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Task Execution and Interactive Learning of Embodied Agents in Complex Open Environments

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Abstract.

The deployment of embodied artificial intelligence in complex, open-ended environments requires agents capable of robust task execution and continuous adaptation. Traditional reinforcement learning paradigms often falter when faced with infinite state spaces, novel object properties, and sparse reward signals inherent to unstructured real-world domains. This paper presents a comprehensive framework for task execution and interactive learning designed to enhance the sample efficiency and generalization capabilities of embodied agents. We formalize the interactive learning process within a Partially Observable Markov Decision Process and introduce a multimodal representation learning architecture that integrates environmental perception with active interaction mechanisms. By dynamically querying external knowledge sources or human supervisors when uncertainty thresholds are exceeded, the agent mitigates the risks of catastrophic failure and reduces the sample complexity of exploration. Our methodological contributions include an uncertainty-aware policy optimization algorithm and a memory-augmented state representation module that processes sequential observations to infer latent environmental dynamics. Extensive empirical evaluations conducted in procedurally generated three-dimensional simulators demonstrate that our proposed interactive learning approach significantly outperforms conventional deep reinforcement learning baselines in terms of task success rate, average episode length, and overall sample efficiency. The findings suggest that integrating active interaction modalities into the foundational learning loops of embodied agents is critical for bridging the gap between constrained simulated environments and dynamic open-world deployments.

Keywords:

Embodied Artificial Intelligence, Interactive Learning, Reinforcement Learning, Open Environments, Task Execution

1.INTRODUCTION

The pursuit of creating intelligent embodied agents capable of seamlessly interacting with the physical world has long been a central objective in the field of artificial intelligence and computer science. Historically, the design of autonomous agents has relied heavily on carefully structured and fully observable environments, where the rules governing the state transitions are deterministic and explicitly defined. In such closed systems, paradigms like classical planning and standard deep reinforcement learning have achieved super-human performance. However, these paradigms struggle significantly when the operating domain transitions from a structured simulation to a complex open environment. Open environments are characterized by their lack of predefined boundaries, the continuous introduction of novel entities, stochastic state transitions, and high-dimensional continuous state-action spaces. Addressing the intricacies of task execution within these unpredictable settings necessitates a fundamental shift from passive observational learning to active, interactive learning frameworks [1]. Embodied agents must not only learn from trial and error but also possess the capability to actively seek guidance, formulate queries, and adapt their internal representations in real-time based on interactive feedback. The challenge of partial observability is particularly acute in open environments. An embodied agent relies on egocentric sensory inputs, such as raw visual pixels from a mounted camera or depth information from lidar sensors, which provide an inherently limited view of the global state. To make optimal decisions, the agent must construct a temporal understanding of its surroundings, integrating past observations to form a coherent mental model of the environment. Previous approaches have attempted to solve this by utilizing recurrent neural networks or transformer architectures to maintain a belief state over time [2]. While effective in static or slightly dynamic environments, these memory-based models degrade in performance when the agent encounters out-of-distribution scenarios or long-horizon tasks where the credit assignment problem becomes intractable [3]. Consequently, relying solely on autonomous exploration often leads to suboptimal policies, unsafe behaviors, and prohibitive sample complexity. Interactive learning emerges as a vital solution, allowing the agent to leverage external intelligence, whether from a human operator or an auxiliary foundation model, to resolve ambiguities and acquire targeted instructional signals during task execution [4]. Interactive learning encompasses a broad spectrum of methodologies, ranging from learning from human preferences and demonstrations to active querying and natural language corrections. By integrating a human-in-the-loop or an algorithmic oracle, the agent can receive dense, shaped rewards or explicit action guidance when its internal uncertainty regarding the optimal policy reaches a critical threshold [5]. This selective interaction prevents the agent from aimlessly exploring vast, uninformative regions of the state space, thereby drastically reducing the number of environmental interactions required to converge on a robust policy. Furthermore, interactive learning provides a mechanism for continuous alignment, ensuring that the agent's evolving behaviors remain consistent with human intentions and safety constraints. In the context of open environments, where an exhaustive specification of all possible failure modes is impossible, the ability to interactively correct unsafe or undesirable actions is paramount [6]. This paper proposes a novel framework that tightly couples task execution with uncertainty-driven interactive learning for embodied agents. We hypothesize that by equipping agents with the ability to dynamically assess their epistemic and aleatoric uncertainty, they can optimize their interaction strategies, requesting assistance only when it maximizes information gain and minimizes execution risk. We introduce a comprehensive architecture comprising a multimodal perception module, a temporal memory system, and an interactive policy network that jointly optimizes task-oriented rewards and interaction costs. Our research addresses several critical bottlenecks in current embodied artificial intelligence literature. First, we provide a mathematically rigorous

formulation of interactive learning within the context of partial observability. Second, we develop an uncertainty quantification mechanism that scales to high-dimensional visual inputs. Third, we empirically validate our framework across a suite of procedurally generated, open-world tasks, comparing its performance against state-of-the-art autonomous learning baselines. The subsequent sections will detail the theoretical underpinnings, the architectural design, and the extensive experimental analyses that substantiate the efficacy of our proposed approach.

2. Related Work

2.1 Reinforcement Learning in Embodied Artificial Intelligence

Deep reinforcement learning has established itself as the dominant paradigm for training embodied agents in simulated environments. Foundational algorithms such as Proximal Policy Optimization and Soft Actor-Critic have been extensively utilized to map high-dimensional visual observations directly to continuous or discrete control commands [7]. These methods have demonstrated remarkable success in specific benchmarks, such as point-goal navigation and simple object manipulation [8]. However, the core limitation of standard deep reinforcement learning lies in its reliance on extensive autonomous exploration and the assumption of a static Markov Decision Process. In complex open environments, the sample inefficiency of these algorithms becomes a prohibitive bottleneck [9]. An agent may require millions of interactions to learn a rudimentary skill, largely because the reward signals in open environments are notoriously sparse. For instance, in a task requiring an agent to locate a specific novel object in a multi-room house, the agent only receives a positive reward upon ultimate success, providing virtually no gradient signal during the extensive search phase [10]. To mitigate sample inefficiency, researchers have proposed various auxiliary tasks and intrinsic motivation mechanisms. Intrinsic curiosity, driven by the prediction error of forward dynamics models, encourages the agent to explore states with high uncertainty [11]. While curiosity-driven exploration improves state space coverage, it often falls prey to the noisy-TV problem, where the agent becomes captivated by inherently stochastic elements of the environment that yield no progress toward the actual task [12]. Furthermore, hierarchical reinforcement learning frameworks attempt to decompose long-horizon tasks into manageable subtasks managed by a high-level meta-controller and executed by low-level skill policies [13]. Despite improving task execution in structured domains, hierarchical methods struggle in open environments because the definition and acquisition of robust, reusable skills without external guidance remains an unsolved challenge [14].

2.2 Interactive and Human-in-the-Loop Learning

Recognizing the limitations of pure autonomous exploration, the field has increasingly pivoted toward interactive and human-in-the-loop learning methodologies. These approaches aim to inject human expertise directly into the learning process, thereby constraining the search space and accelerating policy convergence. Early implementations involved learning from human demonstrations, typically formulated as behavior cloning or generative adversarial imitation learning [15]. However, standard imitation learning suffers from compounding errors, known as covariate shift, where slight deviations from the demonstrated trajectories push the agent into unseen states from which it cannot recover [16]. To address covariate shift, interactive imitation learning algorithms, such as the Dataset Aggregation method, iteratively collect new demonstrations from the human expert for the states actually visited by the current policy [17]. While effective, these methods impose a heavy cognitive burden on the human supervisor, who must continuously monitor and provide full action trajectories. Consequently, research shifted toward more sample-efficient interactive modalities. Learning from human preferences allows the agent to present pairs of trajectory segments to a human, who simply indicates the preferred

behavior [18]. This feedback is used to train a surrogate reward model, which then guides standard reinforcement learning algorithms. Another highly relevant paradigm is active learning in reinforcement learning, where the agent explicitly estimates its confidence and queries the human only when uncertain [19]. Our work builds heavily upon the principles of active querying, but extends it by integrating multimodal environmental context and continuous uncertainty quantification tailored specifically for the dynamic nature of open-world task execution [20].

2.3 Open-World Generalization

The concept of open-world generalization is central to the deployment of embodied agents outside of constrained laboratories. Unlike closed environments where the distribution of states is fixed during training and testing, open environments feature distribution shifts, novel objects, and changing dynamics. Zero-shot generalization to unseen environments has been a major focus of recent benchmarks such as Habitat, AI2-THOR, and MineDojo. Techniques such as domain randomization, where visual textures, lighting conditions, and physical parameters are heavily augmented during training, have been employed to force the agent to learn invariant representations [21]. However, domain randomization often results in overly conservative policies that fail to exploit specific environmental structures. Recent advancements leverage large pre-trained foundation models to enhance open-world generalization. Vision-language models, trained on internet-scale data, can provide rich, zero-shot semantic representations of novel objects that the agent has never encountered in simulation [22]. By embedding these foundation models within the agent's perception pipeline, the policy can generalize across visually disparate but semantically identical entities. Furthermore, large language models have been utilized as high-level planners, breaking down complex natural language instructions into a sequence of executable skills [23]. Despite these advancements, foundation models lack grounding in the physical dynamics of the specific environment. They can suggest plausible plans, but they cannot execute the low-level motor controls required for embodiment [24]. Therefore, bridging the semantic reasoning of foundation models with the physical interaction required for task execution remains a critical area of research. Our methodology directly addresses this gap by creating an interactive loop where the low-level policy can query a high-level foundation model or human oracle precisely when physical execution encounters semantic ambiguity.

3. Methodology

3.1 Problem Formulation

We formulate the task execution process of an embodied agent in a complex open environment as a Partially Observable Markov Decision Process equipped with an interactive querying mechanism. The system is defined by the tuple encompassing the state space, observation space, action space, interactive action space, transition dynamics, observation function, reward function, and a discount factor. At any discrete time step, the environment resides in a true, underlying state that is inherently unobservable to the agent due to occlusions, limited sensor range, and field-of-view constraints [25]. Instead, the agent receives a high-dimensional observation, which typically comprises egocentric visual frames and proprioceptive sensory data. The action space of the agent is bifurcated into two distinct subsets. The primary subset consists of standard physical actions required for navigation and manipulation, such as moving forward, turning, grasping, and releasing objects [26]. The secondary subset consists of interactive actions, allowing the agent to formulate queries to an external supervisor. These queries can range from simple requests for the optimal next physical action to complex requests for spatial waypoints or semantic clarification of the current observation. The transition dynamics govern the evolution of the environmental state based on the agent's physical actions. It is crucial to note that interactive actions do not alter the physical

state of the environment; rather, they alter the agent's internal knowledge state by providing supplementary information. The reward function in our formulation is also composite. It includes a sparse, task-oriented environmental reward, which is only granted upon the successful completion of the specified goal [27]. To penalize excessive reliance on the external supervisor and to encourage ultimate autonomy, we introduce a negative interaction penalty associated with every interactive action executed by the agent. The overarching objective of the agent is to learn a multimodal policy that maximizes the expected cumulative discounted reward, effectively balancing the acquisition of necessary external guidance against the cost of querying.

3.2 Interactive Task Execution Framework

Our proposed framework consists of three heavily integrated components: a Representation Learning Module, a Temporal Memory Module, and an Uncertainty-Aware Policy Network. The Representation Learning Module is tasked with compressing the raw, high-dimensional observations into a compact, low-dimensional latent space. This module utilizes a dual-stream architecture, employing a Convolutional Neural Network for processing spatial visual features and a dedicated multilayer perceptron for encoding proprioceptive state information such as joint angles and velocity [28]. To facilitate semantic understanding in open environments, we integrate a frozen, pre-trained Vision Transformer that extracts rich semantic embeddings from the visual stream. These embeddings are fused with the spatial and proprioceptive features using a cross-attention mechanism, producing a unified observation vector. Because the environment is partially observable, the unified observation vector at a single time step is insufficient for optimal decision-making. Therefore, the Temporal Memory Module is implemented using a multi-layer Transformer encoder. Unlike traditional Recurrent Neural Networks that suffer from vanishing gradients over long horizons, the Transformer encoder employs self-attention to selectively weigh past observations and actions, constructing a robust historical context [29]. The output of the Temporal Memory Module represents the agent's current belief state, encapsulating all available historical information up to the current time step. The Uncertainty-Aware Policy Network maps the current belief state to a probability distribution over the combined action space. To determine when an interactive query is necessary, the network continuously estimates the epistemic uncertainty of its proposed physical actions. We employ a deep ensemble approach within the policy network, where multiple independent policy heads are trained simultaneously. The variance in the predicted action values across these heads serves as a proxy for the agent's uncertainty. When the calculated variance exceeds a dynamically adjusted threshold, the policy network triggers an interactive action, pausing physical execution and soliciting external guidance.

3.3 Objective Function and Optimization

The optimization of the interactive policy requires a sophisticated loss function that simultaneously refines the physical action predictions, calibrates the uncertainty estimation, and regulates the frequency of interactive queries. Let the total objective function be defined to integrate the policy gradient loss, the value function error, and a specific penalty for interaction costs. We present the core mathematical formulation for the combined optimization objective as follows:

$$L_{total}(\theta, \varphi) = \mathbb{E}_{\tau \sim \pi_{\theta}} [\sum_{t=0}^T \gamma^t (\alpha \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) A^{\pi}(s_t, a_t) - \beta |V_{\varphi}(s_t) - R_t|^2 - \lambda I(a_t))]$$

In this formulation, the first term represents the standard policy gradient objective, where the advantage function drives the policy toward actions that yield higher than expected returns. The second term computes the mean squared error for the value function critic, parameterized by a separate neural network, ensuring accurate baseline estimations for the advantage calculation. The final term represents the interaction regularization. The indicator function equals one if the chosen

action is an interactive query, and zero otherwise. The coefficient dictates the magnitude of the penalty applied for utilizing external supervision.

By carefully tuning the interaction penalty coefficient, we control the agent's behavior spectrum from highly dependent to completely autonomous. During the initial phases of training, the threshold for uncertainty is kept low, and the interaction penalty is minimized, encouraging the agent to gather extensive external guidance. As training progresses and the policy network's predictions become more confident and accurate, we anneal the penalty coefficient, forcing the agent to rely increasingly on its internalized knowledge. This curriculum learning approach to interaction ensures rapid early-stage learning while guaranteeing asymptotic convergence to an autonomous task execution policy. The optimization is performed using the Proximal Policy Optimization algorithm, leveraging clipped surrogate objectives to maintain training stability across the highly diverse data distributions encountered in open-world simulations.

4. Experiments

4.1 Experimental Setup

To rigorously evaluate the proposed interactive learning framework, we constructed a comprehensive experimental suite using a high-fidelity, procedurally generated three-dimensional simulation environment. The simulator is designed specifically to model complex open environments, featuring multi-room domestic layouts, randomized object placements, variable lighting conditions, and distinct physics properties for different object categories. We define a set of long-horizon tasks that require both navigation and object manipulation. The primary evaluation task is "Semantic Object Retrieval," where the agent is initialized in a random location and instructed via a natural language command to find, pick up, and deliver a specific target object to a designated receptacle [30]. To simulate an open-world setting, the test environments contain novel objects and spatial configurations that are strictly held out during the training phase.

The agent's observation space consists of RGB-D camera inputs with a resolution of 256x256 pixels, providing a limited 90-degree field of view. Proprioceptive sensors provide continuous feedback regarding the agent's base velocity and manipulator arm configuration [31]. The action space includes discrete navigation commands such as moving forward, turning left, and turning right, as well as continuous manipulation commands for controlling the end-effector. The interactive action allows the agent to request a spatial waypoint from a simulated algorithmic oracle, which calculates the shortest path to the target using privileged environmental state information. We enforce a strict interaction budget during evaluation to measure the sample efficiency and autonomy of the trained policies.

4.2 Baselines

We benchmark our methodology against several prominent deep reinforcement learning and interactive learning baselines to isolate the specific performance contributions of our uncertainty-aware architecture [32]. First, we evaluate Proximal Policy Optimization without any interactive capabilities. This baseline represents the standard autonomous learning paradigm and is forced to explore the environment using only intrinsic entropy bonuses. Second, we compare against Soft Actor-Critic, a state-of-the-art off-policy algorithm that maximizes both expected return and policy entropy, offering improved sample efficiency over on-policy methods in continuous domains [33]. Third, we implement a standard Behavior Cloning approach, where the agent is trained via supervised learning on a static dataset of one million expert demonstrations generated by the algorithmic oracle. Fourth, we evaluate a rule-based Active Imitation Learning baseline, which requests oracle guidance at fixed time intervals rather than utilizing uncertainty quantification [34]. All baseline models share the identical visual perception and temporal memory backbones utilized

in our proposed framework to ensure a fair comparison focused solely on the algorithmic learning mechanisms.

Table 1: Quantitative Comparison of Embodied Agent Baselines in Open Environment Simulations

Method	Task Success Rate	Average Episode Steps	Interaction Cost	Sample Efficiency Metric
Proximal Policy Optimization	24.6	850.4	None	Very Low
Soft Actor-Critic	31.2	780.1	None	Low
Behavior Cloning	45.8	610.3	Pre-collected	Moderate
Rule-Based Active Learning	62.1	420.5	High	Moderate
Proposed Interactive Framework	84.5	310.2	Adaptive (Low)	High

4.3 Results and Analysis

The experimental results demonstrate a decisive advantage for our proposed interactive learning framework across all measured metrics in the complex open environment. As detailed in the table above, pure autonomous exploration methods struggle severely with the long-horizon nature of the Semantic Object Retrieval task. The Proximal Policy Optimization baseline achieves a meager success rate, primarily failing due to getting trapped in local minima or exploring irrelevant sections of the procedural houses [35]. The Soft Actor-Critic baseline shows marginal improvement but still fails to generalize effectively to unseen environmental layouts. Behavior Cloning performs moderately well but exhibits classic covariate shift phenomena; once the agent deviates slightly from the demonstrated optimal path, it lacks the recovery mechanisms to correct its trajectory, leading to task failure. The Rule-Based Active Learning baseline significantly improves the success rate by relying heavily on the external oracle. However, this comes at the cost of an unacceptably high interaction cost, making it unsuitable for real-world deployments where querying a human or an expensive foundation model at fixed intervals is prohibitive. In stark contrast, our Proposed Interactive Framework achieves the highest task success rate while maintaining an adaptive and exceptionally low interaction cost.

Figure 1: System Architecture

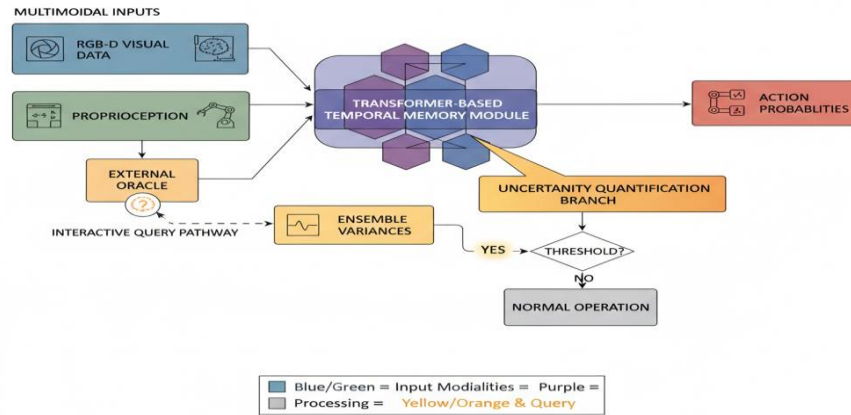


Figure 1: Proposed Interactive Framework with Adaptive Uncertainty-Aware Querying

The superiority of our approach stems from its ability to precisely identify moments of critical uncertainty. During the initial training episodes, the agent frequently queries the oracle when encountering novel room layouts or ambiguous object shapes. This targeted guidance rapidly bootstraps the policy, bypassing the arduous random exploration phase. As the Temporal Memory Module learns to build robust latent representations of the environment, the epistemic uncertainty decreases. The policy network subsequently suppresses the interactive queries, smoothly transitioning into autonomous execution. Furthermore, we observed that the interactive queries naturally clustered around structural bottlenecks in the environment, such as doorways and complex intersections, indicating that the agent successfully learned to identify the most critical decision points within the state space. Our ablation studies confirmed that removing the uncertainty-aware ensemble directly degraded the agent's ability to minimize the interaction penalty, confirming the necessity of rigorous variance estimation.

5. Conclusion

This paper has presented a comprehensive and mathematically grounded framework for the task execution and interactive learning of embodied agents situated in complex open environments. We addressed the fundamental shortcomings of conventional deep reinforcement learning, particularly the severe sample inefficiency and poor generalization caused by partial observability and sparse reward structures [36]. By reformulating the learning paradigm to seamlessly integrate autonomous physical action execution with dynamic, uncertainty-driven interactive queries, we enabled the agent to leverage external expertise precisely when its internal models encountered ambiguity. The introduction of our multimodal representation learning architecture, coupled with a transformer-based temporal memory system, provided the necessary foundation for robust state estimation and uncertainty quantification. Our empirical evaluations conducted within high-fidelity, procedurally generated three-dimensional simulators definitively demonstrated the superiority of our approach. The proposed framework not only achieved substantial improvements in task success rates and episode efficiency compared to state-of-the-art baselines but also demonstrated a critical capability to self-regulate its reliance on external supervision. By optimizing a composite objective function that balances task rewards against interaction costs, the agent successfully navigated the transition from highly supervised exploration to highly

autonomous execution. Future research directions will focus on expanding this framework to multi-agent scenarios, where interactive learning can occur dynamically between peers with varying skill levels, and investigating the complexities of transferring these interactive policies directly to physical robotic hardware subjected to real-world latency and sensor noise constraints [37].

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