Relay Hindsight Experience Replay: Continual Reinforcement Learning for Robot Manipulation Tasks with Sparse Rewards

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Abstract—Learning with sparse rewards is usually inefficient in Reinforcement Learning (RL). Hindsight Experience Replay (HER) has been shown an effective solution to handle the low sample efficiency that results from sparse rewards by goal relabeling. However, the HER still has an implicit virtual-positive sparse reward problem caused by invariant achieved goals, especially for robot manipulation tasks. To solve this problem, we propose a novel model-free continual RL algorithm, called Relay-HER (RHER). The proposed method first decomposes and rearranges the original long-horizon task into new sub-tasks with incremental complexity. Subsequently, a multi-task network is designed to learn the sub-tasks in ascending order of complexity. To solve the virtual-positive sparse reward problem, we propose a Random-Mixed Exploration Strategy (RMES), in which the achieved goals of the sub-task with higher complexity are quickly changed under the guidance of the one with lower complexity. The experimental results indicate the significant improvements in sample efficiency of RHER compared to vanilla-HER in five typical robot manipulation tasks, including Push, PickAndPlace, Drawer, Insert, and ObstaclePush. The proposed RHER method has also been applied to learn a contact-rich push task on a physical robot from scratch, and the success rate reached 10/10 with only 250 episodes.

Index Terms—Deep reinforcement learning, Robotic manipulation, Continual Learning, Residual Policy Learning

I. INTRODUCTION

Learning a model-free deep reinforcement learning (RL) agent with sparse rewards in real-world robot manipulation tasks has long been a prominent goal in robotics research [1]–[8]. The efficiency problem has always been an important reason for limiting the application of deep RL on physical robots, which is often caused by sparse rewards. Because the agent cannot distinguish which action is better when all actions have the same reward [9].

After the HER [1] method was proposed, a huge breakthrough has been made in these methods for obtaining reward signals only from whether the task is completed or not. It does not require complex professional knowledge to design the reward function, but it relabels the failure goal with the state achieved. In this study, the reward obtained by the agent’s actual failed exploration is termed real-negative (r=1) reward.

On the contrary, the success reward obtained by using HER to modify the desired goal is termed virtual-positive (r=0) reward.

However, there is an interesting phenomenon: the agent can quickly converge for a one-stage task (reaching task); but for a two-stage task (such as FetchPush, which needs to approach and then operate the object) will converge after about 500K interactions [1]. This phenomenon implies that the early exploration of HER encountered some kind of dilemma. As shown in Fig. 1(a), for a one-stage reaching task, though the explored episodes failed, the agent can get successful episodes by relabeling desired goals with HER to solve the real-negative sparse reward problem. However, when it comes to the manipulation example shown in Fig. 1(b), the achieved goals (the object’s position) are identical for all actions if the object is untouched by the agent, which is still a difficult sparse reward case for learning. In other words, the original samples are sparse rewards with negative, meanwhile, the virtual modified data by HER is a positive sparse reward in a certain sense, which is termed virtual-positive sparse reward problem.

To solve this new implicit sparse reward problem, an intuitive idea is to combine the continual learning (CL) [10]–[13] with HER-based RL. Continual RL is an important direction of Deep RL [14], [15], and it can be adapted to help the agent learn from simple to complex tasks stage by stage. Therefore, the agent can quickly learn an initial policy that guides the robot to reach the target object. With this initial policy guidance, the target policy can learn the whole manipulation more easily, because the achieved goals are changed by the agent. To the best of our knowledge, there...
is no such application of continual learning in manipulation tasks using a multigoal-based and model-free RL with sparse rewards.

Since object manipulation tasks have clear logic and stages, taking one single object manipulation as an example, as shown in Fig. 2(c), the full task can be decomposed into two stages: 1) approaching the object; 2) object manipulation. Then, two increasingly complex tasks are defined by the stages, reaching task and target task, with grip-goal and object-goal respectively. Inspired by one hot, a multi-task network can be designed by encoding goal space. With this structure, for each task, the agent can generate corresponding successful samples by HER, so that the agent can overcome the real-negative sparse reward problem. Furthermore, based on the goal-conditioned structure and the experience buffer of RL, all policies can be updated simultaneously to avoid the catastrophic forgetting of backward transfer, and the data can be shared across tasks to facilitate the positive forward transfer.

In addition, a Random-Mixed Exploration Strategy (RMES) is developed, which makes the easier task guide the harder task to change the corresponding achieved goals quickly for solving the virtual-positive sparse reward problem. The contributions of this study can be summarized as follows:

1) This paper develops an elegant sample-efficient goal-conditioned continual RL algorithm, RHER, based on HER for manipulation tasks to solve the real-negative and virtual-positive sparse reward problem.

2) The proposed RHER method is more sample-efficient than vanilla-HER and state-of-the-art methods, which are validated in by the standard manipulation tasks in the OpenAI Gym [16].

3) The generality of RHER is verified through three other different types of simulated manipulation tasks, and even on a physical robot task.

II. RELATED WORK

HER paves a promising path toward the sparse reward problem. Through the Universal Value Function Approximators (UVFA) [17] with neural networks, it can even be generalized to the unseen actual goal. HER has extremely high efficiency in handling long-horizon reaching tasks [1], [2], but it is not efficient in multi-stage robot manipulation tasks. In order to improve the sample efficiency of HER, many variants of HER have been proposed: 1) curriculum learning to maximize the diversity of achieved goals [3], [5]; 2) providing demonstrations [18], 3) generating more valuable desired goals [19]; 4) curiosity-driven exploration [20]; 5) model-based RL methods [21]. These methods have improved the performance of HER to a certain degree, but the virtual-positive sparse reward problem is still unsolved.

The problem of achieved goal is previously reported in [4], the solution of which is to directly filter those transitions with \( r(s_{t-1}, a_{t-1}, g) = 0 \), which is not suitable for common robotic arm operation tasks. The problem is further discussed in [5]. The researchers propose a SHER algorithm that learns a reaching policy first and then transfers the reaching policy to more complex tasks. However, the policy transfer may have the risk of catastrophic forgetting. To simplify the long-horizon manipulation tasks, inspired by [8], the manipulation tasks can be decomposed into two stages according to the distance between the gripper and the object. Previous works use hierarchical RL (HRL) approaches to solve these subtasks [22]–[25]. Specifically, [25] shares the critic network and data across subtasks. However, these methods do not explicitly use the learned policy to guide a more complex policy during exploration.

Different from the aforementioned HER-based or HRL-based algorithms, this study adopts the continual RL scheme to solve long-horizon robotic tasks. CL has drawn increasing attention from the RL community over the last few years. Current mainstream continuous learning has three solutions to keep the previous tasks from forgetting [13]. The first is the regularization-based scheme [26], [27], which is difficult to update as the number of tasks increases and requires additional computation. The second is the modular approaches [28], [29], for example, by designing a task-conditioned architecture, this solution can accommodate both previous and new tasks [13]. The third is the memory-based method which needs to revisit previous task data when training for a new task [30], [31]. Inspired by these solutions, the proposed RHER takes into account the latter two solutions by developing multi-task networks and an inherent experience buffer of RL.

For robot manipulation tasks, few methods use Deep RL with CL. [14] trains a hyper-network to get dynamics models with different dynamics tasks. In order to sidestep the exploration dilemma, this work places the object close to the gripper. [15] filters out samples not suitable for the target task, then relabel the remaining samples to pre-train a separate policy for a new task. In contrast to the above methods, RHER can share data across all tasks, nor do we need to design a heuristic reward function for each task, which means that it can be adapted to various tasks and scenarios with little effort.

Considering that the RHER algorithm can quickly obtain a reaching policy, which can be regarded as a guide-policy to accelerate exploration-policy, and the closest related work is the Residual-RL, which expects to combine the strengths of a model-based controller and Deep RL in two different ways. The first way is to superpose the signals of both policies [32]–[35]. What these studies have in common is that the guide-policies are fixed and contain prior knowledge. The second way is to select a policy according to the certain probability [36], [37], which is suitable for this work because the guide-policy will be updated online. In this manner, we mix policies with the same probability in RMES.

III. PRELIMINARIES

The background and some definitions of the RHER will be introduced in this section. First, background on the goal-conditioned RL and HER algorithm will be provided. Then, the decomposition and rearrangement of manipulation tasks will be defined, and how to use continual learning to handle these.

A. Goal-conditioned Reinforcement Learning and HER

According to the HER methods, manipulation tasks can be modeled as a finite-horizon, discounted Markov Decision Pro-
cess (MDP). The whole state $S$ contains not only the observation $S_o$, but also a desired goal $S_{dg}$, where $S_{dg} \in S_o$. The policy $\pi(a|s_o, s_{dg})$ is usually a neural network model that maps the $t$ step state $s_t = (s_o, s_{dg})$ to the action $a_t \in A$. The MDP has some other necessary components: a discount factor $\gamma \in (0, 1)$, horizon length $T$ and a reward function $r: S \times A \rightarrow R$. The goal of the agent is to acquire an optimal policy $\pi(a|s_o, s_{dg})$ that maximizes the expected sum of discount rewards.

For a fair comparison, this paper chooses the DDPG-HER (OpenAI baselines) as the baseline [2], the RL algorithm here is Deep Deterministic Policy Gradient (DDPG), and adopts DDPG-HER to DDPG-RHER. It is noted that any off-policy algorithms or variants of HER can be replaced in this method. For the DDPG architecture, there are two main parts, an actor neural network denoted as $\pi_\theta(a|s_o, s_{dg})$, for generating actions, and a critic network denoted as $Q_\theta(s_o, s_{dg}, a)$, for evaluating the action performance. In order to stabilize the learning process, there is also a set of target actor $\pi_\theta$ and target critic $Q'_\theta$ with the same structure but delayed update. The critic network parameter $\phi$ is learned by minimizing the Bellman error, and the loss function is defined as (1),

$$Loss_\phi^{(i)} = \vert Q_\phi(s_o, s_{dg}^{(i)}, a_t) - y_t \vert^2,$$

where the target $y_t = r_t + \gamma Q'_\phi(s_{o_{t+1}}, s_{dg_{t+1}}, a_{t+1})$; $a_{t+1}$ is generated by $\pi'_\theta(s_{o_{t+1}}, s_{dg_{t+1}})$. To extend multi-task setting, let $s_{dg}^{(i)}$ denote the desired goal of $i^{th}$ task.

Based on the Q function, the policy network parameter $\theta$ is trained using the gradient descent method with the loss represented as (2),

$$Loss_\theta^{(i)} = -E_{s_o, s_{dg}^{(i)}}Q[s_o, s_{dg}^{(i)}, \pi_\theta(s_o, s_{dg}^{(i)})],$$

Usually, the reward feedback is sparse, represented as (3),

$$r(s_o, s_{dg}, a) = -[s_{ag} = s_{dg}],$$

where $s_{ag} \in S_o$ is the achieved goal in the current state.

### B. Decompose Manipulation Tasks and Continual Learning

In order to reduce the exploration complexity of RL, the achieved goals need to be changed with the action of the agent. For common manipulation tasks, if there are N objects to operate in order, it can be divided into $2N$ stages, as shown in Fig. 2(b), the aim of stage $2i-1$ is to reach the $i^{th}$ object and prepare to the stage $2i$, and the stage $2i$ is to operate the $i^{th}$ object to reach its target goal. Based on this scenario, we rearrange these stages into different tasks. Considering that some manipulations, such as pushing and sliding, require continuous decision-making, we combine these into 2N tasks, and the relationship between the tasks and stages is denoted as (4),

$$task_i = \sum_{i=1}^{2N} stage_i,$$

from which one can see that the difficulty of tasks increases gradually with the increase of task index $i$, and the policy of task$_i$ is denoted as $\pi'(\cdot)$.

Without loss of generality, this paper focuses on the single object tasks ($N=1$). Specifically, the task$_1$ here means controlling the end-effector to reach the object, termed reaching-task, as shown in Fig. 2(b). The achieved goal here is the gripper’s position, named grip-pos; the desired goal is the coordinate of the object, denoted as $g_{g}^{(i)}$, $i=1$. As for the task$_2$, it is essentially the original task, namely target-task, where the achieved goal is the position of the object, represented as obj-pos, and the desired goal is denoted as $g_{obj}^{(i)}$. Finally, $\pi'$ and $\pi''$ correspond to the reaching policy and the target policy, respectively (as shown in Fig. 2(b)). Of course, this task setting can also be easily extended to the tasks of multiple objects.

When the original task is decomposed into 2N tasks with increasing difficulty, the most intuitive solution is to use the idea of CL to resolve these tasks in order. The objective of CL is to learn new knowledge of the current task continuously, while the performance on previous tasks is not forgotten. In the above task setting, the current task is the task$_2$ (target-task), and the previous task is task$_1$ (reaching-task).

In this manner, a network structure that can deal with multiple tasks is required. A multi-task RL policy is proposed here and denoted as $\pi_\theta(a|s_o, s_{dg}^{(i)}) = e_g^{(i)}$, where $a \in A$ represents the action comprised of a 4-D vector for controlling 3-D position and 1-D opening of the gripper in this study; $s_o \in S$ represents the system states comprised of Cartesian positions, linear velocity of the gripper and the position and velocity information of the object; $e_g^{(i)}$ represents the goal space embedding of the $i^{th}$ task for $\pi'$ and $\pi''$ (as shown in Fig. 2(d)) formulated as (5),

$$e_g^{(i)} = [g_{g}^{(i)}|0^3], \quad e_{g}^{(i+1)} = [0^4]|g_{obj}^{(i)}] \in R^{6 \times 1},$$

where $|$ denotes vector concatenation. Such a multi-task model serves as the foundation of the following data transfer and policy guidance.

### IV. METHODS

This section will present a novel sample-efficient framework, RHER, which consists of four components as shown in Fig. 2(a): 1) This component decomposes the original task into multi-stages and then combines these stages into multi-tasks with increasing complexity; 2) This part designs a multi-task RL model to tackle the above tasks; 3) By utilizing HER, this component overcomes the problem of real-negative sparse rewards and shares data collected from different tasks; 4) In order to solve the virtual-positive sparse reward problem by HER, the RMES approach is proposed, which enables the agent to learn from the simplest task, then the easier task can serve to “bootstrap” the harder task, similar to a relay.

The whole method only introduces two extra insensitive hyper-parameters in contrast to the vanilla-HER methods, one is in the task segmentation, the threshold of the distance object needs to be set in advance, and the other is the exploration ratio in RMES. The full RHER algorithm is described in Algorithm1, and the details of these four parts are introduced as follows.

#### A. Task Decomposition and Rearrangement

For many object manipulation tasks, the regular HER methods confront the problem of virtual-positive sparse rewards. To tackle these complex long-horizon tasks, a common idea
is to decompose them. To separate the object manipulation tasks, a distance to the object $d$ need to be defined in advance (ablation experiments are shown in Section VI-C). The stage can be determined by (6),

$$stage = \begin{cases} 
1 & \text{if dist > d} \\
2 & \text{if dist \leq d} 
\end{cases} \quad (6)$$

where $dist$ is the distance between the gripper (end-effector) and the object.

After the decomposition is done, the next step is to form new tasks. There are two strategies, one is that one task corresponds to one stage, and the other is that each task processes one more stage based on the previous task. Considering the dynamic continuous tasks such as pushing and sliding, the latter is more stable, and for the pick-related tasks, the first strategy is easier for learning. Detailed ablation experiments will be conducted in Section VI-B.

**Algorithm 1:** Relay Hindsight Experience Replay

```
Initialize the agent and replay buffer R
for each episode do
    Sample an observation dictionary
    for each time step do
        Check stage as (6)
        Sample an action with RMES as (7)
        Execute the action and get new observation
    Store the transition
    for each gradient step do
        for desired-goal = ($g^i_t, g^k_{obs}$) do
            Sample a mini-batch episodes $B$ from R
            Replace the current desired-goal with the achieved goal with a probability of 0.8
            Perform optimization of (1), (2) based on $B$
```

**B. Multi-tasks RL Model**

The multi-tasks need a corresponding RL structure. Inspired by the one-hot encoding method commonly used in multi-task networks, this study encodes the multiple-goal into a similar structure as (5). Such a structure allows a network to handle multi-tasks simultaneously without interfering with each other. Compared with multiple independent networks, this method requires fewer parameters, which facilitates deployment.

**C. Maximize the Use of All Data by HER**

When a network that can handle multiple tasks is developed, it will generate plenty of data during the process of exploration, not only from failure experiences but also from different policies.

The CL methods aim to transfer knowledge effectively. In the RHER framework, a policy update can not only use its own explored data but also relabel the data collected by other policies by the HER strategy. Therefore, the RHER scheme can realize both the forward and backward transfer together for CL, and solve the real-negative sparse reward problem.

**D. Random-Mixed Exploration Strategy (RMES)**

Compared with standard CL, continual RL not only needs to share data but also needs to interact with the environment to obtain new valuable data, and even needs online exploration to eliminate the accumulation of error of inference caused by offline data. What’s more, due to virtual-positive sparse rewards, the achieved goals of the target-tasks need to be changed. Therefore, an efficient and stable exploration strategy is required.

Inspired by the idea of a relay, when a traveler needs to explore further, he/she needs to be escorted by some experts, then he/she can quickly pass through the area that the expert is familiar with, and finally explore new areas by himself/herself.
As for the robotic RL agent, RHER mixes the previous and current policies in equal proportions in the previous stage. Even though the current policy deviates a little from the optimal, the previous policy can correct it in time, so that the agent can quickly reach the next stage. An example diagram can be found in Fig. 2(d). Such an exploration strategy introduces the second hyper-parameter, and the probability $\alpha$ of the guide-policy can be sampled. A detailed ablation study will be conducted to show that this hyper-parameter is also insensitive (see Section VI-D). Specifically, for exploration, actions are selected according to (7):

$$a = \begin{cases} 
\pi' & \text{if } z < \beta \\
\pi_1 & \text{if in stage}_1 \text{ and } \beta \leq z < \beta + \alpha \\
\pi_2 & \text{if in stage}_2 \text{ and } \beta + \alpha \leq z 
\end{cases}$$

(7)

where $\pi'$ is a random policy, the probability of random actions is $\beta$, and the random number $z$ is sampled from $\text{rand}(0, 1)$.

V. EXPERIMENTAL SETUP

In this section, the setup of six simulations and a real robot experiment is introduced to answer the following questions:

a) How does RHER compare with HER in terms of efficiency and final performance?
b) How well does RHER perform in preventing forgetting and transferring knowledge across tasks?
c) Are the two hyper-parameters sensitive introduced by RHER?
d) Can the same set of hyper-parameters tackle other operational tasks and real-world scenarios?

A. Setup of the Simulation Environments

Three standard simulations are conducted in the gym fetch manipulation environments: FetchPush, FetchPickAndPlace, and FetchSlide. To illustrate that RHER can be generalized to other manipulation tasks, three additional tasks are carried out as shown in Fig. 8, of which the details are elaborated as follows.

**FetchDrawer**: To slide the drawer to a specific position by pulling the handler.

**FetchInsert**: To insert a closed gripper into a hole with a random position. This paper creatively sets a virtual object in the insertion task, when the gripper reaches the vicinity of the hole, the virtual object will be moved by the gripper, so that HER can be applied.

**FetchObstaclePush**: To push an object to a specific position in the presence of an obstacle that is unknown in size and shape in between.

The reward functions are still the most common binary rewards described in (3). The other settings are referred to [1] (details can be found in Gym).

B. Setup on a Physical Robot

**CuePush**: To push a wooden cylinder, which is 2.5 cm in radius and 3 cm in height, to a specific position by a metal cue that is attached at the end of a 7-DOF manipulator (SCR5, Siasun Co., Shenyang, China), with the positions of the cue and the cylinder extracted by a monocular camera (ZED, Stereolabs, San Francisco, CA, US). This study even executes an open-loop automatic reset script to avoid human bias. Limited by the automatic reset script, the workspace of the robotic arm controlled by RL is only $9 \times 14$ cm. Therefore, the distance threshold in the simulation is reduced from 5 cm to 2 cm.

C. Details of the Training Procedure

For each episode, the agent performs 40 optimization steps on mini-batches of size 256 sampled uniformly from a replay buffer consisting of 1e6 transitions. The network structure and input scaling are default as [2].

**Multi-processing training**: Since the sample efficiency and the performance of the HER increases with the number of parallel training processes [2], the proposed method is compared to the baselines in a multi-processing setting to validate its superiority.

In this setting, 50 epochs are trained with 19 CPU cores (one epoch consists of $19 \times 50 = 950$ full episodes), in which each episode consists of 50 steps.

**Single-processing training**: Considering that there is usually only one robotic arm for online learning in the real world, we also make a comparison with vanilla-HER in a single-processing setting. Due to the lower sample diversity of single-processing, the agent learns the tasks with 1200 epochs.

In this setting, the RHER and HER have 400 and 1200 epochs, a total of $400 \times 50$ and $1200 \times 50$ episodes, respectively, in which each episode consists of 50 steps. For the real environment, 15 epochs are set for training, and each episode just has 20 steps.

VI. RESULTS

This section will demonstrate the efficiency and effectiveness of RHER compared with baselines (HER). Ablation experiments will be conducted to illustrate the effect of each component or hyper-parameter, and three extra simulation tasks and a real world experiment will be carried out to show the generality of the RHER method.

A. Comparison with Baselines

**Multi-processing**: As shown in Fig. 4b, RHER achieves dramatically higher sampling efficiency, better performance,
and lower variance (less sensitive to random seeds) in Fetch-Push and FetchPickAndPlace. However, in the FetchSlide task, the performance of RHER is slightly worse than that of vanilla-HER. This may be due to the FetchSlide task being more sensitive [38].

**Single-processing:** As shown in Fig. 4(d), in the single-processing cases, the HER exhibits quicker learning as well as more stable performance. To be specific, the method proposed needs only 78K interaction steps (31 epochs) to achieve a success rate of 95% in the FetchPush task, demonstrating sample efficiency 17 times higher than that of the vanilla-HER (550 epochs). Counterintuitively, it is shown that the single-processing cases have higher sample efficiency compared with the multi-processing because the latter wastes more sampling opportunities in the early stage. Therefore, the results show that RHER has more potential to be applied to realistic scenarios.

**Continual RL:** For continual RL, it is necessary to evaluate whether the previous tasks are forgotten as the training process proceeds. As shown in Fig. 4(a), (c), the policies of the previous task (task1) can converge quickly without guidance whether in the multi-processing or the single-processing case, which proves that the previous tasks are retained by the agent all the time.

**Comparison among Combinations:** First, according to the task decomposition (see Section IV-A), the original task is divided into $2N(N=1)$ stages, but what kind of relay-style (policy combination) needs to be determined. As shown in Table I, for training or testing, $stage_1$ can be processed by $\pi_1$ and $\pi_2$ so that there are three policy combinations: $\pi_1^1$, $\pi_2^1$, and a mix of $\pi_1^1$ and $\pi_2^1$, denoted as $(\pi_1^1, \pi_2^1)$. When the $stage_1$ is processed only by $\pi_2^2$ in training, it is the same as the original HER, thereby excluding this option. There remain $2 \times 3 = 6$ combinations and the corresponding results of these six cases are shown in Fig. 5. For example, for Case0, the agent mixes the $\pi_1^1$ and $\pi_2^2$ to explore the $stage_1$ in training, whereas $\pi_2^2$ in testing (whether in training or testing, the agent can only use the $\pi_2^2$ in $stage_2$). It can be seen from Fig. 5, that only Case0 (ours) takes into account both performance and efficiency.

**Other Results:** There are some other interesting results in Fig. 5. 1) In Case4, $\pi_2^2$ does not explore $stage_1$ in the training process, so it cannot handle $stage_1$. This is largely attributed to the distributional shifts of actor-critic models using offline data. Details can be found in Fig. 7, which shows that $\pi_2^2$ requires a certain percentage of exploration to correct bias from offline data. 2) Combined with Case1, Case2, and Case0, the results show that, in testing, the performance of $\pi_2^2$ is damaged by other policies. The visualization results for the push task show that the agent always pushes the object forward by $\pi_1^1$, and the two policies cannot be toggled well, especially in the scene that needs the end-effector to reach the back of the object.

Through the above experiments, an appropriate relay-style (Case0) that satisfies both efficiency and performance can be determined.

![Fig. 4. Learning curves for the reaching-tasks and target-tasks. Results are shown over 5 independent runs. The training curve represents the mean with standard deviation (based on 5 independent runs).](image)

**B. Ablation 1: Policy Combinations in Stage1**

**Comparison among Combinations:** First, according to the task decomposition (see Section IV-A), the original task is divided into $2N(N=1)$ stages, but what kind of relay-style (policy combination) needs to be determined. As shown in Table I, for training or testing, $stage_1$ can be processed by $\pi_1$ and $\pi_2$ so that there are three policy combinations: $\pi_1^1$, $\pi_2^1$, and a mix of $\pi_1^1$ and $\pi_2^1$, denoted as $(\pi_1^1, \pi_2^1)$. When the $stage_1$ is processed only by $\pi_2^2$ in training, it is the same as the original HER, thereby excluding this option. There remain $2 \times 3 = 6$ combinations and the corresponding results of these six cases are shown in Fig. 5. For example, for Case0, the agent mixes the $\pi_1^1$ and $\pi_2^2$ to explore the $stage_1$ in training, whereas $\pi_2^2$ in testing (whether in training or testing, the agent can only use the $\pi_2^2$ in $stage_2$). It can be seen from Fig. 5, that only Case0 (ours) takes into account both performance and efficiency.

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![Fig. 5. Ablation study of task rearrangement. Details of these cases are described in Table I](image)

| Table I. Different combinations of policies in the previous stage $(stage_1)$. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| Case  | (Case0(Our)) | Case1  | Case2  | Case3  | Case4  | Case5  |
| Training | $\pi_1^1$, $\pi_2^2$  | $\pi_1^1$, $\pi_2^1$ | $\pi_1^1$, $\pi_2^2$ | $\pi_1^1$, $\pi_2^1$ | $\pi_1^1$, $\pi_2^2$ |
| Testing  | $\pi_2^2$  | $\pi_1^1$, $\pi_2^1$ | $\pi_1^1$, $\pi_2^2$ | $\pi_1^1$, $\pi_2^1$ | $\pi_1^1$, $\pi_2^2$ |

**C. Ablation 2: Distance Threshold**

This subsection evaluates the effect of the distance threshold $d$ on performance. This is the first hyper-parameter introduced by RHER, which will affect the efficiency of exploration. However, Fig. 6 shows that if $d$ is too large ($d = 0.12m$), the performance will be degraded because the agent will also be hard to affect the achieved goals of the target-task. If it is too small ($d = 0.0m$), it will hinder from learning the target-task. However, as long as this distance is slightly larger ($d \in \{0.03m, 0.05m\}$) than the size of the object (0.025m), the performance is highly sample-efficient. In other words, this hyper-parameter can be easy to choose.
Fig. 6. Ablation study of different distance thresholds between gripper to the object.

Fig. 7. Ablation study of exploration rate of RMES. Where the ratio of random policy $\pi^r$ is fixed at 0.2, $\alpha$ is the sampling probability of the guide-policy $\pi_1$ in stage 1.

**D. Ablation 3: The Rate of Guide-policy in RMES**

This subsection evaluates the guidance rate in stage 1, which is the second hyper-parameter in RHER. As shown in Fig. 2(b), in the reaching stage, there are three policies, the reaching policy $\pi_1$, the target policy $\pi_2$, and the random policy $\pi^r$. In this study, we fix the probability of $\pi^r$ as 0.2 and then increase the probability of the guidance policy $\pi_1$. From Fig. 7 it is clear that as long as there is guidance ($\alpha \in \{0.2, 0.3, 0.4, 0.5, 0.6\}$) by $\pi_1$, the target policy $\pi_2$ will be accelerated. It confirms that RMES is a crucial element that makes the exploration more effective.

Interestingly, for two extreme cases, the experimental results can dispel some doubts. If there is no guidance from $\pi_1$ in stage 1 ($\alpha = 0.0$), the agent uses the offline data to train an auxiliary task, such as a reaching-task, which does not speed up the target-task. If there is no exploration of $\pi_2$ in stage 1 ($\alpha = 0.8$), the agent is unable to solve the target-task by using offline data from $\pi_1$.

**E. Extending RHER to Three Extra Challenging Robotic Tasks**

To validate the robustness of RHER, three extended simulation tasks are conducted with the same hyper-parameters as the above three classical tasks. As shown in Fig. 8, in three challenging tasks, RHER still maintains high exploration efficiency and good performance, especially in single-processing. It is noted that RHER learns the FetchInsert task from scratch within 65K time steps, which may have a positive impact on the industry. In contrast, vanilla-HER has a very high variance in all tasks, which means that some random seeds can be lucky to explore valuable data, while others remain stuck in local optima.

**F. Learning on A Physical Robot from Scratch**

In CuePush, the end-effector is a smooth cue, and the object is a cylinder. As a result, the task is hard to design a suitable controller, and the automatic reset script usually pushes the object off the reset goal so that it needs to take multiple attempts. However, RHER learns this push task with the success rate of 10/10 within 5K steps (250 episodes) and reduces the distance error to about 1cm, which is still efficient and stable, as shown in Fig. 9. If the workspace is larger, there will be more improvement compared with vanilla-HER.

**G. Comparison with State-of-the-art Methods**

To further evaluate the sample efficiency of RHER, a comparison of RHER with other HER-based state-of-the-art algorithms in the literature can be found in Table II. Since some papers do not release their code, this study uses the results of their paper for comparison. We compare the number of interactions required when achieving the same mean test success rate of 95%. Even though the IHER is a type of model-based method and ACDER has dynamic initial states to alleviate the virtual-positive sparse rewards, RHER still requires minimal interactions in two standard robotic tasks, as shown in Table II.

|                      | FetchPush(95%) | FetchPickAndPlace(95%) |
|----------------------|----------------|------------------------|
| vanilla-HER [20]     | 580K           | 1680K                  |
| ACDER [20]           | 110K           | 260K                   |
| IHER [21]            | ~80K           | ~300K                  |
| RHER(ours)           | 78K            | 250K                   |

**VII. DISCUSSION AND CONCLUSION**

In this paper, we propose a concise and extremely sample-efficient continual RL algorithm, called RHER, which solves...
the critical virtual-positive sparse reward problem of HER. The simulation experiments show that RHER can achieve stable and efficient performance on five long-horizon manipulation tasks with only one set of hyper-parameters, especially in the single-processing training. Finally, we trained an agent to complete the push task from scratch on a physical robot, requiring only 5K interaction steps. These results indicate that RHER is generalized to long-horizon manipulation tasks and that RHER has application potential to real tasks without building a corresponding simulation. It is worth mentioning that this relay-style idea can inspire multi-agent or hierarchical RL. In future work, we will extend our approach to multiple and dynamic objects.

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