Efficient Robotic Task Generalization Using Deep Model Fusion Reinforcement Learning

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***Abstract*— Learning based methods have been used to programming robotic tasks in recent years. However, extensive training is usually required not only for the initial task learning, but also for generalizing learnt model to the same task but different environment. In this paper, we propose a novel Deep Reinforcement Learning algorithm for efficient task generalization and environment adaptation in robotic task learning problem. The proposed method is able to efficiently generalize the previously learnt task by model fusion to solve the environment adaptation problem. The proposed Deep Model Fusion (DMF) method reuses and combines the previously trained model to improve the learning efficiency and results. In addition, we also introduce a Multi-objective Guided Reward (MGR) shaping technique to further improve training efficiency. The proposed method was benchmarked with previous methods in various different environments to validate its effectiveness.**

***Index Terms*— Reinforcement Learning, task generalization, model fusion.**

I. Introduction

As a result of the rapid development of robotic technologies, robots have been widely used in various applications in recent years. Nevertheless, programming the robot for given tasks is still manual and costly. For many robotic applications, extensive manual teaching or offline programming is required to program robotic tasks. Even for the same category of robotic tasks with slightly different environment, trajectory adjusting or fine-tuning is still required. To improve the efficiency and reduce the effort required for the robotic programming, learning-based methods can be used to program the robotic tasks. With learning-based methods, robot programming can be done without much manual programming or tuning of the trajectories. Compared to traditional manual teaching or offline programming, learning-based methods are also more general and robust to handle the same category of task.

Among the learning-based methods, Reinforcement Learning (RL) is one commonly used method to tackle robotic task learning problem [1], [2]. RL algorithms have been successfully applied to robotic applications such as assembly [3], pouring [4], and insertion [5] in recent years. The robots learn a policy with RL after training stage, then they are able to generate actions with the learnt policy based on the current state/observations. The RL-based methods usually work well for the same tasks with similar environment settings after extensive initial training.

However, in many robotic programming applications, the environment may change over time for the same robotic task (e.g. pushing, grasping). The performance of the learnt policy may thus drop for the same robotic task, when applying the learnt model to changed environment [5], [3]. Therefore, additional training would be required for the learnt model to generalize and adapt to the new environment in order to improve the results. Such an additional training for task generalization and environment adaptation is usually costly. Thus reducing the cost of additional training for task generalization and environment adaptation is desired, to improve the efficiency.

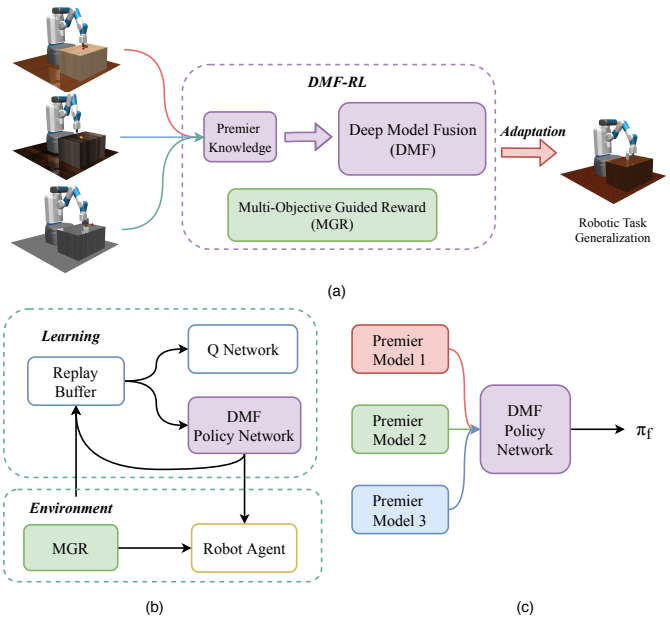

Fig. 1: (a) The DMF-RL system that combines the knowledge from previous learnt model for efficient robotic task generalization (b) The robot agent learning structure using DMF-RL system (c) DMF policy network structure

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In this paper, we propose a novel algorithm for efficiently generalizing the robotic task learning problem to new environment. The proposed method uses model fusion to reuse the previously learnt knowledge and thus speed up the training in task generalization process and improve the system performance. The main contributions of the proposed method are:

- a Deep Model Fusion (DMF) method to store and combine the previous trained knowledge, which speeds up the training process for task generalization and improves the results when the environment changes;
- a Multi-objective, Guided Rewards (MGR) system that converts the sparse rewards of typical RL problem to a multi-objective dense rewards system; and
- extensive studies to benchmark and validate the proposed methods in different environment settings.

II. Related Work

Reinforcement Learning (RL) has demonstrated great success in many applications during past few years [1], [6], [7]. Value-based RL methods such as Deep Q-Learning (DQN) and its variants have outperformed human beings in various Atari Games [6] [8]. Value-based RL methods employs a $argmax$ to select the action with the maximum Q-value, which makes the value-based based more suitable for the applications with discrete action spaces. RL has also been applied to many robotic learning problems [9], [10] with continuous action spaces. Because of the continuous action space of the robotic applications, policy-based methods are more suitable and usually used [11]. The policy-based methods compute the gradient of the parameterized policy and improve the policy based on the policy iteration mechanism [12]. Policy-based algorithms such as Deterministic Policy Gradient [13], Deep Deterministic Policy Gradient (DDPG) [14] and Proximal Policy Optimization (PPO) [15] have been successfully applied to address the continuous action space problems in various robotic applications.

RL usually requires large amount of data to train the model. In order to improve the training efficiency, different importance sampling methods have been proposed to sample from the experience into the replay buffer, such as prioritized replay buffer [16] and Hindsight Experience Replay (HER) [17]. Asynchronous Advanced Actor-Critics (A3C) [18] has also been proposed to parallelize and improve the computational efficiency of training. Generalization and adapting to new environment is also an important research direction for RL applications in robotics [19], [20]. The performance of the previously trained model would drop even when applying it to similar tasks with different environment settings. Methods such as training from scratch, or additional training from existing model, could be used to train the model to improve the performance. Transfer learning could also be applied to RL problems as well [21]. However, these learning paradigms are not designed to handle the environment adaption problems in robotic task learning applications; and they still require extensive training when the environment changes. In this paper, we propose a model fusion method to reuse the previously trained knowledge to improve the training efficiency and system performance when environment changes.

III. Proposed Method

In this paper, we propose a novel Deep Model Fusion Reinforcement Learning (DMF-RL) method for efficient robotic task generalization. The proposed method aims to improve the efficiency when generalizing the learnt task to the similar tasks with different environments settings. The proposed DMF methods utilizes the knowledge and combines the previously trained models to reduce the training required for task generalization. A multi-objective guided rewards system is also proposed along the method to convert the sparse rewards to dense rewards and thus further speeds up the training process. The proposed method is illustrated in Figure 2.

A. Markov Decision Process

A finite-horizon Markov Decision Process (MDP) is used to model the robot task learning problem in this paper. MDP could be represent as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{T}, r, \lambda)$, where $\mathcal{S}$ is the state space; $\mathcal{A}$ is the action space; $\mathcal{T} : \mathcal{S} \times \mathcal{A} \Rightarrow \mathcal{S}$ is the state transition model; $r : \mathcal{S} \times \mathcal{A} \Rightarrow r \in \mathbb{R}$ is the rewards by taking an action at a certain state; and $\lambda \in [0, 1]$ is the discount factor. The return $R = \sum_{i=0}^{N} \lambda^i r_i$ of an episode is the summation of discount rewards received during the episode.

For the robotic task learning applications discussed in this paper, the state space $s \in \mathcal{S}$ is a 1-D vector that consists of the robot joint angles and joint velocities, as well as the current positions, orientations and velocities of the objects.

B. RL for Robotic Task Learning

With the MDP formulation, RL algorithm could be used to train the agent for the robotic task learning. As shown in Figure 2, we utilizes a actor-critic RL framework, where a Q-network (critic) is used to approximate the Q-value, and a policy network (actor) is used to generate the action based on the current state. Q learning is adapted to update the Q value. The policy gradient is computed to update the policy network.

C. Policy Network with Deep Model Fusion

In this paper, Deep Model fusion (DMF) is proposed to reuse previously trained knowledge in the policy network, in order to improve the training efficiency and improve the

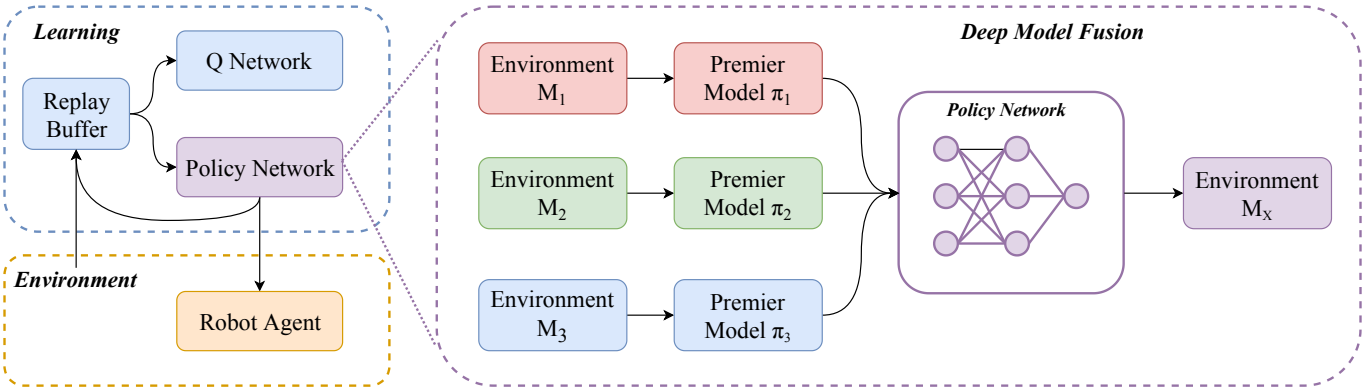


Fig. 2: Deep Model Fusion Reinforcement Learning Architecture.

model performance. With the proposed DMF, we use primitive policy models learnt from several different environments in previous training. The fusion model is embedded as the policy network to be trained on the robot agent in the changed environment. With the primitive knowledge embedded in the fusion model, the agent robot is capable of adapting to new environments rapidly with better performance.

Typically, the primitive knowledge is generated by training the robot agents in several premier environments with different features. Suppose those environments, $\{\mathcal{M}_{p_1}, \mathcal{M}_{p_2}, \ldots, \mathcal{M}_{p_n}\}$, are identical except the state transition probabilities $\mathcal{P}(s_{t+1}|s_t, a_t)$. For the actor-critic RL algorithm such as DDPG, the policy is represented as π and the policy network is usually a neural network with parameters θ_π. By training the robot agent under different environments $\{\mathcal{M}_{p_1}, \mathcal{M}_{p_2}, \ldots, \mathcal{M}_{p_n}\}$, we can obtain different premier policy models whose policies and network parameters are denoted as $\{\pi_1, \pi_2, \ldots, \pi_n\}$ and $\{\theta_{\pi_1}, \theta_{\pi_2}, \ldots, \theta_{\pi_n}\}$, respectively.

When the environment changes, the performance of learnt policy may drop. The new policy model π_f in our DMF-RL method is then generated to improve the performance by fusion of the premier policy models $\{\pi_1, \pi_2, \ldots, \pi_n\}$, as shown in Figure 3. Taking a three model fusion case as an example, the model π_f firstly loads the parameters of $1st$ layer from each premier policy model as θ'_{π_1}, θ'_{π_2}, and θ'_{π_3}, respectively. Since the $1st$ layer of the premier policy networks extract low level features from observations and the observation spaces in premier models are identical, we use the features $\{h_{\pi_1}, h_{\pi_2}, h_{\pi_3}\}$ extracted from the $\{\theta'_{\pi_1}, \theta'_{\pi_2}, \theta'_{\pi_3}\}$ as the primitive knowledge of the environments. All of the environmental features of premier models contain useful information, so we combine them to further boost the performance of π_f.

Given the features $\{h_{\pi_1}, h_{\pi_2}, h_{\pi_3}\}$ extracted from the previously trained premier models, we use element-wise addition ($\oplus$), element-wise multiplication ($\odot$) and concatenation ($\|$) followed by a fully connected layer ($\mathcal{F}_{fc}$) to combine the feature information from the premier models. Addition and multiplication operations allow additive and multiplicative interaction among different features without changing the feature dimension d, while the $\mathcal{F}_{fc}$ allows interaction among all elements and then maps to the original feature dimension d. Thus, the policy π_f after mode fusion is formulated as:

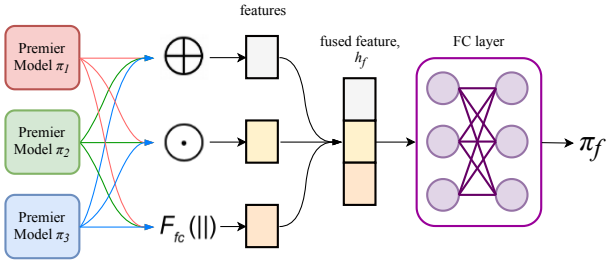


Fig. 3: The Architecture of Policy Network with Deep Model Fusion.

$$
\begin{aligned}
h_f = &(h_{\pi_1} \oplus h_{\pi_2} \oplus h_{\pi_3}) \\
&\| \, (h_{\pi_1} \odot h_{\pi_2} \odot h_{\pi_3}) \\
&\| \, \mathcal{F}_{fc}(h_{\pi_1} \, \| \, h_{\pi_2} \, \| \, h_{\pi_3}).
\end{aligned} \tag{1}
$$

where $\mathcal{F}_{fc}(x) = \boldsymbol{\omega}_{fc}^\top x + \mathbf{b}_{fc}$, $\boldsymbol{\omega}_{fc} \in \mathbb{R}^{3d \times d}$ and $\mathbf{b}_{fc} \in \mathbb{R}^d$ are the weight and bias of full connected layer, respectively.

For more general case, $\mathcal{N}$ premier models are represented in a sequence $\boldsymbol{\Theta} = (\theta'_{\pi_1}, \ldots, \theta'_{\pi_n})$ and the corresponding features are denoted as $\mathbf{h} = (h_{\pi_1}, \ldots, h_{\pi_n})$, then the fused

feature of π_f is represented as:

$$\begin{aligned} h_f =& (h_{\pi_1} \oplus \cdots \oplus h_{\pi_n}) \\ & \| \, (h_{\pi_1} \odot \cdots \odot h_{\pi_n}) \\ & \| \, \mathcal{F}_{fc}(h_{\pi_1} \| \ldots \| \, h_{\pi_n}). \end{aligned} \tag{2}$$

Finally, the fused feature h_f is fed into a fully connected layer of neural network to build up the fusion model policy π_f. The DMF-RL framework takes π_f as the policy network. With the primitive knowledge of the previous environments in π_f, the robot agent is able to adapt to the new environment rapidly.

D. Multi-objective Guided Rewards

We propose a Multi-objective, Guided Rewards (MGR) system for the robotic task environment with sparse reward to improve training efficiency. In many robotic applications (e.g. pushing, peg-in-hole), a binary sparse reward is given to the robot agent depending on whether it achieved the desired goal. However, the sparse reward does not provided useful information to train the robot agent, so the exploration in the early stage is random and thus inefficient.

The MGR is designed to encourage the agent to explore the state space, and also to guide the robot to the target with the estimated immediate rewards. The MGR system consists of three parts driven by three objectives: the final goal, the sequential objectives (e.g. initial objective, the secondary objective), and the prevention objective. The final goal is represented by the binary sparse reward judging whether the final desired goal is achieved. The sequential objectives are the objectives that guide the robotic behaviors in sequential phases to achieve the final goal. Finally the prevention objective is to prevent any hindrance (e.g. obstacles, traps) during the task process. The general MGR is formulated as:

$$r = \alpha_1 G_f + \sum_{i=2}^{n} \alpha_i O_i + \alpha_{n+1} O_p \tag{3}$$

where G_f is the final goal, N is the number of sequential objectives, O_i is the sequential objectives, O_p is the prevention objective, and α_i is the constant scale factor.

Taking the robot pushing task as an example, the sequential objectives are decreasing the distance between the robot end-effector and the object d_{oe} the distance between the object and target goal d_{og}. We also consider a new scenario for the pushing and sliding that there are obstacles on the table. So the prevention objective is also driven by moving away from the obstacles increasing the distance between the robot end-effector and the obstacle d_{es}. The MGR for robot pushing task is formulated as:

$$\begin{aligned} r(d_{og}, d_{oe}, d_{es}) =& \alpha_1(\|d_{og} > \eta\|) + \alpha_2(-d_{oe}) + \alpha_3(-d_{og}) \\ & + (\|d_{es} < \mu\|)(\log d_{es} - \log \mu) \end{aligned} \tag{4}$$

where d_{og} is the distance between the object and the target goal, d_{oe} is the distance between the object and the robot end-effector, d_{es} is the distance between the robot end-effector and the obstacle, α_1, α_2 and α_3 are weights for multiple objectives, η is the distance threshold to measure whether a goal is achieved, and μ is the distance threshold to measure whether the obstacle is too closed.

IV. Experiment and Discussion

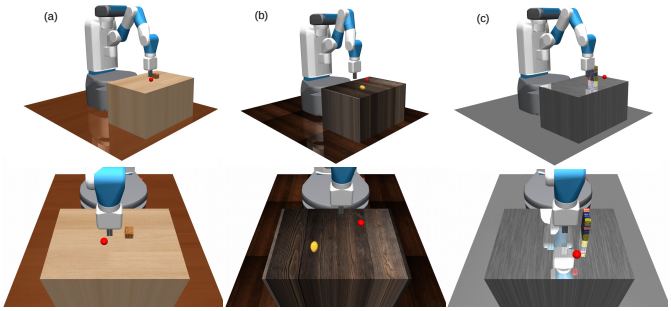


Fig. 4: Robot pushing environments with different surfaces and different object shapes (a) Bread (b) Lemon (c) Cereal Box

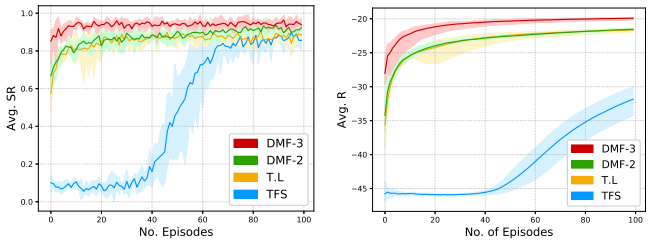
A. Experiment Setup

OpenAI gym [22] simulation environment was used to test the proposed method. We implemented the tests with *FetchPush*, and *FetchSlide* environment with *MuJoCo* [23] physics engine. For each task, we also customized environment settings with different surfaces, object shapes and obstacles to test the task generalization and environment adaptation, as shown in Figure 4. DDPG-HER algorithm is implemented and benchmarked based on OpenAI stable-baselines [24]. A Multi-Layer Perception (MLP) based policy network was implemented as policy network in this work for the premier model.

The finite episode was set as 50 steps. In an episode, the robot agent received a reward -1 in each step if it didn't achieve the desired goal, otherwise it received a reward 0. The curiosity-driven reward function was implemented with the weights $\alpha_1 = 0.3$, $\alpha_2 = 0.35$ and $\alpha_3 = 0.35$. The distances among the object, the target goal, and the robot end-effector were extracted from the simulation environment. In real-world, the distance information is usually measured with noise, so random noise was added to the distances d_{og}, d_{oe} and d_{es} during the tests. In this paper, we used robot pushing and sliding tasks as examples to test our algorithm, in various different environment settings.

TABLE I: Success rate comparison of different methods

		DDPG-HER				DDPG-HER + MGR				DMF-2 + MGR				DMF-3 + MGR			
		50	100	150	200	50	100	150	200	50	100	150	200	50	100	150	200
Push	env-1	0.141	0.458	0.597	0.667	0.608	0.783	0.844	0.875	0.816	0.887	0.913	0.926	0.951	0.962	0.964	0.966
	env-2	0.175	0.518	0.648	0.718	0.445	0.657	0.733	0.773	0.828	0.859	0.875	0.885	0.868	0.892	0.9	0.904
	env-3	0.074	0.079	0.106	0.157	0.089	0.216	0.387	0.507	0.839	0.875	0.890	0.897	0.906	0.913	0.917	0.92
Sliding	env-1	0.206	0.342	0.411	0.451	0.342	0.513	0.597	0.645	0.424	0.576	0.647	0.679	0.662	0.726	0.755	0.774
	env-2	0.098	0.158	0.224	0.291	0.183	0.296	0.376	0.425	0.302	0.509	0.606	0.659	0.618	0.725	0.766	0.79
	env-3	0.089	0.13	0.147	0.159	0.323	0.512	0.588	0.632	0.472	0.612	0.672	0.708	0.677	0.738	0.764	0.766



(a) Average success rates (b) Average returns

Fig. 5: Model Fusion for task generalization in robotic pushing task with different environment dynamics

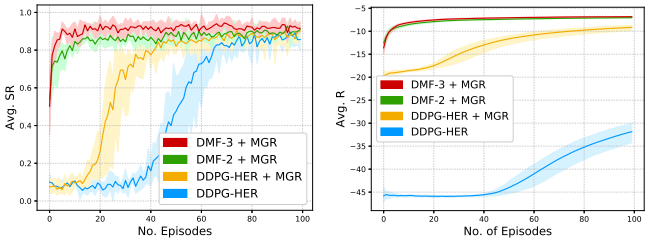
B. Results

We first evaluated the Deep Model Fusion (DMF) and Multi-objective, Guided Reward (MGR)methods independently. Then we also evaluate the overall proposed method with both DMF and MGR. The results obtained in the tests show that the proposed method significantly improved the results in terms of learning speed and task success rate, when adapting to the changed environment.

The proposed method was evaluated in different environments (e.g. with different surfaces, different geometric shapes) for each task. We implemented the proposed DMF method that combined two models (labeled as DMF-2) and three models (labeled as DMF-3), and compared them with transfer learning (labeled as T.L), as well as training from scratch (labeled as TFS). Figure. 5 shows that the results of success rate and episodic return in robot pushing application. Compared to training from scratch and transfer learning, the robot agent learnt faster with our method. The robot agent with primitive knowledge from our method demonstrated good capability of task generalization and environment adaptation. The MGR was also evaluated with different environment settings. Figure. 6 shows that the training results of average success rate in robot pushing application. Compared to baseline algorithms, the agent learnt faster with the proposed MGR system.

Additionally, we further evaluated the overall proposed method with both DMF and MGR. Table I shows the results comparison with different other methods at different training stages. We compared the baseline method DDPG-HER, DDPG-HER with MGR, as well as DDPG-HER with MGP and DMF (labeled as *DMF-2 + MGR* for two-model fusion and *DMF-3 + MGR* for three-model fusion) The success rates of the robotic tasks with different methods were compared under three different environment settings (labeled as env-1, env-2 and env-3). The success rates at different training stages (episodes = 50, 100, 150, 200) were also compared in the table.

As shown in Table I, the proposed method demonstrated its effectiveness among different applications in various training stages. The success rate of the proposed method was consistently higher than other methods, in different environments and different training stages.



(a) Average success rates (b) Average returns

Fig. 6: Result comparison of MGR and DMF+MGR methods in robotic pushing application

C. Discussion

In the robotic task learning problem, the performance of learnt model usually drops when there are significant changes in the environment setting, though the learnt policy is also able to adapt to certain change. It is also noticed that the transfer learning converges faster, compared to training from scratch. The proposed method that combines the knowledge from different models outperforms the other methods by both the learning speed and the success rate.

Additionally, as shown in Figure 5, DFM-3 and DMF-2 had very similar success rates and episodic returns, though DMF-3 converged faster than DMF-2. Both DMF-3 and DMF-2 significantly performed better than the baseline method. Though the other methods achieved good success rate in some cases, but their episodic return was still much lower. And as observed in the tests, the agent trained with

the baseline method took longer time to complete the task in one episode.

Overall, the proposed method outperformed the baseline algorithms. The results show that our method is able to generalize the learnt robotic tasks efficiently by combining the knowledge in the previously trained models. The MGR system also helps to convert the sparse rewards to dense rewards with multiple objectives, where each objective could be interpreted intuitively with real-world correspondences. This feature makes the overall system explainable and robust. The proposed DMF and MGR could also be used as flavors on top of other RL algorithms to improve the performance.

V. Conclusion

In this paper, we propose a novel Deep Model Fusion (DMF) method with Multi-objective Guided Reward (MGR) system for generalizing robotic task learning and environment adaptation. The proposed method improves the training efficiency of adapting the previously trained model to new environment by combining knowledge from those models. Our method also improves the performance of the task learning in terms of task success rate and average episodic return. The effectiveness of the proposed method has been validated by extensive studies in different environments settings.

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