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LLM with Physical Factors the Robot Manipulation

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Abstract

Large Language Models (LLMs) have demonstrated significant potential in robot motion planning through their reasoning capabilities, enabling high-level workflow inference and adaptive decision-making. While current LLM approaches excel at abstract task reasoning, they often treat robot motion planning as a series of discrete steps, failing to fully integrate the continuous dynamics and physical limitations of the robot arm. We propose an integrated framework combining LLMs and Knowledge Graphs (KGs) to enhance Task and Motion Planning (TAMP) for robot arms with explicit consideration of physical factors. Our approach incorporates essential physical factors such as inverse kinematics solutions and various environmental constraints into the planning process. We implement an iterative methodology where an LLM Planner generates initial trajectories that undergo physical validation, reasoning-based refinement, execution, and evaluation. System performance is assessed through smoothness and robustness metrics, including jerk analysis and perturbation testing. This work bridges the critical gap between abstract LLM reasoning and physical realities in robotic manipulation, resulting in more realistic, effective, and safe robot motion planning.

Problems

Current research predominantly emphasizes decision-making processes, often neglecting critical considerations related to the physical realities of robotic systems. In robotic manipulation, it is insufficient to depend on high-level task planning without thorough integration of physical constraints and capabilities intrinsic to robotic systems. One fundamental physical consideration central to robot arm motion is the Inverse Kinematics (IK) solution. IK is essential in translating abstract motion commands or goals into actionable joint-level instructions. An accurate IK solution involves various critical physical aspects such as joint velocities, joint limits, and singularities. Joint velocities dictate how rapidly joints can feasibly move without compromising mechanical integrity or precision. Joint limits define the safe operational boundaries beyond which mechanical damage or failure may occur. Singularities, points at which the robot loses degrees of freedom, pose challenges to motion control and necessitate special consideration in IK solutions.

Physical Factors Influence

- Mass: The mass of payloads or robot segments directly impacts inertia and dynamic performance, influencing acceleration and deceleration capabilities.
- Friction: Frictional effects within joints and between mechanical components affect precision, control smoothness, and energy efficiency.
- Elasticity: Structural elasticity, resulting from material deformation under load, affects the accuracy and repeatability of robot motions, particularly in high-speed or high-load scenarios.
- Gravity: Gravity introduces consistent force influences on the robot, affecting static positioning accuracy and dynamic motion profiles, especially when manipulating payloads or operating in various orientations.

Scenarios Setting

We use the Motionbenchmaker [1] tool to create scenarios. The first scenario (a) involves cluttered environments without spatial constraints, where obstacles of different shapes are placed on a single plane. This study solely focuses on motion planning and does not take into account object grasping. The task of the robotic arm is entering the workspace and reaching one of the objects.

The second scenario (b) is established to reduce the workspace and thus added spatial constraints. There is a semi-closed box, and the robotic arm was only capable of planning its movements within the restricted space. The task of the robotic arm is entering inside the box, simulating motion planning in a more confined space compared to the previous workspace, and reaching one of the objects.

The third scenario (c) resembles a living drawer, with an even restricted workspace than the previous two, and the obstacles within the drawer cannot be bypassed directly from the open space above. The task of the robotic arm is entering inside the drawer, simulating motion planning in an even more restricted space compared to the previous two, and reaching one of the objects.

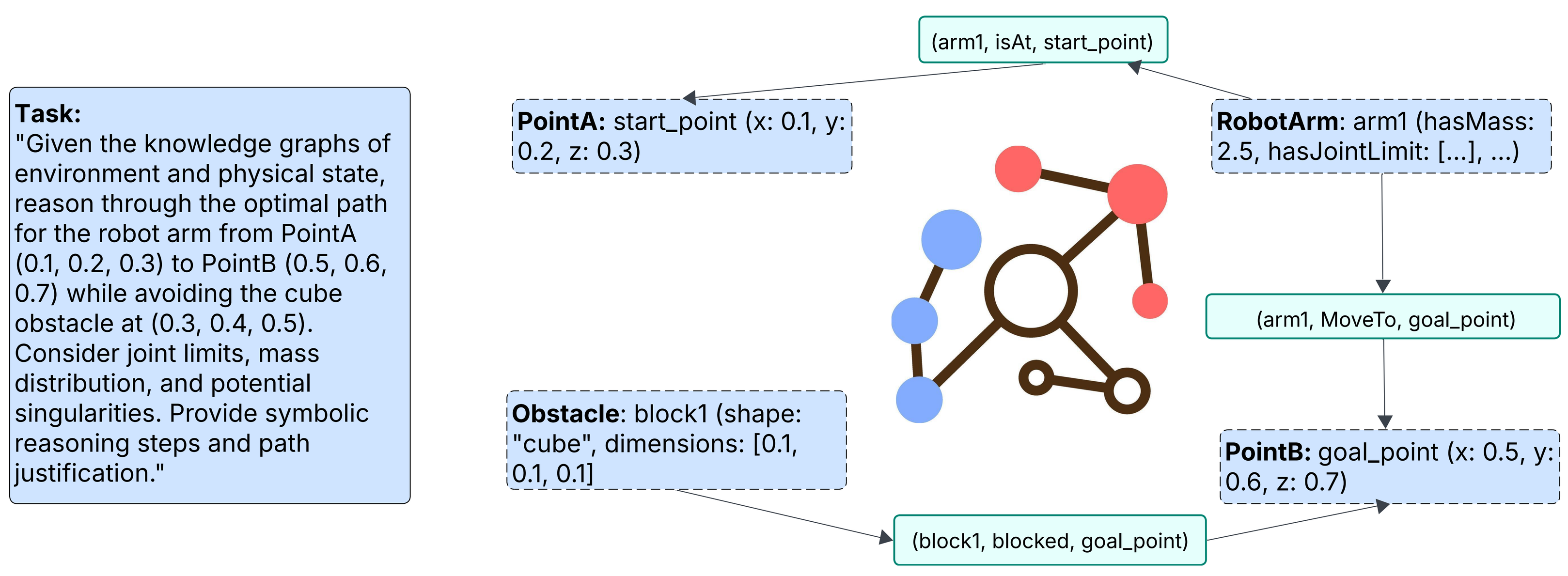

Figure 1. The Environment Knowledge Graph.

Metrics for selection

In this research, various metrics are used in following.

- Time efficiency is defined by the mean time taken by motion planners to compute feasible paths, while success rate assesses the percentage of successful path planning attempts.
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- Smoothness can be evaluated using jerk analysis and spectral arc length (SAL) [?]. Jerk analysis involves assessing the rate of change of acceleration, with lower jerk values indicating smoother motion.
- Robustness can be assessed using methods such as sensitivity analysis and perturbation testing. Sensitivity analysis systematically introduces variations or noise into control inputs, sensor data, or environmental parameters and measures the deviation of the robot's end-effector from the nominal solution.

The Integrated Framework

The integrated framework (Fig. 2) for combining a LLM with a robotic arm to facilitate intelligent, adaptive robotic manipulation. The process begins with the LLM Planner, which serves as the initial planning stage. Here, the LLM interprets high-level commands or task descriptions and translates them into initial joint-space trajectories. These trajectories represent the planned paths of each robotic joint for moving the robotic arm from a defined "Start Position" to a designated "Target Position," as visually indicated on the left side of the figure. The framework leverages two interconnected knowledge graphs - an Environmental Knowledge Graph (Env KG) and a Physical State Knowledge Graph (Physical State KG) - which provide the foundation for the symbolic reasoning process. The Environmental Knowledge Graph captures the spatial and relational aspects of the robot's surroundings. Using onboard sensors, the robot arm autonomously constructs this KG by identifying entities (such as obstacles, target objects, and workspace boundaries), their properties (dimensions, positions, shapes), and the relationships between them (proximity, containment, accessibility). As illustrated in the lower left portion of Fig. 2, the KG represents entities like "RobotArm," "PointA," "PointB," and "Obstacle," along with their attributes and spatial relationships such as "isLocatedAt," "isIn," and "startsAt." Concurrently, the Physical State KG encapsulates the robot's intrinsic characteristics and limitations. This graph incorporates critical physical factors including mass distribution, joint limits, friction coefficients, elasticity properties, gravitational effects, and potential singularities. Each physical factor is represented as a node with associated parameters and threshold values that define the robot's operational capabilities and constraints. Next, the generated trajectories pass through the physical factors module. In this step, the system verifies the physical feasibility of the planned movements by considering real-world constraints, including joint limits, actuator capabilities, workspace boundaries, and environmental obstacles. This module ensures the proposed plan respects physical realities, refining or modifying trajectories as necessary.

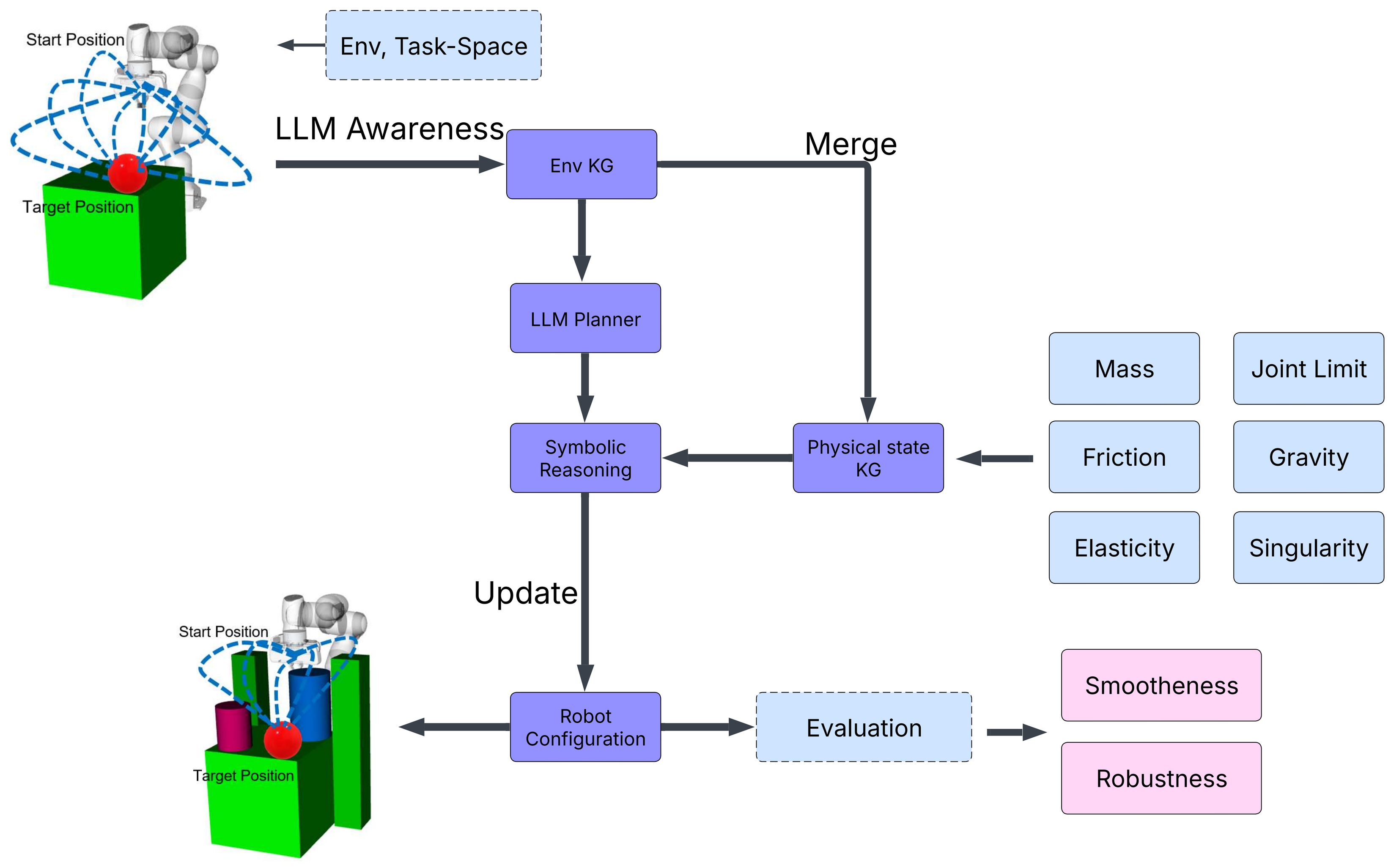

Figure 2. The integrated framework for combining a LLM with a robotic arm to facilitate intelligent, adaptive robotic manipulation.

Evaulation

We try to get the robot arm's motion closer to realistic and natural human-like movements, it is essential to verify and analyze its motion behavior using specific metrics. Two particularly important metrics for assessing naturalness in robotic motion are smoothness and robustness. Smoothness is a fundamental indicator of natural motion, as human movements are typically continuous and flexible without abrupt changes. Smooth robotic motion leads to better interaction performances, reduces mechanical wear, and enhances safety and predictability when interacting with humans or delicate objects. Robustness ensures consistent and reliable performance despite uncertainties or variations in the robot's operating environment. Natural robot motion effortlessly adapts to unexpected disturbances, obstacles, and uncertainties, and robust robotic motion maintains high performance even when faced with external perturbations, sensor inaccuracies, or model uncertainties.

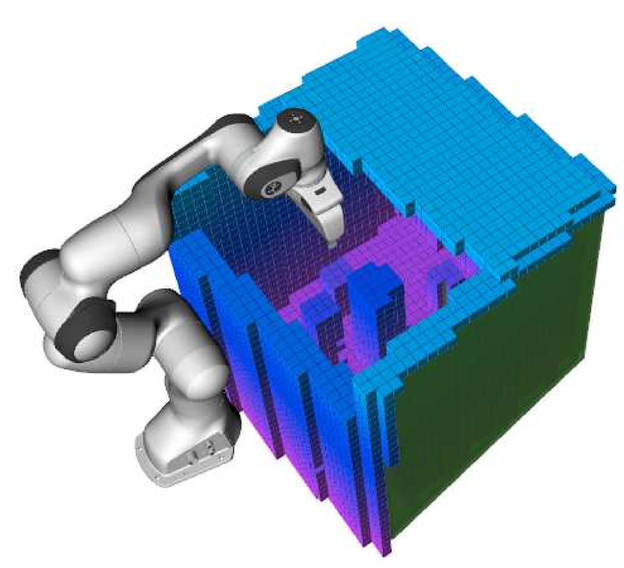

Figure 3. Scenario with Franka robot manipulation.

Conclusions

This paper introduces a novel framework that integrates Large Language Models (LLMs) with Knowledge Graphs (KGs) to enhance robotic manipulation by explicitly accounting for physical factors. The proposed approach addresses a critical gap in current research, which often emphasizes high-level decision-making while neglecting the physical realities that constrain robotic systems. By incorporating factors such as joint limits, singularities, mass distribution, friction, elasticity, and gravitational effects into symbolic reasoning, our framework enables more realistic, robust, and natural robotic manipulation.

References

[1] Constantinos Chamzas, Carlos Quintero-Pena, Zachary Kingston, Andreas Orthey, Daniel Rakita, Michael Gleicher, Marc Toussaint, and Lydia E Kavraki.
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