Deep vs. Deep Bayesian: Faster Reinforcement Learning on a Multi-robot Competitive Experiment

Jingyi Huang[1][a], Fabio Giardina[2][b] and Andre Rosendo[1][c]
[1]*School of Information Science and Technology, ShanghaiTech University, China*
[2]*John A. Paulson School of Engineering and Applied Sciences, Harvard, U.S.A.*

Keywords: Reinforcement Learning, Policy Search, Robotics.

Abstract: Deep Learning experiments commonly require hundreds of trials to properly train neural networks, often labeled as Big Data, while Bayesian learning leverages scarce data points to infer next iterations, also known as Micro Data. Deep Bayesian Learning combines the complexity from multi-layered neural networks to probabilistic inferences, and it allows a robot to learn good policies within few trials in the real world. In here we propose, for the first time, an application of Deep Bayesian Reinforcement Learning (RL) on a real-world multi-robot confrontation game, and compare the algorithm with a model-free Deep RL algorithm, Deep Q-Learning. Our experiments show that DBRL significantly outperforms DRL in learning efficiency and scalability. The results of this work point to the advantages of Deep Bayesian approaches in bypassing the Reality Gap and sim-to-real implementations, as the time taken for real-world learning can quickly outperform data-intensive Deep alternatives.

1 INTRODUCTION

Deep Q-Learning (DQL) algorithms have been commonly used in robotic control and decision making areas ever since (Mnih et al., 2016) first proposed the Deep Q-Network framework. Because DQL trained on samples generated in the replay buffer without emulating a transition model, it usually required tremendous trials to learn a specific task. As a consequence, most applications were performed in simulated environment. (Lillicrap et al., 2016) and (Gu et al., 2016) applied DQL to the continuous control domain merely with simulations. (Rusu et al., 2017) learned to accomplish a real world robot manipulation task by presenting progressive networks to bridge the sim-to-real gap.

Compared to the model-free DQL, model-based RL algorithms are more sample efficient so that they allow a robot to learn good policies within fewer trials. By learning a probabilistic or Bayesian transition model, this sample efficiency can be further improved significantly (Deisenroth and Rasmussen, 2011; Gal et al., 2016; Chua, Kurtland and Calandra, Roberto and McAllister, Rowan and Levine, 2018; Depeweg et al., 2019). (Gal et al., 2016) proposed a deep Bayesian model-based RL algorithm, Deep PILCO, relying on a Bayesian neural network (BNN) transition model. It advanced the DQL algorithms used in (Lillicrap et al., 2016) and (Gu et al., 2016) in terms of number of trials by at least an order of magnitude on the cart-pole swing benchmark task.

Figure 1: The arena used for experiments. As enemies don't change position during iterations, we use two plastic boxes (in black, at the figure) to emulate their positioning, forcing our robots to use LiDAR sensors to localize them.

Utill now, Deep PILCO has been applied on a number of robotic tasks. (Gamboa Higuera et al., 2018) improved Deep PILCO by using random num-

[a] https://orcid.org/0000-0002-3410-7135
[b] https://orcid.org/0000-0002-2660-5935
[c] https://orcid.org/0000-0003-4062-5390

Huang, J., Giardina, F. and Rosendo, A.
Deep vs. Deep Bayesian: Faster Reinforcement Learning on a Multi-robot Competitive Experiment.
DOI: 10.5220/0010601905010506
In *Proceedings of the 18th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2021)*, pages 501-506
ISBN: 978-989-758-522-7

bers and clips gradients, and applied it for learning swimming controllers for a simulated 6 legged autonomous underwater vehicle. In (Kahn et al., 2017), the authors learned the specific task of a quadrotor and an RC car navigating an a priori unknown environment while avoiding collisions using Deep PILCO with bootstrap (Efron, 1982). The advantages of Deep PILCO in learning speed have been proven on simulations and single-robot experiments.

Here we propose, for the first time in the real-world, applications of Deep Learning and Deep Bayesian Learning on a multi-robot confrontation game. Our experiments aimed to solve the decision making problem of robots at the international IEEE ICRA AI Challenge, a problem which was tackled with a different approach in our previous work (Zhang and Rosendo, 2019). We compare a Deep PILCO implementation to a Deep Q Learning algorithm on this very same experiment. Our results prove that Deep PILCO significantly outperformed DQL in learning efficiency and scalability, and these results are discussed in Section 4. We conclude pointing to the advantages of Deep Bayesian Reinforcement Learning implementations over Deep Reinforcement Learning when implemented in the real world.

2 PROBLEM DEFINITION

The real-world experiments were run using a robot manufactured by DJI (Fig. 2). The robot's different hardware compositions sensed the environment and provided sensory data for the experiment. LiDAR and IMU collected data for the robot to localize both itself and the enemy robots in the map. The camera helped detect the armors of the enemy robots, which is essential to accomplish auto firing. Rasberry Pi and TX2 are two computing units of the robot.

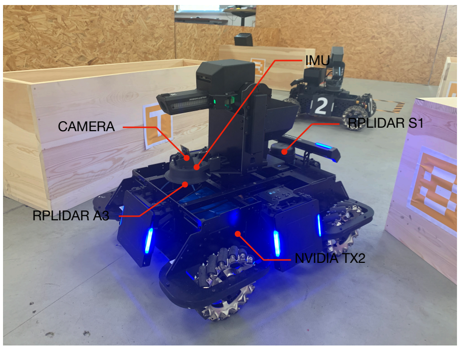


Figure 2: Hardware of the adopted robot. The robot is capable of recognizing the enemy through a combination of a LiDAR and a camera, both sensors sampled by a TX2 and a Raspberry Pi.

The multi-robot competitive problem was divided into several sub-modules as shown in Fig. 3. LiDAR-based localization module and enemy detection module transferred the Cartesian coordinates of the robots to decision making module as inputs. For decision making module, we ran RL algorithms to obtain a policy search strategy. The strategy then generated a goal position for the robot based on the current circumstance and sent it to the path planning module. Afterwards, path planning module planned a feasible path on the map to let the robot arrive at the goal position. In this paper, we focus on the implementation details of the RL methods for the decision making module.

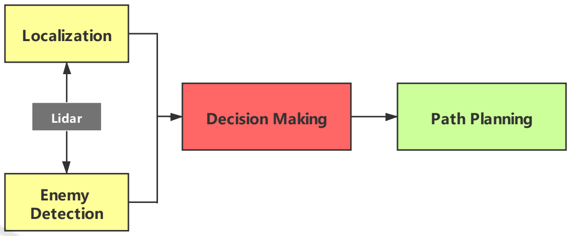


Figure 3: Main modules of the multi-robot competitive problem. We use Deep PILCO and DQL algorithms to train a policy search strategy for the decision making module.

To fulfill the Markovian property requirement of RL problems, we re-formulated the multi-robot competitive problem to be a Markov Decision Process (MDP) as follows. The MDP is composed of states, actions, transitions, rewards and policy, which can be represented by a tuple $<\mathcal{S},\mathcal{A},T,R,\pi>$.

- State: $\mathcal{S}$ is the state space which contains all possible states. Considering the map of the arena is omniscient and path planning module is independent to the RL algorithm, we projected the 3-dimensional coordinate of the robot (x,y,z) to a 1-dimensional coordinate (p), where p represents the position on the map. As shown in Fig. 4, the original map was divided into 30 strategic areas in advance. The size of each area depended on the appearing possibility of the robot during the match. Following this treatment, the state can be denoted by a tuple $(p_M, p_{E_n}, N_E,\ p_M)$ represents the position of the robot itself. p_{E_n} represents the positions of the enemy robots, where $n \in \{1,2\}$ is the index of the enemy robots. N_E represents the number of detected enemy robots discovered by the LiDAR-based enemy detection function.
- Action: $\mathcal{A}$ is the action space which consists of the actions the robot can take. For our problem, an action (p_G) is the next goal position for the robot.
- Transition: $T(s'|s,a)$ is the transition distribution

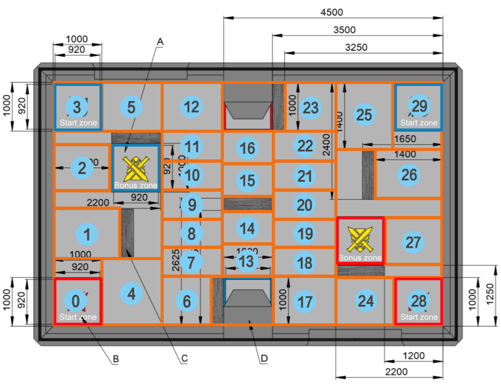


Figure 4: The original arena on the top is divided into 30 strategic areas to discretize the state space, as shown in the figure below. In the original map, the red and blue squares indicate the special regions in the competition, such as starting zones and bonus zones. These marks can be ignored in our experiments.

over the next state s', given the robot took the action a at the state s.

- Reward: $R(s)$ is the immediate reward function over state s. For this experiment, the reward was computed merely based on the number of visible enemy robots of the state s.

$$R(s) = \begin{cases} 0, & s[N_E] \neq n \quad (1a) \\ 1, & s[N_E] = n \quad (1b) \end{cases}$$

where n is the target number of visible enemy robots.

- Policy: $\pi(a|s)$ is a probability distribution of all actions under the state s. The action to be taken is given by the policy based on the state.

3 MATERIALS AND METHODS

3.1 Experimental Design

We ran the experiments in two cases. The first case was 1v1 design, which meant there was only one robot against one enemy robot, while the second case was 1v2 design, as there were one robot against two enemy robots.

The enemy robots kept static at one place during each episode. Therefore, we could just use boxes of similar sizes with the robot to represent enemy robots, as shown in Fig. 1.

3.2 Experimental Methods

3.2.1 Deep Q-Learning

Q-Learning (Watkins and Dayan, 1992) algorithms aim to solve an MDP by learning the Q value function $Q(s,a)$. $Q(s,a)$ is a state-action value function, which gives the expected future return starting from a particular state-action tuple. The basic idea is to estimate the optimal Q value function $Q^*(s,a)$ by using the Bellman equation as an update:

$$Q^*(s,a) = E_{s'}[r + \gamma \max_{a'} Q^*(s',a')|s,a]. \quad (2)$$

DQL is a variant of the Q-Learning algorithm, which takes a deep neural network as a function approximator for the Q value function where samples are generated from the experience replay buffer. Note that DQL is model-free: it solves the RL task directly using samples from the emulator, without explicitly constructing an estimate of the emulator (or transition model) (Mnih et al., 2016). Instead of updating the policy once after an episode in the model-based algorithm PILCO (Deisenroth and Rasmussen, 2011), DQL updates the Q-network with samples from the replay buffer every step.

We implemented the DQL algorithm using the Tianshou library (Weng et al., 2020), whose underlying layer calls the pytorch library (Paszke et al., 2019) for neural network-related computations. As for the model architecture, the input to the Q-network is a state vector. The two hidden layers consist of 128 neurons for simulations, 16 neurons for experiments, activated by ReLU function (Nair and Hinton, 2010). The output layer is a fully-connected linear layer with a single action output. The policy during training is ε-greedy at $\varepsilon = 0.1$. The learning rate is 0.001, and the discount factor is 0.9. The size of the replay buffer is 20000.

3.2.2 Deep PILCO

Compared to model-free deep RL algorithms, model-based RL allows higher sample efficiency, which can be further improved with a probabilistic transition model. Deep PILCO is a prominent example which utilizes a Bayesian neural network (BNN) (MacKay, 1992) to estimate the transition model (Gal et al., 2016; Gamboa Higuera et al., 2018).

The algorithm can be summarized as follows: A policy π's functional form is chosen from scratch, with randomly chosen parameters ϕ. Then, Deep PILCO executes the current policy on the real agents from the current state until the time horizon T. The new observations are recorded and appended to the whole dataset, from which a new probabilistic transition model (or more precisely, the model parameters of BNN) is re-trained. Based on this probabilistic transition model, Deep PILCO predicts state distributions from the current initial state distribution $p(X_0)$ to $p(X_T)$. In detail, the state input and output uncertainty are encoded by using particle methods. Provided with the multi-state distribution $p(X_0,\ldots,X_T)$, the cumulative expected cost $J(\phi)$ is computed, with a user-defined cost function. By minimizing this objective function (using gradient descent method), a newly optimized policy π_ϕ is obtained. Note that here we defined the cost function opposite to the reward: $Cost(X) = 1 - R(X)$.

We implement Deep PILCO in an episodic way so that the algorithm updates the policy after every episode based on the episodic rewards. The episodic reward is the sum of iteration rewards. Each episode consists of 10 iterations. During one iteration, the robot moves from the current position to the goal position given by the action along the planned path. The code is a modified version of an open-source implementation of Deep PILCO algorithm (Gamboa Higuera et al., 2018).

3.2.3 LiDAR-based Enemy Detection Function

We used a 2d obstacle detection algorithm to extract obstacles information from lidar data. Since we knew the map, we knew where the walls are. If the center of a robot was inside a wall, we filtered out this circle (Zhang and Rosendo, 2019). A screenshot taken during the algorithm running is presented in Figure 5.

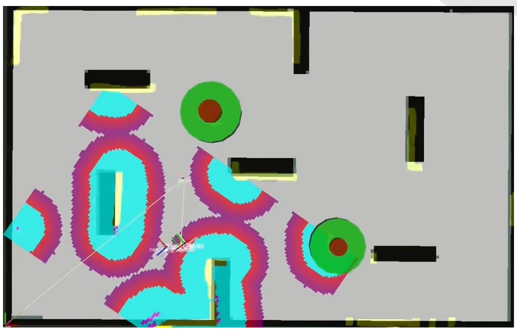


Figure 5: The visualization of the LiDAR-based enemy detection algorithm. The position of the plastic boxes (enemies) are shown in the two green circles. The navigation stack in ROS depicts the contour of the obstacles in yellow, and displays the local costmap in blue, red and purple.

4 RESULTS

We first compare the episodic rewards of DQL and Deep PILCO. In order to reveal the learning trend, we also plot the rolling mean rewards of six neighboring episodes for DQL. For the 1v1 case, both algorithms learned optimal solutions after training. In Fig. 6(a), we can see that Deep PILCO found the solution within 11 episodes, much fewer than DQL, which took around 90 episodes. Furthermore, the result of Deep PILCO stayed maximal after the optimal moment, while the result of DQL was more unsteady.

For the 1v2 case, the results of both algorithms fluctuated more than in the 1v1 case, as shown in Fig. 6(b). While the performance of Deep PILCO kept a similar number of episodes when changing from the 1v1 case to the 1v2 case, DQL failed to converge to an optimal solution even after 400 training episodes.

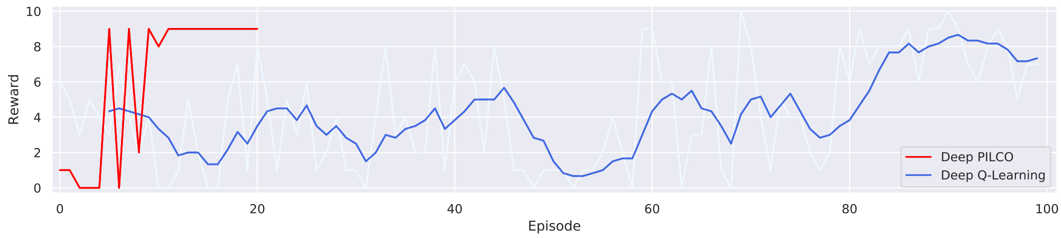
Considering the expensive training cost of real-world experiments, we stopped the experiment after 400 episodes. To eliminate the impact of the hyper parameters, we changed the learning rate parameter of DQL algorithm and reran the experiments, but DQL was still unable to find a stable optimal solution, as we can see in Fig. 7.

With regards to computation time, fewer training episodes are not necessarily equivalent to shorter training time, since each episode costs different clock time for DQL and Deep PILCO. For both algorithms, each episode contains 10 iterations, while each iteration costs about 10 seconds to run. With regards to the computation time, Deep PILCO takes approximately 1 minute per episode, while DQN takes 3 seconds per episode. To sum up, the training time for Deep PILCO is 160 seconds per episode, and 103 seconds per episode for DQL.

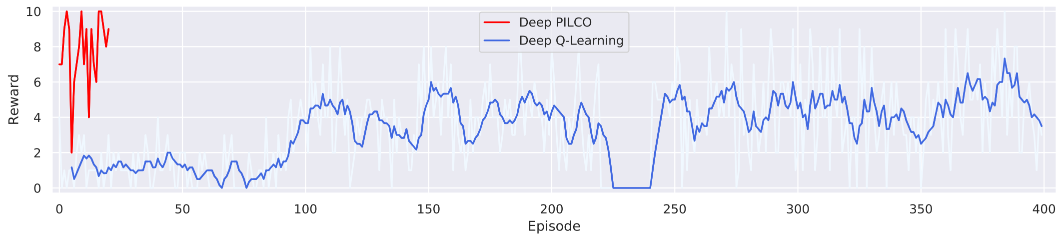
Fig. 8 displays the snapshots of our experiments with Deep PILCO for 1v2 case. The four pictures show different phases of the found optimal policy. We can see that our robot started from the initial state, where it saw none of the enemy robots, and finally navigated to an optimal position where it could see two enemy robots at the same time. In the rest of the episode, it stayed at the optimal position in order to achieve a highest episodic reward.

5 DISCUSSION

Experimental results show that Deep Bayesian RL surpassed Deep RL in both learning efficiency and learning speed. This confirms the findings of previous works in (Deisenroth and Rasmussen, 2011; Gal et al., 2016). Although for each iteration, the calcula-



(a) 1v1 case



(b) 1v2 case

Figure 6: Learning curves tracking the rewards over episodes. Deep PILCO and Deep Q-Learning were running with learning rate $\alpha = 0.001$. (a) Training rewards of DQL and Deep PILCO for 1v1 case. The red curve vanished earlier since Deep PILCO converged to the optimal reward within fewer training episodes. (b) Training rewards of DQL and Deep PILCO for 1v2 case.

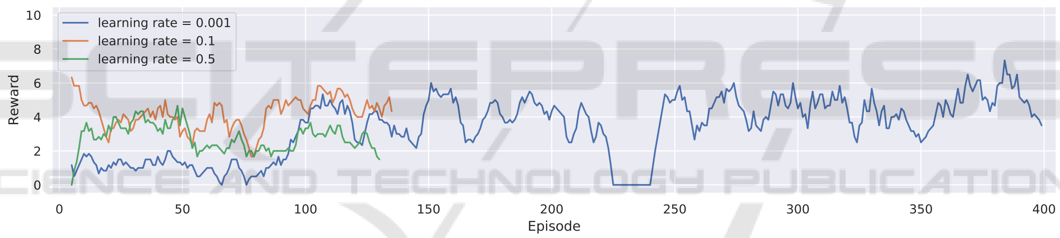


Figure 7: Training results of 3 different learning rate setup for Deep Q-Learning in 1v2 case. Empirically, learning rates with large values hinder the convergence in DQL experiments. With that in mind we ran more trials with the smallest learning rate 0.001. Nonetheless, all three experiments fail to achieve a reasonably high reward.

tion time requires for DQL is much shorter than that of Deep PILCO, the learning efficiency of the latter makes up for the cost. The transistors on a chip will double in each generation of technology as claimed by Moore's law. We presume that Deep Bayesian RL algorithms will learn policies much faster than Deep RL, with foreseeable more advanced computation hardware.

The first few training episodes of Deep PILCO in 1v2 case achieved higher initial reward than 1v1 case, as we can see in Figure 6. This is the result of a better exploration of the initial random rollouts in the 1v2 case. Yet in our experiments, the larger number of initial random rollouts did not guarantee the higher rewards, which verifies the finding in (Nagabandi et al., 2018). In this work, they evaluated various design decisions in model-based RL algorithms, including the number of initial random trajectories. They found that low-data initialization runs were able to reach a high final performance level as well, due to the reinforcement data aggregation.

6 CONCLUSIONS

We proposed a new application of Deep PILCO on a real-world multi-robot combat game. We further compared this Deep Bayesian RL algorithm with the Deep Learning-based RL algorithm, DQL. Our results showed that Deep PILCO significantly outperforms Deep Q-Learning in learning speed and scalability. We conclude that sample-efficient Deep Bayesian learning algorithms have great prospects on competitive games where the agent aims to win the opponents in the real world, as opposed to being limited to simulated applications.

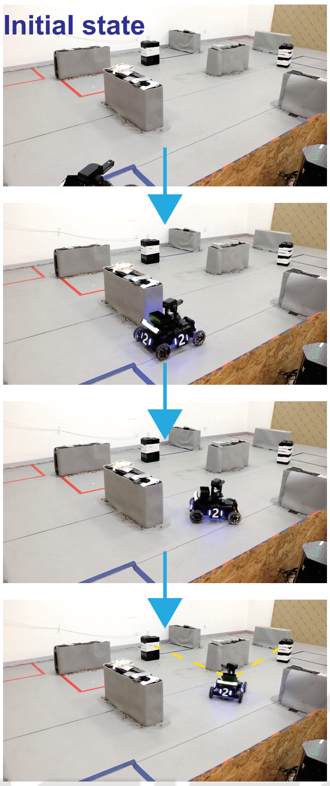


Figure 8: Snapshots of the real-world experiment for the 1 vs 2 situation. After about 15 training episodes, the robot found the optimal position to see the two enemies simultaneously. During the episode that the reward is the highest, the robot started from the initial position, and then navigated to the optimal place at the end of the first iteration. The robot stayed at the optimal place during the rest of the episode to get a maximal reward.

REFERENCES

Chua, Kurtland and Calandra, Roberto and McAllister, Rowan and Levine, S. (2018). Deep Reinforcement Learning in a Handful of Trials using Probabilistic Dynamics Models. *Advances in Neural Information Processing Systems*, (NeurIPS):4754—-4765.

Deisenroth, M. P. and Rasmussen, C. E. (2011). PILCO: A model-based and data-efficient approach to policy search. *Proceedings of the 28th International Conference on Machine Learning, ICML 2011*, pages 465–472.

Depeweg, S., Hernández-Lobato, J. M., Doshi-Velez, F., and Udluft, S. (2019). Learning and policy search in stochastic dynamical systems with Bayesian neural networks. *5th International Conference on Learning Representations, ICLR 2017 - Conference Track Proceedings*, pages 1–14.

Efron, B. (1982). *The jackknife, the bootstrap, and other resampling plans*, volume 38. Siam.

Gal, Y., Mcallister, R. T., and Rasmussen, C. E. (2016). Improving PILCO with Bayesian Neural Network Dynamics Models. *Data-Efficient Machine Learning Workshop, ICML*, pages 1–7.

Gamboa Higuera, J. C., Meger, D., and Dudek, G. (2018). Synthesizing Neural Network Controllers with Probabilistic Model-Based Reinforcement Learning. *IEEE International Conference on Intelligent Robots and Systems*, pages 2538–2544.

Gu, S., Lillicrap, T., Sutskever, U., and Levine, S. (2016). Continuous deep q-learning with model-based acceleration. *33rd International Conference on Machine Learning, ICML 2016*, 6:4135–4148.

Kahn, G., Villaflor, A., Pong, V., Abbeel, P., and Levine, S. (2017). Uncertainty-aware reinforcement learning for collision avoidance. *arXiv preprint arXiv:1702.01182*.

Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., and Wierstra, D. (2016). Continuous control with deep reinforcement learning. *4th International Conference on Learning Representations, ICLR 2016 - Conference Track Proceedings*.

MacKay, D. J. (1992). *Bayesian Methods for Adaptive Models*. PhD thesis, California Institute of Technology.

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., and Riedmiller, M. (2016). Playing Atari with Deep Reinforcement Learning.

Nagabandi, A., Kahn, G., Fearing, R. S., and Levine, S. (2018). Neural Network Dynamics for Model-Based Deep Reinforcement Learning with Model-Free Fine-Tuning. *Proceedings - IEEE International Conference on Robotics and Automation*, pages 7579–7586.

Nair, V. and Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. In *Icml*.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., et al. (2019). Pytorch: An imperative style, high-performance deep learning library. *arXiv preprint arXiv:1912.01703*.

Rusu, A. A., Vecerik, M., Rothörl, T., Heess, N., Pascanu, R., and Hadsell, R. (2017). Sim-to-Real Robot Learning from Pixels with Progressive Nets. *1st Conference on Robot Learning, CoRL 2017*, (CoRL):1–9.

Watkins, C. J. and Dayan, P. (1992). Q-learning. *Machine learning*, 8(3-4):279–292.

Weng, J., Zhang, M., Duburcq, A., You, K., Yan, D., Su, H., and Zhu, J. (2020). Tianshou. https://github.com/thu-ml/tianshou.

Zhang, Y. and Rosendo, A. (2019). Tactical reward shaping: Bypassing reinforcement learning with strategy-based goals. *IEEE International Conference on Robotics and Biomimetics, ROBIO 2019*, (December):1418–1423.