Hierarchical Reinforcement Learning for Multi-agent MOBA Game

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Abstract

Although deep reinforcement learning has achieved great success recently, there are still challenges in Real Time Strategy (RTS) games. Due to its large state and action space, as well as hidden information, RTS games require macro strategies as well as micro level manipulation to obtain satisfactory performance. In this paper, we present a novel hierarchical reinforcement learning model for mastering Multiplayer Online Battle Arena (MOBA) games, a sub-genre of RTS games. In this hierarchical framework, agents make macro strategies by imitation learning and do micromanipulations through reinforcement learning. Moreover, we propose a simple self-learning method to get better sample efficiency for reinforcement part and extract some global features by multi-target detection method in the absence of game engine or API. In 1v1 mode, our agent successfully learns to combat and defeat built-in AI with 100% win rate, and experiments show that our method can create a competitive multi-agent for a kind of mobile MOBA game King of Glory (KOG) in 5v5 mode.

1 Introduction

Since its success in playing game Atari [Mnih et al., 2015], AlphaGo [Silver et al., 2017], Dota 2 [OpenAI, 2018] and so on, Deep reinforcement learning (DRL) has become a promising tool for game AI. Researchers can verify algorithms by conducting experiments in games quickly and transfer this ability to real world such as robotics control, recommend services and so on. Unfortunately, there are still many challenges in practice. Recently, more and more researchers start to conquer real time strategy (RTS) games such as StarCraft and Defense of the Ancients (Dota), which are much more complex. Dota is a kind of MOBA game which include 5v5 or 1v1 multiplayers. To achieve a victory in MOBA game, the players need to control their only one unit to destroy the enemies’ crystal.

MOBA games take up more than 30% of the online gameplay all over the world, including Dota, League of Legends, and King of Glory [Murphy, 2015]. Figure.1a shows a 5v5 map, KOG players control movements by using left bottom steer button, while using skills by control right bottom set of buttons. The upper-left corner shows mini-map, with the blue markers pointing own towers and the red markers pointing the enemies’ towers. Each player can obtain gold and experience by killing enemies, jungles and destroying the towers. The final goal of players is to destroy enemies’ crystal. As shown in figure.1b, there are totally two players in 1v1 map.

The main challenges of MOBA game for us compared to Atari or AlphaGo are as follows: (1) \textbf{No game engine or API.} We need to extract features by multi-target detection, and run the game through the terminal, which indicates low computational power. However, the computational complexity can be up to $10^{20,000}$, while AlphaGo is about $10^{250}$ [OpenAI, 2018]. (2) \textbf{Delayed and sparse rewards.} The final goal of the game is to destroy the enemies’ crystal, which means that rewards are seriously delayed. Meanwhile, there are really sparse if we set $-1/1$ according to the final result loss/win. (3) \textbf{Multi-agent.} Cooperation and communication are crucial important for RTS games especially for 5v5 mode.

In this paper, (1) we propose hierarchical reinforcement learning for a kind of mobile MOBA game KOG, a novel algorithm which combines imitation learning with reinforcement learning. Imitation learning according to humans’ experience is responsible for macro strategies such as where to go, when to offense and defense, while reinforcement learning is in charge of micromanipulations such as which skill to use and how to move in battle. (2) As we don’t have game engine or API, in order to get better sample efficiency to accelerate the training for reinforcement learning part, we use a simple self-learning method which learns to compete with
agent’s past good decisions and come up with an optimal policy. (3) A multi-target detection method is used to extract global features composing the state of reinforcement learning in case of lacking of game engine or API. (4) Dense reward function design and multi-agent communication. Designing a dense reward function and using real-time and actual data to learn communication with each other [Sukhbaatar et al., 2016], which is a branch of multi-agent reinforcement learning research [Foerster et al., 2018]. Experiments show that our agent learns good policy which trains faster than other reinforcement learning methods.

2 Related Work

2.1 RTS Games

There has been a history of studies on RTS games such as StarCraft [Ontanón et al., 2013] and Dota [OpenAI, 2018]. One practical way using rule-based method by bot SAIDA achieved champion on SSCAIT recently. Based on the experience of the game, rule-based bots can only choose the predefined action and policy at the beginning of the game, which is insufficient to deal with large and real time state space throughout the game, and it hasn’t the ability of learning and growing up. Dota2 AI created by OpenAI, named OpenAI Five, has made great success by using proximal policy optimization algorithm along with well-designed rewards. However, OpenAI Five has used huge resources due to lack of macro strategy.

Related work has also been done in macro strategy by Tencent AI Lab in game King of Glory [Wu et al., 2018], and their 5-AI team achieved 48% winning rate against human player teams which are ranked top 1% in the player ranking system. However, 5-AI team used supervised learning and the training data can be obtained from game replays processed by game engine and API, which ran on the server. This method is not available for us because we don’t have game engine or API, and we need to run on the terminal.

2.2 Hierarchical Reinforcement Learning

Due to large state space in the environment, traditional reinforcement learning method such as Q-learning or DQN is difficult to handle. Hierarchical reinforcement learning [Barto and Mahadevan, 2003] solves this kind of problem by decomposing a high-dimensional target into several sub-target which is easier to solve.

Hierarchical reinforcement learning has been explored in different environments. As for games, somewhat related to our hierarchical architecture is that of [Sun et al., 2018], which designs macro strategy using prior knowledge of game StarCraft (e.g. TechTree), but no imitation learning and no high-level expert guidance. There have been many novel hierarchical reinforcement learning algorithms come up with in recent years. One approach of combining meta-learning with a hierarchical learning is MLSH [Frans et al., 2017], which is mainly used for multi-task and transferring to new tasks. FeUdal Networks [Vezhnevets et al., 2017] designed a Manager module and a Worker module. The Manager operates at a lower temporal resolution and sets goals to Worker. This architecture also has the ability of transferring and multitask learning. However, it’s complex and hard-to-tune.

2.3 Multi-agent Reinforcement Learning in Games

Multi-agent reinforcement learning (MARL) has certain advantages over single agent. Different agents can complete tasks faster and better through experience sharing. There are some challenges at the same time. For example, the computational complexity increases due to larger state and action space compared to single agent. Based on the above challenges, MARL is mainly focus on stability and adaption. Simple applications of reinforcement learning to MARL is limited, such as no communication and cooperation among agents [Sukhbaatar et al., 2016], lack of global rewards [Rashid et al., 2018], and failure to consider enemies’ strategies when learning policy. Some recent studies relevant to the challenges have been done. [Foerster et al., 2017] introduced a concentrated criticism of the cooperative settings with shared rewards. The approach interprets the experience in the replay memory as off-environment data and marginalize the action of a single agent while keeping others unchanged. These methods enable the successful combination of experience replay with multi-agent. Similarly, [Jiang and Lu, 2018] proposed an attentional communication model based on actor-critic algorithm for MARL, which learns to communicate and share information when making decision. Therefore, this approach can be a complement for us. Parameter sharing multi-agent gradient descent Sarsa($\lambda$) (PS-MASGDS) algorithm [Shao et al., 2018] used a neural network to estimate the value function and proposed a reward function to balance the units move and attack in the game of StarCraft, which can be learned from us.

3 Methods

In this section, we introduce our hierarchical architecture, state representation and action definition firstly. Then the network architecture and training algorithm are given. At last, we discuss the reward function design and self-learning method used in this paper.

3.1 Hierarchical Architecture

The hierarchical architecture is shown in Fig.2. There are four types of macro actions including attack, move, purchase and learning skills, and it’s selected by imitation learning (IL) and high-level expert guidance. Then reinforcement learning algorithm chooses specific action $a$ according policy $\pi$ for making micromanagement in state $s$. The encoded action is performed and we can get reward $r$ and next observation $s'$ from KOG environment. Defining the discounted return as $R_s = \sum_{t=0}^{T} \gamma^t r_t$, where $\gamma \in [0,1]$ is a discount factor. The aim of agents is to learn a policy that maximizes the expected discounted returns, $J = \mathbb{E}_\pi[ R_s ]$.

With this architecture, we relieve the heavy burden of dealing with massive actions directly, and the complexity of exploration for some sparse rewards scenes such as going to the front at the beginning of the game. Moreover, the tuple $(s, a, r)$ collected by imitation learning will be stored in ex-
Experience replay buffer and be trained through reinforcement learning network.

From the above, we can see that there are some advantages in the hierarchical architecture. First, using of macro actions decreases the dimension of action space for reinforcement learning, and solves the problem of sparse rewards in macro scenes to some extent. Second, in some complicated situations such as team battling, pure imitation learning algorithm is unable to handle well especially when we don’t have game engine or API. Last but not least, the hierarchical architecture makes training resources lower and design of the reward function easier. Meanwhile, we can also replace the imitation learning part with high-level expert system for the fact that the data in imitation learning model is produced by high-level expert guidance.

### 3.2 State Representation and Action Definition

#### State Representation

How to represent states of RTS games is an open problem without universal solution. We construct a state representation as inputs of neural network from features extracted by multi-target detection, image information of the game, and global features for all agents, which have different dimensions and data types, as illustrated in Table 1. Big-map information includes five gray frames from different agents and mini-map information is one RGB image from upper left corner of the screenshot.

Extracted features includes friendly and enemy heroes’ and towers’ position and blood volume, own hero’s money and skills, and soldiers’ position in the field of vision, as shown in Fig. 3. Our inputs in current step are composed of current state information, the last step information, and the last action which has been proven to be useful for the learning process in reinforcement learning. Moreover, states with real value are normalized to [0,1].

#### Action Definition

In this game, players can control movements by using left bottom steer button, which is continuous with 360 degrees. In order to simplify the action space, we select 9 move directions including Up, Down, Left, Right, Lower-right, Lower-left, Upper-right, Upper-left, and Stay still. When the selected action is attack, it can be Skill-1, Skill-2, Skill-3, Attack, and summoned skills including Flash and Restore. Meanwhile, attacking the weakest enemy is our first choice when the action attack is available for each unit. Moreover, we can go to a position through path planning when choosing the last action.

### 3.3 Network Architecture and Training Algorithm

#### Network Architecture

Table reinforcement learning such as Q-learning has limit in large state space situation. To solve this problem, the micro level algorithm design is similar to OpenAI Five, proximal policy optimization (PPO) algorithm [Schulman et al., 2017]. Inputs of convolutional network are big-map and mini-map information with a shape of \(64 \times 64 \times 5\) and \(32 \times 32 \times 3\) respectively. Meanwhile, the input of fully-connect layer 1 (fc1) is a 170 dimensions’ tensor extracted from feature. We use the rectified linear unit (ReLU) activation function in the hidden layer, as demonstrated by

\[
    f(x) = \max(0, x)
\]

where \(x\) is the output of the hidden layer. The output layer’s activation function is Softmax function, which outputs the probability of each action, as demonstrated by

\[
    \sigma(z)_j = e^{z_j} / \sum_{k=1}^{K} e^{z_k}
\]

where \(j=1, \ldots, K\). Our model in game KOG, including inputs and architecture of the network, and output of actions, is depicted in Fig.3.
Figure 3: Network Architecture of Hierarchical reinforcement learning model

**Training Algorithm**

We propose a hierarchical RL algorithm for multi-agent learning, and the training process is presented in Algorithm 1. Firstly, we initialize our controller policy and global state. Then each unit takes action $a_t$ and receive reward $r_{t+1}$ and next state $s_{t+1}$. From state $s_{t+1}$, we can obtain both macro action through imitation learning and micro action from reinforcement learning. In order to choose action $a_{t+1}$ from macro action $A_{t+1}$, we do a normalization of the action probability. At the end of each iteration, we use the experience replay samples to update the parameters of the policy. In order to balance the trade-off between exploration and exploitation, we take the loss of entropy and self-learning into account to encourage exploration. Our loss formula is as follows:

$$L_t(\theta) = E_t[w_1 L^v_t(\theta) + w_2 N_t(\pi, a_t) + L^p_t(\theta) + w_3 S_t(\pi, a_t)]$$  \hspace{1cm} (3)

where $w_1, w_2, w_3$ are the weights of value loss, entropy loss and self-learning loss that we need to tune, $N_t$ denotes the entropy loss, and $S_t$ means the self-learning loss. $L_t^v(\theta)$ and $L_t^p(\theta)$ are defined as follows:

$$L_t^v(\theta) = E_t[(r(s_t, a_t) + V_t(s_t) - V_t(s_{t+1}))^2] \hspace{1cm} (4)$$

$$L_t^p(\theta) = E_t[min(r_t(\theta)A_t, clip(r_t(\theta), 1 - \varepsilon, 1 + \varepsilon)A_t)] \hspace{1cm} (5)$$

where $r_t(\theta) = \pi_\theta(a_t|s_t)/\pi_{\theta_{old}}(a_t|s_t)$, $A_t$ is advantage computed by the difference between return and value estimation.

**3.4 Reward Design and Self-learning**

**Reward Design**

Reward function is significant for reinforcement learning, and good learning results of an agent are mainly depending on diverse rewards. The final goal of the game is to destroy the enemies’ crystal. If our reward is only based on the final result, it will be extremely sparse, and the seriously delayed reward makes agent difficult to learn fast. Obviously, dense reward gives more positive or negative feedback to the agent, and can help to learn faster and better. As we don’t have game engine or API, damage amount of an agent is not available for us. In our experiment, all agents can receive two parts rewards including self-reward and global-reward. Self-reward contains own money and health points (HP) loss/gain of agent, while global-reward includes tower loss and death of friendly/enemy players.

$$r_t = \rho_1 \times r_{self} + \rho_2 \times r_{global}$$

$$= p_1((money_t - money_{t-1})f_m + (HP_t - HP_{t-1})f_H) + p_2(towerloss_t \times f_t + playerdeath_t \times f_d)$$  \hspace{1cm} (6)

where $towerloss$ is positive when enemies’ tower is broken, negative when own tower is broken, the same as $playerdeath_t$. $f_m$ is a coefficient of money loss, the same as $f_H$, $f_t$ and $f_d$. $\rho_1$ is the weight of self-reward and $\rho_2$ means the weight of global-reward. The reward function is effective for training, and the results are shown in the experiment section.

**Self-learning**

There are many kinds of self-learning methods for reinforcement learning such as Self-Imitation Learning (SIL) proposed by [Oh et al., 2018] and Episodic Memory Deep Q-Networks (EMDQN) presented by [Lin et al., 2018]. SIL is applicable to actor-critic architecture, while EMDQN combines episodic memory with DQN. However, considering better sample efficiency and easier-to-tune of the system, we migrate EMDQN to our reinforcement learning algorithm PPO. Loss of self-
Algorithm 1 Hierarchical RL Training Algorithm

**Input:** Reward function $R_{s_t}$, max episodes M, function IL(s)

**Output:** Hierarchical reinforcement learning neural network.

1: Initialize controller policy $\pi$, global state $s_t$ shared among our agents;
2: for episode = 1, 2, ..., M do
3: Initialize $s_t, a_t$;
4: repeat
5: Take action $a_t$, receive reward $r_{t+1}$, next state $s_{t+1}$;
6: Choose macro action $A_{t+1}$ from $s_{t+1}$ according to $IL(s = s_{t+1})$;
7: Choose micro action $a_{t+1}$ from $A_{t+1}$ according to the output of RL in state $s_{t+1}$;
8: if $a_{t+1} \notin A_{t+1}$, where $i = 0, \ldots, 16$ then
9: $P(a_{t+1}^i|s_{t+1}) = 0$;
10: else
11: $P(a_{t+1}^i|s_{t+1}) = P(a_{t+1}^i|s_{t+1})/\sum P(a_{t+1}^i|s_{t+1})$;
12: end if
13: Collect samples $(s_t, a_t, r_{t+1})$;
14: Update policy parameter $\theta$ to maximize the expected returns;
15: until $s_t$ is terminal
16: end for

learning part can be demonstrated as follows:

$$S_i(\pi, a_t) = E_t[(V_{t+1} - V_H)^2] + E_t[min(r_t(\theta)A_{Ht}, clip(r_t(\theta), 1 - \varepsilon, 1 + \varepsilon)A_{Ht})]$$ (7)

where the memory target $V_H$ is the best value from memory buffer, and $A_{Ht}$ means the best advantage from it.

$$V_H = \max_i((\max_i(R_i(s_t, a_t))), R_i(s_t, a_t)), \text{ if } (s_t, a_t) \in \text{ memory}$$

$$A_{Ht} = V_H - V_{t+1}(s_{t+1})$$ (9)

where $i \in [1, 2, \ldots, |E|]$, $E$ represents the number of episodes in memory buffer that the agent has experienced.

4 Experiments

In this section, we introduce the experiment setting first. Then we evaluate the performance of our algorithms on two environments: (i) 1v1 map including entry-level, easy-level and medium-level built-in AI which don’t include difficult-level, and (ii) a challenging 5v5 map. For a better comprehension, we analyze the average rewards and win rates during training.

4.1 Setting

The experiment setting includes terminal experiment platform and GPU cluster training platform. In order to increase the diversity and quantity of samples, we use 10 vivo X23 and NEX phones for an agent to collect the distributed data. Meanwhile, we need to maintain the consistency of all the distributed phones when training. In the training process, we transmit the data and share the parameters of network through gRPC. As for the features obtained by multi-target detection, its accuracy and category are depicted in Table 2. In our experiment, the speed of taking an action is about 150 APM compared to 180 APM of high level player, which is enough for this game. For going to somewhere, we use A-star path planning algorithm.

4.2 1v1 mode of game KOG

As shown in Figure 1b, there are one agent and one enemy player in 1v1 map. We need to destroy the enemies’ tower first and then destroy the crystal to get the final victory. We draw the episodes needed to win when our agent fights with different level of built-in AI and different genres of internal AI.

Episodes until win

Figure 4 shows the length of episodes for our agent Angela to defeat the opponents. Higher level of the built-in AI, longer our agent need to train. Moreover, for different kinds of enemies, the training time is not the same as well. The results when our AI play against AI without macro-strategy, without multi-agent, without global reward and without self-learning method are listed in Table 3. 50 games are played against AI.1:without macro strategy, AI.2:without multi-agent, AI.3:without global reward and AI.4:without self-learning method, and the win rates are 80%, 50%, 52% and 58% respectively.

Table 2: The accuracy of multi-target detection

| Category               | Training Set | Testing Set | Precision |
|------------------------|--------------|-------------|-----------|
| Own Soldier            | 2677         | 382         | 0.6158    |
| Enemy Soldier          | 2433         | 380         | 0.6540    |
| Own Tower              | 485          | 79          | 0.9062    |
| Enemy Tower            | 442          | 76          | 0.9091    |
| Own Crystal            | 95           | 17          | 0.9902    |
| Enemy Crystal          | 152          | 32          | 0.8425    |

Table 3: Win rates playing against AI.1:AI without macro strategy, AI.2:without multi-agent, AI.3:without global reward and AI.4:without self-learning method
method used about 300 thousand game replays under the advantage of API. Another way is using PPO algorithm that OpenAI Five used [OpenAI, 2018] without macro strategy, which achieves about 22% win rate when combatting with entry-level internal AI. Meanwhile, the results of our AI playing against AI without macro strategy, without multi-agent, without global reward and without self-learning method are listed in Table 3. These indicate the importance of each method in our hierarchical reinforcement learning algorithm.

**Average rewards**

As shown in Figure 7, the total rewards are divided by episode steps in the combat. In three levels, the average rewards are increasing overall. For medium-level internal AI, it’s hard to learn well at first. However, the rewards are growing up after 500 episodes and stay smooth after almost 950 episodes. Although there are still some losses during training. This is reasonable for the fact that we encounter different lineups of internal AI which make different levels of difficulty.

**5 Conclusion**

In this paper, we proposed hierarchical reinforcement learning for multi-agent MOBA game KOG, which learns macro
strategies through imitation learning and taking micro actions by reinforcement learning. In order to obtain better sample efficiency, we presented a simple self-learning method, and we extracted global features as a part of state input by multitarget detection. Our results showed that hierarchical reinforcement learning is very helpful for this MOBA game.

In addition, there are still some works to do in the future. Cooperation and communication of multi-agent are learned by sharing network, constructing an efficient global reward function and state representation. Although our agents can successfully learn some cooperation strategies, we are going to explore more effective methods for multi-agent collaboration. Meanwhile, this hierarchical reinforcement learning architecture’s implementation encourages us to go further in 5v5 mode of game King of Glory especially when our agents compete with human beings.

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