Multi-Agent Deep Reinforcement Learning with Human Strategies

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Abstract

Deep learning has enabled traditional reinforcement learning methods to deal with high-dimensional problems. However, one of the disadvantages of deep reinforcement learning methods is the limited exploration capacity of learning agents. In this paper, we introduce an approach that integrates human strategies to increase the exploration capacity of multiple deep reinforcement learning agents. We also report the development of our own multi-agent environment called Multiple Tank Defence to simulate the proposed approach. The results show the significant performance improvement of multiple agents that have learned cooperatively with human strategies. This implies that there is a critical need for human intellect teamed with machines to solve complex problems. In addition, the success of this simulation indicates that our developed multi-agent environment can be used as a testbed platform to develop and validate other multi-agent control algorithms. Details of the environment implementation can be referred to [http://www.deakin.edu.au/~thanhthi/madrl_human.htm].

1 Introduction

Reinforcement learning (RL) [1] has been increasingly popular due to its ability to mimic human learning behaviors while interacting with environment and achieving long-term planning. However, traditional RL methods cease to work in high-dimensional environments in which computational expense for action prediction increases drastically with the number of dimensions, leading to the curse of dimensionality. As a result, RL is faint in practical applications. To overcome this shortcoming, one solution is to use a neural network as the function approximator for action prediction. This approach essentially brings in remarkable results in complicated problems such as backgammon [2, 3], IBM WATSON’s “Daily-Double” wagering [4], Atari domain [5], and the game of Go [6].

However, using the neural network as the function approximator may result in instability and divergence in estimations of action-value function (known as Q-value function) [7]. The primary cause of this chaos is the ability

![Environment diagram]

Figure 1: Using human strategies to present a biased environment as a target map.
of RL’s online learning, i.e., sequential data from its environment contain underlying correlative information. As a result, each update of the Q-value function tends to estimate a biased value and hence coerces the agent into local minimum solutions. Recently, various technical approaches have been proposed to break the correlation of samples. For instance, correlative samples are first collected and stored in an experience replay memory \([5]\), and are later retrieved in a random order to estimate the Q-value function. The use of a different network (known as a target network \([5]\)) also prevents the use of correlative samples, as the target network is only updated at infrequent intervals. Another approach, named double Q-learning \([8]\), performs action selection and action evaluation separately in two different networks. To further enhance correlative dilation, each sample in the experience replay is assigned a priority number based on its temporal difference error \([9]\). Moreover, particularly in stochastic environments, an asynchronous approach based on multithreading or intranet structure proves helpful. Specifically, the aim is to create multiple, simultaneous agent-environment instances. Each agent is trained individually in its replica environment, but afterward jointly updates its estimation to a shared policy network \([10]\). Finally, a recent study of Open AI \([11]\) uses a heuristic search procedure to optimize a designated objective by undergoing evolutionary generations via thousands of workers.

However, what if an observed environment is profoundly biased (e.g. the Multiple Tank Defence game described in Section \([3]\)), or if the biased data take a major portion of the environment’s data distribution? In these cases, all the algorithms mentioned above are vulnerable and may no longer work, as the training agent is tricked into the greedy pursuit of a biased solution. In extreme cases, the agent is unable to determine its actual goal, turns into a “zombie”, and behaves peculiarly. One straightforward solution is to extend the training time or to allocate more computational power resources such that further exploration may be attained. However, extending the training time is not desirable, and may even prove intractable if the observed environment is fully biased. More importantly, this phenomenon is prevalent in cases of contradiction between the feedback reward and the actual goal. For instance, given an agent that controls a fighter jet over a battlefield with a variety of enemies, the jet will crash if it collides with an enemy or if it runs out of fuel. The jet may replenish its fuel by flying over a fuel depot. However, shooting the fuel depot will earn a high reward, which misleads the agent to shoot all the fuel depots to assure the highest score achievement. As a result, the agent rarely advances to the next stage because of fuel depletion and becomes stuck in a local minimum solution. Multiple Tank Defence is another example of such an environment and will be described in Section \([3]\).

The present work tackles biased problems by mimicking human learning strategies. Firstly, humans retain essential training information that combines with intrinsic preferences to seek a suitable strategy for actual goal achievement. For instance, in the previous example, the desired agent should control the jet to shoot fuel depots to accumulate rewards but should recognize when fuel is low, and refill the fuel. By using this strategy, the player can prolong the jet’s lifetime and achieve a higher score in the long run. Secondly, humans often divide a complicated problem into several simpler tasks. Humans then conquer each discrete task by adopting a suitable strategy. In this way, humans explore all corners of data distribution and achieve designated goals proficiently without impairment by biased data. From a technical perspective, we represent an observed environment using a target map (e.g., a navigation map for drivers). Depending on the problem domain, we divide a target map into various spotty regions. In each region, we define a set of targets. These targets can be dynamically changed over time. Finally, an agent is trained to understand the target map and to achieve the targets in each region of the map. In this way, the agent can change its behavior to adapt to its environment without retraining by redefining the targets in the map. Fig. 1 illustrates our approach to biased environments using a target map and human strategies. Details of the target map are introduced in Sections \([5.1]\), \([5.2]\), and \([5.3]\).

Moreover, to facilitate the use of the target map, we have designed a high-level system architecture called the Multi-Strategy Control System (MSCS), which resolves various problem domains. More precisely, MSCS easily controls agent behaviors in real-time using a switching gate. In short, MSCS can operate in two different settings: a single-agent setting, and a multi-agent setting. In the former setting, MSCS controls the agent by switching among various regional policy networks. In the latter, MSCS enables cooperation between agents by scheduling each agent to follow a regional policy network. We will describe MSCS in greater detail in Section \([5.4]\).

Last but not least, the Arcade Learning Environment (ALE) \([12]\) is a normative testbed for deep RL in the Atari domain. However, ALE is a ROM-based single-agent emulator, which offers a lack of customizable features. Therefore, ALE restricts our study of agent behaviors and human-agent interactions. For this reason, we have developed a highly-strategic multi-agent environment called Multiple Tank Defence, which was inspired by the old-school retro game “Battle City 1990.” The experimental results of our proposed schemes in Multiple Tank
Defence can be found in Section 6 of this paper.

In summary, the paper contributes the following two key findings:

- We developed Multiple Tank Defence as a multi-agent environment to analyze agent behaviors and human-agent interactions in deep RL. Moreover, Multiple Tank Defence was designed in the spirit of an Atari game. Therefore, we can reuse any Atari-related deep RL algorithms without changing the existing parameter settings.

- The proposed target map and MSCS have unlimited potential in real-world applications. First, the target map can be combined with any deep RL algorithm to address various problem domains. Second, MSCS enables cooperation between heterogeneous agents in large-scale multi-agent systems. Finally, MSCS controls agent behaviors in real-time without requiring human feedback.

This paper is organized as follows. The next section summarizes the related work and its shortcomings. Section 5 describes the concept of target map and the implementation details of MSCS. Section 6 presents the experimental results of our proposed schemes in Multiple Tank Defence in two different settings: single-player setting and two-player setting. Finally, Section 7 concludes our work.

2 Related Work

Since the advent of DQN [5], a variety of improvements have been made to DQN, such as double Q-network [8], dueling network [13], and prioritized experience replay [9]. However, these DQN variants require a lengthy training time to achieve human-level performance on Atari games. In 2016, Mnih et al. [10] derived an asynchronous approach based on actor-critic architecture [14] entitled asynchronous advantage actor-critic (A3C), which requires less than 12 hours to surpass 3–4 days of using solely DQN to train an agent to play an Atari game. Recently, Jaderberg et al. [15] proposed an improved version of A3C entitled unsupervised reinforcement and auxiliary learning that simultaneously optimized three additional unsupervised pseudo-reward functions including pixel control, reward prediction, and value function replay. However, unlike first-person games such as Labyrinth, the use of the pixel control task to maximize spatial exploration is redundant in a fixed spatial environment such as Multiple Tank Defence. Therefore, for this paper, it is sufficient to use A3C as the baseline algorithm to examine our proposed schemes.

Alongside the rapid increase in the lateral complexity of applications, there has been a rising demand to provide human feedback in the agent training process, i.e., the goal is to tell the agent what we expect and what we do not expect from it. Christiano et al. [16] have undertaken a state-of-the-art study of this problem. The idea is to periodically provide feedback to the agent after observing its behaviors during the training process. However, this approach obligates a human operator to review thousands of pairs of the agent’s clips, which is onerous and infeasible in real-world applications. To overcome this limitation, we initially set up a target map before the training process. Instead of providing human feedback in real-time, we expressed our preferences as abstract representations in a target map and allowed the agent to learn the map. Moreover, a target map is easy to construct by using a suitable localization method [17] or a hard-coded algorithm. Therefore, our scheme can be used extensively in real-world applications.

Another challenge in RL is navigation of environments with sparse rewards. In such cases, agents become easily stuck in local minimum solutions due to insufficient exploration. One solution is to split a complicated task into hierarchical subtasks in which a parent subtask has higher abstraction than its successors [18]. By combining hierarchical subtasks with the agent’s intrinsically-motivated rewards [19]. Kulkarni et al. [20] successfully instructed an agent to accomplish its goal in the Atari game Montezuma’s Revenge. However, this approach requires training of two policies simultaneously: one that estimates goal-value function and one that estimates action-value function. By adopting temporal abstraction with the target map, our proposed scheme does not require to train an additional policy network over goals and enables smooth cooperation within agents and also between humans and agents. Moreover, as a target map is independent of policy networks and deep RL algorithms, our approach is more robust and can deal with a broader range of applications.

Finally, in multi-agent systems, the most crucial task is to determine how to cooperate multiple agents to jointly fulfill a designated goal. The studies presented in [21, 22] leveraged a shared communication utility for training agents to collaborate in a centralized manner. However, these approaches, which were primarily based on a notable network, only scale with a relatively small number of agents. In 2017, Gupta et al. [23] proposed a decentralized
parameter-sharing method that provides a feasible solution for large-scale multi-agent systems, but that restricts
work with homogeneous agents. In this study, by using the target map wisely, agents are allowed to operate
cooperatively in heterogeneous multi-agent systems. We will address this issue in greater depth in Section 5.4.

3 The Multiple Tank Defence Environment

In this section, we briefly introduce the game Multiple Tank Defence, including its gameplay and features. We have
also included a source code of Multiple Tank Defence and its sample code. Fig. 2 describes the gameplay of Multiple
Tank Defence in two different settings: single-player setting and two-player setting. There are always five enemies
(red tanks) in the battlefield, and if an agent destroys an enemy, another enemy will appear randomly in the top
half of the screen. Therefore, the game is highly stochastic. Multiple Tank Defence has two simultaneous goals: to
achieve the highest score and to prolong the base’s lifetime. The base is the gray block at the bottom of the scene.
The level of difficulty of the game increases as the agent reaches a certain high score. The enemies gradually move
and shoot faster at this benchmark. The game is over when the base is shot or when there are no agents left in the
battlefield. Each agent receives a reward of 10 if it destroys an enemy.

To promote highly strategic intrigue, we created various terrains within the battlefield. For instance, a
hard wall
cannot be collapsed by a bullet, so it can be used as a shield to hide from enemy attacks. In contrast, a soft wall
can be collapsed by a bullet. Finally, agents or enemies cannot move through a pond tile, but bullets can pass through it.

Multiple Tank Defence is an intractable environment if we only use a deep RL algorithm
without any human guidance, even with a state-of-the-art algorithm such as A3C. During the training procedure,
the agent is easily tricked by the environment to become an attacker that greedily destroys as many enemies as
possible to reach the highest possible score. However, as an attacker, the agent embarks on the battlefield without
any protection. As a result, the agent is easily shot. Moreover, when the agent focuses primarily on attacks, it will
not protect the base, and hence the game is over quickly.

In brief, the Multiple Tank Defence environment provides the following features:

• Multiple Tank Defence is a customizable multi-agent environment. By alternating a variety of terrains, the
number of enemies, and the number of agents, we can produce an unlimited number of different stages.

• The game is highly stochastic and has a complicated goal. It requires a suitable strategy to obtain a high
score. Therefore, Multiple Tank Defence is a decent option to study agent behaviors.
• Multiple Tank Defence supports human-machine interactions in real-time, i.e., a human player can cooperate with an autonomous agent to play the game.

• We designed the game to retain all details when it is rescaled to $84 \times 84$. Therefore, we can reuse an existing Atari-related deep RL algorithm without changing its parameter settings.

4 Behavior Analysis

In this section, we consider agent behaviors before and after adjustment by a target map in two different settings: single-player setting and two-player setting. The goal of the study is to create an agent that is human-like. A video
4.1 Single-player setting

Fig. 3a illustrates an A3C-N agent in the gameplay. Without any human guidance, the agent easily becomes stuck in the local minimum solution by restrictively moving in the green area. In this way, enemies in the central area can easily shoot the base (the dangerous area in red), and hence the game is over. In this scenario, the agent does not protect the base and becomes an attacker by greedily shooting as many enemies as possible.

However, in Fig. 3b, an A3C-RG1 agent is guided by the target map, which works as expected. Concisely, it protects the central area and actively destroys any enemies in the dangerous area. Therefore, this agent protects the base and becomes a defender. Therefore, it prolongs the base’s lifetime and achieves a higher score in the long-term.

In the case of A3C-RG2, the agent is located in a surprising location, as shown in Fig. 3c. The agent utilizes a hard wall to protect itself from enemy attacks. Much like A3C-N, however, the agent does not protect the central area and hence cannot achieve a high score. However, the agent is a passive defender, as its purpose is to maximize the base’s lifetime.

Finally, we use a MSCS to manually manipulate an agent from RG1 to RG2 whenever the base is in danger, as shown in Fig. 3d. In this case, the agent’s behaviors are more human-like, as the agent can move to different areas to protect the base. If we create more regions in the target map, the agent’s behaviors are more human-like, and strictly follow our guidance.

4.2 Two-player setting

In the two-player setting, two A3C agents are located in separate regions of the battlefield (left and right) and the cooperation between the two agents is limited. They do not protect the central area, as shown in Fig. 4a. As a result, the total score is low. The two agents seem to be more competitive than cooperative, as each agent tries to destroy as many enemies as possible to achieve a higher score than its ally.

Now, we placed an A3C-RG1 agent and an A3C-RG2 agent in the battlefield, as shown in Fig. 4b. The two agents imperceptibly created a two-level defense scheme that blocked all directions of enemy attacks. As a result, the scheme achieved a remarkable result that even surpassed the human competent level in both evaluation metrics, the mean total of reward and the mean total of steps per episode.

Finally, we used MSCS to slightly improve the previous scheme by narrowing the working area of the agents (chiefly to increase productivity). To do this, we modified the target definition in the target map so that the targets only appeared in the green region of the green tank and the yellow region of the yellow tank. In this way, we changed the behaviors of the agents in real-time without conducting any training procedures. This scheme is illustrated in Fig. 4c.

5 Proposed Scheme

In this section, we describe the definition of a target map as well as its properties. Next, we provide an example of the application of a target map and its implementation in Multiple Tank Defence. We then explain how to train an agent to learn the target map. Finally, we describe MSCS, which is a system architecture based on the target map.

5.1 Target map

**Definition 1.** Given a state $S = \{x | x \in \mathbb{R}^n\}$ of an observed environment, where $n \in \mathbb{Z}^+$, a set $R$ is a region of $S$ if $R$ is a subset of $S$, i.e., $R \subseteq S$.

**Definition 2.** Given a region $R$, a set $T$ is a target of $R$ if $T$ is a strict subset of $R$, i.e., $T \subset R$.

**Definition 3.** Given a region $R$ and $m$ targets $T_i$ of $R$, where $m \in \mathbb{Z}^+$ and $i = 1..m$, a set $Z$ is a target group of $R$ if $Z$ is a union set of $m$ targets $T_i$, i.e., $Z = T_1 \cup T_2 \cup \ldots \cup T_m$.

**Definition 4.** Given a state $S$, $m$ regions $R_i$ of $S$, and $m$ corresponding target groups $Z_i$, where $m \in \mathbb{Z}^+$, $i = 1..m$, and $R_j \neq R_k, \forall j \neq k$ and $j, k \in \{1, 2, \ldots, m\}$, a set $M$ is a target map of $S$ if $M$ is defined as: $M = \bigcup_{i=1}^{m} \{R_i, Z_i\}$.

**Property 1.** Given a state $S$ and $m$ regions $R_i$ of $S$, where $m \in \mathbb{Z}^+$ and $i = 1..m$, a target map $M$ of $S$ is complete if $R_1 \cup R_2 \cup \ldots \cup R_m = S$. In contrast, $M$ is incomplete.
Figure 4: Different schemes in the two-player setting. a) Two A3C-N agents. b) An A3C-RG1 agent and an A3C-RG2 agent. c) An A3C-RG1-R agent and an A3C-RG2-L agent.

Property 2. Given a state $S$ and $m$ regions $R_i$ of $S$, where $m \in \mathbb{Z}^+$ and $i = 1..m$, a target map $M$ is exclusive if $R_i \cap R_j = \emptyset$, $\forall i \neq j$ and $i, j \in \{1, 2, \ldots, m\}$. In contrast, $M$ is inclusive.

Property 3. Given a region $R$, $R$ is a multi-target region if $R$ has at least two targets. In contrast, $R$ is a single-target region.

5.2 Implementation details

In Multiple Tank Defence, a state $S$ is a 2D color image that captures the gameplay at time $t$, as shown in Fig. 5a. In this example, we assumed the use of two-player setting in Multiple Tank Defence. Before creating the target map of $S$, we examined the game and proposed the following strategies to achieve the best result. Because the goal of the
Figure 5: An example of the target map in Multiple Tank Defence. a) An observed state $S$ in Multiple Tank Defence. b) Human strategies applied to $S$ where RG-1 is the yellow region and RG-2 is the green region. c) A target map of $S$ by definition. d) Implementation of the target map through the use of target masks.

The game is to control the agents (one agent in single-player mode and two agents in multi-player mode) and to protect a base as long as possible, we designed a two-level defense scheme to protect the base from being shot by enemies, as shown in Fig. 5b. Specifically, an agent (yellow tank) is in charge of destroying any enemies (target 1 and target 2) that invade the yellow region. Because an enemy in the central area (target 1) can directly shoot the base, the yellow tank should be located in the gray areas of the yellow region at all times and should destroy any enemies in the central area. Likewise, another agent (green tank) is assigned to the green region. However, unlike the yellow tank, the green tank only considers destroying the enemy (target 3) that is closest to the base.

Based on the above strategies, we created the target map, as shown in Fig. 5c. In the map, for visualization purposes, the target is illustrated by a white disc. Based on the properties outlined in Section 5.1, the map is incomplete and exclusive. The yellow region (RG-1) is a multi-target region, and the green region (RG-2) is a single-target region.

Finally, to implement the target map in an efficient manner, for each region, we created an image mask in black called the target mask, which has the same dimension (width × height) as the original state $S$. We then converted the target mask into grayscale and scaled it by a ratio $r < 1$. Thereby, each target in the region is masked by a white square area in the target mask, as shown in Fig. 5c. The actual boundary of the region and its targets’ definition are stored in a specific data structure. This data structure can be combined with a suitable localization method, e.g. [17], to detect targets in real-time. After an agent is trained to learn the target mask, we can easily change the agent’s behaviors without retraining by modifying the target definition in the data structure. The next subsection will explain how to train the agent to learn the target map.

5.3 Training process

Initially, we created a separate regional policy network that corresponded with each region of the target map. The regional policy network is used to train the agent to achieve targets in that region. For instance, we created two regional policy networks for RG-1 and RG-2 using the target map described in Fig. 5. Fig. 6 describes the regional policy network for RG-1. The regional policy network for RG-2 can be constructed in a similar manner. Initially, we converted a history of four Multiple Tank Defence frames from an RGB format to 8-bit grayscales and then rescaled them to $84 \times 84$. The transformed images were then used as inputs to a deep RL algorithm’s policy network that included convolutional layers. In this paper, we use the A3C’s policy network to demonstrate the use of the target map. At the same time, four 8-bit target masks, each with the dimensions $84 \times 84$, were also generated. These masks were passed through convolutional layers to generate the target map’s features. These features were combined with the state’s features (like in inception network [24]) in the A3C network before propagating to additional layers. In this way, the target map can be applied to any deep RL algorithm’s network without obstructing the existing
structure of the network. Moreover, the training agent is given a reward only if it achieves a target on the target map. Once the agent has been trained with the regional policy network, we can easily control the agent’s behaviors by redefining targets in the target map. For example, we initially defined any enemies in the battlefield as targets and used this definition to train the agent, but later redefined any enemies in the proper area of the battlefield as targets. As a result, the agent altered its behaviors to focusing on protecting the specified area without conducting a retraining process.

5.4 Multi-Strategy Control System

To complete our proposed scheme, we utilized the target map in a general system architecture called Multi-Strategy Control System (MSCS), which can undertake a variety of applications in real-world scenarios. Fig. 7 describes the system architecture of MSCS in detail. The system receives human preference data and observed environment states as input. Based on this input information, each region boundary and its target definition are stored in a specific data structure. The target map generator uses this data structure, together with the observed state, to generate target masks for each regional policy network. Finally, a set of switching conditions are utilized to control a switching gate in real-time to identify which regional policy network should be used according to human tactical strategies. These switching conditions can be manually controlled by humans (human-in-the-loop control), a hard-coded algorithm, or a learning neural network. In single-agent systems, MSCS aids an agent to switch to a regional policy network (switch strategy) in real-time based on human preferences. In multi-agent systems, each agent is assigned to a regional policy network, and MSCS schedules each agent’s activities using the switching gate.

Finally, we suggest the following strategy to train a large-scale heterogeneous multiagent system using MSCS. We created $N$ regions corresponding with $N$ agent types (in which $N$ is relatively small). We then assigned each
Figure 8: A comparison of mean total of reward and mean total of steps per episode among three schemes (A3C-N, A3C-RG1, and A3C-RG2) in the single-player setting.

6 Performance Evaluation

In this section, we present the experiments that were performed in Multiple Tank Defence to evaluate the proposed target map and MSCS in two different settings: single-player setting and two-player setting. As explained in Section 2, we will use A3C as the baseline algorithm for each proposed scheme using the target map and MSCS. The A3C’s network parameters and algorithm settings are the same as in [10], except the following changes. We ran each A3C variant in an 8-core CPU. The initial learning rate was 0.004. Before applying to the A3C network, we passed target masks into two convolutional layers: one layer with 16 filters of size $8 \times 8$ and a stride of 4, followed by another layer with 32 filters of size $4 \times 4$ and a stride of 2. Finally, we used the input processing as in [5], but with an action repeat of 5 for both target mask generation and state input in Multiple Tank Defence.

Moreover, we trained each A3C variant in 10 million steps (50 million game frames). This took approximately two days for A3C without the use of the target map and three days for A3C with the use of the target map. The extra day of expenditure serves chiefly to generate target masks in real-time. For unbiased comparison, we reran the training process five times for each A3C variant and selected the peak performance regarding reward distribution. During the training process, we also collected 20 checkpoints of the policy network in different training steps. In each checkpoint, we undertook an evaluation of 50,000 steps (250,000 game frames) to obtain the mean total of reward and the mean total number of steps per episode. Therein, the mean total of steps per episode was used to evaluate how long an agent could protect the base. Finally, to formulate reference points, we included two different levels of human performance in Multiple Tank Defence: novice level and competent level. The human novice level was recorded with people who did not have any experience with the game, whereas the human competent level was recorded with people who were trained at least 500,000 steps. Both levels were recorded by playing Multiple Tank Defence to 50,000 steps.

6.1 Single-player setting

In the single-player setting, we compared the experimental results of three different A3C variants: A3C without using the target map (A3C-N), A3C using the target masks for RG-1 (A3C-RG1), and A3C using the target masks for RG-2 (A3C-RG2). As shown in Fig. 8, A3C-RG1 and A3C-RG2 obtained comparable performance, and both performed slightly better than A3C-N regarding number of peak reward achievements. Moreover, A3C-RG1 and
A3C-RG2 require only 18–21 training hours to surpass the human novice level while A3C-N requires at least 26 hours to achieve the same level. Considering the mean total of steps per episode, A3C-RG2 is the only strategy that could reach the competent level, and it was 50% better than A3C-N. We infer an important remark from the results of this experiment. A3C-N tends to train an agent to become an attacker, as it is tricked by the biased environment to greedily destroy as many enemies as possible (to achieve the highest possible score). As a result, the agent is easily shot and forgets to protect the base. By adjusting the agent’s behaviors to become a defender, A3C-RG1 and A3C-RG2 prolonged the base’s lifetime and at the same time maintained a high score achievement in the long run.

6.2 Two-player setting

In the two-player setting, we compared the performance of two different schemes. The first scheme included two A3C-N agents, and the second scheme included one A3C-RG1 agent and one A3C-RG2 agent. In the former scheme, we concurrently trained 10 million steps of two policy networks using A3C-N, which shares parameters in convolutional layers. As shown in Fig. 9, the latter scheme achieved a remarkable result as it surpassed the human competent level and proved 200% better than the first scheme in both the mean total of reward and the mean total of steps per episode. The reason behind the low performance of the first scheme is that the two agents did not protect the central area. In contrast, the cooperation between the two agents in RG1 and RG2 created a securely two-level safeguard that protected the base from all enemies’ attack directions.

Finally, we used MSCS to adjust agent behaviors and hence derived the following improved variants. In the single-player setting, we manipulated the agent to work in RG1 to RG2 and vice versa during the playtime (A3C-RG1 ↔ A3C-RG2). By combing the strong point of each separate scheme, A3C-RG1 ↔ A3C-RG2 slightly improved A3C-RG1 in both evaluation metrics. In the two-player setting, we modified the target definition such that the agent in RG1 focused more closely on destroying any enemies on the right side of the battlefield, and the agent in RG2 focused on destroying any enemies on the left side of the battlefield (A3C-RG1-R + A3C-RG2-L). By narrowing the target area, this scheme achieved a remarkable result that surpassed the A3C-RG1 + A3C-RG2. Finally, we added an interesting scheme that represented the cooperation between human and machine by including the A3C-RG1 agent with a human player on the battlefield (A3C-RG1 + Human). Table 1 summarizes the mean total of reward and mean total of steps per episode among the various schemes discussed here. Further details regarding agent behaviors can be referred to subsection 4.2.

7 Conclusions

This paper proposed the novel concept of the target map and the design of MSCS that essentially adjusts agent behaviors in real-time. By following human strategies, agents easily attain an expected solution in a short training
Table 1: Experimental results on different schemes using target map and MSCS.

| Name | Scheme description | Mean reward | Mean total of steps/episode |
|------|--------------------|-------------|----------------------------|
| A3C-RG1 ↔ A3C-RG2 | We use MSCS to manually control an agent to switch between RG1 and RG2 during playtime | 149 | 152 |
| A3C-RG1 + Human | We use the A3C-RG1 agent to cooperate with a human player | 301 | 234 |
| A3C-RG1-R + A3C-RG2-L | We modify the target definition such that the agent in RG1 focuses on the right and central areas, and the agent in RG2 focuses on the left area | 363 | 295 |

Time without using a notorious burden of human feedback. Moreover, agents do not become stuck in local minimum solutions and act more human-like in biased environments such as Multiple Tank Defence. Finally, the use of the target map and MSCS also eases the cooperation between humans and agents, or among agents in a heterogeneous system. Therefore, the study provides a promising framework that aims to attract considerable attention to building a human-like agent in large-scale systems with deep RL.

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