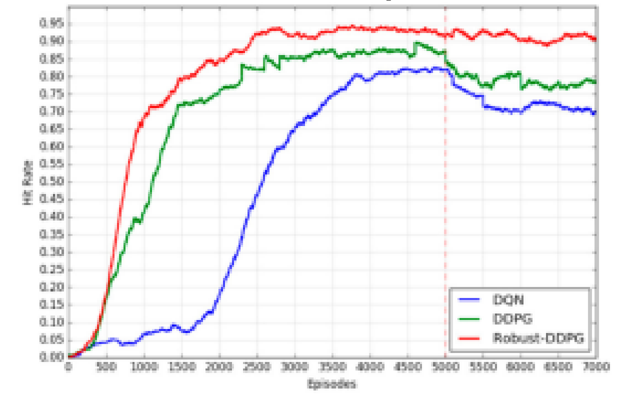
Mixed Exposition Trick

Algorithm 3: Mixed exploration trick (with DDPG)
1: **ActionExplore**$(\mu(s\|\theta^\mu), s_t, \epsilon_t)$
2: **if** $rand < \epsilon_t$ **do**
3: $a_t = Uniform(a_{low}, a_{high})$
4: **else do**
5: $a_t = \mu(s_t\|\theta^\mu) + OU(u, \vartheta, \sigma)$
6: $a_t = clip(a_t, a_{low}, a_{high})$
7: **end if**
8: **return** a_t

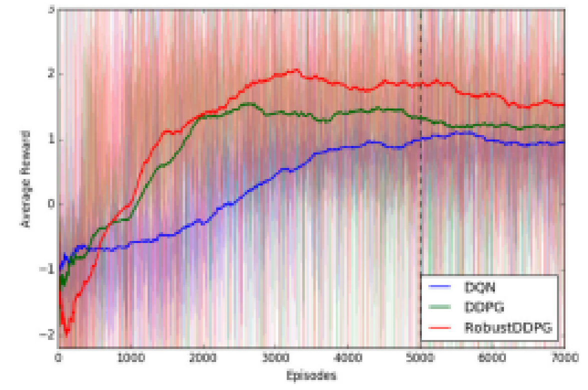
Function which randomly chooses, depending on the € parameter, between a uniform action or one influenced by noise OR. The action is either uniformly selected between [alow, ahight) or adjusted by noise OR and clipped within the allowed limits.

Results

Hit Rate VS Episodes



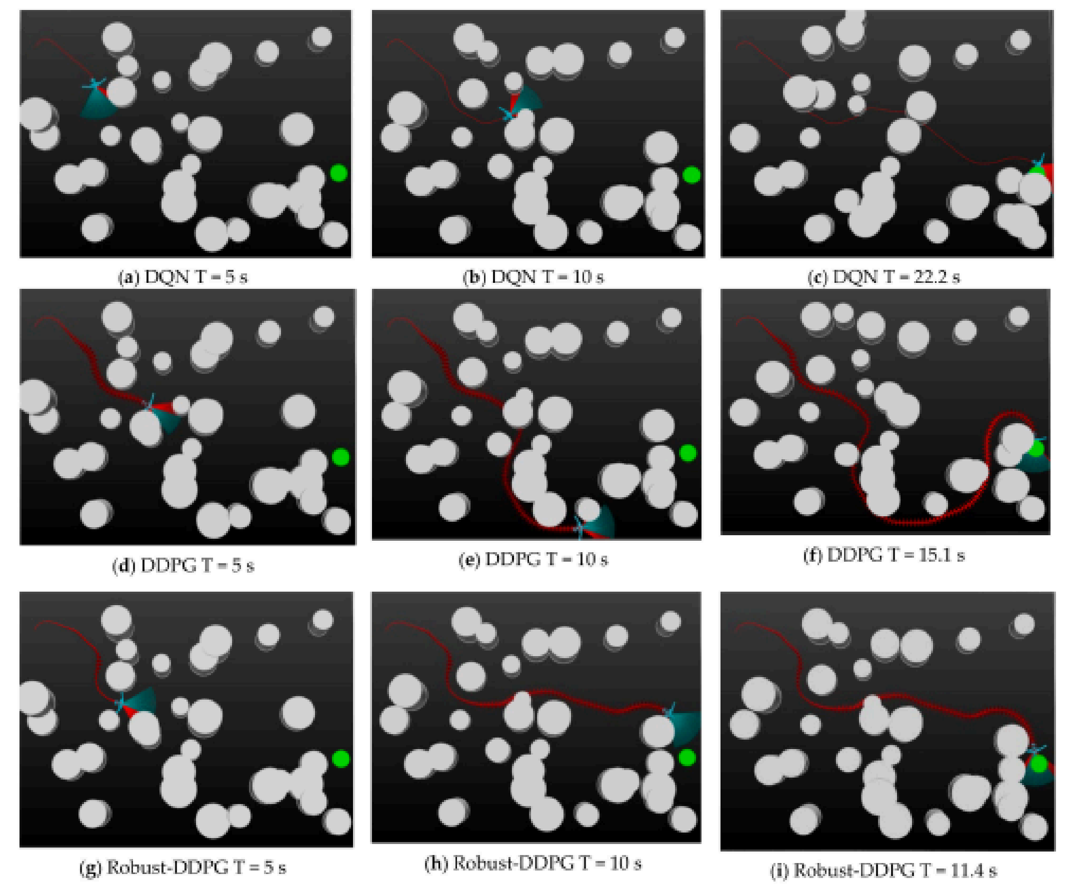
Average Reward VS Episodes



Set of results on several algorithms

	Learning Stage			Exploiting Stage		
	Hit Rate	Crash Rate	Lost Rate	Hit Rate	Crash Rate	Lost Rate
DQN	82.4%	15.1%	2.5%	70.2%	22.1%	7.7%
DDPG	88.7%	9.8%	1.5%	78.9%	17.9%	3.2%
Robust-DDPG	**92.6%**	**6.8%**	**0.6%**	**91.0%**	**7.4%**	**1.6%**

Test

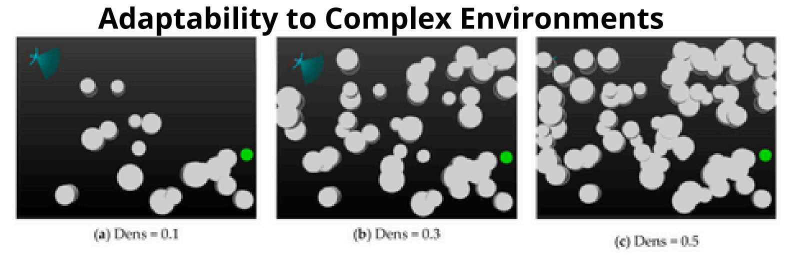


(a) DQN T = 5 s (b) DQN T = 10 s (c) DQN T = 22.2 s
(d) DDPG T = 5 s (e) DDPG T = 10 s (f) DDPG T = 15.1 s
(g) Robust-DDPG T = 5 s (h) Robust-DDPG T = 10 s (i) Robust-DDPG T = 11.4 s

Set of results on several algorithms

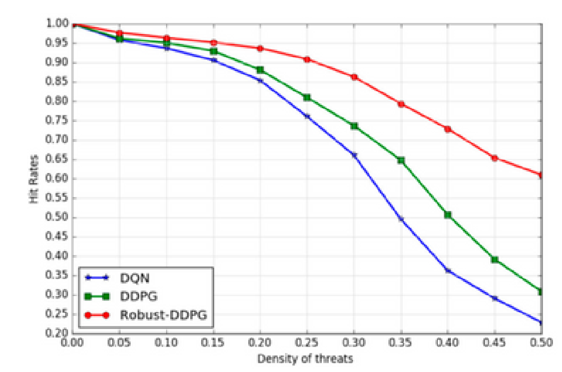
Agent	Flight Time	Path Length
DQN	22.2 s	463.2 m
DDPG	15.1 s	651.1 m
Robust-DDPG	**11.4 s**	**443.5 m**

Adaptability to Complex Environments

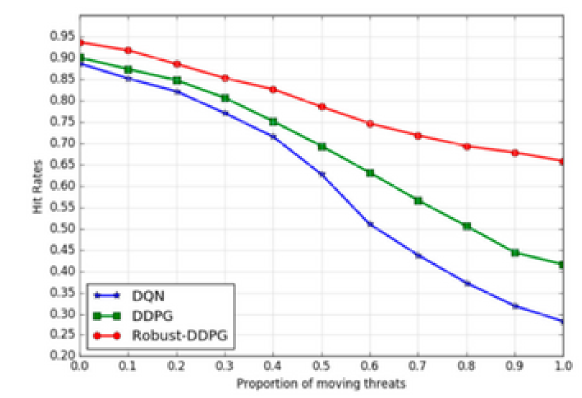


(a) Dens = 0.1 (b) Dens = 0.3 (c) Dens = 0.5

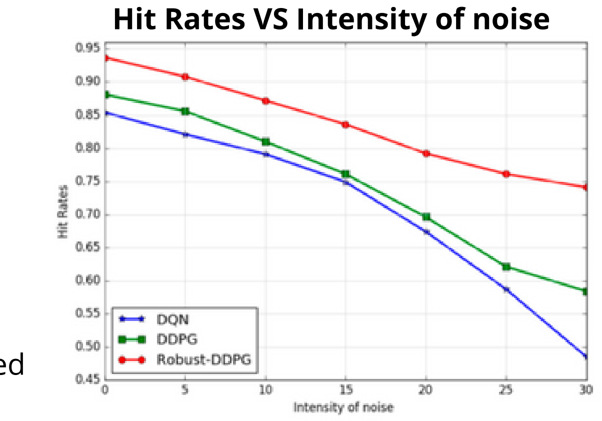
Hit Rates VS Density of threats



Hit Rates VS Proportion of moving threats



Hit Rates VS Intensity of noise



Sources

Article 1: HAL open science : véhicule autonome avec RL
Article 2 : HAL open science : Machine Learning UAV-Assisted
Article 3: HAL open science : drones à base RL
Article 4 : Remote Sensing : Robust-DDPG