ReMAC: Large Language Model-Driven Reward Design for Multi-Agent Manipulation Collaboration

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Abstract

Multi-agent collaboration, such as in multi-robot systems, often relies on carefully crafted reward functions. These functions are crucial for learning collaborative policies. However, designing efficient reward functions for multi-agent systems remains an open challenge. To bridge this gap, we propose **ReMAC**, a novel large language model-driven **Re**ward generation framework for **M**ulti-**A**gent **C**ollaboration. ReMAC employs a hierarchical approach to generate and optimize multi-agent reward functions: The upper level maintains and iteratively optimizes a population of reward functions from both team-level and individual-agent perspectives. The lower level applies multi-agent reinforcement learning algorithms (MARL) to learn collaborative policies. This hierarchical design ensures efficient learning and optimization of multi-agent policies. Motivated by recent advances in robotics, especially in embodied AI, we observe that existing multi-agent benchmarks fall short in supporting collaborative manipulation tasks. To bridge this gap, we design the Multi-Agent Manipulation Collaboration benchmark, **ManiCraft**, aiming to advance research on robotic manipulation in the MARL community. Experimental results demonstrate that ReMAC successfully constructs high-quality reward functions that outperform even those manually designed by human experts. The visualization videos are available at Anonymous Link.

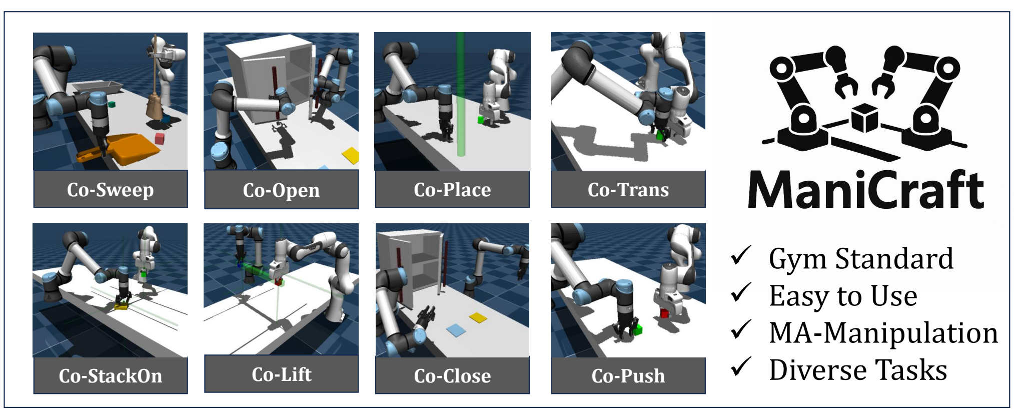

Figure 1: ManiCraft: A Multi-Agent Manipulation Benchmark for Collaborative Policy Learning.

1 Introduction

Multi-Agent Reinforcement Learning (MARL) has gained significant interest due to its capability to tackle complex real-world challenges [1–5], with practical applications spanning Game AI [6–8], Robotics Control [9–11], and Intelligent Transportation Systems [12–14]. Despite these promising developments, learning efficient policies for collaboration in MARL remains a persistent challenge [15–19]. In MARL, individual agents interact with the environment and with each other to collect samples. After executing the decisions made by the policies, they receive reward signals to evaluate their performance. With value function approximation, MARL can optimize the policies using gradient updates. However, achieving efficient collaboration critically depends on the reward quality. Designing reward functions often requires expert involvement, making the process time-consuming and challenging. Thus, how to construct high-quality reward functions is a key challenge in the MARL field.

Large language models (LLMs) have recently gained significant attention, demonstrating human-level performance in areas such as code generation, planning, and reasoning [20–23]. Some works employ LLM to design rewards, such as Text2Reward [24] and Eureka [25], which use LLMs to generate reward function code for the single-agent problem. Critic GPT [26] and RLAIF [27] leverage LLMs to provide preference for training reward models. However, research on LLMs for MARL remains relatively limited [28]. Most efforts have focused on utilizing the reasoning and planning capabilities of LLMs to build more powerful high-level abilities [29–31], with less attention given to constructing lower-level policies. Multi-Agent Reward design, as a critical component for training lower-level collaborative policies, has not been sufficiently explored.

To bridge this gap, we propose a novel LLM-driven framework for **Re**ward generation in **M**ulti-**A**gent **C**ollaboration (ReMAC). ReMAC leverages the extensive domain knowledge and coding capabilities of LLMs to generate structured reward functions for MARL. Specifically, the LLM first analyzes the individual skills required by each agent and the coordination demands at the team level. Based on this analysis, ReMAC constructs two types of rewards—*agent-level* and *team-level*—which are then combined to produce the final reward for each agent. To ensure high-quality reward design, we maintain a reward population $\mathbb{P}_{\mathrm{R}}$, where each individual comprises both agent- and team-level reward functions. For every reward function, we instantiate a corresponding MARL agent, forming a MARL population $\mathbb{P}_{\mathrm{MARL}}$. The team policies in $\mathbb{P}_{\mathrm{MARL}}$ interact with the environment to generate experiences. Each experience is then labeled with rewards by the reward population and stored in a shared replay buffer for learning. At regular intervals, the best-performing team is summarized and fed back to the LLM, which reflects on the design from skill, individual, and team perspectives. Based on this reflection, the LLM generates improved reward functions to replace the suboptimal ones in $\mathbb{P}_{\mathrm{R}}$, which are then used for subsequent policy training.

Although the robotics field has made significant progress in recent years, we observe that the current MARL community still lacks a collaborative manipulation benchmark for low-level policy learning. Thus we propose a new and challenging benchmark ManiCraft. ManiCraft is built on MuJoCo and uses Mocap for end-effector pose control. It consists of 11 manipulation tasks of varying difficulty. We carefully design the state space, action space, and reward functions to ensure that each task can be learned using current MARL algorithms. ManiCraft is encapsulated using the Gym standard, with clean and easy-to-use code for invocation and development. We evaluate ReMAC on ManiCraft, and the experiments show that the reward functions generated by ReMAC often outperform human-designed reward functions.

Our contributions are summarized as follows: 1) We propose an LLM-driven reward generation framework, ReMAC, which efficiently designs multi-agent reward functions that are competitive with or better than human-designed reward functions. 2) ReMAC constructs a reward function population from both the agent-level and team-level perspectives, and optimizes these functions across three dimensions: skill, individual, and team, enabling efficient reward function optimization. 3) We introduce the ManiCraft benchmark to address the current lack of diverse multi-manipulation collaborative tasks in the MARL community. To the best of our knowledge, ManiCraft is the first benchmark specifically designed for collaborative manipulation tasks in MARL, with a focus on low-level policy learning.

2 Background

Multi-Agent RL: We consider a fully cooperative multi-agent task, which can be modeled as a *Decentralized Markov decision process* (Dec-MDP) [32] by a tuple: $\langle \mathcal{N}, \mathcal{S}, \mathcal{U}, \mathcal{T}, \mathcal{R}, \gamma \rangle$. Here, $\mathcal{N} = \{1, \cdots, N\}$ denotes the set of N agents. In a Dec-MDP, the complete state of the environment

$s_t \in \mathcal{S}$ is fully observable to the agents at each time step t. Each agent i uses a stochastic policy π_i to select actions $u_t^i \sim \pi^i(\cdot|s_t) \in \mathcal{U}^i$, resulting in a joint action $u_t = \{u_t^i\}_{i=1}^N \in \mathcal{U}$. After executing the joint action u_t in state s_t, the environment transitions to the next state s_{t+1} according to the transition function $\mathcal{T}(s_t, u_t)$, and the policies receive the reward(s) r_t from the reward function $\mathcal{R}(s_t, u_t)$, $\gamma \in [0, 1)$ is a discount factor. We denote the joint policy as $\pi = \{\pi^1, \cdots, \pi^N\} \in \Pi$, where Π is the joint policy space. In cooperative MARL, the collaborative team aims to find a joint policy that maximizes the total expected discounted return, denoted as $J(\pi) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t r_t\right]$. MARL algorithms vary, with some focusing on communication [33–35, 34, 36], non-stationarity [37–39], and credit assignment [40–43], diversity [44–47], exploration [48–50], and convergence properties [51–53]. In this paper, we aim to design reward functions in code form that guides MARL to learn the collaborative policies.

Reward Design and Shaping: Various methods have been proposed to construct high-quality reward signals. In Inverse RL, reward functions are learned from expert demonstrations [54–59]. Preference-based methods [60–65] leverage human feedback and preference data to guide the learning process. Additionally, methods like trial-and-error manual design [66, 67] and evolutionary algorithms [68, 69] optimize reward functions using predefined templates, relying on domain knowledge from experts. Some works employ LLMs to generate reward function code. Text2Reward [24] generates reward functions based on task descriptions, while Eureka [25] uses reward function population for iterative improvement. Other works focus on reward shaping [70–75] to enhance exploration or collaboration.

LLM for Multi-Agent System: Recent works leverage LLMs to strengthen multi-agent reasoning, communication, and decision making [28, 76]. DyLAN [29] dynamically dispatches LLM agents for cooperative reasoning and coding. FAMA [77] uses a centralized critic to guide agents in free-form text negotiations for optimal joint policies. Other studies show LLM agents can achieve numerical consensus through iterative dialogue [78] or employ a rudimentary Theory-of-Mind to infer teammates' hidden states and intentions [79]. γ-Bench [80] demonstrates that chain-of-thought prompting steadily improves GPT performance in cooperative games. MetaGPT [81] encodes human Standard Operating Procedures into multi-agent LLM pipelines with role-based task decomposition and cross-verification. Beyond text-only environments, LLMs are integrated into embodied frameworks: CoELA [82] combines LLM-based memory, planning, and chat channels so agents can discuss and execute household tasks; SMART-LLM [83] decomposes high-level language instructions into coalition-level robot plans; RoCo [30] equips each robot arm with an LLM-based planner for collision-free coordination. Co-NavGPT [31] dispatches a single LLM to coordinate multi-robot exploration.

3 Method

This section provides an overview of ReMAC framework. We first introduce the optimization process of ReMAC. Then, we provide a detailed description of how to construct individual and team rewards. Finally, we present how to optimize the reward functions and use them to guide policy training.

3.1 Overview

ReMAC leverages the broad domain knowledge, coding capabilities, and reasoning abilities of LLMs to design reward functions for multi-agent systems. In brief, ReMAC designs both agent-level and team-level rewards to guide agents in learning coordinated policies. To achieve efficient optimization of reward functions, ReMAC employs an evolutionary paradigm, wherein a reward population is constructed and improved through iterative evolutionary processes. The overall optimization process of ReMAC is illustrated in Figure 2. Specifically, ReMAC consists of three key steps:

Multi-Agent Reward Population Construction ReMAC begins by providing the LLM with the task description, environment code, and predefined prompts (e.g., reward function templates and design tips). Based on these inputs, the LLM identifies the role of each agent and generates a pair of reward functions: agent-level rewards for guiding individual skill learning and team-level rewards for promoting coordination. This process is repeated n times to construct a reward population $\mathbb{P}_{\mathrm{R}}$.

Parallel Training and Knowledge Sharing For each reward function pair in $\mathbb{P}_{\mathrm{R}}$, we initialize a MARL instance composed of policies and critics for all agents. These instances collectively form a MARL population $\mathbb{P}_{\mathrm{MA}}$. Each team in $\mathbb{P}_{\mathrm{MA}}$ interacts with the environment to collect experi-

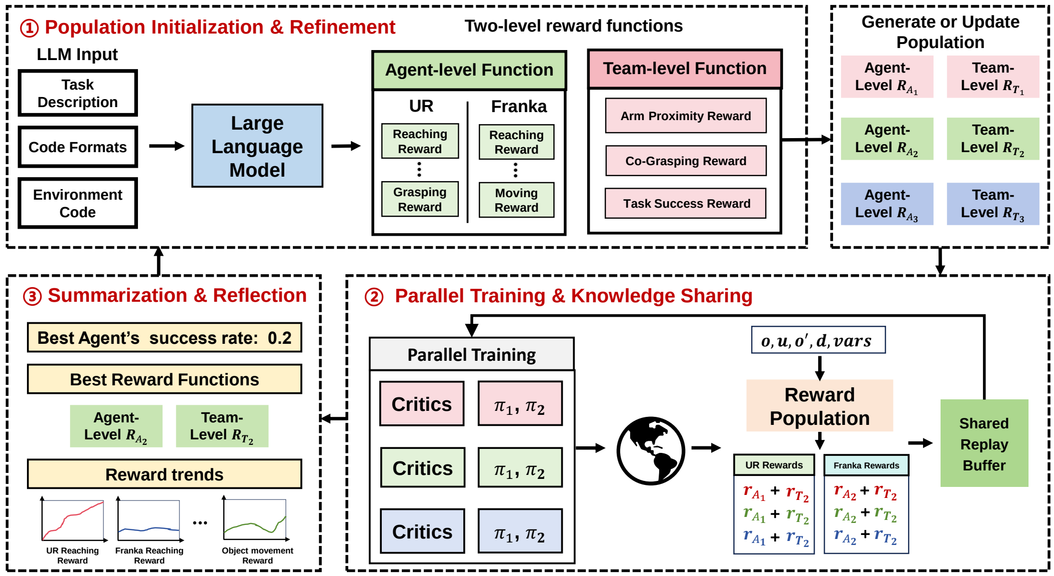

Figure 2: The overview of ReMAC. The process contains three steps: ① The task description, code templates, and environment code are taken as inputs to the LLM. The LLM generates both the agent-level reward function and the team-level reward function. Repeat this process n times to form a reward population. ② For each reward function pair, the corresponding MARL critics and policy teams are instantiated and trained through interactions with the environment. ③ At regular intervals, the reward functions associated with the best-performing policies are selected. The training details are summarized and fed back into the LLM for reflection to improve the reward functions.

ences, which are stored in a shared replay buffer $\mathcal{D}$. Each collected experience is re-labeled by its corresponding reward function and then used for MARL training and optimization.

Periodic Summarization and Reflection At regular intervals, we select the top-performing teams and summarize their corresponding reward functions, success rates, and the trends of each reward components during training. This information is fed back to the LLM for reflection, allowing it to further refine and improve the reward population.

The above process is performed iteratively until the maximum number of interaction steps is reached. To provide a clearer illustration of the algorithm, we present its pseudocode in Algorithm 1. Next, we provide a detailed introduction of the multi-agent reward function generation, as well as policy learning and reward function optimization.

Algorithm 1 ReMAC Framework

```
Initialization: Task description L, environment code M, coding LLM 𝕃𝕃𝕄, designed prompt p
Hyperparameters: maximum steps T_total, pop size n, evolution frequency T_evo
Stage I: Initialize population ℙ_R & ℙ_MARL:
{f^1_reward, ..., f^n_reward} = 𝕃𝕃𝕄(L, M, p)
Initialize a MARL instance for each f^i_reward
for step t = 1 to T_total do
    Stage II: Interaction & Learning
    Interaction and label rewards with ℙ_R
    Store experiences in D
    Optimize MARL in parallel
    Stage III: Summarization & Reflection
    if t%T_evo == 0 then
        Select f^best_reward with training details d for reflection.
        Update population ℙ_R = 𝕃𝕃𝕄(f^best_reward, d, p)
```

3.2 Reward Generation from Individual and Team Perspectives

Unlike in single-agent RL, reward design in multi-agent systems must account for both individual skill acquisition and coordination among agents and their behaviors. This requires more fine-grained reward design and credit assignment.

To address these challenges, ReMAC leverages the strong reasoning capabilities and domain knowledge of LLMs. Given a task description $\mathcal{T}$, ReMAC proceeds in two steps: 1) Analyzes the skills each agent needs to master in order to complete the task, and constructs corresponding agent-level reward functions. 2) Identifies the necessary inter-agent constraints for coordination, and builds team-level reward functions accordingly.

We formalize both agent-level and team-level reward functions. The agent-level function outputs a list of total rewards (one for each agent) and a reward dictionary, whereas the team-level function outputs a single total reward and a corresponding dictionary. The total reward is used for policy learning, while the reward dictionary provides a basis for analyzing the trends of the reward modules. Besides, each reward function consists of multiple reward modules, each targeting a specific skill or collaboration objective. For example, a reaching reward that guides the robotic arm to a target position, or a collaborative grasping reward that encourages agents to grasp an object simultaneously. Based on the above design, the guiding reward for each agent is formulated as the sum of individual and team components, i.e. $r_i = r^i_{\text{Individual}} + r_{\text{Team}}$, facilitating more efficient credit assignment and coordinated policy learning.

3.3 Multi-Agent Policy Learning & Reward Evolution

Constructing a single pair of reward functions for policy learning is inefficient and prone to suboptimal solutions. To solve the problem, we construct n pairs of reward functions, forming a reward population $\mathbb{P}_{\text{R}}$. For each pair of reward functions in $\mathbb{P}_{\text{R}}$, a corresponding MARL instance is initialized, thereby forming a MARL population $\mathbb{P}_{\text{MARL}}$. Each team policy in $\mathbb{P}_{\text{MARL}}$ interacts with the environment to collect experiences. For each experience, rewards are computed using the reward population $\mathbb{P}_{\text{R}}$, labeling n rewards per experience. These different rewards guide the learning of different MARL individual within $\mathbb{P}_{\text{MARL}}$. This data sharing approach significantly improves sample efficiency. Additionally, considering the computational intensity of population-based training, we employ parallel training to substantially reduce time overhead.

Every T_{evo} environment steps, we select the best team and summarize its success rate, the reward functions it relies on, and the trends of each reward modules. This information is fed back to the LLM for reflection. To achieve efficient optimization of reward functions, we guide the analysis of the current reward function from three perspectives:

- **Skill perspective** focuses on analyzing whether each reward module successfully guides the skill learning, often requiring adjustments to the internal implementation of modules.
- **Individual perspective** analyzes whether the agent-level rewards are comprehensive or redundant, involving adding necessary guidance or removing unnecessary disruptive rewards.
- **Team perspective** analyzes whether the team-level reward effectively promotes collaboration among agents, which may involve optimization of the collaboration module.

Based on these three levels, LLM optimizes both the agent-level and team-level reward function by adding, removing, or adjusting reward modules. Ultimately, the reward functions generated through LLM reflection will replace non-optimal reward functions in $\mathbb{P}_{\text{R}}$. Besides, we continue optimization based on the best-performing MARL instance to avoid learning from scratch.

4 ManiCraft Benchmark

Recent advancements in the robotics field, particularly in embodied intelligence [84, 85], have been remarkable. However, we observe that the MARL community lacks a benchmark for multi-agent manipulation tasks aimed at low-level collaborative policy learning [86, 87, 11, 88–90]. To bridge the gap, We propose **ManiCraft**, a benchmark that the following key features:

- **Diverse MA-Manipulation Tasks**: A diverse set of collaborative manipulation tasks designed to facilitate low-level coordination policy learning.
- **Easy to Use & Extend**: Implemented following the Gym standard [91], with each task implemented in a single file, making it easy to use and extend.
- **Fine-grained design for MARL**: Carefully designed action space, state spaces and reward functions to ensure each task is learnable by MARL algorithms.

Table 1: Tasks included in ManiCraft and their descriptions

Task	Description
Co-Sweep-Easy	Panda holds the broom to sweep one cube into the dustpan held by UR.
Co-Sweep-Mid	Panda holds the broom to sweep two cubes into the dustpan held by UR.
Co-Sweep-Hard	Panda holds the broom to sweep three cubes into the dustpan held by UR.
Co-Push	The Panda and UR push the cubes at their sides together.
Co-Stack-On	The Panda places the cube from its side onto the coaster next to the UR.
Co-Trans	The UR grasps the cube next to the Panda.
Co-Open	Two URs work together to open the cabinet door.
Co-Close	Two URs work together to close the cabinet door.
Co-Place	Move the object next to the Panda to the target position next to the UR.
Co-Lift	UR and Panda work together to lift a rectangular object.
Co-Grasp	UR and Panda work together to grasp a rectangular object.

Specifically, ManiCraft is developed based on MuJoCo [92] and utilizes MoCap for end-effector pose control. We design 11 manipulation collaborative tasks, which typically require the coordination of a UR robotic arm and a Franka Panda robotic arm, or the coordination of two UR robotic arms. Each robot is mounted on opposite sides of a table, with the target objects to be placed on the table. Detailed task descriptions and settings are provided in Table 1. Besides, ManiCraft also supports the rapid construction of collaborative scenarios involving more than two robotic arms, and we plan to release more coordination tasks in the future. Below, we present the design of the action space, state space, and reward functions in ManiCraft.

Action Space Design. The action space of each agent is defined as a 2-tuple consisting of the end-effector's positional delta in 3D space and a normalized torque value applied by the gripper fingers. Each action is bounded within the range $[-1, 1]$. For some tasks, we extend the action space to include rotation control via Euler angles.

State Space Design. In our current setup, all agents have global observations. All task-related states are encapsulated within the observations, such as the end-effector pose of the gripper, the gripper's opening and closing size, the arm's velocity, and the position of the target object. In the future, we consider incorporating local observations to create more challenging collaborative scenarios.

Manually Designed Reward Functions. To ensure that each task can be handled by current MARL algorithms, we carefully design the reward functions and demonstrate that, for each task, the MARL algorithms can achieve a certain success rate. The basic principle behind our reward design is to construct reward components, ranging from 0 to 1, based on factors such as distance and grasping decisions, and combine them with different weights. Through extensive testing, we select the most efficient reward function configurations.

In summary, ManiCraft is a multi-agent manipulation benchmark tailored for the MARL community to facilitate the development of low-level coordination policies. We refer readers to Appendix D for additional implementation and design details of ManiCraft. The subsequent sections provide experimental validation and analysis using ManiCraft.

5 Experiments

5.1 Experiment Setup

We conduct experiments on ManiCraft to demonstrate the effectiveness of ReMAC. At the same time, we use the performance of various MARL algorithms to validate the rationality of the task design. The benchmark includes a diverse set of tasks, each requiring different types of collaborative policies to succeed. For a fair comparison, all algorithms adopt MASAC as the MARL backbone, and all LLM-based methods use GPT-4o as the language model. MASAC follows the centralized training with decentralized execution (CTDE) paradigm. It maintains an individual policy for each agent, along with a centralized critic to guide policy learning. The detailed network architecture and training hyperparameters are provided in Appendix B and C.

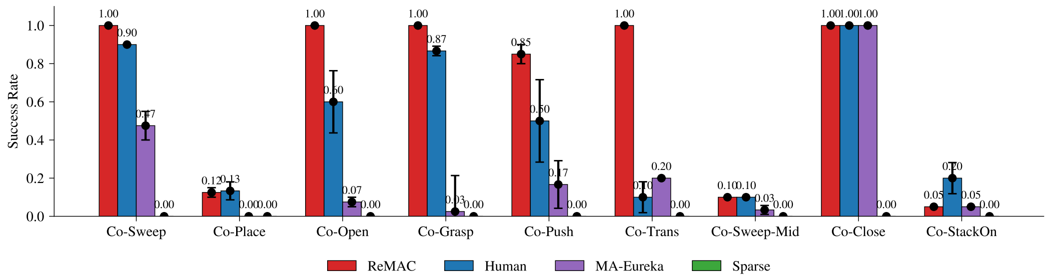

Figure 3: Performance comparison between ReMAC and other baselines on ManiCraft. ReMAC achieves performance comparable to, and in some cases surpassing, that of algorithms guided by meticulously human-designed reward functions.

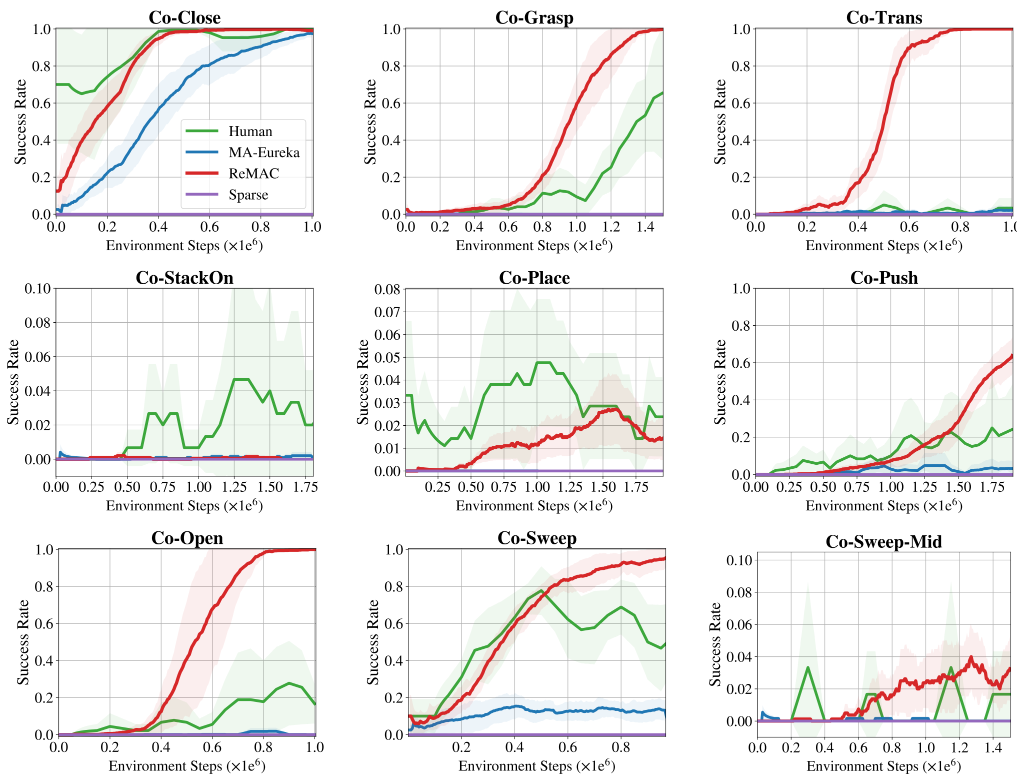

Figure 4: Training curves on various tasks. ReMAC significantly outperforms other baselines and surpasses human-designed rewards in most tasks.

Baselines: We consider the following three baselines: 1) MASAC with human-designed reward functions, where the reward is manually crafted through trial-and-error to guide learning effectively. 2) MASAC with sparse rewards, where agents receive a reward only upon successful task completion. 3) Multi-agent extension of Eureka, where we adapt the original Eureka framework to the MARL setting by using a single reward function to guide all agents collectively. Hyperparameters are kept consistent across all methods to eliminate confounding factors.

Evaluation Metric: We primarily compare the task success rate under the same number of environment steps, which reflects the sample efficiency of different algorithms. All statistics are obtained from 5 independent runs. We report the average with 95% confidence regions.

5.2 Performance Evaluation

We first compare performance across 9 different tasks in the ManiCraft benchmark. As shown in Figure 3, ReMAC demonstrates performance on par with, and in some tasks superior to, MARL algorithms using human-designed reward functions. The MARL algorithms trained with sparse rewards consistently fail to learn effective collaborative policies across all tasks. Besides, ReMAC outperforms the multi-agent extension of Eureka in both efficiency and performance. This advantage stems from two key factors: (i) the construction of reward functions from both agent-level and team-level perspectives, and (ii) the ability of ReMAC to more effectively leverage experience collected from different teams.

We present the learning curves of different algorithms in Figure 4. We can observe that ReMAC achieves sample efficiency comparable to or even better than that of manually designed reward functions. MA-Eureka is only able to learn effective collaborative policies on relatively simple tasks, such as Co-Close. When the task difficulty increases even slightly, MA-Eureka tends to fail. In contrast, ReMAC is capable of achieving stable learning across a wider range of tasks. However, we also observe that in certain tasks—such as Co-StackOn and Co-Place—which involve more complex or temporally dependent coordination, both ReMAC and human-designed reward functions struggle to enable efficient learning. This may be due to the difficulty of decomposing complex tasks, especially those with long-horizon temporal dependencies or intricate inter-agent coordination. In these cases, ReMAC performs worse than human-designed rewards. The main reason is that ReMAC relies on trial-and-error optimization, which leads to more frequent failures in complex tasks. These failures reduce sample efficiency and hurt final performance. Addressing above limitations will be an important direction for future work.

5.3 Ablation & Analysis

In this section, we perform ablation studies to analyze several core components of ReMAC. Specifically, we seek to answer the following three questions: Q1: Does constructing reward functions from both the agent-level and team-level perspectives lead to more effective learning? Q2: Is population-level iteration necessary for improving reward function optimization? Q3: Does experience sharing among individuals in ReMAC contribute to learning efficiency?

To answer Q1, we analyze the necessity of constructing reward functions from both the agent-level and team-level perspectives. We compare our approach with a unified reward design, which treats the multi-agent system as a single-agent task by constructing team rewards to guide the learning of all agents. As shown in Figure 5, ReMAC demonstrates higher efficiency compared to variants that rely on single team rewards. This advantage primarily stems from its decoupled design, which explicitly allocates credit by decomposing the reward, thereby guiding policy learning more effectively.

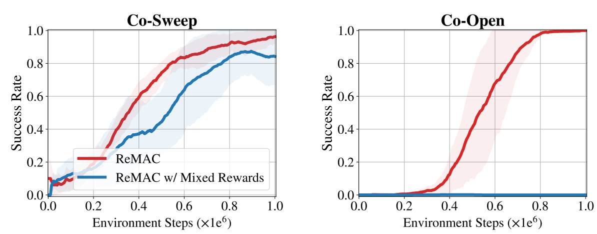

Figure 5: Ablation on Dual-Level Reward Construction

To answer Q2, we analyze the necessity of maintaining a reward population. As shown in Figure 6, removing the population leads to a significant performance drop in ReMAC. This is primarily because population-based optimization provides a diverse set of reward functions, which facilitates more effective exploration. In contrast, relying on iterative optimization with a single reward function tends to increase the risk of falling into suboptimal solutions. Therefore, population-based optimization is necessary for improving the efficiency of multi-agent reward function optimization.

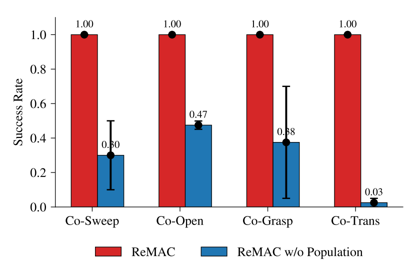

Figure 6: Ablation study on population

To answer Q3, we conduct an ablation study on knowledge sharing in ReMAC. In this setting, knowledge is no longer shared across teams—each team in the population is trained solely based on its own interaction experiences. As shown in Figure 7, ReMAC w/o Sharing has a noticeable decline in both final performance and convergence speed. Without experience sharing, the diversity of experiences available to each individual significantly decreases, which in turn hinders policy learning and optimization. Besides, we present the generated reward functions for the CoStackOn task. ReMAC decomposes the complex collaboration into meaningful components—both UR and Panda receive reaching and object moving rewards, while the team reward encourages inter-arm coordination and joint placement.

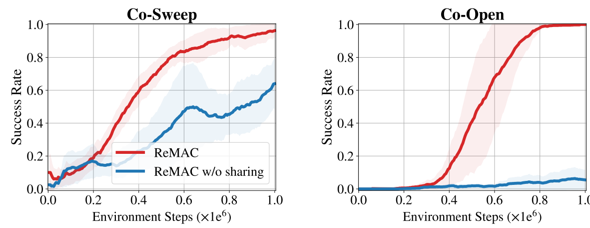

Figure 7: Ablation study on knowledge sharing

Agent-level Reward Function

```
# Calculate distances
panda_to_cube_dist, ur_to_coaster_dist,
    cube_to_coaster_dist = ...
# Panda reward components
grasp_reward = 1.0 if is_panda_grasped else 0.0
reach_reward_panda = np.exp(-panda_to_cube_dist)
move_to_goal_reward = np.exp(-cube_to_coaster_dist)
panda_reward = 0.5 * grasp_reward + 1.0 *
    reach_reward_panda + 2.0 * move_to_goal_reward
# UR reward components
reach_reward_ur = np.exp(-ur_to_coaster_dist)
ur_reward = 0.5 * reach_reward_ur + 2.0 *
    move_to_goal_reward
```

Team-level Reward Function

```
distance = np.linalg.norm(cube_position - coaster_position)
success_reward = 100.0 if success else 0.0
combined_grasp_on_coaster_reward = 1.0 if is_panda_grasped
    and is_object_on_coaster and (distance < 0.05) else 0.0
team_proximity_reward = np.exp(-distance)  # Encourage
    reducing distance to coaster
# Team-level reward
team_reward = 50.0 * combined_grasp_on_coaster_reward +
    success_reward + 1.0 * team_proximity_reward
```

6 Conclusion

To enable efficient automatic reward generation in multi-agent reinforcement learning (MARL), we propose ReMAC, a large language model (LLM)-based framework for multi-agent reward design. ReMAC adopts a two-layer architecture. The upper layer focuses on reward optimization by leveraging the LLM's broad domain knowledge and coding capabilities. It generates a population of reward candidates from both the agent-level and team-level perspectives. This population is iteratively refined based on reflective feedback from skill, individual, and team dimensions. The lower layer employs MARL to learn coordinated policies, enabling efficient experience sharing among agents. To advance research in the MARL community, we introduce ManiCraft, a benchmark suite of diverse multi-agent manipulation tasks that emphasizes low-level coordination policy learning. Experimental results on ManiCraft show that ReMAC's automatically generated rewards outperform expert-designed reward functions, significantly improving both learning efficiency and final policy performance.

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