RoboSurgery

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Abstract

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Contents

1 Introduction

The goal of this project is to simulate a surgical robot for exploring lungs of patients.

2 Related Work

3 Probkem Statement

4 POMDP

Formal description of Partially Observable Markov Decision Process as in [3]

Formally, a POMDP is a 7-tuple $(S, A, T, R, \Omega, O, \gamma)$, where:
S is a set of states,
A is a set of actions,
T is a set of conditional transition probabilities between states,
$R : S \times A \to \mathbb{R}$ is the reward function.
Ω is a set of observations,
O is a set of conditional observation probabilities,
$\gamma \in [0, 1)$ is the discount factor.

5 Mathematical Formulation

5.1 State Space

We are interested in the estimation of the deformaition parameters of an object in a 2D space.

$$s = (\theta)$$

θ represents the deformation tensor.

5.2 Action Space

The action space is the set of all possible actions that the robot can take, Forwards, Backwards, Left, Right.

5.3 Observation Space

The observation space is the set of all possible observations that the robot can make, i.e. the presence or absence of an obstacle in its field of view.

5.4 Bayesian estimation

rendere il belief indipendente dalla posizione e orientazione del robot, dipenderò unicamente dalla deformazione

$$b(s) = b(theta) * \delta(xyphi = real(xyphi))$$

real(xyphi) = x* from now on x = xyphi

$$\begin{aligned}
b'_{a,o}(x', \theta') &= \eta \cdot \delta(x' = x^* + a) \cdot p(o|x', \theta') \cdot \sum_{x,\theta} p(x', \theta'|x, \theta, a) b(x, \theta) \\
&= \eta \cdot \delta(x' = x^* + a) \cdot p(o|x', \theta') \cdot b(x' - a, \theta') \\
&= \eta \cdot \delta(x' = x^* + a) \cdot p(o|x', \theta') \cdot \delta(x' - a = x^*) b(\theta') \\
&= \eta \cdot \delta(x' = x^* + a) \cdot p(o|x', \theta') \cdot b(\theta') \\
&= \eta \cdot \delta(x' = x^* + a) \cdot b'_{a,o}(\theta')
\end{aligned}$$

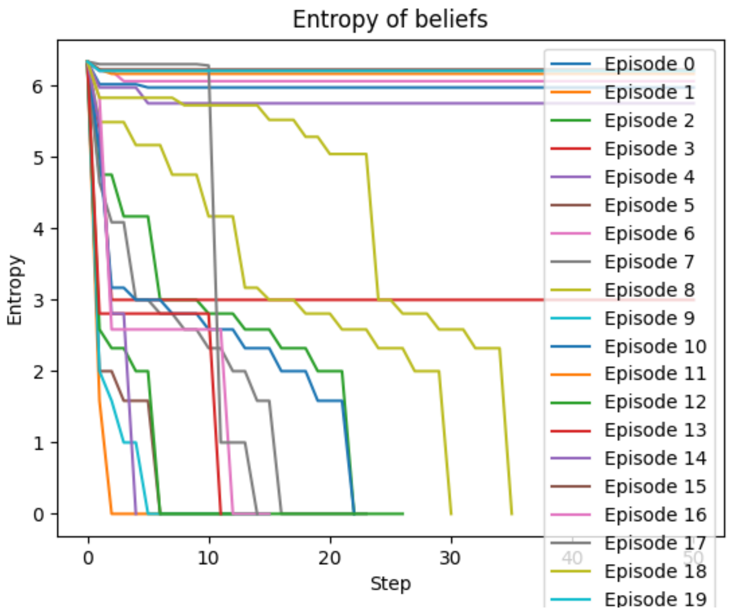
dunque a seconda della azione scelta i non zero saranno i 4 x raggiungibili con a

$$\begin{aligned}
p(o|b, a) &= \sum_{x,\theta} p(o|x, \theta) b(x.\theta) \\
&= \sum_{\theta} p(o|x^*, \theta) b(\theta)
\end{aligned}$$

6 Results

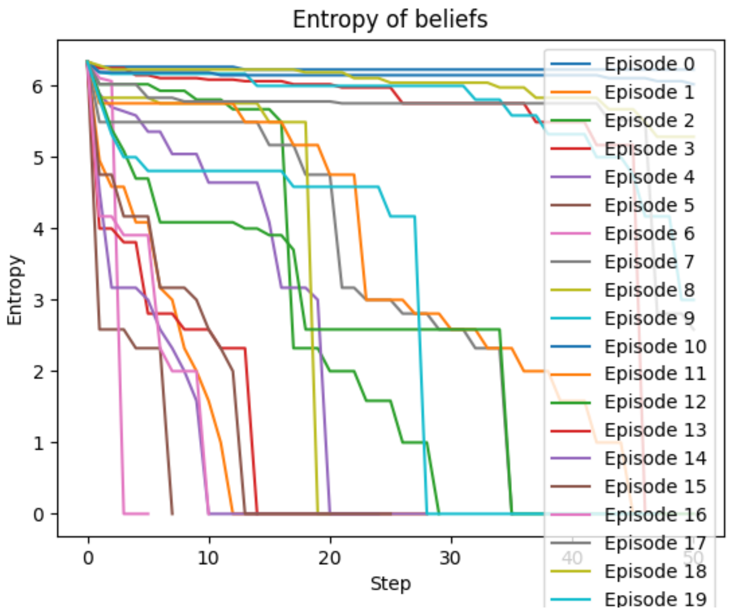
6.1 MDP Solution

6.2 QMDP



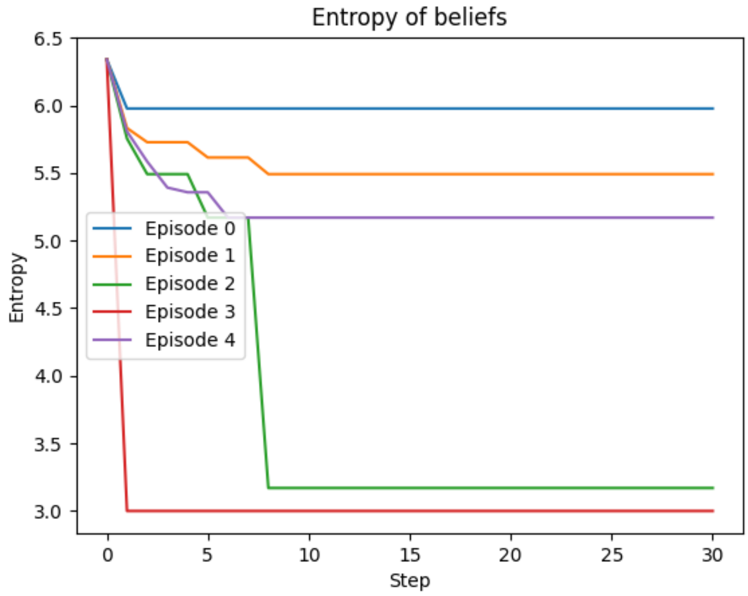
reaching target 13 out of 20 times.

6.3 Thompson Sampling



reaching target 14 out of 20 times.

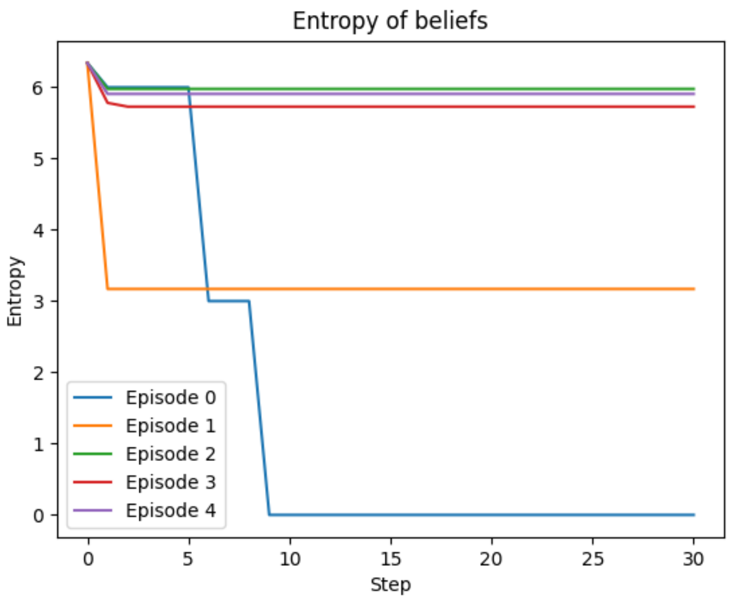
6.4 Infotaxis



reaching target 15 out of 20 times.

6.5 Information Directed Sampling

[2]



reaching target 0 out of 5 times

6.6 DQN

References

[1] Aurore Loisy and Christophe Eloy. Searching for a source without gradients: how good is infotaxis and how to beat it. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 478(2262), June 2022.

[2] Daniel Russo and Benjamin Van Roy. Learning to optimize via information-directed sampling, 2017.

[3] Matthijs T. J. Spaan. *Partially Observable Markov Decision Processes*, pages 387–414. Springer Berlin Heidelberg, Berlin, Heidelberg, 2012.