A Survey of Task Planning and Mobile Manipulation in Long-Horizon Robotics

Abstract

This survey paper provides a comprehensive examination of the advancements in task planning, mobile manipulation, and long-horizon robotics, focusing on the integration of these components to enhance the capabilities of autonomous systems. The paper highlights the significance of task planning and mobile manipulation as foundational elements for executing complex tasks in dynamic environments. It explores the interdisciplinary challenges faced in robotics and AI, emphasizing the need for robust algorithms to address uncertainties and dynamic interactions. The survey presents key frameworks and methodologies, such as the SyDeBO and HYPERmotion frameworks, which integrate symbolic decision-making and reinforcement learning to optimize long-horizon tasks. It also discusses the importance of anticipatory planning and algorithmic strategies for predicting and adapting to future tasks. Recent advancements in learning-based approaches, including the use of Large Language Models and hierarchical reinforcement learning, are highlighted for their role in enhancing the adaptability and efficiency of robotic systems. The paper concludes by identifying future research opportunities, including the expansion of motion libraries, improvements in object identification and grasping techniques, and the integration of learning techniques with optimization-based planning. These insights underscore the transformative potential of integrating task planning, mobile manipulation, and long-horizon planning to develop intelligent and adaptable autonomous systems capable of navigating complex environments.

1 Introduction

1.1 Significance of Task Planning and Mobile Manipulation

Task planning and mobile manipulation are integral to the advancement of autonomous systems, enabling robots to perform complex tasks in dynamic environments. These components facilitate the autonomous learning of navigation and grasping skills, essential for real-world operations [1]. Task planning involves creating symbolic representations that enhance robot capabilities, allowing for a wider range of autonomous tasks.

In humanoid robots, task planning and mobile manipulation are vital for executing hybrid motions in diverse settings, such as material handling and household chores, which are crucial for long-horizon tasks [2]. The limitations of earlier methodologies, including Task and Motion Planning (TAMP) and hierarchical reinforcement learning, highlight the need for robust approaches that generalize to novel tasks without incurring high data acquisition costs [3].

In multi-robot systems, these elements are essential for coordinating multiple agents, particularly in assembly tasks where efficiency and precision are critical [4]. Legged robots exhibit advantages in navigating challenging terrains due to their unique locomotion patterns, underscoring the versatility of mobile manipulation [5].

Mobile manipulation is also crucial for service robots, which must navigate confined spaces and diverse object structures while coordinating movements between the robot's base and arm [6]. The

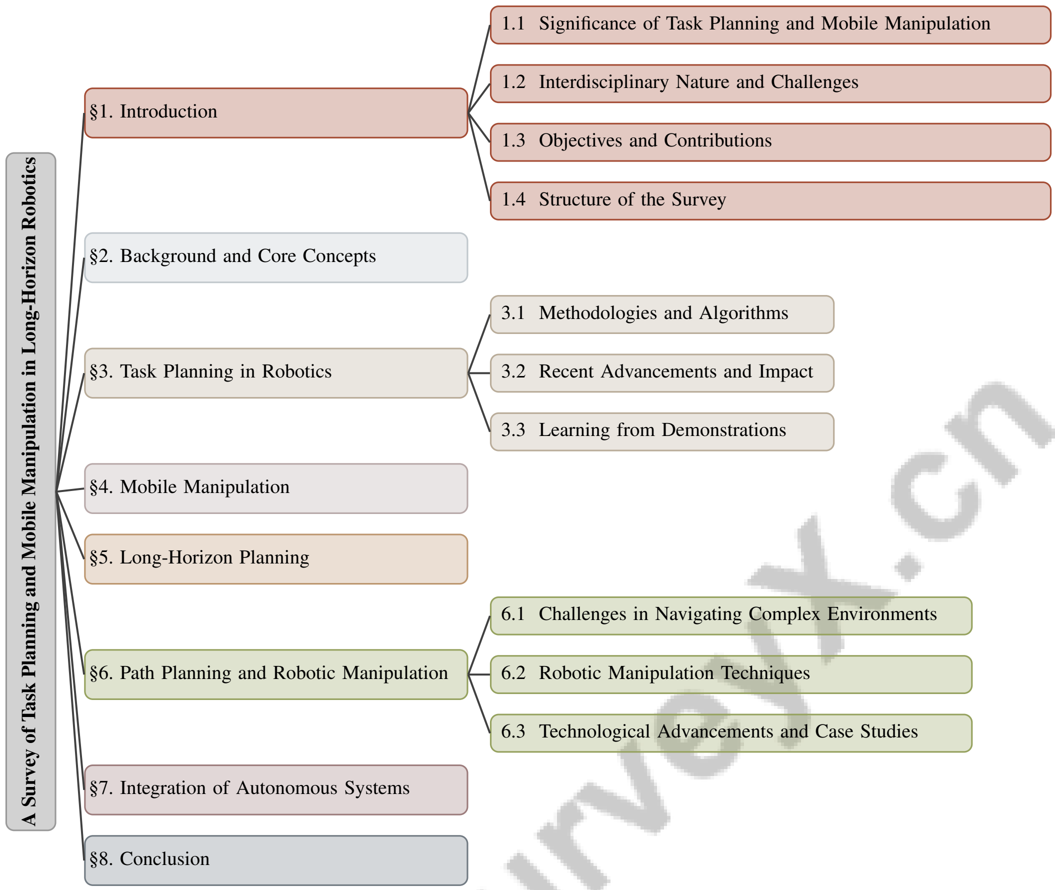


Figure 1: chapter structure

ability to perform contact-rich tasks in dynamic environments further emphasizes the need for adaptable solutions in robotics [7].

1.2 Interdisciplinary Nature and Challenges

The interdisciplinary nature of robotics and artificial intelligence (AI) is evident in the integration of diverse methodologies to tackle the complex challenges posed by dynamic and uncertain environments. A significant challenge is the sensitivity of methods like simultaneous localization and mapping (SLAM) to odometry errors, necessitating robust algorithms that function reliably in real-world scenarios [8]. The evolution of mobile robotics has further prompted the development of algorithms that ensure drivability while respecting kinodynamic constraints, particularly in applications such as last-mile delivery and automated platform lifts [9].

Decentralized collaboration among heterogeneous robots presents additional challenges, especially in communication and task allocation, which are essential for effective multi-agent systems [10]. Traditional control methods often lack adaptability, failing to account for dynamic interactions between robotic components, such as the arm and base in mobile manipulation [5]. The absence of a unified approach that integrates base and arm movements complicates the manipulation of various objects in cluttered environments [6].

Training mobile manipulators in uninstrumented environments without human supervision exemplifies the interdisciplinary challenges faced by robotics and AI, requiring innovative solutions to enhance autonomy and adaptability [1]. The computational intractability of hybrid optimization problems, alongside their sensitivity to initial conditions, poses significant obstacles, as optimization-based methods often struggle to ensure completeness in identifying feasible solutions [11]. Furthermore, reliance on specific, known positions for manipulation does not adequately address the uncertainties inherent in real-world scenarios [12].

The demand for flexible, skill-based control systems in robotics further highlights the interdisciplinary challenges between robotics and AI, particularly in managing diverse tasks and environments [7]. Extended planning and sparse rewards in long-horizon tasks illustrate the complexities involved in developing effective robotic systems [13]. The interdisciplinary nature of these fields is crucial for advancing planning techniques and frameworks capable of addressing the increasing complexity and demands of modern autonomous systems.

1.3 Objectives and Contributions

This survey provides a comprehensive examination of advancements in task planning and mobile manipulation within long-horizon robotics. A primary objective is to bridge existing knowledge gaps by integrating symbolic decision-making with bilevel optimization. The SyDeBO framework exemplifies this integration, optimizing long-horizon manipulation tasks in dynamic environments [14]. Additionally, the survey aims to enhance the generalizability and scalability of planning algorithms, demonstrated by the autonomous learning of symbolic predicates and actions from raw data [15].

The survey also highlights the HYPERmotion framework, which merges reinforcement learning with language model capabilities, enabling robots to select and plan actions based on learned behaviors [2]. This approach addresses challenges in generating and generalizing task conditions for long-horizon manipulations involving novel objects and unseen tasks [3]. Emphasis is placed on executing abstract plans derived from Functional Object-Oriented Networks (FOON) in real-world applications, combining object-level knowledge with execution capabilities [16].

The introduction of the DELTA method, which integrates Large Language Models (LLMs) with Scene Graphs (SGs) to decompose long-term tasks into manageable sub-goals, represents a notable contribution, facilitating efficient planning [17]. Additionally, the survey presents a visually grounded hierarchical planning algorithm that performs high-level task planning and low-level motion generation conditioned on specified task goals [18]. The HiDe method enhances transferability and generalization across unseen tasks in long-horizon control through a novel hierarchical reinforcement learning approach [13].

Furthermore, the survey discusses a skill-based control platform that integrates knowledge representation and task planning to improve robot adaptability across various hardware setups [7]. A comprehensive review of optimization-based Task and Motion Planning (TAMP) is included, addressing the integration of high-level task planning and low-level motion planning to enhance robot autonomy in complex environments [11].

Significant advancements in intelligent robotic systems are highlighted, showcasing innovative frameworks and methodologies that enhance the efficiency and effectiveness of robots in executing complex tasks. The survey emphasizes adaptive task planning for human-robot collaboration, enabling robots to autonomously allocate tasks based on human preferences and performance, thereby improving team dynamics. Additionally, it explores the integration of large language models to facilitate decentralized collaboration among heterogeneous robots, allowing for seamless communication and task execution. The research also addresses the challenges of multi-user task planning, proposing a framework that leverages human expertise and robot influence to optimize decision-making, ultimately contributing to the development of more autonomous and capable robotic systems across various real-world applications [19, 20, 10, 21]. Insights into the synergies between task planning, mobile manipulation, and long-horizon planning are provided, fostering the development of autonomous systems capable of navigating modern robotics' increasing complexity and demands.

1.4 Structure of the Survey

The survey is structured to guide readers through the intricate landscape of task planning and mobile manipulation in long-horizon robotics. It begins with an introduction that establishes the significance of these fields, emphasizing their foundational role in autonomous systems and the interdisciplinary challenges they present [1]. The introduction outlines the objectives and contributions of the survey, setting the stage for the comprehensive exploration that follows.

The second section delves into the background and core concepts, providing foundational understanding necessary for grasping subsequent discussions [22].

Following the background, the survey transitions into an in-depth analysis of task planning methodologies and algorithms, highlighting recent advancements and their impact on autonomous systems. This is complemented by a discussion on mobile manipulation, exploring the integration of mobility and manipulation in detail, showcasing innovative approaches and real-world applications [23].

The survey then examines long-horizon planning strategies, emphasizing the importance of anticipating future tasks and optimizing long-term objectives. Case studies and examples of successful implementations are highlighted, providing practical insights into the application of these strategies [24].

In the subsequent section, path planning and robotic manipulation techniques are analyzed, focusing on navigating complex environments and achieving specific goals through advanced technological solutions. This is followed by a discussion on the integration of autonomous systems, exploring the synergies between task planning, mobile manipulation, and long-horizon planning [25].

Finally, the survey concludes with a summary of key findings and insights, along with a discussion of future directions and research opportunities in the field. This comprehensive structure ensures that the survey not only provides a thorough examination of current advancements but also offers a roadmap for future research and development in robotics [26].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Background and Core Concepts

The development of autonomous systems is founded on essential concepts such as task planning, mobile manipulation, long-horizon task execution, path planning, and robotic manipulation. These enable robots to efficiently operate in real-world environments, tackling tasks from environmental exploration to complex multi-step operations. Recent advancements in task specification abstraction enhance robot autonomy by identifying optimal transition points between subtasks, minimizing human intervention. The integration of large language models facilitates high-level reasoning and hybrid planning, enabling robots to execute long-horizon tasks requiring advanced locomotion and manipulation skills, thereby improving performance and user interaction across various applications [19, 27]. These elements underpin intelligent robotic systems, allowing them to perform complex tasks in dynamic, unstructured settings.

Task planning is crucial for sequencing actions strategically to meet specific objectives, especially in adapting discrete tasks into continuous motions. The integration of task and motion planning (TAMP) is vital in dynamic scenarios, addressing computational intractability and the need for effective symbolic representations [11]. The complexity of dependencies among sub-goals in open-world environments necessitates frameworks like Functional Object-Oriented Networks for Task Planning (FOON-TAMP), transforming high-level symbolic representations into low-level planning problems.

Mobile manipulation, merging mobility and manipulation capabilities, enables robots to interact effectively with their environments. This integration is essential for performing complex tasks involving both navigation and object manipulation, such as executing service tasks in cluttered environments. By merging perception, localization, motion planning, and grasping capabilities into a cohesive framework, these systems autonomously navigate, locate, manipulate, and transport objects, enhancing operational efficiency and safety in various applications, including domestic and medical settings [19, 28, 29, 25]. The challenge of generating kinematically feasible trajectories while ensuring that end-effectors adhere to task space trajectories underscores the complexity of this integration.

Long-horizon tasks require anticipatory planning, where model-based task planning is enhanced with estimates of expected future costs to optimize long-term objectives. This is particularly relevant in multi-agent systems, where the complexity of long-horizon planning is amplified by non-stationary environments. The challenges of reasoning over these tasks, especially in continuous control with sparse rewards, are significant [13].

Path planning focuses on determining feasible paths for navigating complex environments. This approach often employs probabilistic representations of skills to facilitate efficient navigation and task execution, essential in scenarios requiring maximized information gain within budget constraints.

AI-generated, for reference only.

By leveraging a library of learned skill models, systems optimize trajectories based on feature expectations derived from expert demonstrations, ensuring adaptability to new environments. Additionally, the system actively learns and refines its skill parameter policies through practice, enhancing task success rates by intelligently sequencing actions and managing dependencies between skills, thereby addressing the complexities of long-horizon tasks in realistic settings [30, 31, 32, 33, 34]. Advancements in path planning techniques are critical for improving the efficiency and reliability of autonomous systems.

Robotic manipulation involves executing tasks requiring physical interaction with objects, necessitating a flexible and context-aware approach. In dynamic environments, integrating domain-specific knowledge into task planning enhances the adaptability and precision of TAMP approaches. Recent advancements, particularly in Large Language Models (LLMs), demonstrate that ontology-driven prompt tuning can refine user prompts with contextual reasoning and knowledge-based environment descriptions. This integration improves the semantic accuracy of task plans and enables robots to navigate complex tasks and dynamic conditions effectively, addressing the limitations of traditional static prompting methods. Furthermore, frameworks combining high-level planning with low-level execution facilitate more flexible and efficient task management, allowing for real-time adjustments based on user inputs and environmental changes [35, 36, 37, 38]. The integration of perception modules that estimate object properties from sensory data is essential for effective manipulation, with deep learning techniques enhancing prediction reliability and contributing to robust task planning methodologies.

These foundational concepts are crucial for developing advanced autonomous systems, providing a robust framework for intelligent robotic systems capable of navigating and interacting with intricate environments. This includes enhancing task specification abstraction to improve robot autonomy in real-world applications, enabling decentralized collaboration among heterogeneous robots through large language models, and implementing sophisticated planning methods for service robots to manage and organize home environments efficiently [19, 10, 25]. Their applications span diverse domains, from industrial automation to service robotics, underscoring their significance in the future development of autonomous technologies.

In recent years, the field of robotics has seen significant advancements in task planning methodologies. Understanding the hierarchical structure of these methodologies is crucial for comprehending how various algorithms are applied in practice. Figure 2 illustrates this hierarchical structure, categorizing methodologies and algorithms while also highlighting recent advancements and techniques for learning from demonstrations. This figure serves to underscore the complexity and innovation in robotic task planning by showcasing various integration techniques, optimization approaches, enhanced planning strategies, collaborative systems, and skill acquisition. By examining these elements, we can appreciate the multifaceted nature of robotic task planning and its implications for future research and application.

3 Task Planning in Robotics

3.1 Methodologies and Algorithms

Robotic task planning methodologies and algorithms are crucial for operating in complex, dynamic environments. The Virtual Kinematic Chain (VKC) method integrates mobile robot kinematics with manipulated objects, optimizing motion planning through trajectory optimization to enhance task execution [6]. Hierarchical reinforcement learning architectures, such as HiDe, separate planning from low-level control, promoting modularity and generalization across diverse tasks [13].

SkiROS2 exemplifies the integration of knowledge representation and task planning, using a skill-based control approach to transfer robot skills across various hardware setups, enhancing adaptability and efficiency [7]. Optimization-based Task and Motion Planning (TAMP) methods merge classical approaches with contemporary learning innovations, showcasing the synergy between optimization techniques and learning algorithms for robust task planning in dynamic environments [11].

The Action-Related Places (ARPlace) method introduces a probabilistic representation of task-related locations, addressing uncertainties in robot and object positioning to enhance task execution reliability in uncertain environments [12]. These methodologies signify substantial advancements in robotics task planning, combining optimization, symbolic reasoning, and hierarchical control to address

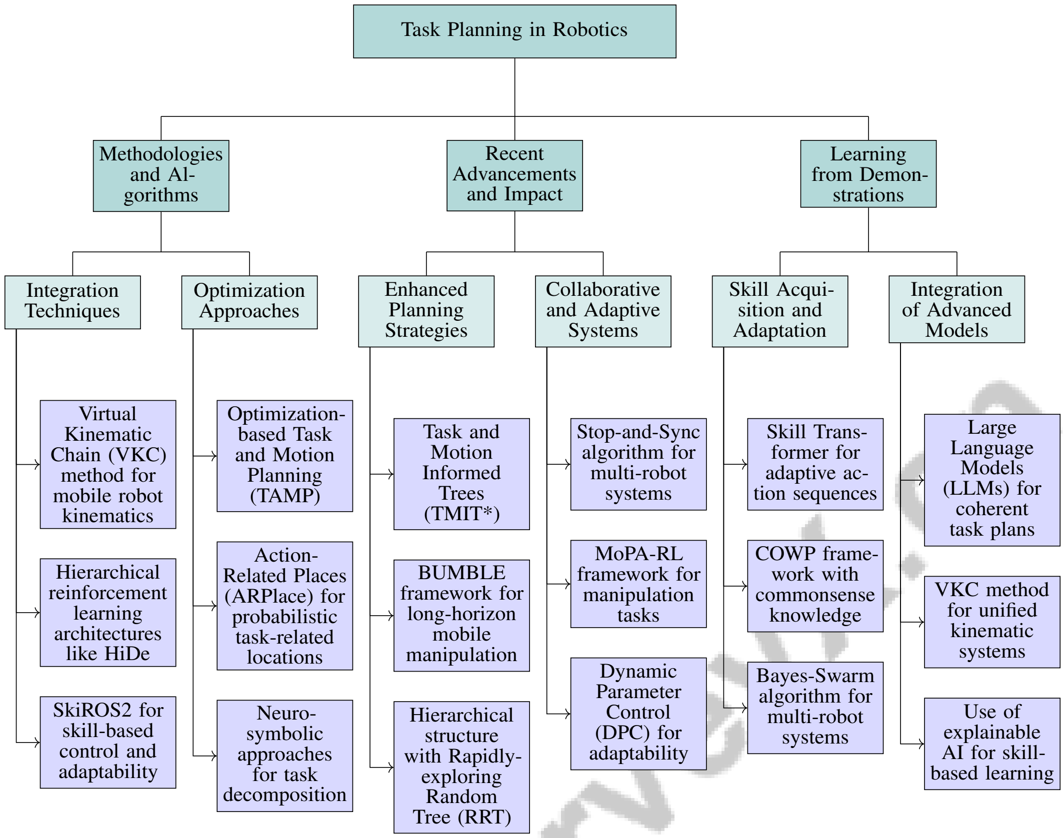


Figure 2: This figure illustrates the hierarchical structure of task planning in robotics, categorizing methodologies and algorithms, recent advancements, and learning from demonstrations. It highlights integration techniques, optimization approaches, enhanced planning strategies, collaborative systems, skill acquisition, and the integration of advanced models, showcasing the complexity and innovation in robotic task planning.

the complexities of dynamic settings. Innovations like neuro-symbolic approaches that decompose tasks into subgoals and the incorporation of symbolic decision-making within bilevel optimization frameworks further enhance planning efficiency and scalability for long-horizon manipulation tasks [39, 36, 14, 40, 11].

Figure 3 illustrates the key methodologies in robotic task planning, focusing on motion planning, hierarchical control, and skill-based systems. Each category highlights specific approaches and innovations that address the complexities of dynamic environments, thereby providing a visual representation that complements the discussed methodologies.

3.2 Recent Advancements and Impact

Recent advancements in task planning have significantly bolstered robotic capabilities in complex environments. The Task and Motion Informed Trees (TMIT*) method improves initial solution times and costs over previous Task and Motion Planning (TMP) methods, indicating more efficient planning strategies [41]. The BUMBLE framework excels in long-horizon mobile manipulation by integrating open-world perception and a diverse skill library, thus expanding robotic adaptability [42].

In multi-agent systems, a hierarchical structure combining a high-level Rapidly-exploring Random Tree (RRT) planner with adaptive policies enhances coordination and obstacle avoidance beyond traditional methods [43]. The PAAMP framework formulates motion planning as a Mixed-Integer Linear Programming (MILP) problem, simplifying trajectory searches and reducing computational complexity compared to nonlinear programming approaches [44].

AI-generated, for reference only.

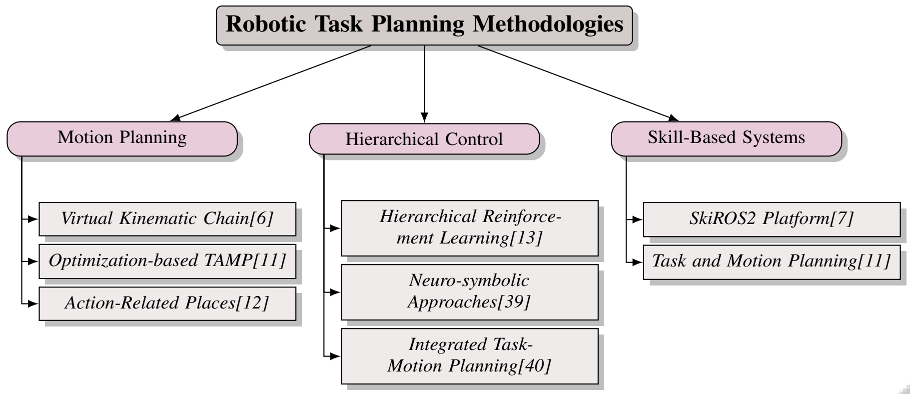


Figure 3: This figure illustrates the key methodologies in robotic task planning, focusing on motion planning, hierarchical control, and skill-based systems. Each category highlights specific approaches and innovations that address the complexities of dynamic environments.

Collaborative object transportation has progressed with the Stop-and-Sync algorithm and Proportional Navigation Guidance, improving synchronization and trajectory tracking in multi-robot systems [45]. The MoPA-RL framework enhances training efficiency and safety in manipulation tasks through reinforcement learning [46]. The Plan-Guided Reinforcement Learning (PGRL) approach uses structured plans to guide exploration, improving adaptability in real-world applications [47].

Dynamic Parameter Control (DPC) dynamically adjusts control parameters using reinforcement learning, enabling robots to adapt to various tasks and disturbances [5]. The ARPlace method enhances decision-making robustness in uncertain environments by probabilistically representing robot base locations associated with successful manipulation probabilities [12].

Innovations in task planning are transforming robotics, enabling intelligent, adaptable autonomous systems. These include adaptive frameworks that enhance human-robot collaboration, abstraction of task specifications for improved autonomy, and leveraging large language models for task management in unstructured environments [19, 20, 37]. These developments not only enhance robotic efficiency and flexibility but also foster improved human-robot interactions, paving the way for advanced autonomous applications.

3.3 Learning from Demonstrations

Method Name	Learning Approach	Integration Techniques	Adaptability and Generalization
ST[48]	Demonstration Trajectories	Transformer-based Framework	Dynamic Environments
COWP[26]	User Interactions	Commonsense Knowledge	Dynamic Environments
RLS-RIS[49]	Demonstrations, Interactions	Language Models	Adaptively Gather Information
BS[50]	-	Asynchronous Decision-making	Adaptive Acquisition Function
CLLPS[51]	Task Planning Approach	Constrained Prompt Scheme	Improve Generalization Capabilities
VKC[6]	-	Trajectory Optimization	Mobile Manipulation
SkiROS2[7]	Skill-based Control	Knowledge Representation	Dynamic Environments

Table 1: This table provides a comparative analysis of various robotic task planning methods, highlighting their learning approaches, integration techniques, and adaptability. It underscores the diversity in methodologies, from demonstration-based learning to the use of commonsense knowledge and language models, showcasing their potential in dynamic environments and generalization capabilities.

Table 1 presents a comparative overview of different robotic task planning methodologies, detailing their learning approaches, integration techniques, and adaptability to dynamic environments. Learning from demonstrations is pivotal in robotic task planning, enabling skill acquisition through expert observation. The Skill Transformer uses demonstration trajectories to learn task planning, allowing robots to manage action sequences adaptively [48]. This facilitates the generalization of learned behaviors across various tasks and environments.

The COWP framework enhances task planning by integrating commonsense knowledge, equipping robots to manage unexpected changes during the learning process [26]. Real-time user interac-

AI-generated, for reference only.

tions, exemplified by a remote life support robot, enable robots to learn task planning through user instructions with template variables, improving responsiveness to user needs [49].

The Bayes-Swarm algorithm fosters asynchronous decision-making and knowledge sharing among robots, enhancing multi-robot system flexibility and efficiency [50]. Large Language Models (LLMs) contribute to task planning by integrating primitive actions to generate coherent task plans, leveraging embedded knowledge for improved decision-making [51].

The VKC method allows service robots to plan and execute mobile manipulation tasks by treating the robot and manipulated object as a unified kinematic system, enhancing task execution in cluttered environments [6]. Emphasizing skill-based learning, robots can define and execute skills across different systems, thereby enhancing adaptability and versatility [7].

These methodologies illustrate the transformative effects of learning from demonstrations in robotic task planning. By leveraging high-level skill effect models and explainable AI principles, these approaches enable skill acquisition through observation and interaction, facilitating generalization across tasks. For instance, the open-source platform simplifies robotic task execution complexities for non-experts, enhancing engagement and learning through an intuitive interface and adaptive curriculum generation [52, 53]. This approach enhances robotic adaptability and efficiency, paving the way for more intelligent autonomous applications.

4 Mobile Manipulation

The convergence of mobility and manipulation is a critical research area in robotics, essential for developing autonomous systems capable of interacting with their environments. This section explores mobile manipulation's core aspects, emphasizing its role in enhancing robotic functionalities. By examining the integration of these domains, we gain insight into how technological and methodological advancements improve robotic systems' efficiency and effectiveness. The following subsection will address the integration of mobility and manipulation, highlighting frameworks that facilitate this synergy and their implications for real-world applications.

4.1 Mobile Manipulation and Integration

Integrating mobility and manipulation is fundamental to advancing autonomous robotic systems, enabling complex tasks with greater adaptability and precision. Frameworks that facilitate effective navigation and object manipulation in dynamic environments exemplify this integration [54]. The ReLMM framework illustrates this by allowing robots to learn navigation and grasping skills concurrently, thereby enhancing operational efficacy [1].

The Virtual Kinematic Chain (VKC) method marks a significant advancement by consolidating base and arm kinematics, eliminating intermediate goals and optimizing joint coordination, thus improving task success rates [6]. The ARPlace method also contributes by employing probabilistic mapping for base positions, enabling informed decision-making based on probabilistic assessments [12].

Hierarchical frameworks that combine control theory with reinforcement learning, as seen in legged mobile manipulation, effectively manage disturbances, enhancing task execution in complex environments [5]. This adaptability is further demonstrated in executing contact-rich tasks across various platforms, supported by knowledge representation and task planning architectures [7].

Innovative methodologies like ALGO, which address non-smooth boundaries, strengthen mobile manipulation systems' robustness, crucial for real-world applications [55]. Additionally, leveraging multiple object views enhances shape understanding and grasp planning, crucial for integrating mobility and manipulation [8].

Recent advancements underscore the importance of integrating mobility and manipulation to develop intelligent, versatile autonomous systems. These systems navigate and interact efficiently in diverse environments, as seen in multi-skill mobile manipulation, which incorporates flexible navigation and manipulation capabilities. For example, mobile manipulation skills allow robots to approach objects from various angles, while advanced navigation techniques enable reaching multiple endpoints, reducing task execution errors. This integration enhances operational efficiency in complex environments and addresses challenges in sectors like healthcare and domestic services, leading to safer and more effective automation solutions [28, 29].

AI-generated, for reference only.

4.2 Innovative Approaches and Frameworks

Significant advancements in mobile manipulation have emerged through innovative approaches and frameworks, enhancing robotic systems' capabilities in dynamic, complex environments. The ReachBot framework, utilizing extendable booms as prismatic joints, exemplifies an innovative design that enhances manipulation capabilities without significantly increasing robot mass, providing a lightweight yet effective solution for mobile manipulation tasks [22].

Incorporating physics-based motion planning has been crucial, facilitating the prediction and management of robot-environment interactions, thereby improving task performance involving complex physical interactions [54]. Integrating temporal logic with motion planning further refines this capability by enabling adherence to task-specific constraints in dynamic environments.

Frameworks combining control theory with reinforcement learning have been pivotal, enabling robots to adapt to disturbances and uncertainties, thus improving performance in executing contact-rich tasks across various platforms [5]. This adaptability ensures effective operation in unpredictable real-world scenarios.

Probabilistic mapping techniques, such as the ARPlace method, enhance decision-making by allowing robots to assess multiple potential base positions before task execution [12]. This approach reduces failure risk by providing a comprehensive task environment understanding.

The integration of innovative approaches and frameworks in mobile manipulation—such as modular skill decomposition for long-horizon tasks, advanced navigation and shape completion methods, robust systems leveraging deep learning and synthetic data, and holistic motion control—collectively enhances the development of more intelligent, adaptable, and capable robotic systems. These advancements enable efficient navigation and object manipulation in unstructured environments, significantly improving operational efficiency, quality, and safety in medical and domestic applications [56, 8, 57, 29, 28]. By integrating novel design elements and advanced planning techniques, these innovations pave the way for robots to perform complex tasks with greater efficiency and reliability.

4.3 Applications and Case Studies

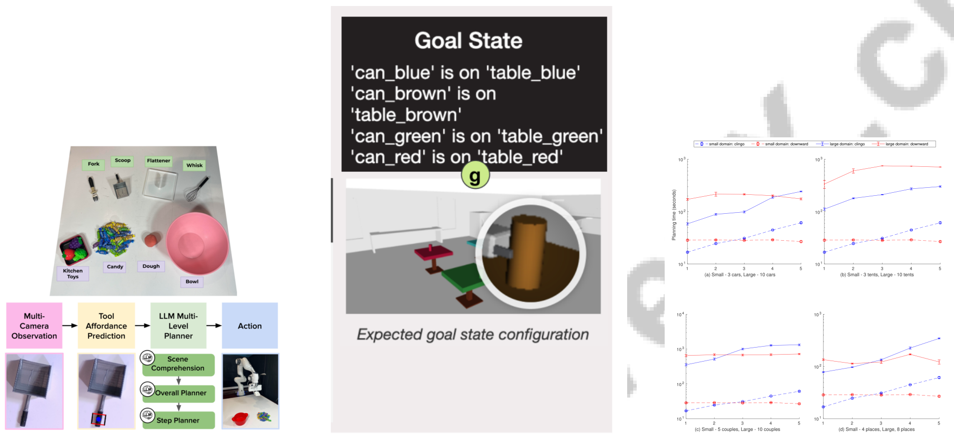
Mobile manipulation has numerous applications across diverse domains, demonstrating its potential to revolutionize various industries. A compelling example is a quadrupedal manipulator tasked with opening doors, highlighting mobility and manipulation integration for complex real-world tasks [58]. This task exemplifies the robot's ability to navigate and interact with its environment, showcasing mobile manipulation's practical utility in service robotics.

In industrial automation, mobile manipulators are increasingly employed for assembly and material handling tasks, where precision and adaptability are paramount. Integrating mobile platforms with robotic arms allows efficient task execution in dynamic environments, reducing the need for fixed automation systems and enhancing operational flexibility. This capability is particularly advantageous in manufacturing, where adapting to fluctuating production demands is essential. Adaptive robot assistance enhances team performance by optimizing task planning and decision-making, enabling effective human-robot collaboration. This adaptability is crucial in agile manufacturing settings, such as Industry 4.0, where versatile and responsive robotic systems are essential to meet varying production requirements [20, 7, 29, 21].

In healthcare, mobile manipulation is utilized for tasks like delivering medications and assisting with patient care. Advanced robotics in hospital settings enhance healthcare delivery by enabling effective navigation and interaction with various objects. This capability streamlines operations, reducing medical staff workload, and improves patient outcomes through efficient task execution. Robots with mobile manipulation systems can autonomously locate and transport medical supplies, while frameworks utilizing large language models facilitate seamless communication and collaboration among heterogeneous robotic systems. These advancements contribute to enhanced surgical precision and operational safety, leading to higher quality care in medical facilities [28, 59, 10].

In agriculture, mobile manipulation advances are remarkable, with robots increasingly utilized for tasks like efficient harvesting, precise crop monitoring, and agricultural operations management. These robots leverage deep learning and simulation to navigate and manipulate objects in dynamic environments, performing complex tasks autonomously and adaptably. Integrating mobile manipulation systems enhances operational efficiency and contributes to improved agricultural productivity and sustainability [57, 28, 56, 8]. Mobility and manipulation capabilities allow robots to navigate uneven terrains and interact delicately with plants, improving agricultural operations' efficiency and precision.

These case studies and applications underscore mobile manipulation's transformative impact across sectors, highlighting its potential to enhance productivity, efficiency, and adaptability in complex environments. As research and development progress, integrating advanced navigation, perception, and motion planning techniques is expected to significantly enhance mobile manipulation applications' capabilities and efficiency. This evolution will facilitate creating more intelligent and autonomous robotic systems capable of performing complex tasks in unstructured environments, addressing pressing challenges in sectors like healthcare and domestic services. By leveraging advancements in deep learning and simulation, these systems will better adapt to diverse conditions and execute intricate operations with improved dexterity and reliability [56, 8, 57, 29, 28].



(a) Multimodal Tool Selection for Kitchen Activities[60]

(b) Goal State Configuration for a Robotic Task[53]

(c) Comparison of Planning Times for Different Domain and Planning Strategies[36]

Figure 4: Examples of Applications and Case Studies

As shown in Figure 4, mobile manipulation is rapidly advancing, with diverse applications and case studies illustrating its potential across domains. One example highlights three scenarios showcasing mobile manipulation tasks' versatility and complexity. The first scenario, "Multimodal Tool Selection for Kitchen Activities," presents a playful kitchen environment where tools and objects simulate cooking or baking activities, emphasizing robots' role in household tasks. The second scenario, "Goal State Configuration for a Robotic Task," demonstrates a structured setup where a robot must achieve a specific goal state, represented by a green circle, amidst a table with differently colored canisters, underscoring precision and goal-oriented behavior in robotic tasks. Lastly, the "Comparison of Planning Times for Different Domain and Planning Strategies" scenario offers a quantitative analysis of planning efficiencies across domains, illustrating domain size and complexity's impact on planning time. These examples underscore mobile manipulation's multifaceted applications, from household assistance to strategic planning, highlighting ongoing innovations and challenges in this dynamic field [60, 53, 36].

5 Long-Horizon Planning

Anticipating future tasks is pivotal for autonomous systems operating in dynamic environments, as it involves executing extended action sequences with responsiveness and adaptability. This section delves into anticipatory planning, highlighting its role in enabling autonomous systems to predict and adapt to future tasks.

5.1 Anticipatory Planning and Future Task Prediction

Anticipatory planning is vital for long-horizon robotics, enabling systems to predict and adapt to future tasks in uncertain environments. The autonomous resetting mechanism by [1] enhances adaptability by recreating diverse training environments. The HYPERmotion framework, integrating learned motion skills with semantic understanding, underscores anticipatory planning's importance in facilitating flexible behavior in complex settings [2]. Large Language Models (LLMs) enhance task anticipation by generating conditions based on commonsense knowledge [3], while the HiDe architecture improves generalization by decomposing state-action spaces [13]. Incorporating visual information into decision-making can further bolster anticipatory strategies [5].

The need for adaptable skill execution in dynamic contexts is highlighted by [7], emphasizing environmental cues for robust task performance. ARPlaces improves robustness and efficiency in mobile manipulation by enhancing anticipation and adaptability [12]. Anticipatory planning strategies significantly boost long-horizon task execution efficiency, allowing robots to consider current actions' implications on future tasks, reducing task completion costs by up to 40.6

5.2 Algorithmic Strategies for Long-Horizon Planning

Algorithmic strategies are crucial for autonomous systems to navigate complex environments over extended periods effectively. Leveraging learned representations improves planning across diverse tasks, as demonstrated by the LAMP framework [15]. Deep reinforcement learning supports supervisory policy development for real-time coordination, optimizing long-horizon planning [61]. The HiDe method employs a hierarchical structure for effective task decomposition [13]. The SHARP framework refines planning by utilizing learned critical regions and abstract actions [62], while focusing on object configurations simplifies planning [63]. The LGP method combines limited horizon approaches with task-specific objectives for complex task decomposition [64].

These strategies advance long-horizon planning by integrating predictive modeling, hierarchical structuring, and learning-based optimization techniques, enhancing performance in dynamic environments. This integration enables robust closed-loop planning, efficient value function approximation for Model Predictive Control (MPC), and LLMs to connect high-level task planning with low-level control actions, improving plan feasibility and real-time adjustments [65, 17, 66, 67, 68].

5.3 Challenges and Solutions

Long-horizon planning in robotics faces challenges due to task execution complexities over extended periods in dynamic environments. LLMs often generate infeasible plans due to hallucinations or insufficient domain information, complicating long-term execution [17]. Task and motion planning disconnects lead to unfeasible action sequences [6], and scalability is critical in expansive domains where search spaces grow exponentially. Predicting future tasks can overwhelm computational resources, and predefined low-level policies restrict managing complex interactions. Recent advancements, such as STAP and BELT, integrate learned skills with model-based planning to enhance task coordination and feasibility assessment. Active learning and competence-aware planning allow robots to refine skill execution autonomously, crucial for improving task success in complex scenarios [31, 33, 69, 21].

Innovative solutions address these challenges. The HTMPC architecture enables faster task completion through hierarchical planning [70]. The VKC-based method enhances success rates and efficiency in mobile manipulation by facilitating coordinated movements [6]. Integrating learning-based strategies with optimization techniques enhances robustness and adaptability to changing conditions [11]. Developing sophisticated long-horizon planning frameworks that are robust, adaptable, and efficient is crucial for navigating dynamic environments. These frameworks must integrate advanced task and motion planning techniques to enhance decision-making and resource management in complex scenarios, ultimately improving the efficiency and effectiveness of processes like architectural construction [17, 64, 71].

6 Path Planning and Robotic Manipulation

6.1 Challenges in Navigating Complex Environments

Navigating complex environments poses significant challenges in path planning due to their dynamic and unpredictable nature. The vast search space of potential actions and the difficulty in accurately perceiving unknown objects lead to inefficiencies in planning and execution [63]. Real-time integration of object detection, tracking, and manipulation further complicates these tasks, with existing methods often proving inadequate [1].

The DELTA framework addresses these challenges by effectively decomposing long-term tasks, enhancing success rates and reducing planning times [17]. However, computational intractability in generating comprehensive task and motion policies as planning horizons extend remains a significant issue [4]. This is compounded by the synchronization and load rigidity required in collaborative tasks within multi-agent systems [4].

The ReLMM system enhances navigation and manipulation capabilities by enabling continuous learning and adaptation without human intervention [1]. Additionally, the Lazy INSAT method optimizes manipulation tasks by employing bracing contacts to minimize actuator torque, demonstrating the value of environmental interactions in task execution [72].

The framework for transferable legged mobile manipulation shows marked improvements in sample efficiency, requiring fewer samples for migration compared to original model training [5]. This efficiency is crucial for adapting to the often unpredictable conditions of real-world environments.

Addressing the challenges of navigating complex environments necessitates the development of advanced algorithms and frameworks capable of managing dynamic settings. By integrating high-level semantic reasoning with low-level execution, autonomous systems can operate safely and efficiently, processing incomplete information intelligently and adapting to changing conditions. Advanced planning systems utilize natural language processing for actionable goal generation and continuous sensing for monitoring environmental changes, ensuring robots can detect and mitigate potential conflicts during task execution. Systematic analyses of integration strategies reveal how various approaches to combining high-level reasoning and low-level checks can optimize plan quality and computational efficiency, enhancing robotic performance across diverse scenarios [73, 74, 15, 37].

6.2 Robotic Manipulation Techniques

Robotic manipulation techniques have advanced significantly to address the complexities and uncertainties of dynamic environments. A notable development is the integration of task and motion planning within a unified framework, exemplified by the HPlan algorithm, which enhances adaptability and precision in complex settings [75]. This integration facilitates effective manipulation, allowing robots to navigate intricate task environments more efficiently.

The MLDT method illustrates a hybrid approach that generates action sequences for subtasks, promoting efficient execution and adaptability to environmental changes [76]. By breaking tasks into manageable components, this method improves the robot's goal achievement capabilities.

The MoPA-RL framework demonstrates the effectiveness of combining direct action execution with motion planning, utilizing reinforcement learning for enhanced manipulation [46]. This integration is crucial for enabling robots to perform complex tasks with greater efficiency and adaptability.

Incorporating static stability evaluations into path planning is essential for achieving specific goals in robotic manipulation [64]. This ensures that robots maintain balance and precision during manipulation tasks, particularly in dynamic environments.

The SLCF method enhances robotic manipulation by decoupling task scheduling from motion planning, enabling rapid adjustments to changes in environment or task requirements [61]. This decoupling is vital for maintaining flexibility and responsiveness in dynamic settings.

The PSM* method introduces a novel steering strategy for effective pathfinding, ensuring probabilistic completeness and asymptotic optimality under certain conditions [19]. This technique refines coordination between task-level objectives and motion-level execution.

Utilizing a motion library for selecting appropriate motion skills is critical for robotic manipulation, as highlighted in the HYPERmotion framework [2]. This approach allows robots to adaptively select and execute motion skills based on task requirements.

Robotic manipulation techniques are further enhanced through a skill-based control platform, which supports effective task execution in contact-rich scenarios [7]. This platform emphasizes the importance of leveraging domain-specific knowledge to improve the adaptability and efficiency of robotic systems.

Collectively, these techniques advance robotic manipulation by integrating innovative control strategies, such as disturbance predictive control and modular skill-based approaches, with predictive modeling and precise execution. This integration enables robots to adapt to diverse and challenging environments, including varying terrains in legged mobile manipulation and low-gravity conditions for compact robots like ReachBot, achieving specific goals in complex tasks such as object rearrangement and navigation [5, 22, 29].

6.3 Technological Advancements and Case Studies

Recent technological advancements in path planning and robotic manipulation have significantly enhanced the capabilities of autonomous systems, enabling them to perform complex tasks with improved efficiency and reliability. The S3O-GROP* framework exemplifies these advancements, outperforming existing Task and Motion Planning (TAMP) algorithms in task completion rates and execution times, thereby validating its effectiveness in optimizing task-motion planning [77]. This framework demonstrates substantial improvements in planning efficiency, particularly in manipulating rigid objects within complex environments.

The MoPA-RL framework has been validated through experiments in various simulated manipulation tasks, showcasing its applicability for real-world scenarios [78]. By integrating motion planning with reinforcement learning, MoPA-RL enhances the robot's ability to adapt to dynamic environments, crucial for maintaining operational efficacy in unpredictable settings.

Mehta et al.'s mixed-method approach significantly outperforms traditional reinforcement learning methods in both simulated and real-world environments, highlighting the efficacy of integrating different strategies for long-horizon dexterous manipulation tasks [79]. This underscores the importance of combining methodologies to enhance task execution efficiency and adaptability.

In mobile manipulation, Watkins et al. emphasize the use of real-time visual feedback and advanced mapping techniques, which greatly enhance the navigation and manipulation capabilities of unmanned ground vehicles (UGVs) [8]. These innovations are crucial for improving the adaptability and precision of robotic systems in dynamic environments, allowing them to surpass traditional single-view approaches.

The SyDeBO framework illustrates significant improvements in planning time and trajectory optimization accuracy, showcasing advancements in path planning and manipulation techniques [14]. By effectively utilizing relational symbols, SyDeBO enhances planning performance and adaptability, demonstrating potential for more efficient task execution [80].

The SHARP framework's performance, based on path planning computation time and success rates across multiple trials, highlights the efficacy of high-level strategy abstraction to manage the complexities inherent in long-horizon tasks [62].

Recent advancements in path planning and robotic manipulation, as illustrated by various case studies, signify a transformative shift in mobile robot capabilities. Innovations include adaptive task planning frameworks that enhance human-robot collaboration by aligning with human preferences, modular approaches to mobile manipulation that improve object rearrangement efficiency, and integrated systems that combine perception, navigation, and grasping skills for effective operation in unstructured environments. Furthermore, robust mobile manipulation systems leveraging big data and deep learning enable robots to adapt to diverse conditions and perform complex tasks with greater accuracy and reliability. Collectively, these advancements represent a significant leap forward in robotics, offering promising solutions for real-world applications [20, 56, 8, 29, 28]. By integrating innovative methodologies and frameworks, these advancements enhance the ability of robots to execute complex tasks with increased precision and reliability, paving the way for the development of more intelligent, adaptable, and capable autonomous systems.

7 Integration of Autonomous Systems

7.1 Synergies between Task Planning and Mobile Manipulation

Integrating task planning with mobile manipulation is crucial for enhancing the capabilities of autonomous systems, enabling them to perform complex tasks efficiently and adaptably. The framework by Wang et al. exemplifies this integration by achieving high autonomy in task execution and effective failure detection, which is essential for operations in dynamic environments [23]. The Points2Plans framework further enhances operational flexibility by allowing robots to adapt to varied tasks and environments without extensive retraining [81].

TAMPURA integrates risk awareness into task planning, enhancing safety and reliability in navigating complex environments [82]. The fusion of task planning with relational symbol learning, as demonstrated by Ahmetoglu et al., showcases the importance of symbolic reasoning in managing complex object interactions [80]. The Prompt-Driven Task Planning Method (PDTPM) illustrates efficient multi-drone operations, highlighting the potential for coordinated task execution among multiple agents [83]. The MHRC framework supports diverse robotic types, enhancing adaptability and effectiveness [10].

Recent advancements in modular approaches to long-horizon tasks and comprehensive mobile manipulation systems underscore the transformative potential of this integration. These advancements enable intelligent robotic systems to navigate and interact with dynamic environments, improving efficiency in applications such as object rearrangement, grasping in unstructured settings, and service automation in medical and domestic contexts [28, 8, 29].

7.2 Frameworks for Integrated Planning

Frameworks integrating high-level planning with motion control are pivotal for advancing autonomous systems, facilitating precise and adaptable task execution. Effective coordination between strategic planning and real-time motion execution enhances performance in dynamic environments, particularly benefiting legged robots through robust decision-making and maneuvering capabilities. Techniques like the Virtual Kinematic Chain perspective and neural feasibility checking simplify planning, reduce computational demands, and improve system efficiency in response to environmental changes [84, 85, 11, 86].

The SyDeBO approach exemplifies symbolic decision-making integration with motion control through bilevel optimization, optimizing long-horizon manipulation tasks [14]. The DELTA method utilizes Large Language Models (LLMs) with Scene Graphs (SGs) to decompose long-term tasks into manageable sub-goals, enhancing planning efficiency [17]. The HiDe method employs a hierarchical planning framework, promoting modularity and scalability across tasks [13]. ReLMM emphasizes combining high-level planning with motion control to enhance real-world task execution [1].

The SkiROS2 platform integrates knowledge representation with task planning, utilizing a skill-based control approach to implement transferable robot skills across different hardware setups [7]. These frameworks highlight the transformative potential of integrating high-level planning with motion control, paving the way for intelligent robotic systems capable of navigating diverse environments. This integration significantly improves operational efficiency, enabling intricate task execution with reliability, as demonstrated in applications like cooperative robotic manipulation, robotic surgery automation, multi-drone task planning, and adaptive human-robot collaboration. Examples include deep reinforcement learning to coordinate multiple robotic manipulators for complex tasks, surgical automation combining task-level reasoning with dynamic movement, and prompt-driven methods in multi-drone systems for streamlined human-machine interaction [20, 83, 87, 59, 61].

7.3 Learning-Based Approaches

Learning-based approaches are crucial in enhancing autonomous systems, providing innovative solutions to challenges in dynamic environments. These approaches leverage advanced machine learning techniques, such as deep learning and large language models, to improve adaptability, efficiency, and robustness. By enabling mobile robots to manipulate objects in diverse environments, they enhance precision in tasks like exploration, transportation, and organization. The use of realistic simulation data accelerates the development of advanced perception, planning, and grasp execution algorithms, while decentralized collaboration among heterogeneous robot types optimizes task allocation and communication [56, 10].

A significant advancement is using Large Language Models (LLMs) in task planning and execution. Integrating LLMs with scene understanding frameworks, such as Scene Graphs (SGs), allows decomposition of long-term tasks into sub-goals, enhancing planning and execution [17]. The ReLMM framework exemplifies reinforcement learning and motion control fusion, enabling concurrent learning of navigation and manipulation skills [1].

Hierarchical reinforcement learning architectures, like the HiDe method, illustrate the potential of learning-based approaches by separating high-level task planning from low-level motion control, enhancing flexibility and scalability [13]. The SkiROS2 platform demonstrates integrating knowledge representation with task planning through a skill-based control approach, facilitating transferable robot skills across hardware setups [7].

These learning-based approaches advance autonomous systems by combining machine learning techniques—such as graph-based spatial temporal logic for specification mining, LLMs for high-level task planning, and deep reinforcement learning for real-time control—with advanced planning and control frameworks. This synergy enables robots to learn new skills, adapt behaviors, and perform complex tasks in dynamic environments [56, 65, 87, 88, 61]. By enhancing adaptability, efficiency, and robustness, these approaches pave the way for more intelligent autonomous systems capable of navigating and interacting with diverse environments.

8 Conclusion

8.1 Future Directions and Research Opportunities

The future of robotics research is poised to explore several avenues that promise to enhance the adaptability and efficiency of autonomous systems in complex environments. Expanding motion libraries and refining dynamic planning capabilities within language models are critical for improving robot perception and task execution, thereby increasing scalability and versatility in path planning. Enhancing trajectory generators and leveraging Large Language Models (LLMs) in robotic manipulation can significantly bolster the generalization capabilities of planning algorithms, ensuring their robustness in uncertain and dynamic settings.

Research into the Virtual Kinematic Chain (VKC) method should focus on advancing object identification and robust grasping techniques, which are vital for adapting to unforeseen changes and optimizing task execution. In long-horizon manipulation, exploring the application of HiDe in real-world scenarios and multi-agent contexts presents significant research opportunities, crucial for ensuring safe and reliable operations in complex environments.

For hierarchical planning frameworks, optimizing path velocities and force application, along with integrating additional robotic platforms, will enhance the architecture's performance, adaptability, and precision across various scenarios. The ARPlace method's future research should aim to refine its representation and expand its applications beyond mobile manipulation, thereby strengthening long-term task planning strategies.

Improving the robustness of optimization-based Task and Motion Planning (TAMP) methods through the integration of learning techniques and addressing real-world complexities are essential future research directions. These efforts aim to optimize task execution efficiency and adaptability. In multi-robot systems, enhancing algorithm speed, incorporating execution uncertainty, and exploring multi-query planning techniques are vital for optimizing coordination and collaboration among multiple robots in dynamic environments.

Lastly, extending the ReLMM framework to tackle more complex tasks while improving its efficiency and robustness in diverse contexts is a critical research direction. These initiatives aim to elevate the adaptability and operational efficacy of autonomous systems, enabling them to effectively navigate and interact within intricate environments. Collectively, these research opportunities underscore the potential for significant advancements in robotics, paving the way for more intelligent, adaptable, and capable autonomous systems.

References

[1] Charles Sun, Jędrzej Orbik, Coline Devin, Brian Yang, Abhishek Gupta, Glen Berseth, and Sergey Levine. Fully autonomous real-world reinforcement learning with applications to mobile manipulation, 2021.

[2] Jin Wang, Rui Dai, Weijie Wang, Luca Rossini, Francesco Ruscelli, and Nikos Tsagarakis. Hypermotion: Learning hybrid behavior planning for autonomous loco-manipulation, 2024.

[3] Haoyu Zhou, Mingyu Ding, Weikun Peng, Masayoshi Tomizuka, Lin Shao, and Chuang Gan. Generalizable long-horizon manipulations with large language models, 2023.

[4] Valentin Noah Hartmann, Andreas Orthey, Danny Driess, Ozgur S. Oguz, and Marc Toussaint. Long-horizon multi-robot rearrangement planning for construction assembly, 2022.

[5] Qingfeng Yao, Jilong Wan, Shuyu Yang, Cong Wang, Linghan Meng, Qifeng Zhang, and Donglin Wang. A transferable legged mobile manipulation framework based on disturbance predictive control, 2022.

[6] Ziyuan Jiao, Zeyu Zhang, Xin Jiang, David Han, Song-Chun Zhu, Yixin Zhu, and Hangxin Liu. Consolidating kinematic models to promote coordinated mobile manipulations, 2021.

[7] Matthias Mayr, Faseeh Ahmad, Alexander Duerr, and Volker Krueger. Using knowledge representation and task planning for robot-agnostic skills on the example of contact-rich wiping tasks, 2023.

[8] David Watkins, Peter K Allen, Henrique Maia, Madhavan Seshadri, Jonathan Sanabria, Nicholas Waytowich, and Jacob Varley. Mobile manipulation leveraging multiple views, 2022.

[9] Steve Macenski, Matthew Booker, and Joshua Wallace. Open-source, cost-aware kinematically feasible planning for mobile and surface robotics, 2024.

[10] Wenhao Yu, Jie Peng, Yueliang Ying, Sai Li, Jianmin Ji, and Yanyong Zhang. Mhrc: Closed-loop decentralized multi-heterogeneous robot collaboration with large language models, 2024.

[11] Zhigen Zhao, Shuo Cheng, Yan Ding, Ziyi Zhou, Shiqi Zhang, Danfei Xu, and Ye Zhao. A survey of optimization-based task and motion planning: From classical to learning approaches, 2024.

[12] Freek Stulp, Andreas Fedrizzi, Lorenz Mösenlechner, and Michael Beetz. Learning and reasoning with action-related places for robust mobile manipulation, 2014.

[13] Sammy Christen, Lukas Jendele, Emre Aksan, and Otmar Hilliges. Learning functionally decomposed hierarchies for continuous control tasks with path planning, 2021.

[14] Zhigen Zhao, Ziyi Zhou, Michael Park, and Ye Zhao. Sydebo: Symbolic-decision-embedded bilevel optimization for long-horizon manipulation in dynamic environments, 2020.

[15] Naman Shah, Jayesh Nagpal, Pulkit Verma, and Siddharth Srivastava. From reals to logic and back: Inventing symbolic vocabularies, actions, and models for planning from raw data, 2024.

[16] David Paulius, Alejandro Agostini, and Dongheui Lee. Long-horizon planning and execution with functional object-oriented networks, 2023.

[17] Yuchen Liu, Luigi Palmieri, Sebastian Koch, Ilche Georgievski, and Marco Aiello. Delta: Decomposed efficient long-term robot task planning using large language models, 2024.

[18] Yifeng Zhu, Jonathan Tremblay, Stan Birchfield, and Yuke Zhu. Hierarchical planning for long-horizon manipulation with geometric and symbolic scene graphs, 2021.

[19] Isabel M. Rayas Fernández. Advancing robot autonomy for long-horizon tasks, 2023.

[20] Ali Noormohammadi-Asl, Stephen L. Smith, and Kerstin Dautenhahn. To lead or to follow? adaptive robot task planning in human-robot collaboration, 2024.

AI-generated, for reference only.

[21] Abhinav Dahiya and Stephen L. Smith. Adaptive robot assistance: Expertise and influence in multi-user task planning, 2023.

[22] Stephanie Schneider, Andrew Bylard, Tony G. Chen, Preston Wang, Mark Cutkosky, and Marco Pavone. Reachbot: A small robot for large mobile manipulation tasks, 2021.

[23] Jin Wang, Arturo Laurenzi, and Nikos Tsagarakis. Autonomous behavior planning for humanoid loco-manipulation through grounded language model, 2024.

[24] Aman Aryan, Manan Modi, Indranil Saha, Rupak Majumdar, and Swarup Mohalik. Optimal integrated task and path planning and its application to multi-robot pickup and delivery, 2024.

[25] Akira Taniguchi, Shota Isobe, Lotfi El Hafi, Yoshinobu Hagiwara, and Tadahiro Taniguchi. Autonomous planning based on spatial concepts to tidy up home environments with service robots, 2021.

[26] Yan Ding, Xiaohan Zhang, Saeid Amiri, Nieqing Cao, Hao Yang, Chad Esselink, and Shiqi Zhang. Robot task planning and situation handling in open worlds, 2024.

[27] Yutao Ouyang, Jinhan Li, Yunfei Li, Zhongyu Li, Chao Yu, Koushil Sreenath, and Yi Wu. Long-horizon locomotion and manipulation on a quadrupedal robot with large language models, 2024.

[28] Kenneth Blomqvist, Michel Breyer, Andrei Cramariuc, Julian Förster, Margarita Grinvald, Florian Tschopp, Jen Jen Chung, Lionel Ott, Juan Nieto, and Roland Siegwart. Go fetch: Mobile manipulation in unstructured environments, 2020.

[29] Jiayuan Gu, Devendra Singh Chaplot, Hao Su, and Jitendra Malik. Multi-skill mobile manipulation for object rearrangement, 2022.

[30] Tao Huang, Kai Chen, Wang Wei, Jianan Li, Yonghao Long, and Qi Dou. Value-informed skill chaining for policy learning of long-horizon tasks with surgical robot, 2023.

[31] Christopher Agia, Toki Migimatsu, Jiajun Wu, and Jeannette Bohg. Stap: Sequencing task-agnostic policies, 2023.

[32] Chris Paxton, Marin Kobilarov, and Gregory D. Hager. Towards robot task planning from probabilistic models of human skills, 2016.

[33] Nishanth Kumar, Tom Silver, Willie McClinton, Linfeng Zhao, Stephen Proulx, Tomás Lozano-Pérez, Leslie Pack Kaelbling, and Jennifer Barry. Practice makes perfect: Planning to learn skill parameter policies, 2024.

[34] Danfei Xu, Ajay Mandlekar, Roberto Martín-Martín, Yuke Zhu, Silvio Savarese, and Li Fei-Fei. Deep affordance foresight: Planning through what can be done in the future, 2021.

[35] Muhayy Ud Din, Jan Rosell, Waseem Akram, Isiah Zaplana, Maximo A Roa, Lakmal Seneviratne, and Irfan Hussain. Ontology-driven prompt tuning for llm-based task and motion planning, 2024.

[36] Yuqian Jiang, Shiqi Zhang, Piyush Khandelwal, and Peter Stone. Task planning in robotics: an empirical comparison of pddl-based and asp-based systems, 2019.

[37] Yue Zhen, Sheng Bi, Lu Xing-tong, Pan Wei-qin, Shi Hai-peng, Chen Zi-rui, and Fang Yi-shu. Robot task planning based on large language model representing knowledge with directed graph structures, 2023.

[38] Boyi Li, Philipp Wu, Pieter Abbeel, and Jitendra Malik. Interactive task planning with language models, 2025.

[39] Minseo Kwon, Yaesol Kim, and Young J. Kim. Fast and accurate task planning using neuro-symbolic language models and multi-level goal decomposition, 2024.

[40] Caelan Reed Garrett, Rohan Chitnis, Rachel Holladay, Beomjoon Kim, Tom Silver, Leslie Pack Kaelbling, and Tomás Lozano-Pérez. Integrated task and motion planning, 2020.

AI-generated, for reference only.

[41] Wil Thomason, Marlin P. Strub, and Jonathan D. Gammell. Task and motion informed trees (tmit*): Almost-surely asymptotically optimal integrated task and motion planning, 2022.

[42] Rutav Shah, Albert Yu, Yifeng Zhu, Yuke Zhu, and Roberto Martín-Martín. Bumble: Unifying reasoning and acting with vision-language models for building-wide mobile manipulation. *arXiv preprint arXiv:2410.06237*, 2024.

[43] Yuming Feng, Chuye Hong, Yaru Niu, Shiqi Liu, Yuxiang Yang, Wenhao Yu, Tingnan Zhang, Jie Tan, and Ding Zhao. Learning multi-agent loco-manipulation for long-horizon quadrupedal pushing, 2024.

[44] Akshay Jaitly and Siavash Farzan. Paamp: Polytopic action-set and motion planning for long horizon dynamic motion planning via mixed integer linear programming, 2024.

[45] Sumanta Ghosh, Subhajit Nath, Sarvesh Sortee, Lokesh Kumar, and Titas Bera. On the collaborative object transportation using leader follower approach, 2023.

[46] Jun Yamada, Youngwoon Lee, Gautam Salhotra, Karl Pertsch, Max Pflueger, Gaurav Sukhatme, Joseph Lim, and Peter Englert. Motion planner augmented reinforcement learning for robot manipulation in obstructed environments. In *Conference on Robot Learning*, pages 589–603. PMLR, 2021.

[47] Mengchao Zhang, Jose Barreiros, and Aykut Ozgun Onol. Plan-guided reinforcement learning for whole-body manipulation, 2023.

[48] Xiaoyu Huang, Dhruv Batra, Akshara Rai, and Andrew Szot. Skill transformer: A monolithic policy for mobile manipulation, 2023.

[49] Yoshiki Obinata, Haoyu Jia, Kento Kawaharazuka, Naoaki Kanazawa, and Kei Okada. Remote life support robot interface system for global task planning and local action expansion using foundation models, 2024.

[50] Payam Ghassemi and Souma Chowdhury. Informative path planning with local penalization for decentralized and asynchronous swarm robotic search, 2019.

[51] Ruoyu Wang, Zhipeng Yang, Zinan Zhao, Xinyan Tong, Zhi Hong, and Kun Qian. Llm-based robot task planning with exceptional handling for general purpose service robots, 2024.

[52] Jacky Liang, Mohit Sharma, Alex LaGrassa, Shivam Vats, Saumya Saxena, and Oliver Kroemer. Search-based task planning with learned skill effect models for lifelong robotic manipulation, 2022.

[53] Rushang Karia, Jayesh Nagpal, Daksh Dobhal, Pulkit Verma, Rashmeet Kaur Nayyar, Naman Shah, and Siddharth Srivastava. Using explainable ai and hierarchical planning for outreach with robots, 2024.

[54] Muhayyuddin, Aliakbar Akbari, and Jan Rosell. Physics-based motion planning with temporal logic specifications, 2017.

[55] Rahul Shome, Daniel Nakhimovich, and Kostas E. Bekris. Pushing the boundaries of asymptotic optimality in integrated task and motion planning, 2020.

[56] David Watkins. Learning mobile manipulation, 2022.

[57] Jesse Haviland, Niko Sünderhauf, and Peter Corke. A holistic approach to reactive mobile manipulation, 2022.

[58] Elena Arcari, Maria Vittoria Minniti, Anna Scampicchio, Andrea Carron, Farbod Farshidian, Marco Hutter, and Melanie N. Zeilinger. Bayesian multi-task learning mpc for robotic mobile manipulation, 2023.

[59] Michele Ginesi, Daniele Meli, Andrea Roberti, Nicola Sansonetto, and Paolo Fiorini. Autonomous task planning and situation awareness in robotic surgery, 2020.

[60] Arvind Car, Sai Sravan Yarlagadda, Alison Bartsch, Abraham George, and Amir Barati Farimani. Plato: Planning with llms and affordances for tool manipulation, 2024.

[61] Sander De Witte, Tom Lefebvre, Thijs Van Hauwermeiren, and Guillaume Crevecoeur. A supervisory learning control framework for autonomous real-time task planning for an underactuated cooperative robotic task, 2023.

[62] Multi-task option learning and discovery for stochastic path planning.

[63] Anthony Simeonov, Yilun Du, Beomjoon Kim, Francois Hogan, Joshua Tenenbaum, Pulkit Agrawal, and Alberto Rodriguez. A long horizon planning framework for manipulating rigid pointcloud objects. In *Conference on Robot Learning*, pages 1582–1601. PMLR, 2021.

[64] Valentin N. Hartmann, Ozgur S. Oguz, Danny Driess, Marc Toussaint, and Achim Menges. Robust task and motion planning for long-horizon architectural construction planning, 2020.

[65] Murtaza Dalal, Tarun Chiruvolu, Devendra Chaplot, and Ruslan Salakhutdinov. Plan-seq-learn: Language model guided rl for solving long horizon robotics tasks. *arXiv preprint arXiv:2405.01534*, 2024.

[66] Murtaza Dalal, Tarun Chiruvolu, Devendra Chaplot, and Ruslan Salakhutdinov. Plan-seq-learn: Language model guided rl for solving long horizon robotics tasks, 2024.

[67] Nathan Hatch and Byron Boots. The value of planning for infinite-horizon model predictive control, 2021.

[68] Jinghan Li, Zhicheng Sun, Fei Li, Cao Sheng, Jiazhong Yu, and Yadong Mu. Closed-loop long-horizon robotic planning via equilibrium sequence modeling, 2024.

[69] Brian Ichter, Pierre Sermanet, and Corey Lynch. Broadly-exploring, local-policy trees for long-horizon task planning, 2020.

[70] erarchical task model predictive.

[71] Valentin N Hartmann, Ozgur S Oguz, Danny Driess, Marc Toussaint, and Achim Menges. Robust task and motion planning for long-horizon architectural construction planning. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 6886–6893. IEEE, 2020.

[72] Ramkumar Natarajan, Garrison L. H. Johnston, Nabil Simaan, Maxim Likhachev, and Howie Choset. Long horizon planning through contact using discrete search and continuous optimization, 2024.

[73] Esra Erdem, Volkan Patoglu, and Peter Schüller. Levels of integration between low-level reasoning and task planning, 2013.

[74] Guowei Cui, Wei Shuai, and Xiaoping Chen. Semantic task planning for service robots in open world, 2020.

[75] Naman Shah and Siddharth Srivastava. An anytime hierarchical approach for stochastic task and motion planning, 2022.

[76] Yike Wu, Jiatao Zhang, Nan Hu, LanLing Tang, Guilin Qi, Jun Shao, Jie Ren, and Wei Song. Mldt: Multi-level decomposition for complex long-horizon robotic task planning with open-source large language model, 2024.

[77] Xiaohan Zhang, Yifeng Zhu, Yan Ding, Yuqian Jiang, Yuke Zhu, Peter Stone, and Shiqi Zhang. Symbolic state space optimization for long horizon mobile manipulation planning, 2023.

[78] Jun Yamada, Youngwoon Lee, Gautam Salhotra, Karl Pertsch, Max Pflueger, Gaurav S. Sukhatme, Joseph J. Lim, and Peter Englert. Motion planner augmented reinforcement learning for robot manipulation in obstructed environments, 2020.

[79] Shaunak A. Mehta and Rana Soltani Zarrin. On the feasibility of a mixed-method approach for solving long horizon task-oriented dexterous manipulation, 2024.

[80] Alper Ahmetoglu, Erhan Oztop, and Emre Ugur. Symbolic manipulation planning with discovered object and relational predicates, 2024.

[81] Yixuan Huang, Christopher Agia, Jimmy Wu, Tucker Hermans, and Jeannette Bohg. Points2plans: From point clouds to long-horizon plans with composable relational dynamics, 2024.

[82] Aidan Curtis, George Matheos, Nishad Gothoskar, Vikash Mansinghka, Joshua Tenenbaum, Tomás Lozano-Pérez, and Leslie Pack Kaelbling. Partially observable task and motion planning with uncertainty and risk awareness, 2024.

[83] Yaohua Liu. A prompt-driven task planning method for multi-drones based on large language model, 2024.

[84] Lei Xu, Tianyu Ren, Georgia Chalvatzaki, and Jan Peters. Accelerating integrated task and motion planning with neural feasibility checking, 2022.

[85] Ziyuan Jiao, Zeyu Zhang, Weiqi Wang, David Han, Song-Chun Zhu, Yixin Zhu, and Hangxin Liu. Efficient task planning for mobile manipulation: a virtual kinematic chain perspective, 2021.

[86] Ye Zhao, Yinan Li, Luis Sentis, Ufuk Topcu, and Jun Liu. Reactive task and motion planning for robust whole-body dynamic locomotion in constrained environments, 2022.

[87] Zhiyu Liu, Meng Jiang, and Hai Lin. Specification mining and automated task planning for autonomous robots based on a graph-based spatial temporal logic, 2020.

[88] Prithvi Akella, Anushri Dixit, Mohamadreza Ahmadi, Lars Lindemann, Margaret P. Chapman, George J. Pappas, Aaron D. Ames, and Joel W. Burdick. Risk-aware robotics: Tail risk measures in planning, control, and verification, 2024.

AI-generated, for reference only.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.

AI-generated, for reference only.