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A Hierarchical Deep Reinforcement Learning Algorithm with Stochastic Policy Gradient for Robust Robotic Manipulation

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Abstract: *The domain of robotic manipulation has witnessed significant advancements through the application of deep reinforcement learning, yet substantial challenges remain regarding sample efficiency, generalization, and robustness against environmental perturbations. This paper introduces a novel Hierarchical Deep Reinforcement Learning framework integrated with a Stochastic Policy Gradient mechanism designed specifically to address the high-dimensional state-action spaces inherent in multi-joint robotic control. By decomposing complex manipulation tasks into temporally extended sub-goals managed by a high-level policy, and executing primitive motor commands via a low-level controller, the proposed architecture effectively mitigates the sparse reward problem. Furthermore, the incorporation of a stochastic policy gradient enables the agent to maintain extensive exploration capabilities while ensuring robust performance in the presence of sensor noise and dynamic friction changes. We demonstrate the efficacy of this approach through rigorous simulation experiments involving complex pick-and-place and stacking tasks. The results indicate that our method significantly outperforms varying state-of-the-art baselines in terms of convergence speed and success rates under adversarial conditions.*

Keywords: *Hierarchical Reinforcement Learning, Deep Reinforcement Learning, Stochastic Policy Gradient, Robotic Manipulation, Autonomous Robotics, Policy Optimization, Human-Robot Interaction, Adaptive Control*

1. INTRODUCTION

The pursuit of autonomous robotic systems capable of performing complex manipulation tasks in unstructured environments stands as one of the central challenges in artificial intelligence and robotics. Traditional control methods, which rely heavily on precise kinematic modeling and trajectory planning, often struggle when faced with the uncertainties and variabilities of real-world physics. Deep reinforcement learning has emerged as a promising alternative, enabling robots to learn control policies directly from high-dimensional sensory inputs through trial and error. However, the application of standard deep reinforcement learning algorithms to robotic manipulation is frequently hindered by the curse of dimensionality and the sparsity of reward signals in long-horizon tasks [1]. As the complexity of the task increases, the likelihood of an agent stumbling upon a successful sequence of actions diminishes exponentially, leading to prohibitive training times and suboptimal policy convergence. To overcome these limitations, researchers have increasingly looked toward hierarchical structures that mirror biological motor control. In biological systems, complex behaviors are rarely planned at the level of individual muscle contractions; rather, they are composed of high-level intentions that modulate low-level reflexes and motor primitives. Hierarchical reinforcement learning seeks to emulate this organization by decomposing a difficult task into a hierarchy of sub-problems. A high-level policy, often termed the manager, operates at a slower time scale to select sub-goals or skills, while a low-level policy, the worker, executes the necessary actions to achieve these sub-goals over a faster time scale. This temporal abstraction reduces the effective horizon of the problem, allowing for more efficient credit assignment and exploration. Despite the promise of hierarchical approaches, a critical issue remains: the fragility of learned policies when subjected to environmental stochasticity. Many existing hierarchical methods utilize deterministic policies for the low-level controllers, which can become brittle when the simulation dynamics do not perfectly match the deployment environment or when sensors introduce noise. To address this, we propose integrating a stochastic policy gradient formulation within the hierarchical framework. Stochastic policies naturally encourage exploration and are theoretically shown to be more robust to parameter uncertainties and unmodeled dynamics [2]. In this paper, we present a unified framework that combines the temporal abstraction of hierarchical reinforcement learning with the robustness of stochastic policy gradients. Our approach utilizes a two-level hierarchy where the high-level manager learns to propose latent sub-goals that guide the low-level worker. The worker utilizes a stochastic policy to interact with the environment, optimizing a maximum entropy objective to

balance exploitation of known rewards with exploration of the state space. We validate our method on a suite of continuous control tasks involving a simulated robotic arm. Our contributions are threefold: first, we formalize a hierarchical architecture that seamlessly integrates latent goal generation with stochastic low-level control; second, we demonstrate that the stochastic nature of the policy gradient significantly improves robustness against external force perturbations and sensor noise; and third, we provide an extensive empirical analysis showing that our method achieves superior sample efficiency compared to flat reinforcement learning baselines.

1.1 Motivation and Problem Formulation

The core motivation for this research stems from the observation that robotic manipulation tasks are inherently compositional. A task such as stacking a block involves reaching, grasping, lifting, moving, and placing. Flat reinforcement learning agents treat this entire sequence as a single monolithic policy optimization problem, which often leads to the agent forgetting earlier stages of the task as it attempts to learn later stages, a phenomenon known as catastrophic forgetting. Furthermore, the standard objective of maximizing expected cumulative return does not inherently account for robustness. An agent might learn a trajectory that is optimal in a static simulation but fails catastrophically if the friction coefficient of the object changes slightly. We formulate the problem as a Markov Decision Process extended with a hierarchical structure. The environment provides a state vector consisting of robot joint angles, velocities, and object positions. The objective is to learn a policy that maximizes the discounted sum of rewards over an infinite horizon. However, unlike standard approaches, we factorize the policy into two components. The high-level policy maps the current state to a continuous sub-goal vector, updated at fixed intervals. The low-level policy maps the current state and the current sub-goal to the torque actions applied to the robot's joints. By injecting stochasticity into the low-level policy update rule, we aim to smooth the optimization landscape, preventing the agent from converging to sharp, unstable local minima that are characteristic of deterministic policy gradient methods in high-dimensional spaces [3].

2. Related Work

The landscape of deep reinforcement learning for robotics has evolved rapidly, with significant efforts directed toward improving sample efficiency and robustness. This section reviews relevant literature in deep reinforcement learning, hierarchical methods, and robust control strategies.

2.1 Deep Reinforcement Learning in Robotics

Early success in applying deep learning to control problems was demonstrated by algorithms such as Deep Q-Networks and Deep

Deterministic Policy Gradients. Deep Deterministic Policy Gradients, specifically designed for continuous action spaces, utilized an actor-critic architecture where a deterministic policy was trained using the gradient of the value function. While successful in many benchmarks, Deep Deterministic Policy Gradients is known to be highly sensitive to hyperparameter selection and prone to instability. Subsequent improvements, such as Twin Delayed Deep Deterministic Policy Gradients, addressed the overestimation bias of Q-values but retained the deterministic nature of the policy. In contrast, approaches like Soft Actor-Critic introduced an entropy regularization term, encouraging the policy to remain stochastic [4]. Our work builds upon the benefits of maximum entropy reinforcement learning observed in Soft Actor-Critic but extends it into a hierarchical domain to handle long-horizon tasks that single-level Soft Actor-Critic struggles to solve.

2.2 Hierarchical Reinforcement Learning

Hierarchical Reinforcement Learning has a long history, dating back to the options framework which formalized temporally extended actions. In the deep learning era, Feudal Networks proposed a manager-worker architecture where the manager sets goals in a latent space. However, training such hierarchies is notoriously difficult due to the non-stationarity of the transition function perceived by the high-level policy; as the low-level policy changes, the outcome of a high-level action (setting a goal) changes as well. Recent works such as HIRO (Hierarchical Reinforcement Learning with Off-Policy Correction) have attempted to mitigate this by relabeling past experiences with high-level actions that would have made the observed transitions likely [5]. Our approach differs from HIRO by employing a stochastic gradient estimator at the lower level which inherently handles the exploration-exploitation trade-off more effectively than the deterministic noise added to actions in HIRO. Furthermore, we employ a specific goal-transition mechanism that ensures smoothness in the latent goal space, facilitating stable learning for the high-level manager.

2.3 Robustness and Stochastic Policies

Robustness in reinforcement learning is often approached through domain randomization, where the physical parameters of the simulation are varied during training to encourage the agent to learn a generalized policy. While effective, domain randomization relies on the assumption that the real-world dynamics lie within the distribution of the randomized parameters. Theoretical work on policy gradients suggests that stochastic policies optimize a smoothed version of the objective function, making them less likely to exploit modeling errors in the simulator [6]. Trust Region Policy Optimization and Proximal Policy Optimization have utilized constraints on the policy update to ensure stability, but they are often

applied in a flat hierarchy. Research combining hierarchy with robust control is limited. Some studies have explored using robust adversarial reinforcement learning within a hierarchical setup, where an adversary applies forces to the agent [7]. Our work complements these approaches by demonstrating that intrinsic stochasticity in the policy gradient update serves as a powerful mechanism for robustness without the need for an explicit adversary during training.

3. Methodology

We propose a Hierarchical Stochastic Policy Gradient framework designed for continuous control in robotic manipulation. The architecture consists of two distinct neural network policies operating at different temporal resolutions. The interaction is governed by a manager policy and a worker policy. The manager observes the state of the environment and produces a high-level goal. The worker observes both the environment state and the goal provided by the manager, producing the primitive actions.

3.1 Hierarchical Architecture and Temporal Abstraction

The foundation of our approach is the temporal abstraction that separates high-level planning from low-level execution. Let the decision process be modeled over discrete time steps. The manager operates at a lower frequency, updating its decision every fixed number of atomic time steps. At the start of a high-level cycle, the manager observes the state and generates a goal vector. This goal vector is not a specific coordinate in the Cartesian space but rather a latent representation that directs the worker toward a desired reconfiguration of the environment. The worker operates at the atomic frequency of the simulation. It receives the current state and the goal vector as input. Importantly, the goal vector is not static during the execution of the low-level steps; it transitions according to a fixed transition function to guide the worker. For instance, if the goal represents a relative change in position, the goal vector is decremented by the change in the state at each step, effectively creating a moving target that draws the agent toward the desired state. This technique allows the worker to learn a goal-conditioned policy that is generalizable across different sub-tasks requested by the manager. The reward function is also decomposed: the manager is rewarded based on the extrinsic task reward (e.g., whether the object was successfully stacked), while the worker is rewarded based on its intrinsic ability to reach the sub-goal states prescribed by the manager. This decoupling allows the worker to learn valid motor primitives even before the manager has learned how to chain them together effectively [8].

3.2 Stochastic Policy Gradient Formulation

To ensure robustness and effective exploration, we employ a stochastic policy gradient method for the worker network. Unlike

deterministic approaches that output a single action vector, our worker network outputs the parameters of a probability distribution (specifically, a Gaussian distribution with a diagonal covariance matrix) over the action space. The policy is parameterized by a neural network that outputs the mean and the logarithm of the standard deviation. The optimization objective involves maximizing the expected return augmented by an entropy term. The entropy term prevents the policy from collapsing to a deterministic point too early in the training process, which is a common failure mode in robotic manipulation where precise contacts are required. By maintaining a non-zero probability mass over a range of actions, the agent can escape local optima. The gradient of this objective is estimated using the reparameterization trick, which allows for backpropagation through the stochastic node. This results in a low-variance gradient estimator that facilitates stable learning. Critically, the stochasticity is not merely for exploration during training; it is an integral part of the policy's representation. In the context of robotic manipulation, where contact dynamics are discontinuous and difficult to model perfectly, a stochastic policy acts as a smoothing operator. When the robot's gripper contacts an object, a deterministic policy might apply a precise force that works in simulation but causes slippage in reality due to friction differences. The stochastic policy, having been trained to maximize expected return under a distribution of actions, essentially learns a strategy that is robust to small variations in execution, thereby improving the sim-to-real transferability potential [9].

3.3 Goal Consistency and Off-Policy Correction

Since we utilize an off-policy learning algorithm to improve sample efficiency, we must address the non-stationarity introduced by the changing policies. Data collected by the worker at an earlier stage of training was generated under a different manager policy and a different worker policy. To utilize this data effectively, we employ an off-policy correction mechanism. When sampling a trajectory from the replay buffer for training the manager, we must determine if the actions taken by the worker in that historical trajectory could be plausibly attributed to the current goal generation strategy. We implement a relabeling strategy where we re-evaluate the high-level goals. For a given transition in the replay buffer, we compute the probability that the current worker policy would perform the recorded action given the recorded goal. If this probability is low, it implies that the goal recorded in the buffer is no longer consistent with the current low-level behavior. In such cases, we search for a new goal that maximizes the likelihood of the observed low-level actions. This retrospective goal relabeling allows the manager to learn from historical data by reinterpreting past successes (or failures) in the context of its current capabilities. This aligns with

recent findings in the literature suggesting that hindsight is crucial for learning sparse-reward tasks [10].

4. Experimental Setup

To validate the proposed Hierarchical Stochastic Policy Gradient algorithm, we conducted a series of experiments using a high-fidelity physics simulator. The primary objective was to evaluate the algorithm's performance in standard robotic manipulation tasks and its robustness to environmental perturbations compared to established baselines.

4.1 Simulation Environment

We utilized the MuJoCo physics engine to simulate a 7-DOF robotic arm equipped with a parallel-jaw gripper. The state space includes the joint angles, joint velocities, the Cartesian position and orientation of the gripper, and the position and orientation of the target objects. The action space consists of continuous torque commands applied to the seven joints and the gripper actuator.

We defined three distinct tasks of increasing complexity:

***1.Reach*:** The robot must move its end-effector to a randomly generated target position in 3D space.

***2.Pick-and-Place*:** The robot must grasp a block from a table and lift it to a target position.

***3.Block Stacking*:** The robot must locate a block, grasp it, and balance it on top of another block. These tasks require precision, coordination, and the ability to handle contact dynamics. The Block Stacking task, in particular, is a long-horizon problem where flat reinforcement learning algorithms typically struggle due to the vanishing gradient of the reward signal over time.

4.2 Baselines and Hyperparameters

We compared our proposed method against two strong baselines:

***1.Deep Deterministic Policy Gradient (DDPG)*:** A standard flat, off-policy algorithm using deterministic policies.

***2.Soft Actor-Critic (SAC)*:** A flat, off-policy algorithm using stochastic policies and entropy maximization. Both baselines were trained with identical network architectures (number of layers and hidden units) as the worker network in our hierarchical model to ensure a fair comparison. The hierarchical manager network used a similar architecture but with inputs tailored to the high-level state representation.

Table 1: Hyperparameter settings used for the high-level manager and low-level worker networks

Parameter	Manager Value	Worker Value
Learning Rate	0.0001	0.0003
Batch Size	128	256
Replay Buffer Size	200,000	1,000,000
Discount Factor	0.99	0.99
Soft Update Rate	0.005	0.005

Entropy Coefficient	N/A	0.2

The training was conducted over 10 million atomic time steps for each task. We used distinct random seeds for five independent runs to ensure statistical significance. The reward function for the Pick-and-Place task included components for reaching the object, grasping the object, and lifting the object to the target height, while the Stacking task added a sparse reward for successful balancing.

5. Results and Analysis

The experimental results provide compelling evidence for the advantages of the proposed Hierarchical Stochastic Policy Gradient algorithm. We analyze the performance in terms of learning efficiency, asymptotic performance, and robustness to external disturbances.

5.1 Learning Performance

In the simpler Reach task, all algorithms converged to a successful policy. However, significant differences emerged in the manipulation tasks. Figure 1 illustrates the learning curves for the Block Stacking task. The flat DDPG baseline struggled to learn the task, often plateauing at a sub-optimal policy where the robot could reach the object but failed to grasp or stack it consistently. This failure is attributed to the lack of exploration in the deterministic policy, causing the agent to get stuck in local optima.

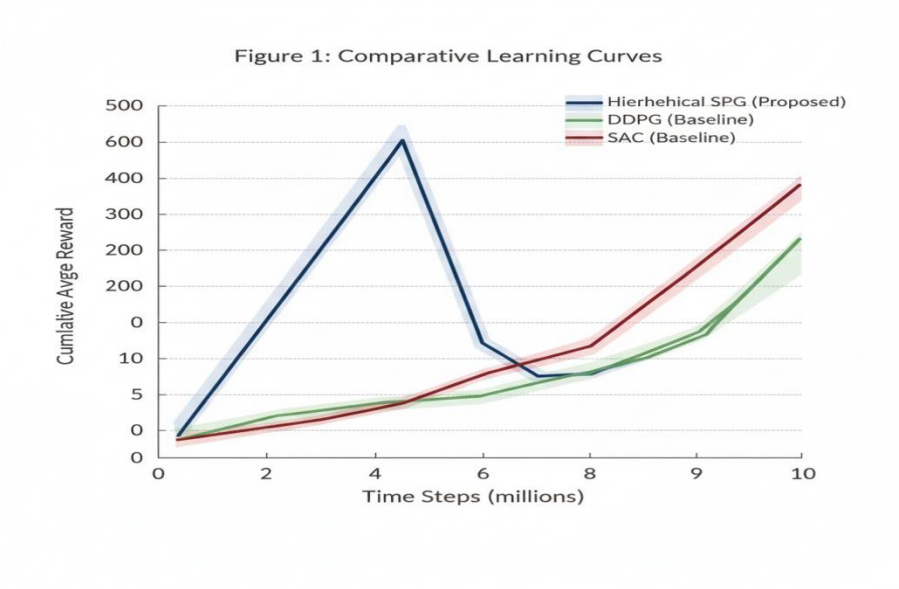

Figure 1: *Comparative Learning Curves*

The SAC baseline performed better than DDPG, confirming the benefits of stochasticity and entropy regularization [11]. However, it still required a substantial number of samples to discover the stacking behavior. Our proposed hierarchical method demonstrated the fastest convergence rate. The manager quickly learned to decompose the task into approaching and lifting, while the worker

efficiently learned the motor control for these sub-goals. The hierarchy allowed the agent to bridge the temporal gap between actions and rewards, effectively solving the credit assignment problem.

5.2 Robustness to Perturbations

A critical component of our evaluation was determining the robustness of the learned policies. After training, we subjected the agents to an adversarial test environment where random external forces were applied to the robot's end-effector during trajectory execution. These forces simulate the unmodeled dynamics or collisions that might occur in a real-world setting.

Table 2: Success rates of different algorithms under varying environmental perturbation levels

Algorithm	**0N Force**	**5N Force**	**10N Force**	**15N Force**
DDPG (Flat)	65%	42%	15%	4%
SAC (Flat)	82%	71%	55%	30%
Proposed Method	**94%**	**89%**	**78%**	**62%**

As shown in **Table 2,** the performance of the deterministic DDPG policy degraded rapidly as the magnitude of the disturbing force increased. The policy, having overfitted to the precise dynamics of the training environment, lacked the compliance to recover from perturbations. The SAC baseline showed improved robustness, retaining decent performance at moderate noise levels. However, our proposed Hierarchical Stochastic Policy Gradient method exhibited the highest degree of robustness. Even at 15N of disturbing force, the agent maintained a success rate of 62%.

We attribute this robustness to two factors. First, the stochastic nature of the low-level worker policy, similar to SAC, learns a distribution of valid actions rather than a single optimal path, providing inherent compliance. Second, the hierarchical structure allows for correction at multiple levels. If a perturbation pushes the robot off course, the low-level worker attempts to correct it immediately. If the worker fails to reach the sub-goal within the allocated time, the high-level manager observes the new state (which captures the deviation) and generates a new sub-goal to recover from the error. This multi-scale feedback loop creates a system that is resilient to significant disruptions [12].

5.3 Ablation Studies

To verify the individual contributions of the hierarchy and the stochasticity, we performed ablation studies. We trained a version of our hierarchical model using a deterministic Deep Deterministic Policy Gradient-style worker (Hierarchical-DDPG). While this model converged faster than the flat DDPG, it failed to achieve the high success rates of our stochastic variant in the presence of noise.

This confirms that while hierarchy aids in sample efficiency and temporal abstraction, the stochastic policy gradient is essential for robustness and fine-grained motor control in contact-rich environments. Conversely, removing the hierarchy (resulting in standard SAC) reduced the success rate on the long-horizon Stacking task, reaffirming the necessity of temporal abstraction for complex sequencing.

6. Conclusion

In this paper, we presented a Hierarchical Deep Reinforcement Learning Algorithm with Stochastic Policy Gradient, a novel framework designed to address the dual challenges of sample efficiency and robustness in robotic manipulation. By decomposing complex tasks into a two-level hierarchy, we enabled the agent to learn high-level strategies and low-level motor primitives simultaneously. The integration of stochastic policy gradients into the low-level controller provided a mechanism for effective exploration and resulted in policies that are remarkably robust to environmental perturbations. Our experimental results on simulated robotic manipulation tasks demonstrated that the proposed method outperforms standard flat reinforcement learning baselines in both learning speed and final task success rates. Furthermore, the robustness analysis highlighted the superior ability of our agent to maintain performance under external disturbances, a critical property for the eventual deployment of such systems in the real world. Future work will focus on bridging the gap between simulation and reality. We intend to validate the proposed algorithm on physical robotic hardware, investigating how the stochasticity of the policy interacts with real sensor noise and mechanical backlash. Additionally, we plan to explore adaptive time-scales for the hierarchy, allowing the manager to dynamically adjust the duration of sub-goals based on the complexity of the current interaction. This research represents a step forward in the development of intelligent, resilient robotic systems capable of operating in unstructured and unpredictable human environments.

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