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Reinforcement Learning with Behavior Primitives for Manipulation Tasks

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Введение. Reinforcement learning has become a fundamental approach for training robots to perform complex manipulation tasks. However, one of the main challenges in robotic learning is the inefficiency of traditional reinforcement learning methods when dealing with long-horizon tasks. These tasks require extensive exploration, which makes learning slow and data-intensive. Furthermore, direct low-level control often leads to poor generalization and increased failure rates in real-world applications. A promising solution to these challenges is the integration of behavior primitives into the learning process. Behavior primitives are structured, reusable motion modules that decompose a task into a sequence of meaningful actions, such as grasping, pushing, or placing objects. Recent research suggests that leveraging such primitives can significantly enhance learning efficiency, improve generalization, and enable more effective task execution. By using a hierarchical framework that combines reinforcement learning with structured primitive-based control, robotic systems can learn more efficiently while maintaining adaptability to new tasks.

Основная часть. Behavior primitives are predefined motion modules that allow robots to execute fundamental actions reliably. These primitives serve as intermediate abstractions between high-level task planning and low-level motor execution. Instead of learning all behaviors from scratch, reinforcement learning algorithms can use these primitives to simplify decision-making and reduce the search space. Key elements in this approach include:

- **Hierarchical Learning Structure** – A two-level policy where a high-level controller selects appropriate behavior primitives, while a low-level controller determines their execution details.
- **Parameterized Primitives** – Each primitive is designed with adjustable parameters, allowing flexible adaptation to various task conditions [1].
- **Efficient Exploration through Affordances** – By introducing affordance-based guidance, the reinforcement learning agent can prioritize meaningful actions, reducing unnecessary exploration.

Behavior primitives have been effectively applied in both reinforcement learning and imitation learning frameworks. Recent studies show that decomposition of task demonstrations into sequences of primitives improves data efficiency and generalization. For instance, a primitive-based imitation learning framework has demonstrated superior performance by automatically parsing demonstrations into meaningful action sequences [2]. This reduces the need for extensive human-labeled data while ensuring structured learning. Furthermore, using primitives in reinforcement learning allows policies to focus on higher-level decision-making rather than low-level motor control. This approach has been successfully applied to a range of robotic manipulation tasks, such as pick-and-place operations, object stacking, and tool use, where learning efficiency is critical.

The main advantages of using behavior primitives in reinforcement learning include:

- **Faster learning and improved task success rates** compared to traditional reinforcement learning approaches.
- **Better compositional learning**, allowing robots to build structured sequences of actions.
- **Greater adaptability**, enabling learned policies to transfer across different task variations [3].

Despite these benefits, challenges remain, including the need for well-designed primitive libraries and the difficulty of optimizing primitive selection policies. Additionally, ensuring robustness in real-world applications requires careful integration of learned models with reliable motion execution strategies.

Выводы. The use of behavior primitives in reinforcement learning provides a structured and efficient way to train robots for complex manipulation tasks. By leveraging hierarchical decision-making, affordance-based exploration, and structured primitive-based control, this approach enhances learning efficiency, improves task performance, and enables better generalization to new scenarios.

Future research directions include expanding the set of behavior primitives, integrating learned primitives with reinforcement learning models, and developing more advanced affordance-based exploration techniques. Further improvements in primitive-based frameworks will enable robots to perform increasingly complex and diverse tasks with greater efficiency and reliability.

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