PIR : Mixed-Initiative Mission

Thomas Vagneron

Summary

- Context
- Theory
- Experiment
- Conclusion

Context and Goal

Human-machine systems

Increasing use of automated systems

aircrafts, cars or even games player (A fresh example is AlphaGo which is a Go playing machine).

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Human factors involved in 80% of AAVs accidents! [Wil]

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- stress (danger, pressure)
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Consequences:

- mental confusion
- attentional tunneling
- mind wandering
- lower vigilance
- ...

increase in accident risk resulting in mission fails

Context and Goal

use of human state feedbacks!

beamer-onera-head

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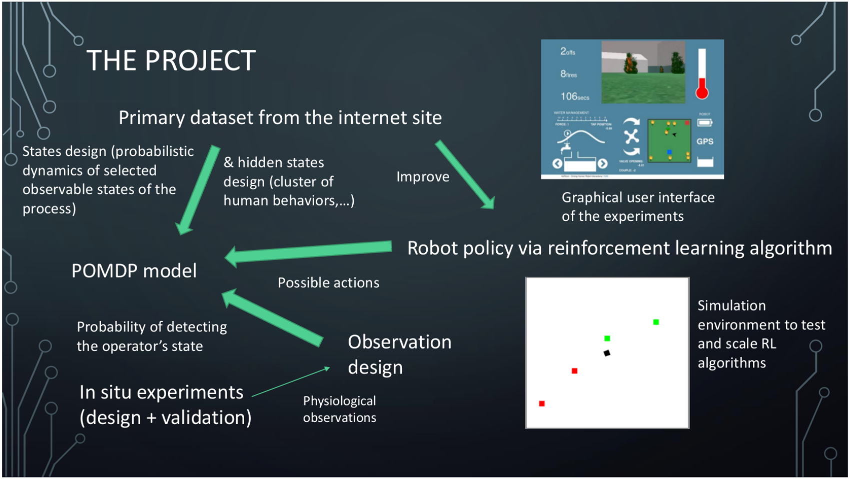
- search and rescue task (AAVs) [GCLD16]
  - **device:** eye tracking
  - **human state:** *current human task* = human gaze
  - **superv. validation:** tested on 10 volunteers

Context and Goal

The Project



Theory

History

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An approach to experimental psychology : Law of effects (Thorndike, 1911)

" The greater the satisfaction or discomfort, the greater the strengthening or weakening of the bond".

Theory

Reinforcement Learning

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- the actions
- the rewards

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RL objectives :

the automatized acquisition of skills for decision making in a complex and uncertain environment and learning by "experience" a behavioral strategy (named policy) reflecting the failures and success (reinforcements or rewards).

Theory

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Markov Chain

a dynamic system with discrete time $(x_t)_{t \in \mathbb{N}} \in X$, where X is space of states such as :

$$\mathbb{P}(x_{t+1} = x | x_t, x_{t-1}, \dots, x_0) = \mathbb{P}(x_{t+1} = x | x_t).$$

Markov Decision Process (MDP)

defined by (X, A, p, r), where :

- X space of states
- A space of actions
- $p(y|x, a)$: probability of transition from a state $x \in X$ to $y \in X$ when the action $a \in A$ is chosen:

$$p(y|x, a) = \mathbb{P}(x_{t+1} = y|x_t = x, a_t = a),$$

- $r(x, a, y)$: reward when passing from x to y using the action a.

Theory

Value function and Bellman operator

Value function

The value function are defined over the state space :
for $x \in X$, $V(x)$ is the mean of the sum of the rewards over time for a process starting in x.

$$V^{\pi}(x) = \mathbb{E}[\sum_{t \geqslant 0} r(x_t, \pi(x_t))]$$

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Bellman operator

Written T^{π}, it is defined by :

$$T^{\pi} = V^{\pi}(x) = r(x, \pi(x)) + \sum_{x'} p(x'|x, a) V(x')$$

Theory

Some solving methods

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- **Direct solving** of the linear system $(I - \gamma P^{\pi})V^{\pi} = r^{\pi}$. That's the Gauss elimination method, but it have a complexity of $O(N^3)$
- **Iteration on the values for a permanent policy** : we iterate on the operator T^{π} (Bellman operator). Considering a given value function V_0, $V_{n+1} = T^{\pi} V_n$. We have then convergence of V_n toward V^{π}. The problem is that the convergence is asymptotical, but the advantage is that it as a lower complexity than the direct solving method ($O(N^2 \frac{log(1/\epsilon)}{log(1/\gamma)})$ for an approximation of ϵ (interesting if γ is not too close from 1)).

- **Monte-Carlo** : we simulate n trajectories $((x_t^i)_{t \geqslant 0})_{1 \leqslant i \leqslant n}$, starting from x and following the policy π : $x_{t+1}^i \; p(.|x_t^i, \pi(x_t^i))$, so :

$$V^{\pi}(x) \approx \frac{1}{n} \sum_{i=1}^{n} \sum_{t \geqslant 0} \gamma^t r(x_t^i, \pi(x_t^i)).$$

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- **Temporal differences TD(λ)** : This is a smart method for using the trajectories to evaluate all the states crossed by those trajectories, by evaluating the value of a state x, by the sum of the observed temporal differences $r_t + \gamma V(x_{t+1}) - V(x_t)$ at the future instants t, weighted by a "trace" λ.

The impact of the temporal differences of future transitions on the estimation of the current state value is controled by λ.
TD(λ) is a compromise between :

- **TD(0)** (to estimate the fixed point of the operator of Bellman T^π):

$$V_{n+1}(x_k) = V_n(x_k) + \eta_n(x_k) d_k.$$

- **TD(1)** (to estimate the mean):

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the choice of λ :

- $\lambda < 1$ allows to reduce the variance of the estimators compared with $\lambda = 1$.
- $\lambda > 0$ allows to propagate faster the rewards compared with $\lambda = 0$.

Theory

TD(λ)

the algorithm TD(λ) After the observation of a trajectory $(x_0, x_1, \ldots, x_K = 0)$, we update V_n to the states $(x_k)_0 \leqslant k < K$ following :

$$V_{n+1}(x_k) = V_n(x_k) + \eta_n(x_k) \sum_{l=k}^{K-1} \lambda^{l-k} d_l,$$

$$\text{where } d_l = r^\pi(x_l) + V_n(x_{l+1}) - V_n(x_l).$$

with η_n the learning step, typically $\frac{1}{n}$.

the algorithm TD(λ) in the actuated case : We can define the actuated value function when, at each time step, the process is stopped with probability $1-\gamma$ with $0<\gamma<1$:

$$V^{\pi}(x) = \mathbb{E}[\sum_{t \geqslant 0} \gamma^t r(x_t, \pi(x_t))].$$

Algorithm TD(λ) becomes

$$V_{n+1}(x_k) = V_n(x_k) + \eta_n(x_k) \sum_{t \geqslant k} (\gamma\lambda)^{l-k} d_l.$$

Experiment

The mission

A search and fight type mission : the firefighter

Experiment

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A search and fight type mission : the firefighter

The objectives : extinguish the maximum number of fire

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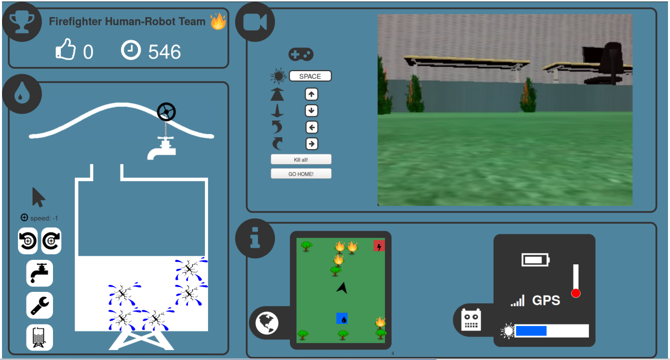
The mission

A search and fight type mission : the firefighter

The objectives : extinguish the maximum number of fire

The drawbacks :

- the battery
- the water level
- the temperature



Experiment
The environments

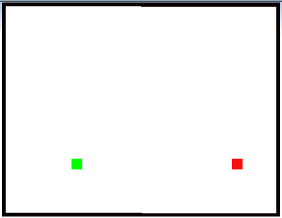


Figure : View of the simulation of the simple environment

Experiment

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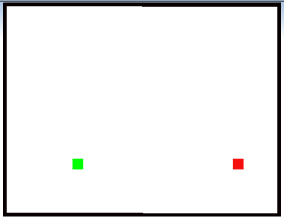

Figure : View of the simulation of the simple environment

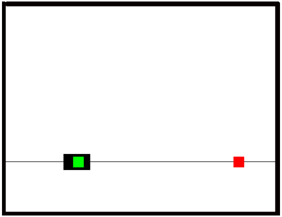

Figure : View of the simulation of the 1D environment

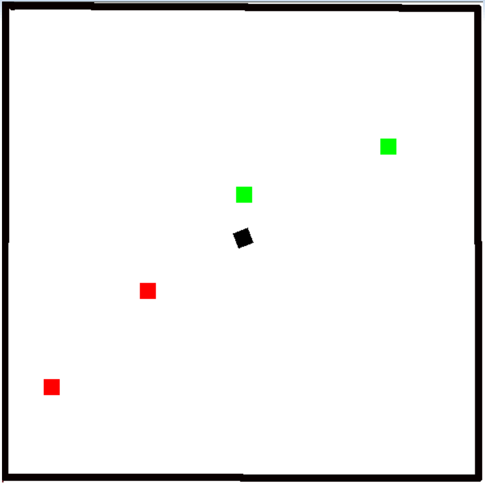

Figure : View of the simulation of the 2D environment

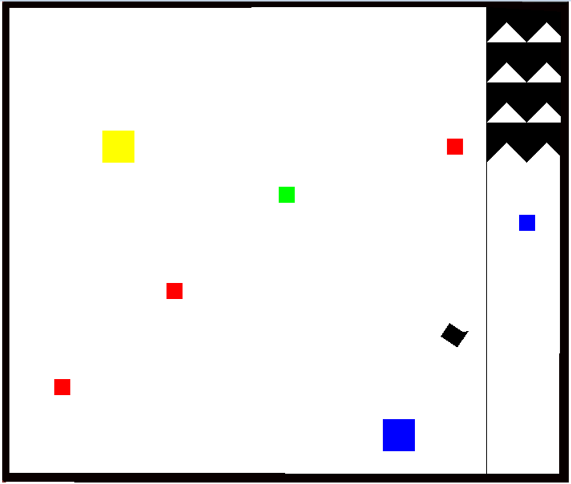

Figure : View of the simulation of the complex 2D environment

Experiment

Results

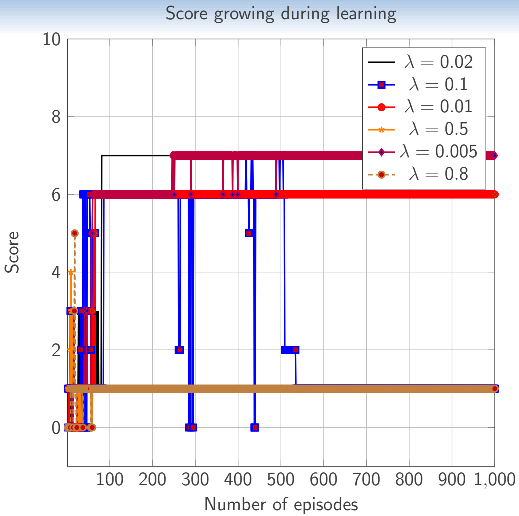

Figure : Score of the deterministic 1D environment for λ

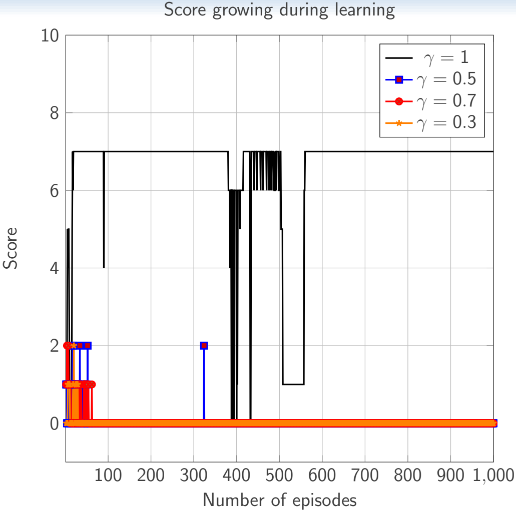

Figure : Score of the deterministic 1D environment for γ

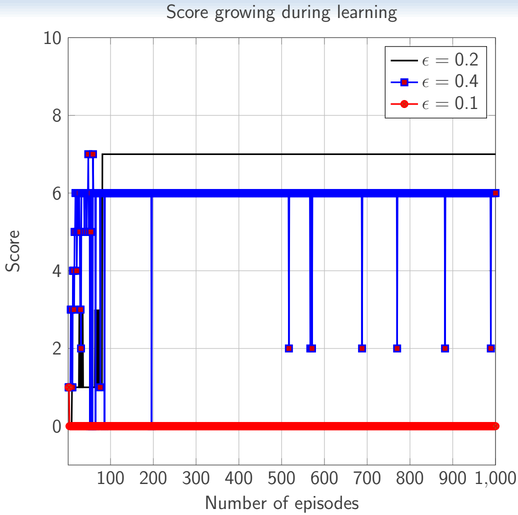

Figure : Score of the deterministic 1D environment for ϵ

Conclusion

Thibault Gateau, Caroline Ponzoni Carvalho Chanel, Mai-Huy Le, and Frédéric Dehais.
Considering human's non-deterministic behavior and his availability state when designing a collaborative human-robots system.
In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, IROS '16, 2016.

Paulo Eduardo Ubaldino de Souza, Caroline Ponzoni Carvalho Chanel, and Frederic Dehais.
Momdp-based target search mission taking into account the human operator's cognitive state.
In *Proceedings of the IEEE International Conference on Tools with Artificial Intelligence*, ICTAI '15, 2015.

Kevin W. Williams.
A summary of unmanned aircraft accident/incident data: Human factors implications.
U.S. Department of Transportation, Federal Aviation Administration, Civil Aerospace Medical Institute.

Thank you!