Paper Reading No.20

Multiple Landmark Detection Using Multi-agent Reinforcement Learning

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1 Brief Paper Intro

- ***Paper ref:*** MICCAI 2019, https://doi.org/10.1007/978-3-030-32251-9_29 https://github.com/thanosvlo/MARL-for-Anatomical-Landmark-Detection
- ***Authors:*** See Fig 1.

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Figure 1: authors' brief intro.

- ***Paper summary:*** **Start point:** anatomical landmarks are independent and non-random within the human anatomy, thus finding one landmark can help to deduce the location of others. This paper proposes a new detection approach for multiple landmarks based on multi-agent reinforcement learning.

- ***Reading motivation:*** Using a multi-agent DQN for finding landmarks, and meanwhile maintaining the relationship or connection between landmark, this concept attract me.

2 Methods

Locating anatomical landmarks accurately is crucial. This paper has a start point that the position of all anatomical landmarks is interdependent and non-random within the human anatomy, thus finding one landmark can help to deduce the location of others. So this paper try to solve this problem by detecting multiple landmarks efficiently and simultaneously by sharing the agents' experience. Authors extend the formulation of landmark detection as a Markov Decision Process (MDP), where artificial agents learn optimal policies towards their target landmarks, which defines a concurrent Partially Observable Markov Decision Process (co-POMDP).

Just like the setting of other RL-based landmark detection [**?**], this paper consider the environment to be a 3D scan of the human anatomy and define a state as a Region of Interest (ROI) centred around the location of the agent. So, each agent can move along the x, y, z axis, a set of six actions. The reward function is defined as the relative improvement in Euclidean distance between their location at time t and the target landmark location.

It's worth mentioned that **till now**, the RL setting is nothing special towards the non-multi-agents RL-based landmark detection methods, where this task is considered a single agent looking for a single landmark.

This paper's multi-agent setting is depicted as Fig 2, called as a col-

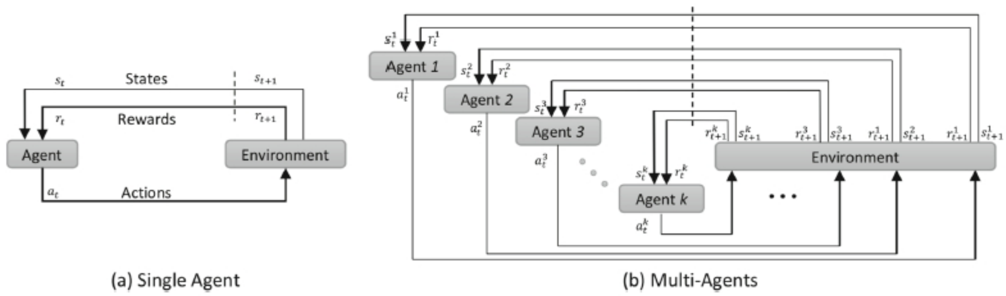

Figure 2: (a) A single agent and (b) multi agents interact within an RL environment.

laborative multi agent landmark detection framework (Collab-DQN). In this setting, each agent still calculated its individual reward. An episode is defined as the time the agents need to find the landmarks (within 1mm) or until they have completed a predefined maximum number of steps.

The architecture of proposed collab-DQN is depicted in Fig 3 (two agents for simply presentation). This architecture is Siamese-like, where the conv layers are shared while the FC layers remain independent.

Sharing the weights across the convolutional layers helps the network to learn more generalized features that can fit both inputs while adding an implicit regularization to the parameters avoiding over-fitting. The shared weights enable indirect knowledge transfer in the parameter space between the agents.

3 Results

The proposed method is tested on landmark detection in brain and cardiac MRI volumes. Fig 4 show the performance of the brain MRI and fetal brain US landmarks using the different approaches. Here, DQN method is chosen, not A3C, because they use siamese model, and the A3C are compu-

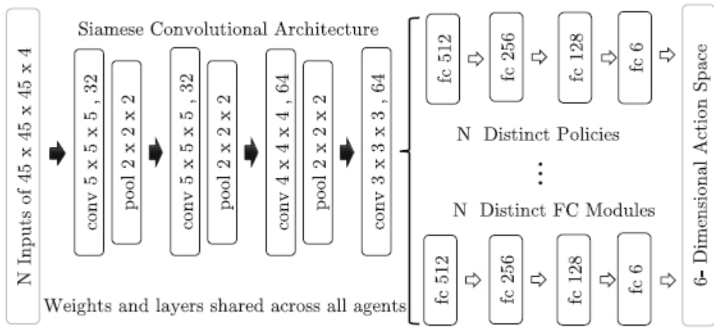

Figure 3: Proposed Collaborative DQN for the case of two agents.

Method	AC	PC	RC	LC	CSP
Supervised CNN	–	–	–	–	5.47 ± 4.23
DQN	2.46 ± 1.44	2.05 ± 1.14	3.37 ± 1.54	3.25 ± 1.59	$\mathbf{3.66 \pm 2.11}$
Collab DQN	$\mathbf{0.93 \pm 0.18}$	$\mathbf{1.05 \pm 0.25}$	$\mathbf{2.52 \pm 2.25}$	$\mathbf{2.41 \pm 1.52}$	3.78 ± 5.55

Figure 4: Results in millimeters for the various architectures on landmarks across brain MRI and fetal brain US. Our proposed Collab DQN performs better in all cases except the CSP where we match the performance of the single agent.

tationally expensive.