C-MARL: Communicative Reinforcement Learning Agents for Landmark Detection in Brain Images

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Introduction

Novel communicative multi-agent reinforcement learning (C-MARL) system to automatically detect landmarks in 3D medical scans

Motivation

Accurate detection of the landmarks is a vital step for several medical applications such as:

- Image registration
- Biometric measurements of anatomical structure
- Extraction of 2D clinical standard planes

Challenges

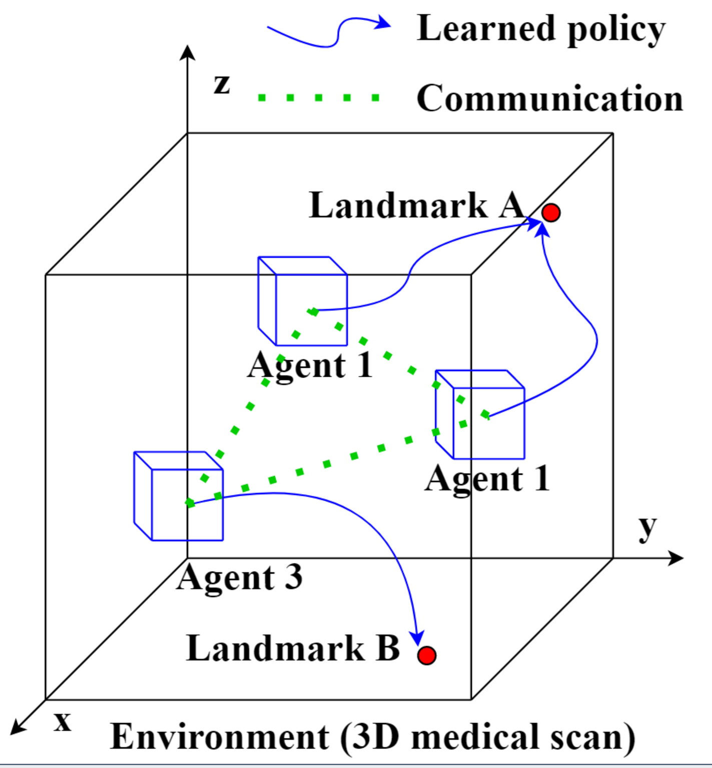
- Noisy scans, large inter- and intra-observer errors
- Requires a lot of scans annotated by expert clinicians

RL Environment

- Multi-agents interact with the 3D image environment ***E***
- At every step, each agent takes an action ***a*** towards a target landmark
- Sequential actions are taken based on the maximum accumulated reward signals ***r***
- The optimized policy is formed by the path between the starting points and the target landmarks
- The policy is learned using the Deep Q-network (DQN) [Mnih et al. 2013] algorithm:

$$L_i(\theta_i) = E_{s,a,r,s'}\left[\left(r + \gamma \max_{a'} \hat{Q}(s',a';\hat{\theta}_i) - Q(s,a;\theta_i)\right)^2\right]$$

- Agents learn to communicate during their search for different landmarks



C-MARL

Environment - 3D medical brain image

States - 4 stacked RoI per agent

Action space - Step in one of six directions (left, right, up, down, forward, and backward)

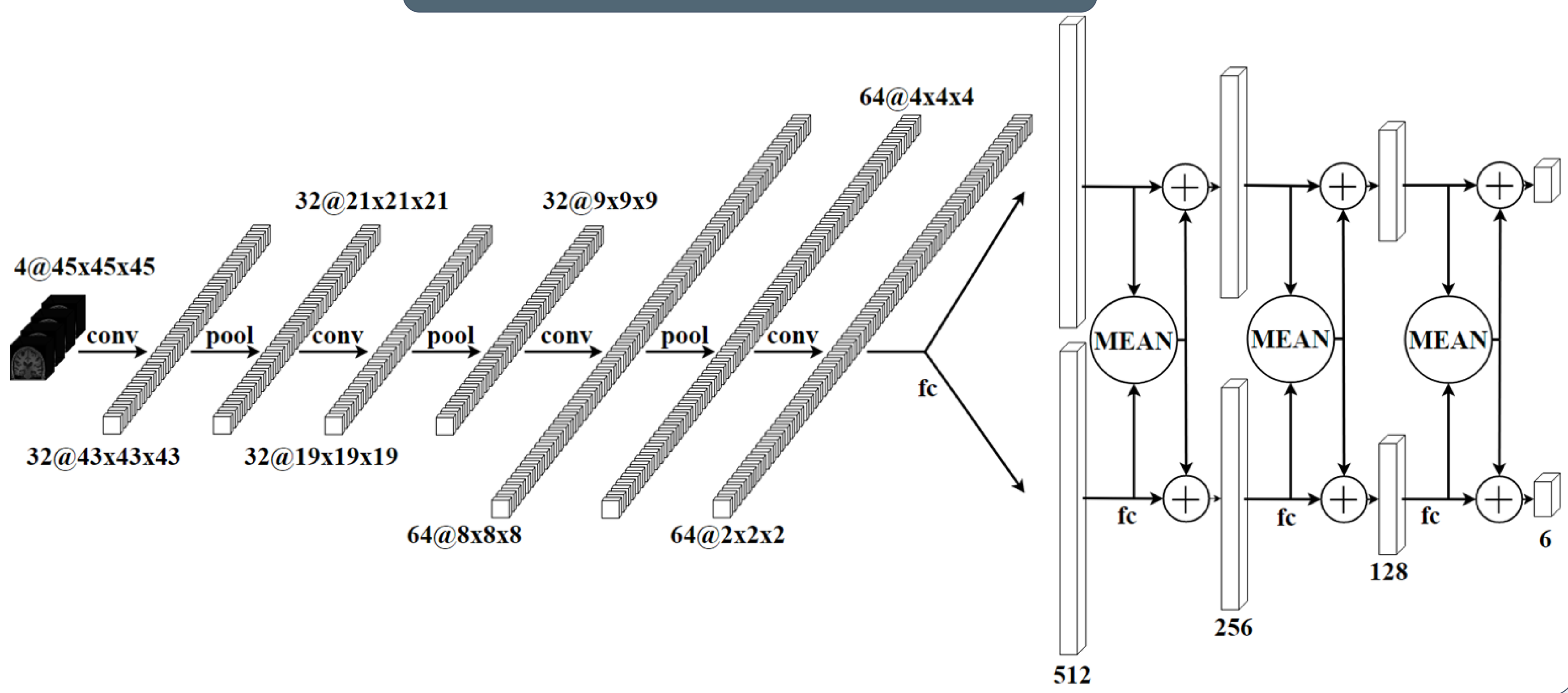
Reward - Euclidean distance difference between the agent's previous distance to the landmark and its current one

Terminal state - The state with the lowest q-values when the agents oscillate [Riedmiller 1998]

Implicit communication - Convolution layers are shared for all agents, allowing them to collectively learn image features

Explicit communication - Each agent has its own fully connected layer, which shares information with other agents via communication channels

C-MARL Architecture (with 2 agents)



Experiments

Training

1. Select random positions for the agents
2. Follow ε-greedy policy
3. When agents oscillate, reduce their RoI and step size (if at lowest scale, end episode)

Evaluation

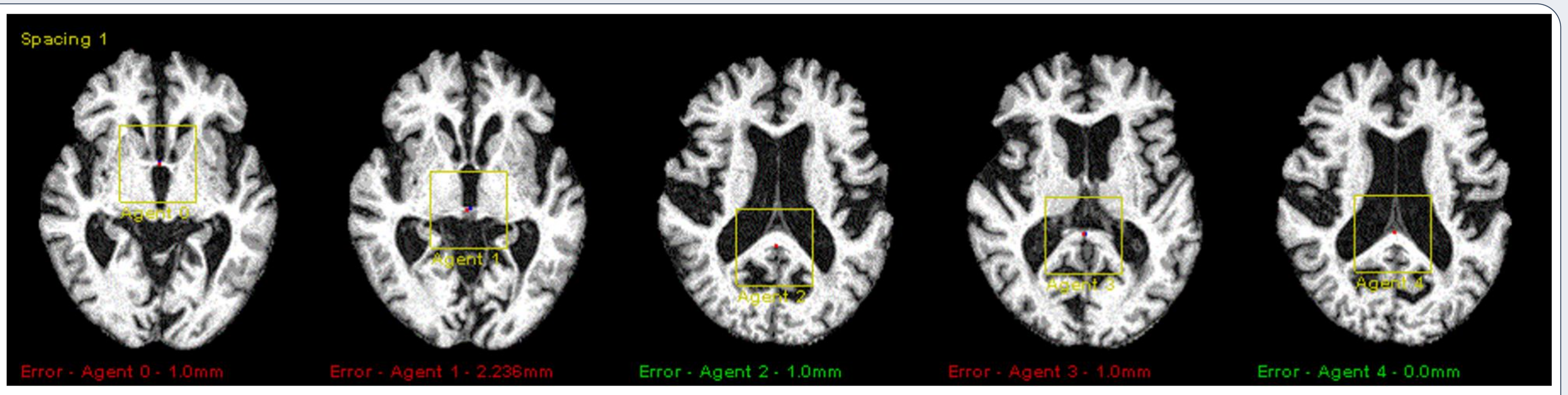
- Distance error between anatomical landmarks and their respective agents

Runtime (GPU: GTX 1080)

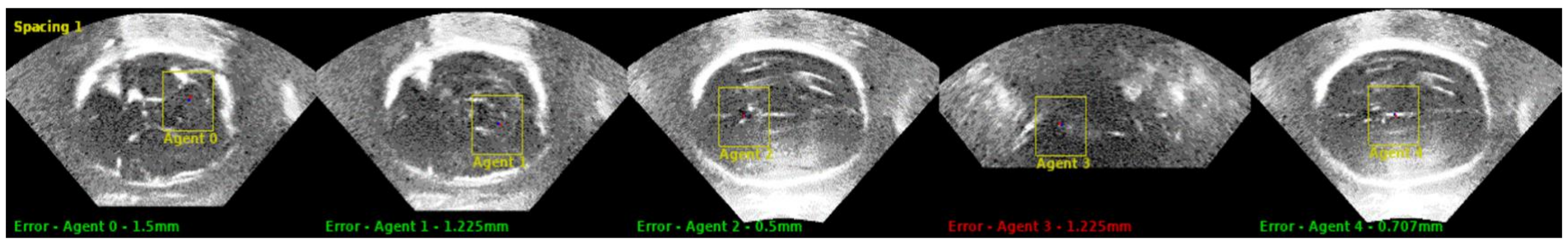
- Training: 2-4 days
- Testing: 2-5 seconds per scan (3-5 agents respectively)

Datasets

- Dataset I: 832 T1-weighted 1.5T MRI brain scans from the ADNI dataset
- Dataset II: 72 3D fetal head ultrasound scans from the iFIND project



Adult MRI



Fetal Head Ultrasound

Results

[Experiment-I] Brain MRI - Multiple agents search for different landmarks

- Each of the 3/5/8 agents look for their respective landmarks
- AC/PC: anterior/posterior commissure, SCC: splenium of the corpus callosum
- All distance errors are in mm
- C-MARL outperforms other methods in most of the landmarks

	Single	Collab-DQN [17]			C-MARL		
Landmark	**agent [2]**	**3 agents**	**5 agents**	**8 agents**	**3 agents**	**5 agents**	**8 agents**
AC	1.14±0.53	1.16±0.59	1.13±0.64	1.21±0.92	**1.04±0.58**	1.12±0.65	1.84±0.91
PC	1.18±0.55	1.25±0.57	1.19±0.61	1.22±0.93	**1.13±0.66**	1.25±0.55	1.38±0.64
Outer SCC	1.47±0.64	1.38±0.75	1.51±0.77	1.46±0.90	**1.35±0.66**	1.62±0.79	5.20±13.49
Inferior SCC	2.40±1.13	-	**1.39±0.85**	1.53±0.87	-	1.50±0.89	1.87±1.28
Inner SCC	1.46±0.73	-	1.53±0.97	2.09±3.65	-	**1.53±0.76**	3.56±9.42

[Experiment-II] Fetal Head Ultrasound - Multiple agents search for different landmarks

- Each of the 3/5/8 agents look for their respective landmarks
- RC/LC: right/left cerebellum, CSP: cavum septum pellucidum, CH/AH: center/anterior head
- C-MARL outperforms other methods in 2 landmarks

	Single	Collab-DQN [17]			C-MARL		
Landmark	**agent [2]**	**3 agents**	**5 agents**	**8 agents**	**3 agents**	**5 agents**	**8 agents**
RC	7.23±3.54	**2.73±1.71**	4.20±3.76	3.39±2.36	6.53±4.21	4.06±2.95	4.75±3.28
LC	4.37±1.45	**4.20±2.87**	5.98±8.58	5.42±4.50	5.10±3.66	4.43±32.26	4.64±3.16
CSP	9.90±3.13	5.18±2.05	8.02±5.34	5.74±5.07	5.78±3.04	**5.13±3.51**	7.08±4.13
CH	29.43±17.83	-	14.45±5.25	16.83±12.54	-	**13.00±4.97**	16.29±8.94
AH	5.73±2.88	-	8.11±5.22	**4.10±2.26**	-	4.33±2.96	8.89±4.91

[Experiment-III] Brain MRI & Fetal Ultrasound - 5 agents search for the same landmark

- All five agents look for the same landmark
- The final location is calculated using the mean of all agents' final location
- C-MARL outperforms previous methods
- Communicating on the same landmark outperforms communication across landmarks

Landmarks	Single agents [2]	Collab-DQN [17]	C-MARL
AC	0.97±0.40	0.81±0.36	**0.75±0.34**
CSP	10.43±4.28	6.66±4.19	**5.10±4.25**

[Experiment-IV] Brain MRI - 4 agents look for 2 landmarks

- Two agents search for the same landmark (Total: 4 agents, 2 landmarks)
- The final location is calculated using the mean of all agents' final location
- Four agents communicating on two landmarks outperform one agent per landmark, but is worse than all agents on the same landmark

Landmarks	Single agents [2]	C-MARL
AC	1.17±0.61	**0.95±0.43**
PC	1.12±0.55	**0.97±0.46**

Conclusion

- Novel communicative multi-agent reinforcement learning system for detecting multiple anatomical landmarks
- Experiments on several landmarks from adult MRI and fetal head ultrasound
- Results show that allowing the agents to communicate can improve the accuracy of finding the target landmark, compared to previous single- and multi-agents approaches

Future Work

- Optimal number of agents and combination of landmarks
- Adaptive communication channels based on distance between agents
- More complex communication channels (e.g. skip connections and temporal units)
- Competitive approaches for communication instead of collaboration between the agents

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Code

https://github.com/gml16/rl-medical

https://github.com/amiralansary/rl-medical