

# Task-Oriented Adaptive Learning of Robot Manipulation Skills

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**Abstract**—The robot’s operating environment and tasks are dynamically changing. Therefore, developing a mechanism that can infer other things from one fact to adapt to various scenarios is crucial for enhancing the robot’s adaptive capabilities. This paper proposes a general Intelligent Transfer System (ITS) to enable rapid skill learning for robots in dynamic tasks. ITS is an advanced system that integrates Large Language Models (LLMs) with human intelligence. It is capable of comprehending new and previously unseen task instructions and automatically generating a process-oriented reward function for these task. In addition, we have designed an Intelligent Transfer Network (ITN) within the ITS. ITN focuses on basic skills and aims to quickly learn complex new tasks by intelligently integrating features of these basic skills. This paper’s method holds promise for enabling robots to independently solve entirely new operational tasks. We conducted a series of evaluations in a simulation environment, and the experimental results show that our method improves the time efficiency of two major tasks by 72.22% and 65.86%, respectively, compared with learning from scratch. Additionally, we compare our method with several outstanding works in the field. Our open source code repository: <https://github.com/JKX-yy/Eureka-jkx/>

## I. INTRODUCTION

Robot operations in the real world are constantly adapting due to dynamic changes in the environment and tasks. Traditional pre-programmed behavioral planning and decision-making methods are difficult to adapt to these changes [1], while reinforcement learning methods need to be re-trained from scratch when the environment and operation objects are slightly changed [2]. Transfer learning, which uses relevant task experience to improve the efficiency of autonomous learning on new tasks, greatly reduces the heavy burden of repetitive learning on robots, and holds new promise for intelligent robot operation [1], [3]. Nevertheless, designing an effective and automated approach to construct a generalized transfer framework for unknown new tasks in the context of long-term robot operation tasks remains a challenge.

Some work has achieved good results in specific settings. When dealing with complex robot manipulation tasks, Hierarchical Reinforcement Learning (HRL) employs high-level strategies to select underlying strategies for performing specific subtasks. The learning process is significantly enhanced by reusing previously learned skills [2], [3]. However, these reused methods cannot be adapted to new, unknown tasks.

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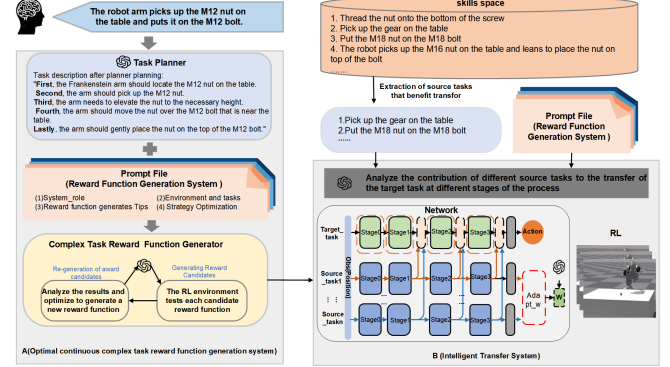


Fig. 1: The Intelligent Transfer System (ITS) is divided into two parts, A reward function automatic generation module and B intelligent transfer module. In A, the generator analyzes the task and environment to generate the optimal reward function through multiple optimization. In B, an Intelligent Transfer Network (ITN) is designed to accelerate the skill learning by fusing the features from different sources.

There is some recent work that combines HRL with imitation learning to solve vision-based long-field-of-view robot manipulation [4], but it suffers from the common limitations of offline datasets and requires task-specific meta-controllers to combine skills for a single task. In another work, expert demonstrations are introduced to guide the strategy search [5], thus accelerating the learning process in sparse reward environments. However, these methods may suffer from reduced algorithmic effectiveness when the demonstration data is very limited or of low quality. In summary, existing skill transfer learning techniques have high requirements for pre-training strategies, are more sensitive to changes in the environment, and rely on human involvement. When new tasks involve unknown underlying strategies, these methods fail due to their inability to autonomously learn new skills.

On the other hand, we consider that LLMs excel in code generation capabilities and semantic planning. [6] utilized ChatGPT for problem solving in robot operations to train a reliable agent RobotGPT significantly improved the task success rate. [7] utilized LLMs for fine-grained task planning and improved the efficiency and effectiveness of task planning. There are several other listed tasks that show the great potential of LLMs for robotics applications [8]. However, whether LLMs can be used to guide transfer learning remains an unexplored question. In this paper, we fully utilize the analytical capabilities of LLMs to replace the human analytical process and use the results to guide task transfer.

To address the challenge of enabling autonomous and rapid learning of new skills for robots in dynamic envi-

ronments, we developed a task-oriented intelligent transfer method, as shown in Figure 1. Given that the learning of robotic skills heavily relies on the design of reward function, we designed an automatic reward function generation scheme. To store learned skills, we constructed a dynamically expandable skills space that assigns source strategies to target task based on the semantic information of skills. Additionally, we integrated transfer learning with LLMs to form an intelligent knowledge-guided ITN. Inspired by [9], we horizontally connected the feature extraction modules of source and target tasks and fused the features of different skills.

We summarize four key contributions of this work: (1) We propose an innovative and generalized ITS that leverages the code generation, problem analysis, and planning capabilities of LLMs to assist robots in autonomous skill learning for new tasks. (2) To reduce the robot's dependence on human intervention and enhance its problem-solving ability, we designed a reward function generator dominated by LLMs. We evaluated its effectiveness in generating reward functions for tasks of varying complexity. (3) To fully utilize empirical knowledge, we developed an intelligent analyzer, dominated by LLMs, that analyzes the contribution relationship matrix between source and target tasks, serving as empirical knowledge for the attention module. (4) To enable the robot to rapidly learn new and unseen tasks, we designed an ITN that incorporates prior knowledge from LLMs. We developed feature fusion modules at three different dimensions to be inserted at various locations within the network, allowing for the extraction of features at varying levels.

## II. RELATED WORK

### A. Transfer Reinforcement Learning

A reinforcement learning task can be described as a tuple  $\langle S, A, P, R, \gamma \rangle$ ,  $S = s_0 \times s_1 \times \dots \times s_n$  is a set of the state of the environment and the state of the agent.  $A = a_0 \times a_1 \times \dots \times a_n$  is the set of all possible actions, and the action represents the operation that can be performed by the agent in a certain situation.  $R = r_0, r_1, \dots, r_n$  is the agent's reward function,  $R(s, a)$  is the immediate reward obtained after taking action  $a$  in state  $s$ . The reward function provides feedback to the agent, guiding it to learn which actions are beneficial and which are harmful;  $\gamma \in [0, 1]$  is the discounting factor used to weigh the importance of current and future rewards. The goal of reinforcement learning is to learn an optimal policy  $\pi^*(a|s)$  to maximize the agent's cumulative reward. The purpose of transfer learning is to use the agent's source domain policy  $\pi = \pi_1, \dots, \pi_n$  to aid in learning the target optimal strategy.

### B. Transfer Learning of Robot Operational Skills

Transfer learning is systematically presented and summarized in the article [1]. Methods like strategy reuse or strategy distillation utilize knowledge from the source domain for action generation [10], [11]. [12] [13] [14] improve the training process of the target task by decoupling or reusing task-invariant features. Recent studies have explored

various ways to combine transfer learning with reinforcement learning to address real-world robotics problems. [15] proposed a method for reconfiguring robot assembly control using Equivalent Compliance Theory (ECT) combined with Weighted Dimensional Policy Distillation (WDPD). [16] employed a graph neural network to represent states and actions during the assembly process, optimizing the strategy for collaborative human-machine assembly using a reinforcement learning algorithm. [17] employed feature selection and adaptive transfer learning to generalize robot pin assembly skills across different geometric features. [18] investigated meta-reinforcement learning to solve simulated industrial insertion tasks and quickly adapt policies in real-world scenarios. [19] and [20] aimed to use transfer learning with reinforcement learning for tasks like stacking and grasping. However, these approaches primarily focus on generalizing parts within the same operational tasks and do not address cross-task transfer between different types of tasks. In contrast, our aim is to efficiently handle various classes of tasks that evolve over time.

### C. Application of LLMs in Robotics

[21] explored how LLMs generate new tasks and simulate behaviors to enhance robots' learning and adaptability. [22] Reducing the Sample Complexity of Reinforcement Learning in Robotics Tasks by Prompt Engineering to Extract Prior Knowledge from LLMs. Additionally, [23] designed human-level reward systems by encoding LLMs, thereby improving the efficiency and performance of robots in task learning. Our approach is similar to this work, but our goal is to design a generalized reward function generation framework for sequential complex robot manipulation tasks, with a focus on the entire process of robot manipulation. In this paper, we leverage the task planning, problem analysis, and code generation capabilities of LLMs to design planners, analyzers, and generators, thereby replacing human intervention and powering the automatic implementation of ITS.

## III. METHOD

The model schematic of the ITS is illustrated in Figure 1. It comprises two modules: A, the reward function automatic generation module, and B, the intelligent transfer module.

### A. Automatic Generation of New Task Rewards

When robots learn complex tasks, traditional hierarchical reinforcement learning methods decompose these tasks into subtasks, designing separate rewards for each, which presents a challenge in ensuring connectivity among subtasks. We propose a generalized reward prompt framework for LLMs that aims to generate a comprehensive reward function for complex tasks, thereby accommodating task variations.

1) *Planning Stage*: When task requirements change, the robot receives a new, concise task command. However, these initial instructions are often unclear. To address this, we designed a task planner capable of analyzing the execution order of subtasks and generating a detailed task description. This description comprises a sequence of subtasks with

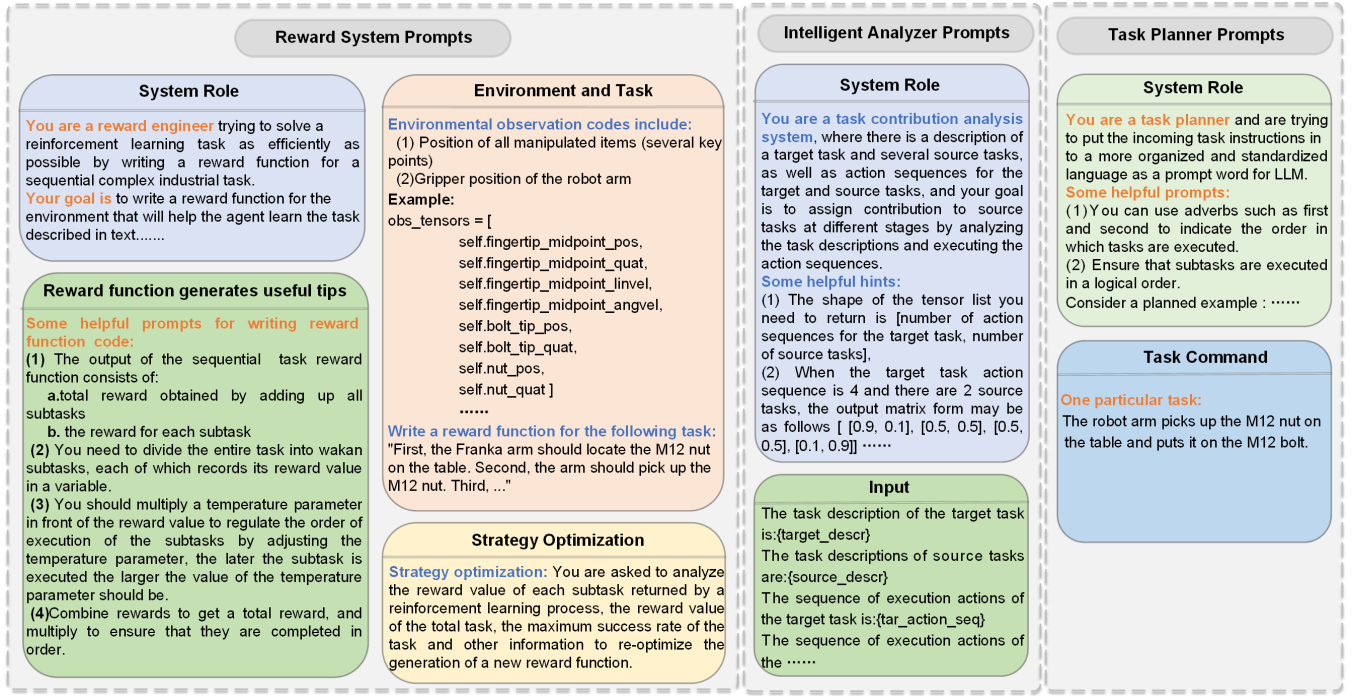


Fig. 2: This paper examines the prompt systems of three LLMs. The first, Reward System Prompts, serves as a management system for designing reward functions for new tasks. The second, Intelligent Analyzer Prompts, enables LLMs to analyze the contribution of different source tasks to the target task at various times through prompt design. The third, Task Planner Prompts, refines user instructions.

adverbial modifiers such as "First," "Second," and so on. Figure 2 illustrates the LLMs prompt used intask planner .

2) *Generation Stage*: An effective prompting approach can significantly enhance the speed of generating executable reward functions and the success rate of task execution. We designed a four-part effective prompt, as shown in Figure 2, The system information describes the system's identity and goals. Environment information comprises environmental observations and the positional information of operating items and robotic arm, the task description uses a fine-grained description generated by the task planner. Generation prompts information includes the proposed form of the reward function, as well as some constraint prompts we give to ensure that the generated reward function can guide the sequential execution of successive tasks, and so on. The strategy optimization information we provide includes several analyzable metrics for generating improved reward functions. Our prompts were comprehensively designed and received a satisfactory response.

3) *Strategy Optimization Stage*: To ensure the generated reward functions correctly guide robots to complete complex skills sequentially, we record the maximum task success rate, per subtask rewards, and total rewards for complex skills in each iteration. The LLMs then adjust the temperature parameter of each subtask to generate a better reward function in the next iteration based on these data. In each iteration, the LLMs generates multiple reward functions based on the sample size and regenerates them if the initial generation fails. Through this self-optimization process, the success rate and accuracy of reward function bootstrapping

are continuously improved. Our method produces reward functions with high interpretability and a higher success rate.

### B. Skill Space Construction and Source Skills Extraction

We constructed a real-time expandable skill space comprising more than 30 skills, including basic and sequential complex skills the robot has already learned. Basic skills such as Pick, Place, Screw, and Insert are used to manipulate various mechanical parts. Sequential complex tasks are designed as assembly tasks containing multiple sub-skills. Each skill in the skill space consists of four attributes: task serial number, task description, pre-trained model, and task execution action sequence.

Methods such as MK-MMD [24] select source tasks similar to the target task by comparing data distributions. However, these methods face high computational complexity in large skill spaces and difficulty in kernel function selection. Considering that tasks operating on different objects can positively transfer to the target task if the execution semantics are the same, we designed a skill extraction method based on SBERT [25]. This method extracts source tasks similar to the target task at the semantic level. It is robust, tends to extract deeper source skills, and is highly interpretable compared to other methods.

### C. Intelligent Transfer Network (ITN)

In this section, we demonstrate the implementation of cross-task skill transfer. First, we describe the generation of a priori knowledge based on the intelligent analyzer. Then, we integrate the intelligent analyzer into the attention module to form an intelligent attention mechanism. Finally, we

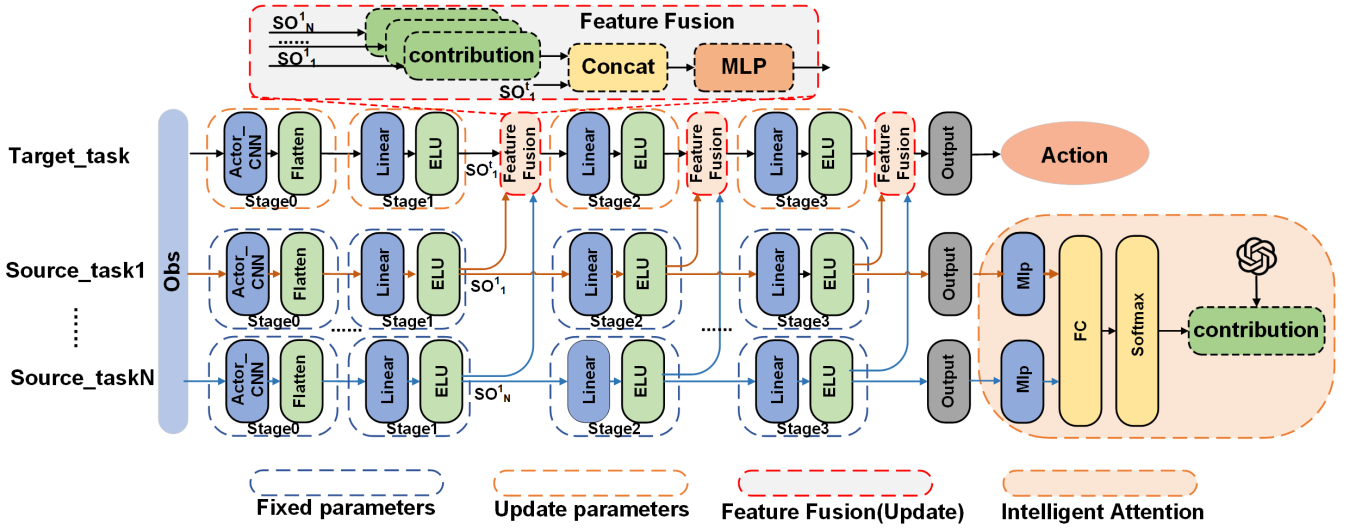


Fig. 3: The Intelligent Transfer Network (ITN) connects the models of subtasks horizontally. The Intelligent Attention module takes the strategies of the source tasks as input and outputs the final contribution values of each subtask in combination with the contribution matrix of the Intelligent Analyzer. The feature fusion layer fuses features from each source task. The final output of the network is the strategy for the new task.

present the intelligent transfer network framework, as shown in Figure 3.

1) *Intelligent Analyzer Acquires Prior Knowledge*: A complex target task is assigned multiple source strategies, each contributing differently at various stages of execution. Many studies, such as [8], use attention networks to learn this contribution from scratch. However, incorporating human-level prior knowledge into the transfer learning process remains an open question. In this section, we aim to have LLMs analyze this contribution matrix and use it as a priori knowledge to correct the attention network. To achieve this, we designed specialized prompts for the intelligent analyzer, as shown in Figure 2.

The prompts for the intelligent analyzer consist of two parts. The system role information sets the goal of the intelligent analyzer and provides analysis tips. The input information offers a framework for receiving task descriptions and execution sequences for both the target and source tasks. Based on these prompts, the intelligent analyzer can accurately divide the entire contribution matrix into  $m \times n$  matrices to guide the attention network, where  $m$  represents the number of segments of the target task and  $n$  represents the number of source tasks involved in the transfer process. Intelligent analyzers fully utilize the analytical capabilities of LLMs to reduce the human burden.

2) *Intelligent Attention Module*: Although source tasks similar to the target task have been extracted from the skill space, these tasks focus on different operational actions. Different stages of the target task execution emphasize different source skills. In this paper, we use the Intelligent Attention to assign contributions to different source strategies. The structure of the Intelligent Attention is shown in the bottom right of Figure 3.

The input to the attention module consists of the strategy output  $\langle \pi_1(s), \dots, \pi_n(s) \rangle$  of the source tasks. Each strategy is processed through the MLP, and the output for the  $j$ th source

strategy is:

$$h_j = \text{MLP}(\pi_j(s); \theta_j) \quad (1)$$

The  $\theta_j$  is the parameter of  $\pi_j$ . The output of the MLP is then processed through a fully connected layer and softmax to obtain the original contribution value matrix.

$$(w'_1, \dots, w'_N) = \text{Softmax}[\text{Linear}(h_1, \dots, h_n); \theta_l] \quad (2)$$

The  $\theta_l$  is the parameter of the fully connected layer. We add the contribution value term  $(w_{G1}, \dots, w_{GN})$  of the intelligent analyzer to this, and output the final contribution value matrix of different source tasks as

$$W = (w_1, \dots, w_N) \quad (3)$$

Since the intelligent analyzer modifies  $(w_{G1}, \dots, w_{GN})$  at different moments of the target task execution, it affects the adaptive weighting network for the purpose of guidelines.

3) *Intelligent Transfer Network*: The intelligent transfer network extracts features on the source task and transfers them to the target task. Figure 3 gives the structure of the network when the source task is 2. In order to transfer features from the source task more efficiently, horizontal connections are used. This structure allows the agent to adopt the experience of the source task while learning new features.

We use the A2C [26] reinforcement learning algorithm in our experiments. Fig.3 illustrates part of the network structure, showing as *Source\_task1* to *Source\_taskN*. The target task network and the source tasks network have exactly the same structure. We divide the transfer process into four phases, generating lateral connections only in stage 1, 2, and 3 to extract features at different levels of the task. To fuse the features of the target task with those of different source tasks, we add a feature fusion module after each feature extraction stage of the target task network. This connection structure is flexible enough to adapt the entire network to different models according to specific needs.



Suppose we have  $N$  source tasks similar to the target task,  $Source\_task1, \dots, Source\_taskN$ , all source tasks are pre-trained strategies with fixed parameters, the target task is  $Target\_task$ . For the source task, the output of the  $j$ th stage of the  $i$ th task is  $SO_i^j$ , and the total output of the  $j$ th stage of the source tasks

$$SO^j = (SO_1^j, \dots, SO_N^j) \quad (4)$$

The equation 3, output from the Intelligent Attention, represents the contribution values of the different source tasks.  $W$  acts on  $SO^j$  and  $U_j$  is generated

$$U_j = SO^j \otimes W = (SO_1^j \cdot w_1, \dots, SO_N^j \cdot w_N) \quad (5)$$

$U_j$  is concatenated with the target output  $SO_t^j$  in the  $j$ th stage to obtain the joint feature matrix  $F_j$

$$F_j = (SO_1^j \cdot w_1, \dots, SO_N^j \cdot w_N, SO_t^j) \quad (6)$$

Processing this matrix through an MLP module as input to the  $(j+1)$ th stage

$$I_{j+1} = MLP(F_j; \theta_{MLP_j}) \quad (7)$$

The  $\theta_{MLP_j}$  denotes the parameters of  $MLP$  in the  $j$ th feature fusion block. Through the feature fusion block, while preserving the results of the target task network (BASE), the features of the source task are fused according to task importance, enabling the entire network to learn new tasks. The features are propagated backward layer by layer until the output layer outputs the action.

$$A = f(MLP(I_l); \theta_{out}) \quad (8)$$

$I_l$  is the input to the last feature fusion layer and  $\theta_{out}$  is the parameter of the output layer.

When training the target task, the policy networks of the source tasks are frozen. The parameters of the target network, along with those of the feature fusion module and the intelligent attention module, are continuously updated during the training of the target task.

#### IV. EXPERIMENTS

Our experiments focus on answering the following questions: 1) Is there value in using generators to design reward functions for new tasks? 2) How well does ITN perform, and how well does it generalize? 3) How does ITN perform in operational tasks of varying complexity compared to other state-of-the-art methods?

**Experimental Environment:** We use the Isaac Gym [27] simulator to implement environmental modeling and conduct reinforcement learning experiments. In the simulation, we use the flexible, lightweight, 7-axis robot Franka Emika Panda. We designed two main types of tasks: the NutBolt task and the PegHole task. Figure 4 illustrates the modeling of the simulation world, where we designed several different sub-experiments for each task. The manipulated items are various assembled parts used for tasks, some of which are illustrated in Figure 5. Table I lists the experimental tasks, with B-Skills representing basic skills and C-Skills

representing complex skills.

**Experimental Setup:** To ensure the reliability of the method, we used five random seeds for 10 experiments and calculated 95% confidence intervals for each experiment. All experiments were conducted using the A2C algorithm for policy learning and optimization. Other experimental parameters are provided in the PPO file of the task. All computational tasks were performed on a device equipped with an NVIDIA RTX A5000 GPU, running Ubuntu 20.04, and the experiments were implemented using the PyTorch framework.

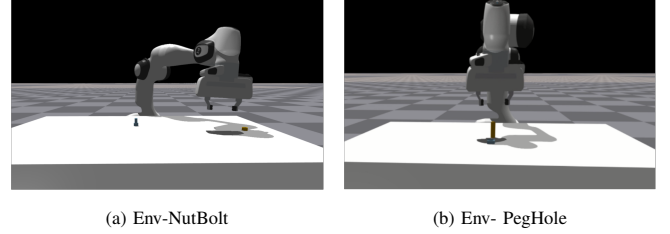


Fig. 4: Modeling the Simulation World of Two Primary Tasks in the Isaac Gym Simulator

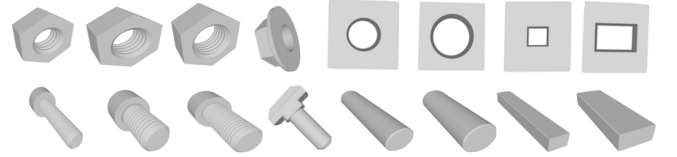


Fig. 5: The figure illustrates the components utilized in the experiment's two primary tasks: the NutBolt tasks and PegHole tasks

##### A. Experiments on Reward Function Generation

We argue that designing a comprehensive reward function is essential for complex robot skills in dynamic environments. We conducted a comprehensive evaluation on manipulation tasks of varying complexity, testing the generator's ability to generate reward functions for both simple and complex skills, as well as its capacity to understand the tasks. We used the GPT-4-0613 variant as an intelligent generator. **Baseline:** We compare the performance of GPT-generated reward functions in a reinforcement learning task with that of human-designed reward functions.

**Training Details:** The generator performs five iterations for each task to generate the reward function. Each iteration performs 10 samples and selects the reward function that maximizes the average task success for the next optimization. After all iterations are completed, the optimal reward function is chosen as the final result of the generator.

**Results:** The generator-generated reward function outperforms the expert-designed reward function. Figure 6 shows the variation in the success rate with the number of iterations for both the expert-designed and GPT-4-generated reward functions in guiding the robot in a reinforcement learning task. Comparing the basic experiments (a) and (b), it is evident that the GPT-4-generated reward function can match or even surpass the performance of the expert design after a few iterations. In the complex tasks (c), (d), (e), and (f), as the number of iterations increases, the reward function

TABLE I: DETAILED INFORMATION ABOUT THE TASK

Type of task	Task commands	Sub-skills	Action	O-object	Model of O-object
B-Skills	Pick up the nut	Pick	approach-grasp-lift	nut	HexNut-M12,HexNut-M16...
B-Skills	Place the nut on the bolt	Place	approach-place	nut, bolt	HexNutBolt-M12,HexNutBolt-M16...
B-Skills	Screw the nut onto the bottom of the bolt	Screw	screw	nut,bolt	HexNutBolt-M12,HexNutBolt-M16...
...	...	...	...	...	...
B-Skills	Insert peg into hole	Insert	insert	peg,hole	RoundPegHole-4mm,RectPegHole-16mm...
C-Skills	Pick up the nut and place it on the bolt	Pick-Place	approach-grasp-lift-approach-place	nut, bolt	HexNutBolt-M12,HexNutBolt-M16...
C-Skills	Pick up the nut, place it on the bolt, and screw it to the bottom of the bolt	Pick-Place-Screw	approach-grasp-lift-approach-place-screw	nut, bolt	HexNutBolt-M12,HexNutBolt-M16...
C-Skills	Pick up the nuts and place them on the bolts	Pick-Place-Pick-Place	approach-grasp-lift-approach-place-screw...	nuts, bolts	HexNutBolt-M12,HexNutBolt-M16...
...	...	...	...	...	...
C-Skills	Pick up the round peg and insert it into the round hole	Pick-Place-Insert	approach-grasp-lift-approach-place-insertion	peg, hole	RoundPegHole-4mm,RectPegHole-16mm...

designed by GPT-4 proves to be significantly more effective than the expert design. This effectiveness arises because the generator can fully understand the task requirements based on prompts and possesses superior analytical, computational, and memory abilities compared to humans. These results demonstrate the higher efficiency and performance of LLM-based methods for task reward design. In tasks (e) and (f), the success rate of the reward function generated with only five iterations is lower due to the higher complexity. To improve the success rate, increasing the number of iterations and samples is one solution. However, for complex tasks containing multiple subtasks, combining the method of this paper with hierarchical learning could yield unexpected results. Our approach has made significant progress on tasks of moderate complexity. We successfully implemented a reward function that represents the entire task, eliminating the need to design separate reward functions for each sub-task. This is particularly important for sequential operating skills, as it saves substantial time and effort.

### B. Intelligent Transfer Experiment

In this section, we provide a comprehensive evaluation of the performance of ITN. First, we evaluate the performance of each ITN module through designed validation experiments. Next, we test the generalization and cross-skill transfer capabilities of ITN. Finally, we analyze ITN's performance in comparison with other leading approaches. All experiments in this section utilize generator-generated reward functions. All a priori skills are derived from the skill space we constructed. We will present the results in the form of graphs for two complex tasks: the *NutBolt-PickPlace* task from Table I and the *PegHole-Insert* task (the first and last complex tasks in the table). The remaining experimental results can be found on our project's website.

1) *Verification Experiment*: We used the baseline commonly used for transfer reinforcement learning as a comparison, which is as follows:

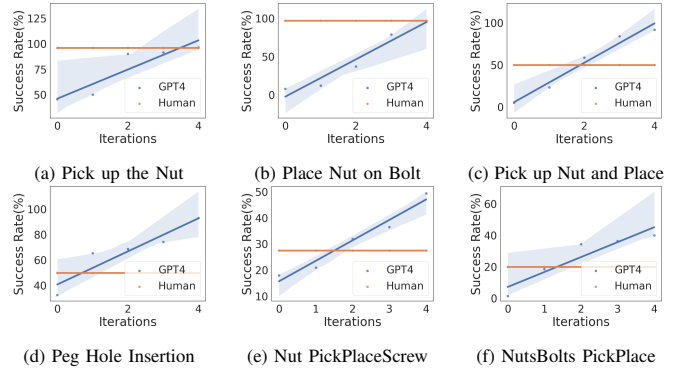


Fig. 6: Comparison of success rates for different tasks using GPT-4 and human-designed reward functions

- *No\_Transfer* does not use experienced skills but learns from scratch through exploration.
- *No Intelligent Attention (NIA)* is the proposed \$ITN\$ model without the Intelligent Attention component, assigning a fixed contribution value to each subtask.
- *Direct Feature Summation (DFS)* is the proposed \$ITN\$ model without Intelligent Attention and Feature Fusion, directly summing features from different source skills.
- *Partial Skills Transfer (PST)* is the proposed ITN method that transfers only a few sub-skills.

The results are shown in Fig. 7. The learning speed of ITN is significantly better than No\_Transfer in both tasks. PST assigns sub-skills at different task stages. The experiments demonstrate that transferring sub-skills at any stage within the ITN framework enhances learning efficiency. This sub-skill independence facilitates cross-skill transfer in dynamic tasks. NIA and DFS validate the strong feature fusion capability of the feature fusion layer. Comparing ITN with NIA shows that the addition of an Intelligent Adaptive model is significantly more effective than a fixed value. ITN improves time efficiency by approximately 72.22% and 65.17% compared to No\_Transfer in the two tasks, respectively.

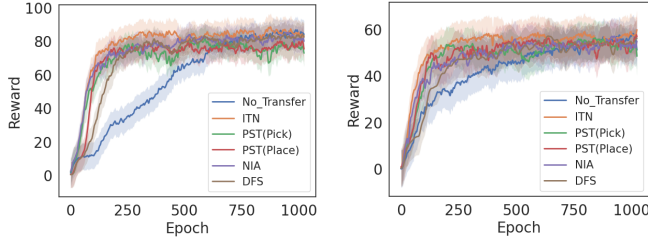


Fig. 7: The left figure is the validation experiment of *NutBolt\_PickPlace* and the right figure is the validation experiment of *PegHole\_Insert*.

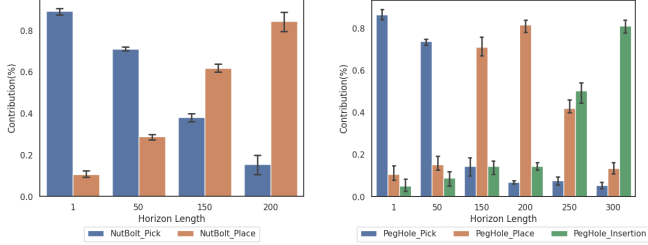


Fig. 8: The left and right graphs show the variation of the subskill attention values over an epoch for ITN in the NutBolt experiment and the PegHole experiment, respectively, as a function of the number of interactions.

Figure 8 shows ITN’s policy allocation concerns. The data, derived from a single interaction cycle after training has stabilized, indicates that the Intelligent Attention allocates attention to source skills differently at various stages of the target task. This allocation is similar to human experience, demonstrating that ITN successfully adapts to diverse tasks by adjusting the attention values of the source skills. This capability establishes a foundation for the robot to swiftly master entirely new tasks.

2) *Generalized Experiment*: This section examines the cross-task transfer capability and generalization of ITN in dynamic environments. We designed five scenarios for each task. We tested the generalizability of ITN by exchanging the source tasks of the two target tasks. Additionally, we assessed the cross-task transfer capability of ITN on new tasks by manipulating previously unseen parts.

The experimental results are illustrated in Figure 9. Curves 3 and 4 demonstrate that, although the target task and the source skills have different operational goals, the ITN can effectively utilize shared action features for transfer. This action feature-based transfer approach addresses various robotic operational challenges in dynamic tasks. Curve 5 shows that the robot quickly achieves high rewards when operating unseen new parts, indicating ITN’s efficiency in handling task variants. Curve 6 demonstrates the best learning speed and the most stable learning curve throughout the training process compared to the other curves, suggesting that the multi-skill fusion strategy is the most effective, significantly improving the learning efficiency and performance of the robot manipulation task.

3) *Comparison Experiment*: This experiment aims to evaluate ITN’s competitiveness in transfer learning for robotic skills by comparing it with two advanced, representative approaches.

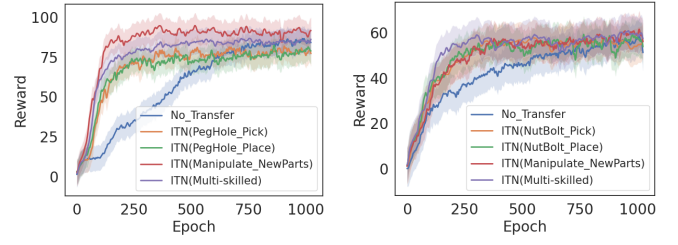


Fig. 9: ITN cross-task transfer experiment with *NutBolt\_PickPlace* task on the left and *PegHole\_Insert* task on the right

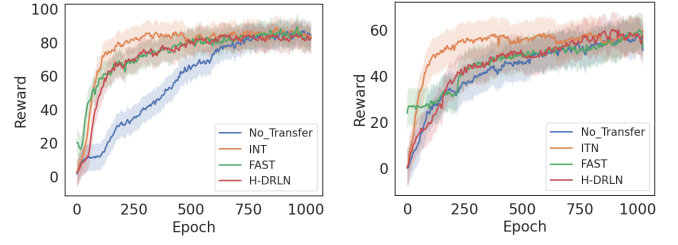


Fig. 10: On the left is a comparison experiment for the task *NutBolt\_PickPlace* and on the right is a comparison experiment for the task *PegHole\_PickPlaceInsert*

Hierarchical Deep Reinforcement Learning Network (H-DRLN) [28] efficiently retains knowledge through skill distillation and deep skill arrays. It learns strategies to determine when to perform original operations or reuse pre-learned skills. The original paper evaluates this method in Minecraft. In this section, we replicate the approach in our experiments.

Feature Selection Adaptive Transfer (FAST) facilitates knowledge transfer between old and new tasks by extracting shared features of the source and target domains [17]. FAST carries out a series of peg-hole tasks in a simulation. We replicated this approach and conducted an experimental comparison within our own experimental setting.

The results are shown in Figure 10. Several methods of transfer learning significantly outperform direct learning. Although FAST performs best in early training by selecting data closer to the target domain to initialize the policy, it is surpassed by ITN after a few dozen iterations. In addition, FAST focuses on extracting shared features and excels in solving transfer problems across manipulated objects, whereas ITN focuses on exploring a generalized transfer approach across tasks. H-DRLN attempts to receive the current environment state as input and outputs the probabilities of new actions and source skills choices, reusing the subskill with the highest probability value. Although this approach incorporates the learning of new strategies, the reuse approach is very limited in terms of usage scenarios. ITNs are not dependent on specific skills and can fully adapt to task changes by considering transfer at the feature level.

We compare the task success rate variation with iteration periods for four methods, as shown in Table II. Our (ITN) method excels in the early and middle stages, achieving initial success rates of 86.64% and 79.56% in two tasks, significantly higher than the other methods. As training progresses, success rates of all methods rise, but ITN achieves

higher rates earlier, demonstrating superior time efficiency and success rate. The method is highly anticipated for its practical value.

TABLE II: THIS TABLE SHOWS THE VARIATION OF TASK SUCCESS RATE WITH TRAINING TIME FOR THE FOUR METHODS IN THE *NUTBOLT\_PICKPLACE* TASK AND *PEGHOLE\_INSERTION* TASK

Methods	200 epo	400 epo	600 epo	800 epo	1024 epo
No.Transfer	34.66%	56.32%	81.03%	90.46%	<b>91.6%</b>
FAST	71.48%	83.47%	89.91%	91.67%	<b>91.78%</b>
H-DRLN	70.96%	85.56%	91.02%	91.54%	<b>92.02%</b>
Our(ITN)	86.64%	<b>92.20%</b>	<b>92.20%</b>	<b>92.20%</b>	<b>92.21%</b>
No.transfer	50.49%	65.79%	71.91%	78.69%	<b>90.73%</b>
FAST	48.96%	71.91%	76.81%	80.09%	<b>91.03%</b>
H-DRLN	58.14%	71.96%	77.52%	87.97%	<b>91.82%</b>
Our(ITN)	79.56%	<b>88.74%</b>	<b>89.66%</b>	<b>90.27%</b>	<b>92.10%</b>

## V. CONCLUSIONS

In this letter, we present a method for robots to autonomously and quickly learn new tasks in dynamic environments. To enable autonomous problem-solving, we divide the system into two parts. First, we utilize LLMs to automatically generate a process-oriented reward function for new tasks. Second, we construct an intelligent transfer module that uses LLMs to generate prior knowledge for the transfer process and intelligently fuse features from source skills. We conducted a series of simulation experiments to verify the efficiency of the method. While our approach performs well in handling tasks of moderate complexity, designing a generalized reward function for highly complex tasks remains challenging. We have high expectations for the transfer performance of our framework on complex tasks. In the future, we plan to further combine our approach with methods such as hierarchical reinforcement learning to conduct experiments on more challenging robot manipulation tasks.

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