Benchmarking MARL on Long Horizon Sequential Multi-Objective Tasks

Extended Abstract

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ABSTRACT

Current MARL benchmarks fall short in simulating realistic scenarios, particularly those involving long action sequences with sequential tasks and multiple conflicting objectives. Addressing this gap, we introduce Multi-Objective SMAC (MOSMAC)[1], a novel MARL benchmark tailored to assess MARL methods on tasks with varying time horizons and multiple objectives. Each MOSMAC task contains one or multiple sequential subtasks. Agents are required to simultaneously balance between two objectives — combat and navigation — to successfully complete each subtask. Our evaluation of nine state-of-the-art MARL algorithms reveals that MOSMAC presents substantial challenges to many state-of-the-art MARL methods and effectively fills a critical gap in existing benchmarks for both single-objective and multi-objective MARL research.

KEYWORDS

Multi-agent Reinforcement Learning; Multi-Objective Multi-agent Reinforcement Learning; Benchmark

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1 INTRODUCTION

Studies on multi-agent reinforcement learning (MARL) have recently garnered significant achievements in various fields, including traffic signal control [4], game-playing [20], and stock-trading [1]. Despite the achievements, these applications commonly entail tasks with short *horizons* and single objectives [20]. In fact, learning over long horizons is a non-trivial challenge of MARL. In such scenarios, challenges like the *exploration* and *temporal credit assignment* become increasingly complex compared to their short-horizon counterparts [9]. In addition, the complexity of the *hypothesis space* for optimal value functions scales with the planning horizon [12], leading to the convergence of action-gaps and trap agents in local optima. However, currently there is still a scarcity of benchmarks for examining methods in long-horizon MARL contexts.

This paper presents a MARL benchmark named *Multi-Objective SMAC* (MOSMAC), which provides a set of multi-objective MARL (MOMARL) tasks that scale to various temporal horizons. Building upon the foundations laid by SMAC [20], SMACv2 [5], and SMAC-Exp [11], MOSMAC differentiates itself with three distinct features: varying temporal horizons, multiple objectives, and sequential subtask assignments. MOSMAC also incorporates scenarios featuring complex terrains including plains, canyons, ramps, and high/low grounds, mirroring real-world scenarios and significantly challenging *multi-agent exploration* in a large state-action space. As a result, MOSMAC provides various interesting scenarios covering the aspects that are not included in most of the existing MARL tasks [2, 3, 18] and benchmarks [5, 11, 20], making it challenging for both MARL and MOMARL [7, 8, 10, 15, 24] domains.

We evaluate nine MARL algorithms [6, 14, 16, 17, 21–23, 25] on MOSMAC with the EPyMARL framework [16]. We find that while several methods exhibit good performance on addressing short-horizon MOMARL tasks, the long-horizon ones are still challenging, highlighting the need for more efficient MARL methods.

2 MULTI-OBJECTIVE SMAC (MOSMAC)

The short-horizon MOSMAC contains a set of MOMARL tasks with stochastic target placements. It contains scenarios with 3, 4, 8, and 12 Siege Tank units in both the ally and adversarial teams. Figure 1(a) shows an example scenario, named *4t*, with four ally units, each controlled by a learning agent. Agents share the winning criteria of occupying a system-selected strategic position. The ally team wins the game if all remaining agents can reach the strategic position. The adversarial units are symmetric to ally units, controlled by the built-in controller of the StarCraft II game with a difficulty level of 7. Adversarial units are configured to guard the strategic position and will attack ally units when they are in close proximity. Similar to SMACv2 [5], units have their default sight and attack ranges, as

[1] Code is available at https://github.com/smu-ncc/mosmac

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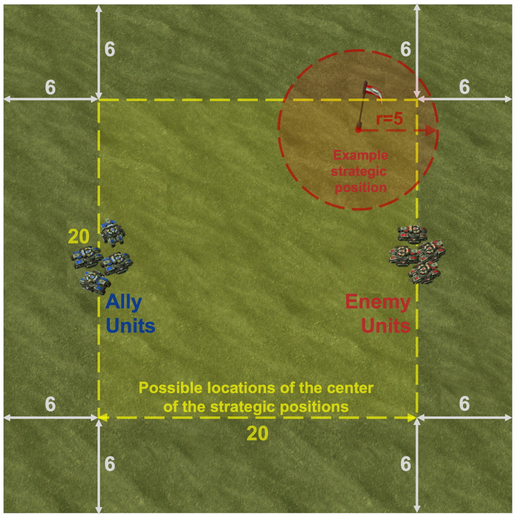
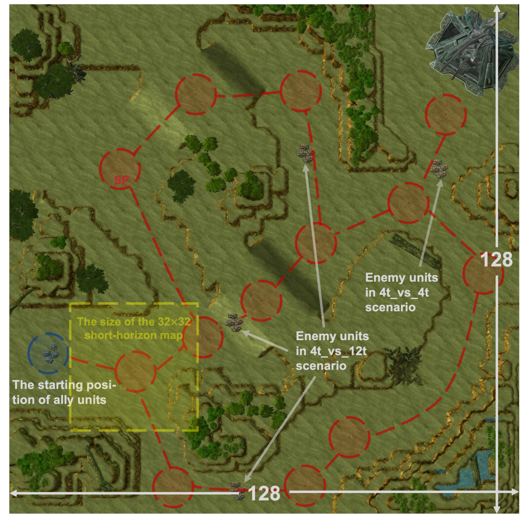


(a) An illustration of the short-horizon MOSMAC, 4t scenario.



(b) An illustration of the long-horizon MOSMAC with terrain features.

Figure 1: Illustrations of short-horizon and long-horizon MOSMAC. (a) The strategic position is marked by the dotted red circle, with a center drawn from a uniform distribution over the 20×20 area, marked by the dotted yellow square. The full map size is 32×32. (b) The yellow area shows the size of the short-horizon scenarios' map, which is depicted in Figure 1(a). 4t_vs_4t and 4t_vs_12t are the names of scenarios with 4 and 12 adversarial units.

in the StarCraft II games. In addition to the default environment information as in SMAC [20] and SMACv2 [5], i.e., units' information and optional terrain features, agents also perceive the relative direction and distance towards the strategic position to navigate effectively. The action space is discrete and contains four *movement* actions, one *attack* action, and one *stop* action. Agents can execute up to 50 decision-making and action cycles in 3t and 4t games, while this limit extends to 100 in 8t and 12t scenarios. The games will be forced to be terminated once agents reach this limit.

Our evaluation takes a *single-policy* approach [13, 19], where the *utility* of multiple objectives is represented by a scalar reward value, while *multi-policy* methods [8] can also be applied. Specifically, the short-horizon MOSMAC contains the following two objectives:

(1) Objective 1 (combat): To maximize the damages to the enemy units.
(2) Objective 2 (navigate): To minimize the distance between agents and the target strategic position.

Therefore, the reward functions for Objective 1 and 2 are:

$$r_{obj1} = \sum_{i=1}^{n} (r_a^i + r_d^i) \tag{1}$$

and

$$r_{obj2} = \sum_{i=1}^{n} r_r^i \tag{2}$$

respectively, where r_a^i and r_d^i are the rewards for attacking and destroying enemy units by agent i, r_r^i is the reward for reducing the Euclidean distance to the strategic position by agent i, and n is the total number of agents. The complete step-wise intermediate reward function r for short-horizon MOSMAC is as follows:

$$r = \alpha \times r_{obj1} + (1 - \alpha) \times r_{obj2} \tag{3}$$

where α is a weight of preference that indicates the *priority* [8] given to Objective 1. Besides r, agents will receive r_w as the terminal reward for winning the game by occupying the strategic position.

The long-horizon MOSMAC features three sets of subtasks, as illustrated in Figure 1(b). Each set of subtasks is derived by dissecting a path that commences at the starting position and ends at the final position, employing segmentation points as intermediate targets. Consequently, each subtask becomes a short-horizon MOMARL task akin to short-horizon MOSMAC. Agents need to address a series of interconnected subtasks, where the completion of one subtask triggers the beginning of the next. Each episode uniformly selects a path with a set of subtasks. In total, a full long-horizon MOSMAC task entails 6-8 subtasks. We expand the map to 128×128 and provide variations including fully flat terrain scenarios and settings with intricate topographical features. The ally team comprises four units, whereas the adversarial team encompasses 0, 4, or 12 units. To maintain parity in combat capabilities with the ally team, enemy units are organized into clusters, each with four units. Ally agents encounter at most one enemy cluster in each episode.

3 RESULTS AND CONCLUSION

This paper introduces MOSMAC, a new MARL benchmark aimed at challenging MARL algorithms with multi-objective long-horizon tasks. Through our experiments, we found that existing MARL methods are able to address short-horizon tasks but struggle when dealing with sequential tasks that involve multiple objectives over a longer horizon. This shows the utility of the proposed benchmark in pushing the performance boundary of the MARL algorithms. Going forward, we aim to extend MOSMAC with new challenging scenarios with a more diverse set of units and provide more evaluation results of MARL methods, particularly in areas such as MARL with hierarchical learning paradigms and MOMARL.

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