Humanoid Locomotion and Manipulation: Current Progress and Challenges in Control, Planning, and Learning

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***Abstract*—Humanoid robots have great potential to perform various human-level skills. These skills involve locomotion, manipulation, and cognitive capabilities. Driven by advances in machine learning and the strength of existing model-based approaches, these capabilities have progressed rapidly, but often separately. Therefore, a timely overview of current progress and future trends in this fast-evolving field is essential. This survey first summarizes the model-based planning and control that have been the backbone of humanoid robotics for the past three decades. We then explore emerging learning-based methods, with a focus on reinforcement learning and imitation learning that enhance the versatility of loco-manipulation skills. We examine the potential of integrating foundation models with humanoid embodiments, assessing the prospects for developing generalist humanoid agents. In addition, this survey covers emerging research for whole-body tactile sensing that unlocks new humanoid skills that involve physical interactions. The survey concludes with a discussion of the challenges and future trends.**

***Index Terms*—Humanoid robotics, Loco-manipulation, Model predictive control, Whole-body control, Imitation learning, Foundation models, and Whole-body tactile sensing.**

I. Introduction

Humanoid robots are well suited for executing human-level tasks, as they are built to (ideally) replicate human motions in achieving various whole-body loco-manipulation tasks, *e.g.*, applications ranging from manufacturing to services, as shown in Fig. 1. Their anthropomorphism makes them stand out from other robot forms in terms of these human-like tasks. Humanoid robots can interact with humans for physical collaboration tasks, such as collaboratively moving a heavy and large table upstairs and human assistance. However, simultaneously achieving these intricate tasks while addressing highly complex robot dynamics is still challenging, let alone safe physical collaborations with humans and/or operations in unstructured environments. As a promising direction to solve this problem, humanoids could exploit the abundance of data available for and/or from humans to quickly acquire motor and cognitive skills. Therefore, leveraging human knowledge for humanoid embodiment is potentially a fast route to embodied intelligence.

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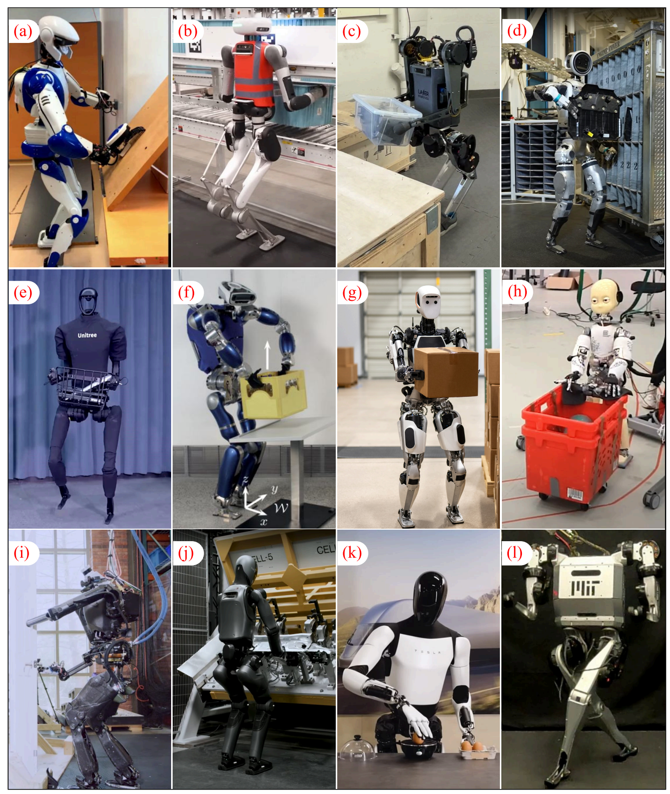

Fig. 1. Humanoids executing locomotion and manipulation tasks: (a) HRP-4 wipes a wood board while adapting to terrain [1]; (b-g) Object pick and place by Digit, Hector [2], Atlas, H1, Justin [3], and Apollo; (h) iCub pushes a cart [4]; (i) Nadia opens a door [5]; (j-k) Object manipulation by Figure 01 and Optimus; (l) MIT humanoid whole-body push recovery [6].

Cognitive and autonomous capabilities in robotics at large are thriving at an unprecedented pace. Perception algorithms can detect, classify, and segment a wide variety of objects in real time. Model-based methods that leverage predictive control and reactive control have enabled agile and reliable locomotion and manipulation. Meanwhile, deep learning policies have demonstrated convincing control results on robot hardware through exploration and imitation. Large foundation models trained on massive, internet-scale datasets began to

Fig. 2. This survey begins by defining relevant concepts of humanoid robots and their locomotion and manipulation capabilities. Centered around achieving humanoid loco-manipulation tasks, the core of this survey delves into two main categories of methods: the traditional planning and control approaches, such as contact planning, motion planning, and control, as well as the emerging learning-based approaches, including skill learning and foundation models. In addition, this survey highlights whole-body tactile sensing as a crucial modality to achieve contact-rich loco-manipulation.

show capabilities of open-world reasoning. Consequently, the building of autonomous humanoid robots for real-world applications has become possible, leading to the emergence of many humanoid robot companies and concrete deployment applications. Especially with powerful GPU-based parallelization capabilities, companies such as NVIDIA and companies with physical humanoid technologies, such as Boston Dynamics, Tesla, and Figure began collaboration on the embodied intelligence of humanoid robots.

Acknowledging the rapid advancements in humanoid robotics, this article reviews recent developments in Humanoid Locomotion and Manipulation (HLM). As laid out in Fig. 2, humanoid robotics is a multidisciplinary field that spans domains in design, actuation, sensing, control, planning, and decision-making. In this survey, we mainly examine task planning, motion planning, policy learning, and control from the perspective of model-based methods and learning-based methods. Each of these topics has extensive studies, and we aim to spotlight representative works within each topic. For each section, we provide survey papers for further reading. We first synthesize traditional model-based methods for planning and control. Then, we shift our focus to more recent learning-based approaches, especially those leveraging reinforcement learning, imitation learning, and foundation models.

Model-based methods serve as the cornerstone for enabling HLM capabilities. These methods depend critically on physical models, which can significantly influence the quality, speed, and guarantees of motion generation and control. Over the past decade, planning and control techniques have shown a trend of converging to the predictive-reactive control hierarchy, employing a whole-body model predictive controller (MPC) or simplified model (centroidal dynamics) MPC coupled with local task-space Whole-Body Controllers (WBC) [7]. These planning and control techniques are usually formulated as Optimal Control Problems (OCPs) that are solved by off-the-shelf or customized numerical solvers. Although these numerical optimization methods are well-established, research continues to focus on enhancing their computational efficiency, numerical stability, robustness, and scalability for high-dimensional systems.

Learning-based approaches have witnessed a rapid surge in humanoid robotics and achieved impressive results that attract an increasing number of researchers to the field. Among the diverse learning approaches, Reinforcement Learning (RL) has proven its ability to achieve robust motor skills. However, despite its ability to discover novel behaviors via trial and error, pure RL without demonstration data is often prohibitively inefficient for HLM tasks, which are characterized by high degrees-of-freedom robots and sparse reward settings. Therefore, training RL in simulation and transferring to the real world has become the prevalent method, though it faces the challenge of bridging sim-to-real gaps. However, imitation learning (IL) from expert demonstrations has proven to be an efficient method of acquiring motor skills. IL techniques such as behavior cloning [8] have shown impressive abilities to mimic a wide range of skills. In pursuit of versatile and generalizable policies through IL, many researchers and companies have focused on scaling data. Whereas robot experience data can be diverse and high-quality, its acquisition is both expensive and time-consuming. Thus, learning from human data, which is abundant and readily available from Internet videos and public datasets, emerges as a pivotal strategy for humanoid robotics. Learning from humans is a unique advantage exclusive to humanoid robots. However, even though humanoid robots may attain human-level motor skills, a deeper question of embodied intelligence persists: how to learn the intentions (source) behind human actions rather than merely replicating the observed motions (outcome). It is hypothesized that understanding human intention is achieved via Foundation Models (FMs) capable of semantic interpretation of the environment and the task. This hypothesis motivates us to include FMs as a part of our survey.

The remarkable success of FMs has sparked a surge in *general* robotics research, as highlighted by several comprehensive surveys [9, 10]. This paper reports on the application of FMs for humanoid robots. FMs offer a promising solution to the persistent challenge of generalizability in robotics by efficiently harnessing internet-scale datasets to acquire extensive knowledge. A pre-trained FM exhibits capabilities for open-world reasoning and multimodal semantic understanding. These capabilities are invaluable for robots engaged in complex physical environments requiring long-term, logically coherent task planning. Within the realm of humanoid robots, FMs have been successfully implemented as task planning modules in hierarchical planning and control frameworks. However, FMs have not yet achieved robust execution of low-level sensorimotor skills in an end-to-end process. Despite the limited number of works dedicated to FMs for humanoid applications, this field is increasingly active and poised for significant future developments.

A. Survey Goals and Roadmap

The survey serves as an effective resource for graduate students and researchers new to the field, offering a comprehensive review of humanoid technical methods, while also providing perspectives for humanoid experts in academia and industry with the latest advancements.

This survey is related to survey papers on humanoid robotics [11, 12], and to the topics of model-based planning [13] and control [7], and learning-based methods [14]. Distinct from these survey papers, which focus on particular sub-fields of humanoid robots, our paper aims to present a broader overview, covering planning, control, and learning topics, including RL, IL, and foundation models. These provide new insights, augment the loco-manipulation capabilities enabled by traditional model-based approaches, and meet the current trends of humanoid robots within both academia and industry. In particular, we ask the following questions:

- Q1: What are the state-of-the-art methods, both model-based and learning-based, that have already achieved loco-manipulation skills on humanoid robots?
- Q2: What gaps still exist in achieving versatile and generalizable humanoid robots?
- Q3: What methods are promising for addressing these gaps?

As shown in Fig. 2, this survey is organized in the following order. We first establish the background, defining humanoid robots and the key capability of locomotion and manipulation in Sec. II. We detail whole-body tactile sensing in Sec. III. We then present traditional approaches that achieve loco-manipulation, including contact planning (Sec. IV), motion planning (Sec. V), and control (Sec. VI).

We then examine the state-of-the-art learning-based algorithms. In Sec. VII, we explore approaches using reinforcement learning and imitation learning to acquire loco-manipulation skills. In Sec. VIII, we discuss how foundation models become the backbone of semantic understanding and decision-making for effective humanoid task planning. Finally, we highlight significant challenges in this field and present our perspectives on potential future research directions and emerging opportunities in Sec. IX.

II. Background

In this section, we discuss the level of anthropomorphism of humanoid robots. We then focus on its main capabilities: bipedal locomotion and whole-body manipulation. Finally, we detail the combined loco-manipulation skills with the state-of-the-art methods and current challenges.

A. Humanoid Robots

A humanoid robot refers to any anthropomorphic robot that resembles the form of a human [11]. Typically, a humanoid robot possesses a torso, two arms, and two legs, though the degree of anthropomorphism may vary. For instance, some humanoid robots feature simple hands or wheeled legs [15]. The level of anthropomorphism can be evaluated in terms of differences (with the human) in weight, limbs' sizes, and the degrees of freedom in all joints.

The primary focus of this review is on humanoid robots that emulate human morphologies and functionalities, rather than those closely mimicking human visual appearance and external look. Because of their similar morphology to humans, humanoid robots could, in principle, exploit the abundant data that can be collected from human demonstration. In this sense, human skills are more conveniently transformable to humanoid robots. By means of scaling data and computation, humanoid robots will be more capable of versatile and generalizable skills.

From the perspective of human-robot interaction, humanoid robots would be more favorably received. This is because their human-like behavior confers in them more trust in usability as a humanoid would generate motions in an expected and predictable way by human users. This facilitates psychological comfort and also promotes effective collaboration between humans and robots, particularly in close-contact interaction tasks. Besides, humanoid robots are well-suited for environments designed for humans.

B. Bipedal Locomotion and Navigation

Bipedal locomotion: Bipedal locomotion is a significant characteristic of humanoid robots. Therefore, in the past three decades, bipedal locomotion has been a prolific field of research in the humanoid domain. Interested readers can refer to the excellent reviews (most of which are recent) [16, 17, 18], and the monographs [19, 20]. In summary, model-based bipedal locomotion has evolved significantly, progressing from passive walking [21, 22] to quasi-static walking [23], and then to dynamic walking [19]. Bipedal walking on flat surfaces has been well explored and mastered through periodic motions with model-based methods [19, 24]. These approaches have also expanded to more agile motions such as jumping [25, 26] and back-flipping [27].

Bipedal locomotion under external perturbations and force loads has been extensively studied. Such capabilities lay the foundation for simultaneous locomotion and manipulation, the focus of this survey. Model-based approaches, such as those in [2, 28, 29, 30], have been developed to achieve such capabilities. For example, a passivity-based controller with task space dynamics is introduced in [29], where external forces are integrated as part of the generalized forces that describe the robot's dynamics. Payload is incorporated into a simplified rigid body model to enable dynamic walking while carrying in [2]. In [28], any external force is incorporated as part of the LIP MPC.

In addition to model-based methods, bipedal locomotion has also been successfully addressed by learning-based methods [31, 32, 33], particularly in the context of periodic motions on flat surfaces. Furthermore, learning-based approaches have also demonstrated capabilities in more complex settings, such as running [34], jumping [35], and handling non-periodic motions such as stair climbing [36] and parkour [37]. Similar to the trend in model-based methods, learning-based methods have further extended their capabilities to handle external forces and payloads [38, 39].

Bipedal Navigation: Proficiency in bipedal locomotion has naturally progressed to advancing humanoid robots' ability to effectively navigate complex environments, including indoor and outdoor areas with uneven terrain and dynamic obstacles. A navigation stack often incorporates a hierarchical structure: a global path planner and a local step planner. The global path planner [40, 41, 42, 43, 44] is typically responsible for understanding the overall navigation task and generating a path that avoids obstacles and reaches the target location. On the other hand, local step planners, *e.g.,* [45, 46, 47] focus on determining the precise foot placements that adhere to the bipedal dynamics within the immediate surroundings of the robot while also tracking the global path.

From the aforementioned navigation stack, bipedal navigation capabilities have progressed from static obstacle avoidance on flat terrain [48] to more challenging scenarios, including locomotion through height-constrained space [43, 49], avoiding dynamic obstacles in a constrained environment [50], navigating dynamic social environments [51], and traversing rough terrains [40, 41, 42, 52, 53, 54]. A persistent challenge for these methods is that they are tailored to specific use case scenarios and lack the versatility to handle a wide range of different situations.

While bipedal locomotion and navigation have been widely studied, real-world deployment remains a significant challenge due to inherent uncertainties. Uncertainty can arise from the environment and the robot model. Real-world environments have uneven, varying terrain, dynamic obstacles, and occlusion, making it difficult to ensure the safety and robustness of bipedal navigation. On the other hand, model uncertainty arises from discrepancies in the mathematical representation of the robot model and the physical system. Model uncertainty also exists in most current navigation frameworks that employ reduced-ordered models at the high level for collision avoidance and goal-reaching tasks and a full-order model at the low level for tracking high-level commands. A coupled framework that considers both the navigation task and whole-body control stability and accuracy is still under-explored. Although previous works have addressed various aspects of environment uncertainties [55] and model uncertainties [56], a comprehensive navigation stack capable of handling the full spectrum of real-world uncertainties is still essential.

C. Whole-body Manipulation

Anthropomorphic manipulation has been the inspiration for bimanual manipulation [57], loco-manipulation, and dexterous manipulation [58]. The ultimate form of anthropomorphic manipulation is whole-body manipulation, referring to the ability to manipulate objects using any part of one's body. For example, humans use their elbows or hips to hold a door open for convenience; humans use their palms or fists instead of fingertips to provide large forces; humans curl their little fingers to hold a small object while still using other fingers for manipulation. In comparison, most robots often have predefined end-effectors, such as foot soles or fingertips, as the only parts allowed to physically interact with the world. Whole-body manipulation is a grand problem that shares challenges in bimanual manipulation, loco-manipulation, and dexterous manipulation. This general ability has yet to be developed, but its emergence will indicate a breakthrough for robotic manipulation.

The idea of whole-body manipulation was originally studied in the whole-arm manipulation community [59]. Whole arm manipulators were designed and built to explore the benefit of manipulating objects with all surfaces of a robot manipulator [60]. This brings a unique challenge that manifests itself in all the system levels in perception, estimation, planning, and control. Since there are an infinite number of such contacts, the planning complexity suffers from the combinatorial explosion of contact modes [61] and exponential computational costs from the high degree of freedom of the system [57].

TABLE I
TAXONOMY OF WHOLE-BODY LOCOMOTION AND MANIPULATION

	(a) Whole-body Manipulation	(b) Whole-body Loco-manipulation	(c) Loco-manipulation
Object movement (Manipulation)	✓	✓	✓
Robot self mobility (Locomotion)	✗	✓	✓
All surface interaction (Whole-body)	✓	✓	✗

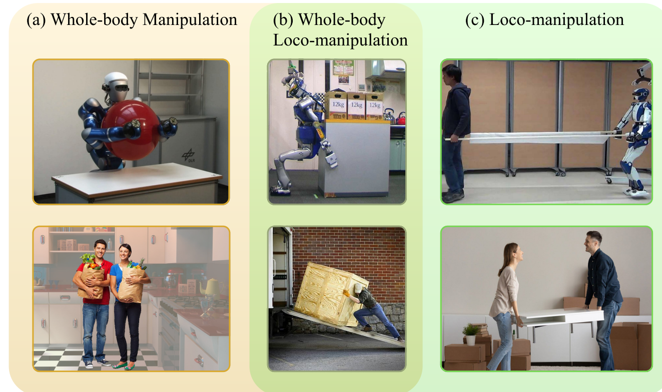

Fig. 3. (a) Whole-body manipulation exemplified by human and humanoid Justin [69] interacting with objects using all surfaces. (c) Loco-manipulation involves simultaneous locomotion and manipulation, as shown in the collaborative tasks performed by humans and a humanoid [28]. (b) Whole-body loco-manipulation is an intersection of (a) and (c), as exemplified by a human and a humanoid HRP-4 [70] pushing heavy objects using their legs and arms.

Numerous breakthroughs in mechanical design, control, and planning have been achieved in the endeavor to address the challenges of whole-body manipulation. On the mechanical design side, robots made with soft materials and full-body sensing, such as Punyo [62], provide whole-body manipulation capability in a built-in manner.

For control, the coordinative and contact-rich nature requires forceful and compliant control. Traditionally, robot arms were hard-coded to switch across different control strategies according to task requirements [57]. Different task requirements, such as reaching a point or wiping a table, require different control strategies, such as pure position control or hybrid force position control. However, it is still unclear how to define and enumerate the control strategies for whole-body manipulation. In addition, a general control framework that can take in the sensor data, perform state estimation, and reactively control each body contact has yet to exist [63]. Such general frameworks require innovations in advanced hardware and algorithm architecture, including whole-body sensing [64] and robot designs with compliance and force control capabilities for reactive manipulation [65].

From the planning perspective, the challenge of whole-body manipulation can be potentially alleviated via human behavior imitation algorithms [66, 67, 68]. Most of these works focus on simple manipulation strategies such as whole-body grasping and pushing. To enable the robot to mimic more complex human whole-body manipulation behaviors, it is important to address the cross-morphology gap between humans and humanoids.

To achieve humanoid whole-body manipulation, full-stack system integration at all system levels is crucial. In the future, we expect to see hardware advances in whole-body sensing, compliant materials, and force-transparent mechanism design. Significant improvements on the algorithm side will also be needed. While classical planning and control approaches suffer from huge complexity issues, pure learning methods lack the flexibility to react to contacts and adapt to different tasks. We foresee that the solution will be an integrated approach, which combines the strength of both. Ultimately, this could lead to more complex, human-like capabilities in humanoid robots, merging improved control, adaptive learning, and comprehensive sensing. Furthermore, addressing the core issues in loco-manipulation will also shed light on whole-body manipulation, as both areas involve handling complex, contact-rich interactions on different body parts.

D. *Loco-manipulation*

One of the key features of humanoid robots is their ability to simultaneously perform locomotion and manipulation (abbreviated as loco-manipulation hereafter) tasks. As suggested by its name, loco-manipulation involves both the movement of objects through manipulation and the mobility of the robot self through locomotion. In a more general case of *whole-body* loco-manipulation, the *whole-body* refers to the use of all body surfaces to interact with the environment. We summarize the relationship between loco-manipulation, and whole-body manipulation in Table I. Both whole-body manipulation and loco-manipulation highlight the importance of utilizing physical contact. As shown in Fig. 3, loco-manipulation considers the movement of the robot itself while it manipulates an object, whereas whole-body manipulation emphasizes leveraging all accessible robot contact surfaces, such as using the chest as extra support to move large objects.

Loco-manipulation capability has been widely demonstrated on quadruped robots, specifically those achieving loco-manipulation capability by using their limbs as manipulators [71, 72, 73]. For quadrupeds with upper-body manipulators, whole-body control is widely adopted for pick and place tasks from the model-based [74, 75] and learning-based community [76, 77].

Loco-manipulation for humanoid robots is particularly challenging, compared with quadrupeds. Humanoid robots have a smaller support region on the ground and a higher center of mass, which is challenging for dynamic balance. Therefore, early humanoid frameworks focus on separate control for locomotion and manipulation. For example, in locomotion tasks, most studies constrain the upper body to remain upright, which simplifies the whole-body problem to a bipedal locomotion problem that considers only the low limbs. Conversely, in most table-top manipulation tasks, the lower body of the humanoid remains stationary [78, 79]. In such cases, any external force exerted on the upper body is treated as a disturbance to the legs, whose goal is to solely maintain balance. On the contrary, in [1], there is no such categorization of contacts: all contacts contribute simultaneously to achieve the task and balance.

Humanoid loco-manipulation requires a holistic and strategic use of the entire body to explore the humanoid's full behavioral capability space. Additionally, whole-body loco-manipulation needs to schedule contact for all limbs to simultaneously achieve robust movement and safe object interaction. Acquiring this technique unlocks a broad range of useful tasks such as opening doors [80, 81], pushing trolleys [82, 83], rolling large bobbins [84], or climbing ladders [85, 86].

Discussion: From the planning and control perspective, should we design a unified framework for humanoid robots to achieve agile locomotion and dexterous manipulation simultaneously, or treat them as separate problems in a hierarchical framework? A unified framework generates coherent whole-body motions, similar to how humans move and manipulate objects. The unified framework would allow simultaneous optimization of locomotion and manipulation, adapting to a wider range of tasks without needing to switch between modes. Considering a hierarchical framework might seem a modular solution since each layer can be optimized independently, the overall framework accommodates new tasks or modifications easily. The main downside is the lack of mutual awareness between layers. For example, if the locomotion layer does not account for manipulation needs (*e.g.*, positioning the robot for optimal reach), the overall performance may be suboptimal.

III. Tactile Sensing

Humanoid locomotion and manipulation involve extensive physical interactions with the environment and objects, requiring multimodal sensing for understanding the environment, tracking manipulated objects, and evaluating how contact impacts the balance of both the robot and the objects. Visual sensors have shown effectiveness in object tracking and simultaneous localization and mapping (SLAM) [84], while proprioceptive sensors are usually combined to estimate contact information in contact-rich tasks [80]. These sensory modalities have been widely adopted in existing systems and have been thoroughly reviewed in the literature [12]. This survey complements existing research by focusing on a less explored but equally critical sensing modality: tactile sensing.

Mimicking the human sense of touch, tactile sensing provides more accurate and comprehensive contact information over large areas of robot skin compared to proprioceptive sensors [87], and allows the robot to perceive complex environments and assess object properties through physical interactions, especially in scenarios where vision is occluded [88]. Additionally, tactile sensing can be used to estimate contact-based object properties such as roughness, texture, and weight, complementing traditional visual information such as location, shape, and color [89]. A combination of tactile with other sensory modalities can significantly enhance humanoid perception capabilities in solving complex loco-manipulation tasks.

Numerous studies have developed tactile sensors based on various transduction principles that can sense normal and tangential forces, vibration, temperature, and pre-contact proximity information. Comparative studies of various sensor designs can be found in [90, 91, 92]. This survey instead focuses on their application in humanoid loco-manipulation, categorized into three areas: (i) tactile sensing on hands, (ii) tactile sensing on foot soles, and (iii) whole-body tactile sensing. The following sections review recent advancements in each domain, emphasizing their roles in balancing control, scheduling contacts, and enhancing interaction capabilities, as illustrated in Fig. 4.

Fig. 4. Tactile sensing on humanoid robots, exemplified by (a) REEM-C fully covered with artificial skin [64] (image copyright: A. Eckert), which cover three body regions: hand, feet, and the whole body. (i) Hand tactile sensors demonstrated by (b) Shadow-Dexterous-Hand equipped with tactile sensors on palm and fingertips [93], (c) Allegro Hand equipped with DIGIT sensors [94], and (d) BioTac [95] tactile sensors for dexterous manipulation; (ii) Tactile sensors on foot soles for (e) obstacle recognition [96] and (f) terrain classification [97]; (iii) Whole-body tactile sensors for (g) whole-body manipulation by Punyo-1 [62] and whole-body human-robot interaction by (h) iCub [98] and (i) REEM-C [99, 100]

A. Tactile Sensing on Hands

Tactile sensors on dexterous hands provide contact information, addressing the challenges in object manipulation such as grasped object controllability and object property estimation. In this subsection, we survey studies that integrate tactile perception into the control, planning, and learning of complex manipulation tasks. Due to the similar nature of contact-rich interactions, the tactile sensing techniques on hands also offer valuable insights for whole-body tactile sensing and manipulation, which is discussed in Sec. III-C.

To achieve the grasping objectives, sensed contact forces serve as real-time feedback in force or impedance control loops to regulate the desired object behavior [101]. Moreover, slip detection and prediction based on tactile sensor data are used to adapt grasping forces, thereby enhancing grasp stability [102, 103, 104].

More complex in-hand manipulation tasks demand interactive perception beyond static object models. Dynamic contact information, including real-time tracking of object states, monitoring contact stability [105], and predicting interaction outcomes [94], *i.e.*, how contact forces affect the balance of both objects and the robot, are crucial to achieving complex interactive behaviors. However, due to the inherent complexity of multi-contact dynamics and increased dimensionality of the contact state space, model-based methods still struggle to match human-level dexterity and versatility in multi-finger manipulation.

Alternatively, model-free Reinforcement Learning (RL) has shown the ability to address complex contact interactions. These approaches integrate tactile measurements directly into the state space to train end-to-end policies [93, 106]. Tactile-based RL faces two main challenges: (i) the high-dimensional input space of raw tactile sensor data and (ii) the difficulty of accurately simulating contact physics for sim-to-real transfer. To tackle these challenges, dimensionality reduction techniques such as spectral clustering, principal component analysis [107] and autoencoders [108] have been explored, while [93] employs Deep Reinforcement Learning (DRL) to manage high-dimensional input space. Moreover, there have been increasing efforts in developing tactile simulators [109, 110] to improve the accessibility of simulated tactile data and facilitate zero-shot sim-to-real transfer [111].

Besides task-specific RL, other learning methods have been sought for more generalizable policies. [112] employs diffusion policy to achieve complex and long-horizon bi-manual manipulation tasks, while recent work has integrated tactile sensing into foundation models alongside vision and language [113, 114]. Though limited to simple control tasks, these models may eventually enable more natural and versatile physical interactions in humanoid robots.

Advancing robot hands with tactile sensing for humanoid tasks requires addressing the dual demands of high dexterity for delicate manipulation and high payload capacity for heavy object lifting. While human hands naturally achieve this balance, most robotic hands prioritize dexterity but support limited payloads. In the short term, swappable modular hands tailored to specific tasks are practical, but the long-term goal should be a unified hand combining both capabilities. A promising approach involves multimodal sensing modules, integrating sensors optimized for different force ranges and resolutions. Progress in sensor design, material science, sensor fusion, and high-fidelity simulation is critical to this effort.

B. Tactile Sensing on Feet

Besides manipulation, tactile sensing has started to gain traction for locomotion problems. For legged locomotion, estimation of Ground Reaction Forces (GRFs) and terrain properties is critical for maintaining whole-body stability on diverse, uneven surfaces. While vision and proprioception sensors can provide an indirect estimation of the terrain, these sensing modules lack the capability of accurately estimating GRFs and various terrain properties. Tactile sensing on foot soles has the potential to provide direct, unobstructed, and accurate contact measurements, but remains largely underexplored.

To measure GRFs, existing works use Force/Torque sensors mounted on ankles [115, 116] or load-cell sensors for point-wise measurement [117]. However, such methods inform only the zero moment point and lack accurate information on contact patch location, force distribution, and detailed terrain properties. To obtain such information, contact sensing arrays [118] and multimodal sensing suites [97, 119, 120] have been integrated into legged robotic systems for diverse contact information.

To date, tactile sensors for legged systems have been mainly applied for monopods, quadrupeds, and hexapods, enabling the functionalities of classifying terrain [121, 122, 123], detecting contact forces and soil flow [124], detecting contact angle [125] and type (*e.g.*, surface, edge, or no contact) [126, 127], and estimating 3D pressure distribution [123].

Building tactile sensors for humanoid feet is more challenging due to larger impulse and shear force during intermittent ground contact caused by fewer legs and heavier robot weight. Another challenge lies in developing robust and reliable sensors capable of withstanding various terrains, prompting researchers to seek durable materials and dependable mechanical designs. In addition, humanoids have stricter requirements for system integration. For example, the computing and power units of an adult-size humanoid robot are potentially more distal from the foot.

Few studies have built tactile sensors for humanoid robots. These sensors are mostly used for applications including terrain classification [97, 128] and ground slope recognition [118]. The sensed tactile information should aid the control of humanoid dynamics and enhance the locomotion performance. A notable work in this direction [96] reconstructs the pressure shape of the foothold, enabling the recognition of uneven terrain and replanning footsteps in real time.

To enable robust humanoid locomotion in the wild, future directions for tactile sensing of feet need to address the following challenges: (i) how to accurately estimate more terrain properties such as stiffness, damping, plasticity, heterogeneity, and porosity; (ii) what are the appropriate metrics to measure the level of terrain complexity such as density, height, slickness, and roughness (*e.g.*, size and wavelength of rocks in terrain), and the effect induced by weather and lighting conditions (*e.g.*, rainy, snowy, sunny, night); and (iii) how to fuse terrain tactile sensing with other conventional sensing modules such as proprioception and visual perception to jointly inform postures, speeds, and gaits for intelligent, terrain-aware locomotion.

C. Whole-body Tactile Sensing

Whole-body tactile sensing extends the aforementioned single-body sensing to all parts of the body, enabling humanoid robots to interact with unknown environments not only by the fingertips or foot soles but also by the arms, legs, and torso.

With explicit tactile feedback, humanoid robots such as iCub and REEM-C have achieved whole-body compliance [99, 129], controlling the contact force from whole-body regions. This level of contact awareness facilitates safe and intuitive physical human-robot interactions including dancing with human [100]. Contact awareness is also useful for improving balance and collision avoidance in unstructured environments.

Large-area tactile sensing significantly enhances a robot's ability to handle *large* objects, including object identification through tactile exploration and whole-body manipulation. For example, [130] enable a humanoid robot NAO, covered with artificial skin over its entire upper body, to classify large, heavy objects with different weights and textures. [88] demonstrate whole-arm tactile sensing by reaching objects in cluttered spaces while regulating contact forces across its arms. Close-proximity whole-body capacitive sensing is implemented in [131], enabling a cobotic humanoid with workers close-presence awareness. The same technology is used to draw semantics in human-humanoid physical interaction in [132]. Moving away from traditional methods [133] that prioritize collision-avoiding trajectories, [134] utilize tactile feedback to detect and clear movable obstacles, thereby solving the problem of navigation among movable objects. Additionally, with tactile sensors covering their arms and chest, humanoid robots HRP-2 and Punyo-1 can use their entire upper body to grasp and lift large, heavy boxes [135, 136] or various household items [62].

However, current works of tactile-based whole-body manipulation are still limited to grasping or simple pick-and-place motions with the upper body. This is due to the significant challenges of whole-body manipulation, as discussed in Sec. II-C, including understanding the complex contact dynamics of multiple contacts, handling the high dimensionality of the sensor data, and addressing the sim-to-real gap.

Despite the promising potential that tactile sensors provide, human-like loco-manipulation with more dynamic interactions and contact shifting, such as transferring weight to one arm to free the other for tasks like opening a door, requires sophisticated integration of all system levels in perception, planning, and control. A major challenge in tactile perception, and a hurdle for a tight integration with planning and control, is the difficulty in dynamically reasoning about contacts. This involves not only estimating contact points and static object models but, more crucially, understanding how these contacts and changes of contacts impact the system in real-time, including the balance of both the robot and the object. Such information is vital for a planner to make informed decisions and, in a learning framework, can enhance sample efficiency.

Conclusion: Tactile sensing is yet an underexplored modality for advancing humanoid loco-manipulation, providing direct contact information necessary for tasks involving complex interactions with environments and objects. While tactile perceptions have significantly enhanced humanoid tasks, achieving human-level dexterity and versatility remains challenging, requiring further research into dynamic perception, and multimodal sensing integration to enable systematic, real-time decision-making during interactions. This includes optimizing contact scheduling on whole-body based on object properties like size and weight, and understanding how contact dynamics affect robot and object balance during simultaneous loco-manipulation. Moreover, the design of whole-body tactile systems should account for varying sensor resolutions and load requirements, *i.e.* hands need higher resolution for delicate tasks, while body skin can operate at lower resolution but withstand higher payloads. For further reading, we recommend a survey paper on humanoid tactile sensing [90], and a book chapter on tactile sensing technologies with an emphasis on deployment on humanoid robot [137].

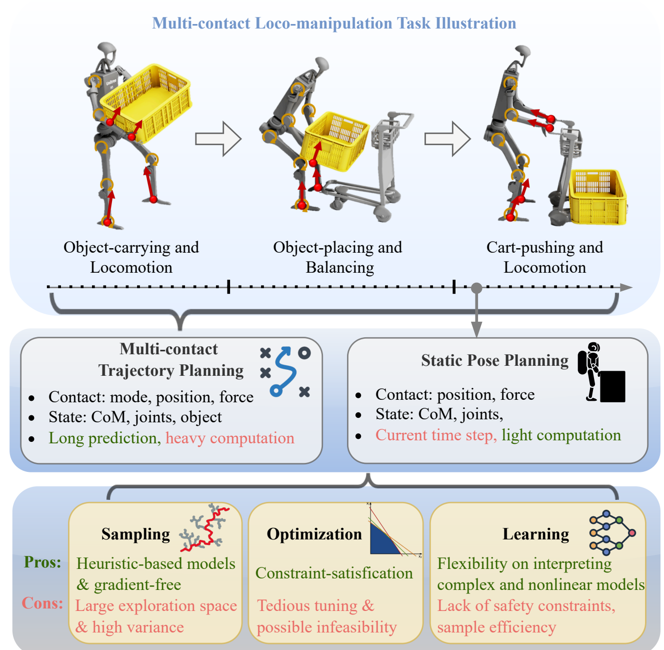

Fig. 5. An illustration of a task sequence for loco-manipulation planning in humanoid robots, involving carrying and placing a box and pushing a cart. The planning techniques explored include (a) multi-contact trajectory planning and (b) whole-body pose planning, highlighting their contact and state planning strategies. Additionally, the pros and cons of categorized approaches in (i) sampling-based, (ii) optimization-based, and (iii) learning-based methods are summarized.

IV. Multi-Contact Planning for Humanoids

Multi-contact planning remains one of the most challenging tasks in robotics. Specifically, in the context of humanoid whole-body loco-manipulation, a planner ought to solve trajectories that handle rich interactions with environments or objects. Particularly, besides robot state trajectories, the planner is also expected to decide *contact position* (or *contact location*), *contact mode*, and *contact force* in a loco-manipulation task. Given the underactuated nature of humanoid robots and the addition of manipulation interaction dynamics, maintaining balance and manipulating objects rely solely on these contact interactions, which already makes multi-contact planning a challenging problem. Moreover, the diverse physical properties of environments and objects (*e.g.*, rigid or soft, fixed or movable) complicate the problem even further.

Over the past decade, the field has produced fruitful results in multi-contact humanoid planning, demonstrating promising potential across various locomotion and manipulation tasks [3, 138, 139, 140]. However, these works require pre-planned contact mode sequences before planning robot whole-body motion trajectories [141], leaving an open problem: how to solve the locomotion and manipulation contact planning problem simultaneously with the whole-body trajectory planning in a unified fashion, *a.k.a*, Contact-Implicit Planning (CIP) [142, 143]. The primary challenge of this CIP lies in its high computational burden and combinatorial complexity

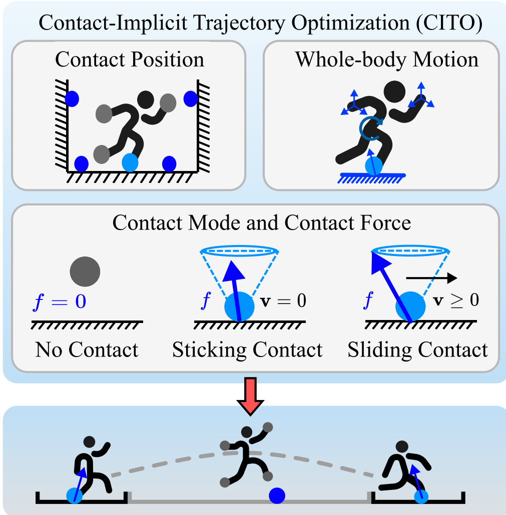

Fig. 6. An illustration of Contact-Implicit Trajectory Optimization (CITO) that simultaneously plans contact mode, contact position, contact force, and whole-body motion. However, solving CITO problems online for humanoid loco-manipulation tasks still poses a challenge.

of identifying potential contact mode sequences. Therefore, selecting suitable approaches depends on the specific problem requirements, including factors such as solving time, numerical robustness of the solution, resolution of the solution, and dependency on numerical models.

To choose appropriate multi-contact planning algorithms for a high degrees-of-freedom underactuated system, state-of-the-art approaches present three main categories: (i) searching, (ii) optimization, and (iii) learning, as illustrated in Fig. 5.

A. Search-based Contact Planning

Search-based approaches employ state expansion that allows exploring configurations to make and break contacts; collisions and kinematic feasibility are often checked during each search step. Heuristics can be applied in search-based methods for efficient exploration. The search result is an optimal sequence of contact modes that ensure stability and task efficiency. Whole-body motions can be optimized during the search to verify the dynamic feasibility of candidate contact sequences [144] or after the search in a *contact-before-motion* style [145]. Search-based methods are commonly used for gait planning in legged robot locomotion [146, 147, 148, 149]. Expanding their capabilities in more intricate multi-contact loco-manipulation planning, [150] implement a graph search method for humanoid grasp contact planning and replanning. [151] introduce a contact-before-motion planner for multi-contact behaviors.

However, search-based methods usually struggle to cover the entire exploration space in a limited time budget for online planning and may result in solutions with high variance. To tackle this, [152] incorporates control variate and importance sampling as statistical variance-reduction techniques for faster solution convergence. [153] avoids the time-consuming replanning by incorporating only forward path expansion with informed possible paths to achieve reliable online kinodynamic motion planning.

Furthermore, the feasibility guarantee of the results via search-based methods can be made through Pose Optimization (PO), a subset of multi-contact planning in humanoid loco-manipulation. This holds true when the contact locations, timings, and manner of interaction are predetermined—such as in scenarios where a humanoid safely assists a person [140] with feasible contact locations through point cloud processing. PO focuses on leveraging optimization-based techniques to plan whole-body poses and kinematic configurations at specific time steps, given a predefined contact mode. While PO is limited to handling discrete keyframes and does not account for continuous dynamics, this makes it highly suitable as a subsequent pose generator for gradient-free multi-contact planners, reducing the kinematic computation load during the search process. Furthermore, task-oriented objectives can be incorporated during PO, such as to maximize the interaction force [154, 155] and to efficiently retarget the operator's motion into safe and feasible robot poses [156]. Given a nominal pushing pose, Farnioli et al. [157] optimizes the distribution of reaction forces among all contacts to guarantee the friction constraints in heavy object pushing. Kinematics-and-mass-model-based posture generator is employed on HRP-4 humanoid to leverage leaning pose and body contacts to improve force in a heavy object pushing task [70]. A kino-dynamics-based PO approach is used in generating optimal humanoid pushing poses for dynamic non-prehensile loco-manipulation [158]. Search-based multi-contact planning and PO are often paired with online whole-body control that effectively tracks the optimal pose while adaptively interacting with the environment and objects. We detail the whole-body control strategies in Sec. VI.

B. Optimization-based Contact Planning

Unlike search-based contact planning, which primarily checks kinematic feasibility for expansion and often requires additional lower-level planning to generate dynamically feasible motion, optimization-based contact planning [142] offers the possibility of *simultaneous* planning of whole-body motion and contact interactions, as illustrated in Fig. 6. This approach integrates dynamics directly into the contact planning process, eliminating the need for a hierarchical structure. A Contact-Implicit Trajectory Optimization (CITO) is formed by incorporating contact dynamics into the trajectory optimization formulation, allowing the solver to determine the contact modes, contact forces, contact positions, and whole-body motions all at once [159, 160, 161].

Due to the inherently large problem size, CITOs often rely on speed-up strategies, such as warm-starting with reasonable initial guesses for fast convergence [162] and separating into contact planning and whole-body motion planning subproblems in a hierarchical fashion [163]. With the increasing demand for computation efficiency, CITOs have witnessed a rise in computation speed via sequential quadratic programming (*e.g.*, [142]), differential dynamic programming (*e.g.*, [164]), and iterative linear quadratic regulator (*e.g.*, [165]). These improvements have even enabled the use of CITO in a Model Predictive Control (*a.k.a.* CI-MPC) framework for real-time planning on quadruped robots [166, 167] and robotic arms [168, 169]. However, for the humanoid robots, applying CITO to loco-manipulation has yet to be achieved.

Migrating such CITO as real-time CI-MPC to humanoid loco-manipulation problems presents its own set of challenges, including high-dimensional space of optimization variables, complex/undifferentiable contact dynamics models, proper modeling of interaction dynamics, resolution of initial guess, and tedious tuning. Although the body of literature on CITO and CI-MPC for humanoid robots is quite limited, recent efforts have demonstrated viable strategies for accelerating such methods. To achieve real-time CITO in multi-contact humanoid motion generation, [164] improves the *time stepping* integrator-based method [170] by introducing a smooth-max function to approximate the contact impulses. [171] incorporates dynamic complementarity conditions in the rigid contact model and improved solving time in contact implicit humanoid locomotion problems. [166] leverages structure exploitation and offsets the time-consuming Linear Complementarity Problems (LCPs) by pre-computing its constant terms offline for improved online computation efficiency.

Furthermore, the potential to harness and combine the advantages of search-based and optimization-based methods remains largely unexplored. For example, [172] enhanced CITO by incorporating a graph-search-based contact sequence generator and neural-network-based capturability prediction for efficient and robust disturbance rejection in humanoid multi-contact locomotion. To improve the robustness of CITO, [173, 174] also show that considering the uncertainty in the optimization results in solutions robust against perturbation from the terrain contact.

C. Learning-based Contact Planning

In addition to search-based and optimization-based methods, learning-based approaches have demonstrated promising potential in planning for multi-contact tasks, such as using reinforcement learning to plan for velocity commands and contact sequences [175, 176]. These learning-based planners are mostly modular, making it possible to form a hierarchical architecture with model-based planners and controllers at the low level. Compared with traditional optimization-based or heuristics-based approaches, learning-based elements enhance the computation efficiency in multi-contact planning. For example, [177] learn a prediction of centroidal dynamics evolution for efficient contact sequence generation under 0.1 s, allowing a 300 times computation speed boost compared to traditional optimization-based methods.

In addition, learning-based approaches can assist contact prediction, which allows additional information for contact (re)planning in real time. Precise contacts are often hard to obtain from motion capture data, making it challenging to learn directly from data. To synthesize plausible motion, a naive supervised learning approach often leads to objects moving without any contact or significant penetration between the predicted human body and the objects. [178] introduced contact correction and predicts motions relative to the contacts predicted. [179] separate the contact prediction and whole-body motion prediction by first predicting the contact positions of a moving object, which are then used as a constraint to synthesize whole-body motion. These models have the potential to serve as a loco-manipulation planner for humanoid robots. [180] learn to find from the video scenes the affordance (*i.e.*, potential contact points for task execution). These contacts can be used as heuristics for subsequent motion planning.

Conclusion: While significant progress has been made in humanoid multi-contact planning, future work should focus on developing more integrated approaches that combine the strengths of search-based, optimization-based, and learning-based methods. Specifically, addressing the computational complexity of CIP and improving real-time performance will be key. Future directions could explore hybrid approaches that incorporate efficient contact sequence generation/contact dynamics, apply contact-implicit constraints in real-time, and achieve learning-based contact prediction to enhance robustness and adaptability in complex loco-manipulation tasks. The readers are recommended to further read the survey on humanoid multi-contact planning [141].

V. Model Predictive Control for Loco-manipulation

Optimization-based Model Predictive Control (MPC) has advanced significantly in robotics. The advantages of its flexibility to define versatile motion objectives, rigorous mathematical formulations, and widely available solvers establish MPC as one of the most popular approaches to trajectory planning for locomotion and manipulation.

A uniform optimization formulation of the loco-manipulation planning problem seeks an optimal state trajectory and control input over a finite horizon in the future. MPC is often formulated as an Optimal Control Problem (OCP):

$$\min_{\boldsymbol{x}(\cdot),\boldsymbol{u}(\cdot),\boldsymbol{\lambda}(\cdot)} \quad \mathcal{L}(\boldsymbol{x}(\cdot),\boldsymbol{u}(\cdot),\boldsymbol{\lambda}(\cdot)) \tag{1}$$

$$\text{s.t.} \quad \dot{\boldsymbol{x}}_k = f(\boldsymbol{x}_k,\boldsymbol{u}_k,\boldsymbol{\lambda}_k) \tag{2}$$

$$h_{\text{task}}(\boldsymbol{x}_k,\boldsymbol{\lambda}_k,\boldsymbol{u}_k) = 0 \tag{3}$$

$$g_{\text{task}}(\boldsymbol{x}_k,\boldsymbol{\lambda}_k,\boldsymbol{u}_k) \geq 0 \tag{4}$$

where $\boldsymbol{x}(\cdot),\boldsymbol{u}(\cdot),\boldsymbol{\lambda}(\cdot)$ are the trajectories of the states, control inputs, and constraint forces, respectively. $\mathcal{L}(\cdot)$ is the cost function. The dynamics is represented in (2). h_{task} and g_{task} are other tasks represented as equality and inequality constraints. h_{task} are holonomic constraint tasks to be enforced strictly (*e.g.*, a contact-explicit formulation [181]), and g_{task} are unilateral constraints to encode set-valued tasks (*e.g.*, joint limits, non-sliding contact with fiction cones, etc.).

Depending on the choice of dynamics models (2), costs, and constraints, the OCP formulation is commonly transformed as a linear convex MPC (*e.g.*, [2, 181]) or a Nonlinear MPC (NMPC) (*e.g.*, [182, 183]). Table II summarizes recent MPC-based works on humanoid robots in loco-manipulation tasks.

A. Simplified Models

In pursuit of high-frequency online planning with lightweight computation for motion control, simplified dynamics models, or reduced-order models (ROMs) are often

TABLE II
RECENT MPC APPROACHES ON HUMANOID LOCO-MANIPULATION

Paper	Robot Model*	Interaction Modeling Method	Locomotion (*L*) and Manipulation (*M*) Planning	MPC Frequency	Solving Method
[185]	SRBM	Optimizing external wrench(es) at contact(s)	Unified	20 Hz	QP
[2]	SRBM	Predefined external force	Unified	300 Hz	QP
[186]	SRBM	Negligible object dynamics	Separated: *L*: MPC; *M*: Keyframe interpolation	–	QP
[187]	LIPM	Negligible object dynamics	Separated: *L*: MPC; *M*: Retargeting through teleoperation	–	QP
[117]	CD	Optimizing external wrench(es) at contact(s)	Unified	offline	SQP
[28]	CD	Predefined external wrench	Unified	–	QP
[188]	CD	Optimizing external wrench(es) at contact(s)	Unified	5 Hz/offline	SQP
[189]	CD	Optimizing external wrench(es) at contact(s)	Unified	10 Hz	Interior-point
[183]	CD	Estimated as external wrench through sensors	Unified	5 Hz	Interior-point
[190]	WBD	Optimizing external wrench(es) at contact(s)	Unified	100 Hz	DDP

* SRBM - *Single rigid-body model*; LIPM - *Linear inverted pendulum model*; CD - *Centroidal dynamics*; WBD - *Whole-body dynamics*.

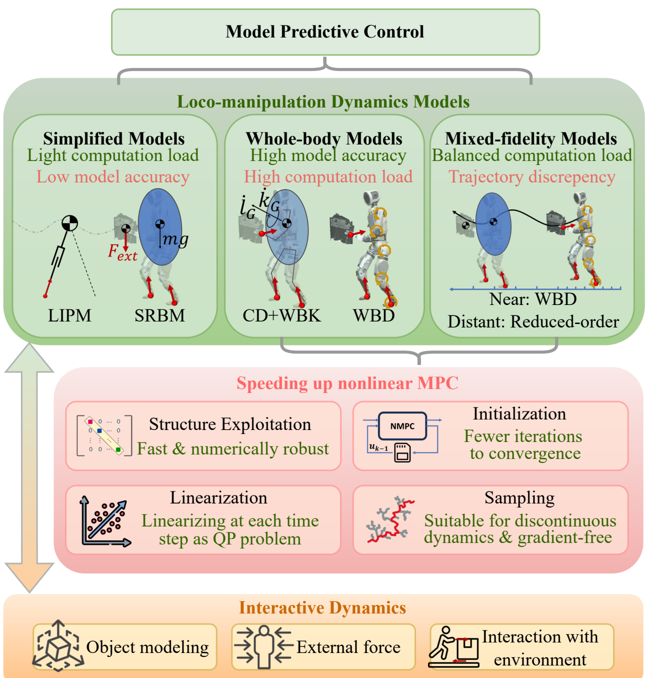

Fig. 7. An illustration of model predictive control in humanoid robotics, showcasing three primary categories of dynamics modeling in loco-manipulation: (i) simplified dynamics, (ii) nonlinear dynamics, and (iii) Mixed-fidelity dynamics. The figure also highlights the consideration of interactive dynamics modeling with environments and/or objects for loco-manipulation tasks. Additionally, four common approaches to speeding up/simplifying NMPC are summarized.

employed in MPC. For example, the Single Rigid Body Model (SRBM) can be linearized by providing explicit foot position sequence reference and be formulated in a linear convex MPC [184]. Using SRBM, [181] realizes dynamic aerobatic behaviors on the MIT humanoid. Extending to humanoid loco-manipulation, [2] achieves object-carrying and rough terrain locomotion by simplifying the interaction dynamics as external gravitational forces applied to robot CoM.

On the other hand, the Linear Inverted Pendulum Model (LIPM) has been a popular choice as a linearized dynamics model for humanoid locomotion [23] and in multi-contact [191]. To further extend the capability of rough terrain walking, the Prismatic Inverted Pendulum Model (PIPM) is used to allow CoM movements on a non-flat surface [192, 193]. Extending LIPM to loco-manipulation tasks is achieved through teleoperation [187]. However, such model inherently lacks the ability to address contact interactions and loco-manipulation dynamics, necessitating a lower-level whole-body control for balancing and manipulation tasks.

B. Whole-body Models

While simplified dynamics models offer computation efficiency, they often lack model accuracy and have limited capability of whole-body motion planning due to high simplification assumptions. Conversely, whole-body models are more accurate representations of the robot dynamics and are better suited for planning versatile motions and interactions with objects and the environment. NMPC comes into play when constraints or cost functions become nonlinear, for example, dynamics constraints formed by kinodynamics and Whole-Body Dynamics (WBD).

In the context of humanoid motion planning, kinodynamic constraints are often referred to as the combination of Centroidal Dynamics (CD) and whole-body kinematics (WBK) constraints [188], where CD is derived from the total momenta of the system, and captures the effect of full-body inertia of a multi-linkage dynamics system [194]. For example, achieving consensus between CD and full-body kinematics in one Trajectory Optimization (TO) generates versatile humanoid motions [188].

On the other hand, leveraging the WBD in MPC has become a popular approach recently. Joint-space WBD, described in (5), accurately models a free-floating articulated robot such as a humanoid robot. WBD provides flexibility in defining arbitrary and allowable contact in dynamics modeling, including interaction forces through manipulation. However, the inherent high nonlinearity and nonconvexity impose significant computational burdens on WBD-based Nonlinear Programs (NLP), making them challenging for real-time planning. The numerical accuracy of solutions is often compromised to exchange for real-time application (*e.g.*, [6]), even with accelerated solving methods for NLPs (*e.g.*, Sequential Quadratic Programming (SQP), Differential Dynamic Programming (DDP)). This computation issue is pronounced in high-degree-of-freedom humanoids performing loco-manipulation tasks, such as human-robot payload transportation, that demand additional modeling of object dynamics, safety-critical control, and robust trajectory solutions. Therefore, a major focus of this section is the discussion of different approaches to speed up NMPC while maintaining its solution accuracy.

C. Mixed-fidelity Models

Instead of using full joint-space dynamics across the entire horizon of an MPC, mixing multiple models of varying abstraction levels demonstrates improved performance and efficiency.

As one way to mix models, cascaded-fidelity models (*a.k.a.* hierarchical dynamics) use different models to govern different segments of the horizon [195, 196, 197]. These methods typically employ high-fidelity (*e.g.*, full-order) models in near horizons and low-fidelity (*e.g.*, simple) models for distant horizons, thus maintaining the solution accuracy in near horizons while solving the myopic issue by allowing a longer horizon using simple models. This approach could be suitable in loco-manipulation tasks as it would either simplify interaction dynamics as simple external forces or impose the object dynamics as part of CD in the far horizons to allow improved real-time computation compared to full dynamics models.

Another way to mix models is to have different dynamics models overlap between their horizons. In such cases, achieving a consensus between these overlapped models is necessary. To solve problems with such mixed-fidelity models, [198] decomposes a single TO that incorporates both dynamics into two subproblems and then alternates between the two to achieve consensus. In a similar vein, [199] alternate between the CD and WBK subproblems. Overall, model simplification over MPC horizons will remain an effective approach [7]. On the other hand, mixed-fidelity models demonstrate superior capability but require careful consideration of combined models.

D. NMPC Speed-up

NMPC Speed-up via Structure Exploitation: NMPC problems often involve complex dynamics and constraints that can be computationally intensive to solve. Exploiting the structure within these problems can significantly enhance their solvability and efficiency, such as extracting variables that directly interact with each other, identifying repetitive and symmetric structures, and arranging block-diagonal structures. One of the most common approaches to solving NMPC is direct methods, which transform NMPC into a Non-Linear Program (NLP) with the complexity of $O(N^3)$, where N is the problem size [200]. Some direct methods, such as direct multiple shooting and direct collocation, result in sparse NLPs, whose computation complexity can be reduced to $O(N)$ [201]. Another approach to solve NMPC is single-shooting methods, such as DDP [202] and its variant, Iterative Linear Quadratic Regulator (iLQR) [203], which only retains the first-order derivative approximation of dynamics and exhibits a linear increase in computation over the horizon [204]. With proper exploitation of the sparsity structure through the hypergraph approach, [205] shows improvement of the nonlinear solver in computation efficiency. Recently, a numerically robust solver, FATROP [206], solves constrained OCP problems in a direct multiple-shooting fashion efficiently by employing a structure-exploiting linear solver. In NMPC problems, FATROP achieves comparable solve time compared to ACADOS SQP solver while retaining similar numerical robustness to the interior-point-method-based IPOPT solver. Furthermore, AdaptiveNLP leverages the previous NLP structure to significantly reduce the overhead and update time for constructing the current NLP [207]. Due to the static nature of most inequality constraints on humanoid robots, such as joint states, actuation, and control barriers function, providing a smaller set of inequality constraints with this memory-aware and adaptive solver has the potential to accelerate humanoid loco-manipulation NMPC. As an increasingly popular approach, structure exploitation has vast potential due to the minimal trade-off in the numerical robustness of the solution.

NMPC Speed-up via Linearization: Another way to tackle computational burdens brought by NMPC is successive linearization, which involves linearization at every timestep around the nominal system state and control input. The linearized dynamics become piece-wise affine, which can be formulated in a large, sparse Quadratic Program (QP) and can be solved online [208, 209]. Aiming for highly efficient optimization-based planning, ReLU-QP [210], a GPU-accelerated QP solver, has improved MPC real-time control frequency in humanoid balancing tasks from original 65 Hz to more than 1300 Hz. Successive linearization, however, sacrifices model fidelity and inevitably results in motion errors compared to using accurate nonlinear models. In practice, trading model accuracy for speed is often a preferred strategy because a controller may not be able to track the accurate full-order trajectory with high precision, and therefore it is not practically beneficial to pursue accurate trajectories generated from the full-order, nonlinear model.

NMPC Speed-up via Warm Start: The real-time requirement motivates many researchers to seek a better initialization. One simple yet effective approach is to warm start with the solution from the previous iteration. While promising in reducing computation burden, this approach highly depends on the quality of previous solutions and is sensitive to changes in dynamics or task constraints across time steps, which are common for contact-rich, multi-task loco-manipulation. Another common approach is to offload the computation burden from online to offline, *e.g.*, the *gait library* [211]. It can be regarded as a specific type of warm-start technique and requires only a cheap online interpolation among the gaits to obtain an approximately optimal full-body trajectory. Similarly, [190] use *memory of motions* to warm-start an MPC and overcome the sensitivity of initial conditions. A proper initialization from memory usually takes only a few iterations to achieve convergence, which enables online NMPC with full-body dynamics. Combining offline memories with online planning is a promising research direction. However, the key challenge lies in the management of massive trajectories with limited storage. In Sec. VII-E, we discuss a solution from the learning community: learning compact models to distill from large-scale offline trajectories.

NMPC Speed-up via Sampling: Real-time sampling-based planning, such as Model Predictive Path Integral (MPPI) control [212], is a simple and effective scheme. However, extending MPPI to high-dimensional loco-manipulation

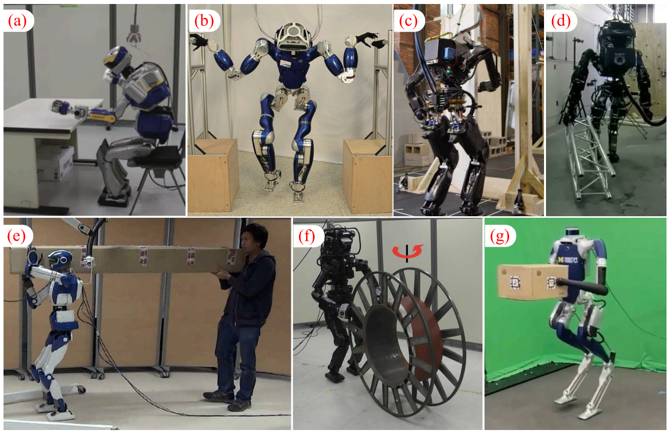

Fig. 8. Loco-manipulation skills from model-based methods. (a) Getting up from a chair [138]. (b) Multi-contact balancing [3]. (c) Door traversal [218]. (d) Transporting a bulky beam [117]. (e) Collaborative carrying [28]. (f) Rolling a bobbin [82]. (g) Box loco-manipulation [219].

tasks presents significant computational challenges, especially within contact-implicit settings. Two primary techniques have enabled the recent success of MPPI: reducing the search space and leveraging parallelization in modern simulators. To limit the search space, researchers use suboptimal planners to guide the search, apply constraints, and employ spline control points to reduce the number of planning knot points [213]. Furthermore, advancements in sampling speed also facilitate real-time planning. For instance, MuJuCo MPC (MJPC) [214] leverages the established parallelization capabilities of MuJuCo [215] on multi-core CPUs. Additionally, modern simulators such as IssacLab [216] and MuJuCo can roll out thousands of samples on GPUs, which allows additional randomization for robust control [217].

E. Environment and Object Interaction Models for Loco-manipulation

In this subsection, we survey motion planning algorithms for loco-manipulation tasks that involve interactions with the environment and/or objects with large weights and sizes, specifically in the context of loco-manipulation MPC. Assuming the sequence of contact modes is defined through contact planning methods outlined in Sec. IV, the loco-manipulation MPC algorithms find a feasible trajectory that leads to a viable state over a horizon, while satisfying the dynamics constraint and contact stability constraints. The existing loco-manipulation MPC algorithms differentiate the interaction with a fixed environment and a manipulated object.

1) Interaction with a static environment: An environment, including static surfaces such as the ground and walls, provides contact forces that contribute to the robot's stability and enable interactive tasks such as walking and pushing. An example of a static environment is in Fig. 8 (a) and (b). Since the environment is static, the robot does not need to consider the environment's state or stability during planning. Instead, the robot is often required to deal with acyclic contact patterns and non-coplanar contacts given specific environment geometries. This challenging problem is referred to as multi-contact planning (MCP) [86, 141, 220]. MCP is a widely studied area that involves both contact planning and motion planning. Since contact planning has been discussed in Sec. IV, in this subsection, we focus on the motion planning aspect of MCP, specifically in terms of real-time multi-contact MPC. Given a sequence of contact modes, MCP aims to find feasible motion and contact wrenches of all contacts.

Multi-contact MPC for humanoid robots can be solved by optimization-based methods [188, 189]. Among these methods, Centroidal Dynamics (CD) is the most common model due to its accurate representation of contact forces and the system's centroidal momentum. Despite the model's accuracy, CD contain a nonlinear term derived from the cross-product between the state (CoM position) and control (contact wrench), posing a challenge to trajectory optimization. Using multi-contact MPC as a motion planning technique also has limited dynamic locomotion capabilities because it treats arms and legs uniformly as general contacts, making it less efficient at handling frequent contact switches compared to pure locomotion models such as the linear inverted pendulum model (LIPM). Although MPC has the ability to plan contact with any surface of the robot, the regularization of the planned contact forces usually requires accurate joint torque sensing or whole-body tactile sensing (Sec. III-C), which still has significant space to explore and presents great potential for rich and safe environment interaction.

2) Modeling interaction with a manipulated object: In the context of loco-manipulation MPC for humanoid robotics, modeling strategies for manipulated objects represent a crucial aspect and an area of ongoing research, alongside contact planning. An object can be a free-floating body (*e.g.* a box), a fixed-base articulated mechanism (*e.g.* a door or drawer), or actuated joints (*e.g.* another robot) [221], as shown in Fig. 8 (c-g). Unlike interactions with a static environment, the contact force exerted by an object depends not only on the robot's joint torque but also on the object's mass and inertia. As a result, interacting with objects in loco-manipulation tasks introduces significant complexity. Planning such tasks typically requires accurate knowledge of the object's state and physical properties, especially when handling heavy, irregular, or dynamically moving objects.

To overcome the challenge of unknown object states and properties, adaptive control schemes and online estimation techniques have been proposed to improve robustness, compensating for dynamic effects and varying external loads. For instance, [222] compensate for the dynamic effects of an object as residual dynamics, thereby avoiding the need for extensive predefined object parameters. [223] estimate the robot's reflected inertia online to compensate for constantly changing external loads. [224] estimate the object's mass to select the optimal whole-body manipulation strategy for bulky objects. In addition, to address object state feedback, wide-angle camera dense tracking is proposed to aid in tracking large objects [84]. However, application to MPC-based approaches poses additional challenges in terms of prediction of compensation for the object dynamics in the preview horizons, prediction of object motion evolution, and increased density of the online computation load due to such integrations. [225] makes the initial step toward estimating and simplifying the evolution of centroidal momentum through supervised learning to maintain a convex CD-based MPC formulation in humanoid locomotion.

Given the diversity of tasks, creating a unified model for the robot-object system is essential. We introduce two common approaches to incorporate object dynamics into the MPC-based planning process [191].

The first approach models the manipulated object as external wrenches and plans the control input to compensate for them [2, 70, 189]. This approach offers a flexible solution, as it integrates well with the MPC regardless of the linearity of the MPC model, which treats all contacts as external wrenches. However, the contact wrench needs to be predefined, for example, to compensate for the gravity of the object or to exert a user-specified pushing force. Obtaining accurate contact wrenches for dynamic tasks like swinging a baseball bat is already inherently challenging, especially when considering their evolution over the entire prediction horizon in MPC. Static/quasi-static assumptions are usually made to neglect the dynamics of the object, resulting in less dynamic loco-manipulation motions. Another aspect to note, the contact wrenches can be applied at the contact location [82] or at the CoM of the robot [2, 28]. In the former setting, the object affects the contact wrenches for both self-balance and object manipulation. In the latter setting, the object affects only the contact wrenches that are responsible for balance, and contact wrenches for object manipulation require additional regulation. For example, the loco-manipulation MPC approach in [2] adjusts the foot contact wrenches to the weight of an object applied to the robot CoM and additionally regulates the object position via hand contact wrenches with a separate controller. Unlike MCP, such loco-manipulation MPC prioritizes mobility over manipulation and typically employs specialized locomotion models, such as a linear inverted pendulum model (LIPM). These models introduce additional assumptions for bipedal locomotion, such as assigning foot contact for locomotion and hand contact for manipulation, maintaining body height, and conserving angular momentum, making them computationally efficient in an online MPC setting but less general.

The second planning approach incorporates the object's dynamics directly into the robot's dynamic equation of motion, creating a unified robot-object dynamic system [158, 191]. This approach eliminates the static/quasi-static assumption from the first approach and leverages the time-varying robot-object dynamics in MPC to achieve more dynamic and adaptive loco-manipulation behaviors. In such planning problems, the interaction wrenches are usually treated as control variables, and contact stability constraint on the interaction wrenches is enforced to securely attach the object to the robot. The planner generates the combined motions for both the robot and the object, leading to their desired states. Compared to modeling objects as external wrenches, this method requires a perfect knowledge of the object's state, which is more challenging from the sensing perspective.

3) Interaction with a dynamic environment or deformable objects: Dynamically changing environments, such as those with a moving surface [226, 227] or with physical human interactions [28], introduce additional challenges to loco-manipulation planning and control. Similar to a dynamic object manipulation problem, the interaction model between the robot and the dynamic environment is also time-varying. Although one can infuse the dynamics of the object with the robot model to form unified dynamics, it is impractical to model the dynamics of the environment numerically in most cases. Therefore, in an MPC setting, the planner may require sensor feedback to predict the movement of the environment and replan the loco-manipulation motion adaptively [226, 228]. For example, interacting with an environment that involves humans requires the anticipation of human intentions for collaborative manipulation such as lifting payload [28]; see a more challenging recent achievement in direct human-humanoid physical interaction [229]. For such tasks, the interaction force is an important way of communicating intentions, which can be measured as force feedback signals to trigger robot movements. However, the evolution of such sensed forces can not be well-predicted beyond the current timestep for MPC to leverage, suggesting further static/quasi-static assumptions are required. Otherwise, the robot can only treat the dynamic environment as a disturbance and counteract it through reactive control (*e.g.*, whole-body control). Given the challenge of dealing with the changing environment, loco-manipulation in a dynamic environment is largely unexplored.

In addition to rigid objects with regular geometries, deformable objects are ubiquitous in our real world, such as those in caregiving or housekeeping scenarios. Modeling the dynamics of these objects requires a deep understanding of their physical properties and behaviors, such as flexibility, elasticity, and deformation under force. Consequently, simplifications tailored to specific problems and applications are often necessary [230, 231]. For example, to plan the manipulation of a deformable belt, [232] simplify the motion of the belt by representing only its tail movement in a 2D plane. However, to fully exploit the object's deforming property for effective loco-manipulation, integrating accurate deformable objects [233] into robot models is essential. Although this area is relatively underexplored for humanoid loco-manipulation, such integration opens up significant opportunities beyond basic pick-and-place operations, enabling robots to tackle more intricate and delicate tasks.

Conclusion: With the advanced capabilities of gradient-based numerical optimization in motion planning, MPC is gaining popularity in humanoid loco-manipulation, showcasing numerous variations in recent years of literature. The essence of this method lies in making reasonable choices regarding the dynamics model, constraint, task definitions, and computation requirements. These choices often require expert design and tuning to trade-offs among task versatility, solution feasibility, and optimality. By identifying the computation intensities and proper dynamics representation of the loco-manipulation tasks, one can offset the computation load by introducing simplified models and relaxed constraints in MPC. In addition, the MPC efficiency can greatly benefit from proper solver choices, an evolving area presenting opportunities for research on both solver-level and problem-formulation-level innovations. For further reading, we recommend the survey on MPC for legged and humanoid robots [13]. Additionally, loco-manipulation tasks present further challenges due to the complexity of dynamic interactions with both the environment and objects, which leaves open questions on how to choose and formulate the interactive dynamics effectively based on the specific task requirements in an MPC setting.

VI. Whole-body control

Whole-Body Control (WBC) represents a body of controllers that generate joint torques, constraint forces, and generalized accelerations to achieve a given set of desired dynamic tasks [11]. Three common cases necessitate a computationally efficient whole-body controller that can track desired trajectories and send torque commands to a physical robot. (i) The desired trajectory is computed based on a reduced-order model. Such a trajectory encodes only an important subset of the robot's full-body motion (*e.g.*, desired CoM and end-effector trajectories in operational space [234]) and does not contain information for all joints. (ii) The trajectories are planned with a full-order model but are too computationally heavy [211] to be used in real-time, particularly for humanoids in loco-manipulation scenarios. (iii) Environmental uncertainties and planning inaccuracies induce disturbances that require robust WBCs to compensate [235]. Therefore, the WBC has been widely used in the humanoid community.

The WBC solves an instantaneous control problem (*i.e.*, only for the current timestep). This control scheme employs Euler-Lagrangian dynamics to express equation (2) as

$$M\ddot{\boldsymbol{q}} - J^T\boldsymbol{\lambda} - S^T\boldsymbol{\tau} = -C\dot{\boldsymbol{q}} - G \tag{5}$$

where the decision variables $\boldsymbol{X} = [\ddot{\boldsymbol{q}}, \boldsymbol{\lambda}, \boldsymbol{\tau}]^T$ are generalized accelerations, external forces, and joint torques, respectively. M, C, G are the spatial inertia matrix, bias terms (*i.e.*, centrifugal and Coriolis forces), and the gravity term, respectively. J is the Jacobian, and S is the selection matrix. Given the selection of decision variables $\boldsymbol{X}$ above, (5) becomes linear, which enables the WBC to be computed in real time.

For a humanoid robot with a floating base, the rank of S is smaller than the dimension of the generalized position $\boldsymbol{q}$. This implies that the humanoid system is underactuated; it requires physical contact with the environment to maintain balance and achieve mobility and manipulation tasks. The contact constraint is described using contact Jacobian J_c:

$$J_c\dot{\boldsymbol{q}} = 0 \Rightarrow J_c\ddot{\boldsymbol{q}} + \dot{J}_c\dot{\boldsymbol{q}} = 0 \tag{6}$$

These underactuated and contact-constrained dynamics (5), (6) represent the main ingredients in solving the WBC for humanoid robots.

A. WBC Dynamic Tasks

A dynamic task vector e_i can be expressed as a linear equation with respect to decision variables:

$$e_i = A_i(\boldsymbol{q}, \dot{\boldsymbol{q}}, t)\begin{pmatrix}\ddot{\boldsymbol{q}}\\ \boldsymbol{\lambda}\\ \boldsymbol{\tau}\end{pmatrix} - \boldsymbol{b}_i(\boldsymbol{q}, \dot{\boldsymbol{q}}, t), \tag{7}$$

where t is the time. Dynamic tasks can be equality constraints ($e_i = 0$), inequality constraints ($e_i \leq 0$), or cost terms ($|e_i|^2$). The main idea of WBC is that the linear equation (7) is sufficient to universally describe a diverse set of locomotion and manipulation tasks.

Although the appropriate set of WBC tasks depends on factors ranging from robot morphology to available hardware sensing, we highlight some of the common tasks for loco-manipulation. A task for tracking reference joint-space accelerations $\ddot{\boldsymbol{q}}^d$ can be formed by setting A_i to a selection matrix and setting $\boldsymbol{b}_i = \ddot{\boldsymbol{q}}^d$. Similarly, a task for tracking a desired operational-space acceleration is derived through the end-effector's Jacobian [236]. A task for tracking a desired centroidal momentum rate $\dot{h}^d$ can be formed by differentiating the centroidal momentum h [237]. Other potential WBC tasks include capture point [238], reference reaction forces [181] and collision avoidance [239]. The source of these dynamic tasks varies and may be predefined, computed online (*e.g.*, from an MPC), or commanded through teleoperation.

MPC is commonly used to provide WBC with dynamic tasks in operational space. For example, an SRBM-based MPC [234, 240] outputs the centroidal trajectories and end-effector trajectories as dynamic tasks in operational space. These operational-space tasks can also be converted to joint accelerations and thus become joint-space tasks. For instance, whole-body inverse kinematics [241] is a common approach for this conversion. Additionally, Riemannian motion policy [239] and kino-dynamics fabric [219] can construct diverse joint acceleration from a hierarchy of primitive motions.

Teleoperation provides an interactive way to generate dynamic tasks such as the robot's posture, walking direction, and grasp targets [242]. WBC setpoints are often mapped to a visual interface, enabling an operator to modify controller setpoints on the fly. This mapping may be direct [243] or retargeted in order to account for the robot's morphology [244] or to ensure the feasibility of the commanded motion [156, 245]. Virtual-Reality (VR) interfaces enable spatially mapping handheld controllers to WBC poses. This approach has been deployed in various loco-manipulation scenarios, including doorway traversal, object grasping, and pushing tasks [246, 247]. Haptic feedback can inform an operator of the WBC state through various modalities, such as force feedback indicating CoM stability margin [248] and vibrating gloves indicating contact during manipulation [116]. Mapping to dynamic WBC setpoints, such as the capture point, has also been demonstrated and can account for variation in the natural walking frequency of the operator and robot [249, 250]. As shown in Fig. 9, to achieve a desired list of dynamic tasks, WBC approaches can be categorized based on closed-form or optimization-based approaches.

B. WBC in Closed Form

An inverse dynamics controller is among the early works that address the WBC problem in closed form. In particular, it solves a single dynamic task: achieving the desired generalized acceleration $\ddot{\boldsymbol{q}} = \ddot{\boldsymbol{q}}^d$. The closed-form torque $\boldsymbol{\tau}$ can be solved from (5) if we can measure all constraint forces $\boldsymbol{\lambda}$. However, $\boldsymbol{\lambda}$ are usually unattainable due to the lack of sensing and estimation capability. To derive torque analytically, several

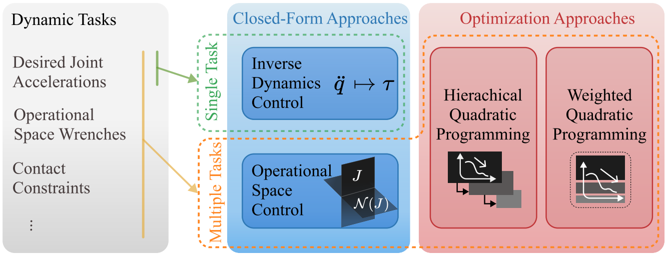

Fig. 9. Whole-body control is categorized into closed-form approaches and optimization-based approaches. Both approaches can incorporate multiple dynamic tasks and resolve task conflicts.

methods [251, 252, 253] project the system dynamics (5) into a constraint-free manifold, establishing an equation between only $\ddot{\boldsymbol{q}}$ and $\boldsymbol{\tau}$. [251] project (5) into the actuated joint space, resulting in an equation of constrained dynamics independent of the constraint forces $\boldsymbol{\lambda}$. [252] use orthogonal decomposition of the constraint Jacobian J to project (5) into the nullspace of the constraints. Although different projection techniques are used, [253] show that these projections produce equivalent torque results. However, from the perspective of solving speed and numerical stability, orthogonal decomposition [252] is favored as it is faster and does not require the inversion of the inertia matrix.

Other than the task of tracking generalized acceleration $\ddot{\boldsymbol{q}} = \ddot{\boldsymbol{q}}^d$, a set of operational-space tasks and constraints can be achieved given the redundancy in the degrees of freedom of humanoid robots. As a multi-task example, a humanoid robot is often tasked to generate interaction forces with a low priority while maintaining the whole-body balance with a high priority. Operational-Space Control (OSC), *a.k.a* task-space control, achieves multiple dynamic tasks by prioritizing tasks in a hierarchy [251, 254]. Tasks with low priorities are solved within the null space of the high-priority tasks, enforcing that hierarchies are strictly maintained among tasks. Such a task hierarchy is also named the stack of tasks [255].

Overall, closed-form approaches are computationally efficient and are straightforward to implement. However, they have difficulty in incorporating inequality tasks, such as joint limit and obstacle avoidance. Although this issue can be addressed within the closed-form approach, such as using a smooth operator [255], much of the community uses optimization-based methods that address this issue efficiently.

C. WBC through Optimization

In contrast with closed-form approaches, there have been a variety of studies formulating the WBC as an optimization problem. These optimization-based methods enhance the flexibility of WBC, enabling the modular addition and removal of dynamic tasks [256, 257], including inequality tasks.

A salient feature of optimization-based WBC is the resolution of conflicting dynamic tasks through two prioritization schemes: strict task hierarchy [258] or soft task weighting [117, 237, 238, 259]. Due to the linear property of both the dynamics equation (5) and dynamic tasks (7), optimization-based WBC is often formulated as a Quadratic Program (QP), which can be solved efficiently to a global optimum and enjoys a wide range of solver selections.

A strict task hierarchy can be ensured through a cascaded hierarchical QP. This method sequentially solves a series of QP subproblems with tasks from high to low priorities; lower-priority QPs produce solutions within the combined null space of all preceding QPs [258]. The sequential solve of QP terminates either when it successfully solves all subproblems or when it encounters an infeasible subproblem and thus skips all the remaining low-priority tasks [260]. Hierarchical QP is essentially equivalent to the closed-form stack-of-tasks approach, with the benefit of incorporating inequality constraints more naturally. However, solving multiple QP subproblems imposes significant computation and memory burdens. Additionally, the hierarchical QP inherits a common issue of OSC: the task Jacobians becomes rank-deficient when approaching singularities, which induce large unstable movements [261].

In contrast, weighted QP addresses these issues via arbitrating dynamic tasks as *soft constraints* in cost functions, using weights to express their relative priority. Therefore, weighted QP can be regarded as a special case of hierarchical QP with only one hierarchy or vice-versa as documented in [262]. Such a setup enjoys the benefit of solving only a single optimization, which is faster than a hierarchical QP and can be further accelerated by exploiting sparsity and warm-start. However, tuning weight parameters can be burdensome for a large number of tasks, and can lead to instability [263]. Even with well-tuned parameters, the loss of strict task priorities means low-priority tasks can interfere with high-priority ones. Nevertheless, weighted QP is still widely applied in many robotics studies due to its easy setup and computation efficiency compared with hierarchical QP. For example, many of the weighted QP methods were designed during the DARPA Robotics Challenge [117, 237, 238, 264].

D. WBC for Loco-manipulation

WBC for loco-manipulation aims to achieve the desired motion while maintaining instantaneous *balance* and *contact stability*. Given the desired motion and contact sequence, loco-manipulation control can be categorized into two folds. (i) When all interactions with the environment and objects are static or quasi-static, they can be modeled as external wrenches. In this case, the WBC solves a robot balancing problem with the external wrenches as dynamic tasks. (ii) When the manipulated object has a substantial mass or is dynamically moving, such as carrying a heavy box, the object becomes an integral part of the robot-object system. Therefore, the WBC must account for the balance of both the robot and the dynamic object.

1) Interaction as an External Wrench: In this first category, a subset of contacts is responsible for interacting with the environment or objects to apply a desired wrench. This desired wrench can be specified by a user or derived from the estimated object weight. Considering the desired wrench from the interaction, the remaining contacts maintain the system balance using three distinct strategies.

The first strategy involves simultaneously optimizing contact wrench, joint acceleration, and joint torque using the robot's full-body dynamics, as detailed in Sec. VI-C. In this approach, the desired wrench for interaction is a dynamic task within the WBC. The WBC must also satisfy the dynamics constraint, contact stability constraint, and balance stability constraint. The contact stability constraint enforces that the resultant contact wrench lies inside the contact wrench cone (CWC) [265], maintaining firm and stable contact. The balance stability constraint designs a desired rate of centroidal momentum, often based on feedback in the CoM position and body orientation [194]. In the presence of state deviations, the balance stability results in a redistribution of the contact wrenches or a movement of the centroidal state to counteract and restore stability [82].

The second strategy, known as pre-optimization [3, 266], involves two stages in sequence. First, it determines the optimal distribution of contact wrenches based on the desired rate of centroidal momentum derived from the balance stability of CD. The second stage computes the joint torques needed to realize the contact wrench using inverse dynamics of full-body dynamics. Note that, deriving the desired rate of centroidal momentum in the first stage is particularly challenging due to the non-holonomy [267] of angular momentum, *i.e.*, the kinetic momentum of rotation is not directly related to the orientation of body links. As a result, the body orientation requires additional regulation (*e.g.*, joint-level postural feedback [3]) beyond simple feedback on angular momentum.

To address the non-holonomy issue, the third strategy uses post-optimization [268]. The main idea is to treat the floating-base robot as a fixed-based system when calculating joint torques. The underactuated portion of the obtained torque is then mapped to contact wrenches through an optimal distribution problem. This method avoids the challenge of specifying the momentum of rotation in the pre-optimization strategy.

2) Interaction as a Unified Robot-Object Model: A unified robot-object system can leverage the additional object to regulate the robot's dynamics. This yields more dynamically feasible behavior when carrying heavy or dynamically-moving objects. The unified model incorporates each manipulated object as an additional "robot" – either a passive object or a real robot – and connects the robot and object via action-reaction force pairs [269]. The balance stability must consider the combined CoM and inertia of the robot-object system [221]. Additionally, the contact stability between the robot and the object is maintained to ensure that the object remains securely attached. While direct control of the interaction forces is feasible, adaptive force control that regulates the relative position between the object and the robot offers greater robustness. This approach mitigates the impact of inevitable inaccuracies in modeling inertia parameters and stiffness properties [191].

Conclusion: The core of whole-body control lies in addressing an inverse dynamics problem to produce joint-level torque control. However, this problem is challenging due to the under-actuation and contact-constrained nature of humanoid robots. Closed-form approaches such as inverse dynamics control and operational-space control are computationally efficient. Therefore, they have been traditionally prevalent. On the other hand, optimization-based strategies, particularly quadratic programs, are increasingly favored as they adapt more effectively to a wide range of task specifications and offer more reliable solutions. Undoubtedly, both lines of WBC research have significantly advanced the progress of humanoid robot control over the past two decades. In the near term, optimization-based WBC will continue to be a popular choice for low-level control to achieve high-level loco-manipulation tasks. We also see neural WBC [270, 271, 272] gaining popularity, as we will discuss in the following section. For further reading, we recommend the survey on optimization-based WBC for legged robots [7] and the chapter on closed-form WBC techniques for humanoid robots [11].

VII. Learning Loco-Manipulation Skills

Robot skill refers to the ability to use its own perception, planning, and control capabilities to complete specified tasks autonomously [273]. Among a variety of robot skills, loco-manipulation is highly valuable for augmenting and complementing human capabilities. Traditionally, loco-manipulation skills are developed from human designer knowledge, distilled into pre-programmed planners or controllers. In contrast, learning-based methods leverage computation and data. Although learning skills require collecting extensive data from either autonomous exploration or expert guidance, this approach is powerful as it tends to yield novel behaviors that are difficult to encode from human knowledge.

This section reviews learning-based approaches that explore two main directions: (i) enhancing a specific skill in terms of agility, robustness, and safety, and (ii) broadening the overall skill set of robots, revolving around two pivotal goals: versatility and generalization. Versatility refers to the capability of a single framework or policy to master *multiple* skills, whereas generalization involves adapting existing skills to new, out-of-distribution tasks and environments.

Among learning-based methods, Reinforcement Learning (RL) without demonstration and learning from demonstration, also known as Imitation Learning (IL), have shown remarkable proficiency for robotic skill learning. RL has been successful in coordinating complex full-body motions for humanoid robots, including dancing [270, 274], agile soccer maneuvers [275], and robust locomotion [35, 39]. However, RL policies are often fine-tuned for specific tasks within specific environments. This limitation largely stems from the reward function being narrowly tailored to a specific task, and the policy only capable of learning from the same or similar environments. In contrast, IL addresses this problem by leveraging large datasets of demonstrations [37, 276]. Recent advancements in IL have demonstrated promising results for scaling to a large number of skills [8], showing potential for solving complex multi-skill tasks.

For the basics of RL and IL, we refer readers to the survey paper [277]. In this section, we discuss these methods for learning humanoid loco-manipulation skills. As shown in Fig. 10, we introduce RL in Sec. VII-A and IL in Sec. VII-B and Sec. VII-C. Thereafter, we discuss the benefits of combining model-based and learning-based methods in Sec. VII-D. Finally, we discuss methods for learning versatile skills with a single policy in Sec. VII-E.

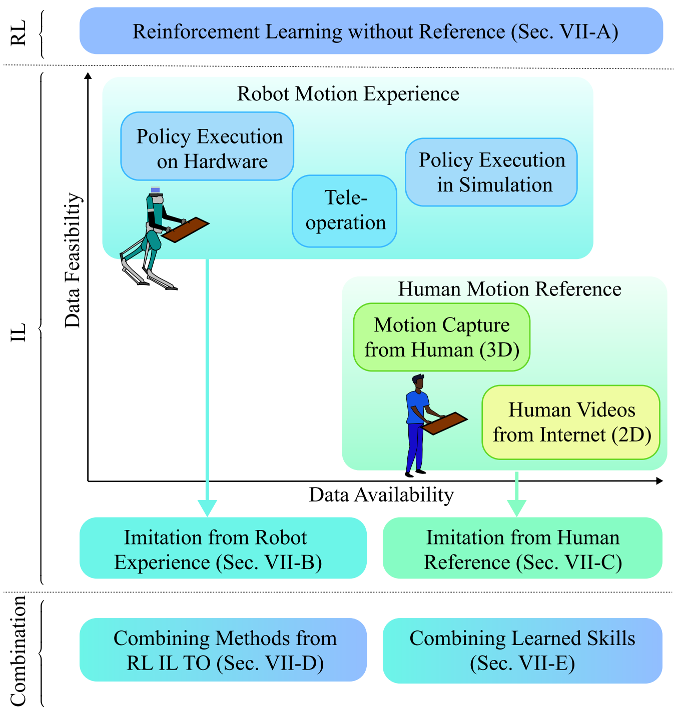

Fig. 10. The organization of approaches for skill learning. RL does not require reference data in a standard setup. IL makes use of four different data sources for efficient learning. The larger the morphology gap or sim-to-real gap is, the more challenging it becomes to learn effectively from these data.

A. Skill Learning: Reinforcement Learning from Scratch

RL, enhanced by modern deep learning toolchains and algorithms, has garnered significant attention in the field of robotics over the past decade. RL promises an effective way to learn motor skills by rewarding desirable behaviors and penalizing undesired behaviors, with minimal or no supervision during training. The end-to-end RL policies translate raw sensory input to actuation and are executable in real time.

RL provides distinct benefits but also comes with its own challenges. Compared with model-based methods, numerous RL methods are model-free (see Sec. VII-E for model-based RL), eliminating the need for accurate dynamics. Furthermore, RL does not require demonstration data, making its training setup straightforward. However, it often requires meticulous design of reward functions to shape the policy's behavior. In addition, deploying a learned policy on robot hardware often encounters a sim-to-real gap, a well-known issue induced by the inaccurate physical model used by the simulator. Policy learning from scratch often requires extensive and time-consuming interactions with the environment without a guarantee for task completion. For example, popular RL algorithms such as Proximal Policy Optimization (PPO) [278] and Soft Actor-Critic (SAC) [279] fail to achieve most humanoid loco-manipulation tasks [280], partly due to the complexity of these tasks, the sample inefficiency, and the sparse reward design.

1) Improving Learning Efficiency: Several approaches have been proposed to improve learning efficiency. Curriculum learning expedites training by allowing the policy to achieve simple tasks in the early stage of training and then progressively increasing the task difficulty and complexity [281]. Another approach is to promote exploration. Researchers use curiosity mechanisms, which encourage visiting unexplored states, to intrinsically motivate learning without explicit reward design [282]. This has been shown to overcome the sparse reward setting and achieve complex loco-manipulation behaviors such as door opening. [274] also incorporates curiosity-based rewards to learn versatile loco-manipulation skills without any motion priors. Lastly, substituting reward terms with constraints in a constrained RL framework can significantly simplify reward tuning while achieving state-of-the-art locomotion performance [283].

2) Addressing Sim-to-real Gap: Sim-to-real is another formidable challenge in RL. Nevertheless, RL has been successfully applied to various areas of robotics, with notable success in quadrupeds [284], where the sim-to-real gap has been consistently overcome. How can we apply the lessons from quadrupeds to humanoids for optimal loco-manipulation while avoiding known pitfalls? The success story of quadrupeds hinges on new investments in infrastructure for affordable hardware and highly parallel physics engines, spearheaded by key players in the robotics community. It is also important to note that quadrupeds benefit from an inherently stable dynamic system similar to manipulators while operating in less complex environments compared to typical loco-manipulation tasks.

In contrast, humanoid loco-manipulation faces steeper sim-to-real challenges. Humanoid robots possess higher DoFs and unstable dynamics, where the center of mass constantly moves out of the support polygon. Therefore, learning whole-body balance control is sensitive to parameters in physics simulation, underlining the sim-to-real gap due to dynamics differences between the virtual and real worlds. In addition, humanoids are expected to perform human-level manipulation tasks where the differences in observation space and the complex environment aggravate the sim-to-real-gap due to appearances.

To address the sim-to-real challenge, a diverse set of mainstream approaches have been explored for humanoid robots. Domain Randomization (DR) is among the most widely adopted approaches. It varies the properties of a robot model, such as mass, friction, and actuator dynamics, to train a generalized policy robust in the real world. Many humanoid works [39, 275] achieve sim-to-real transfer through DR. While DR is straightforward to set up, policy training is sensitive to the parameter randomization range, inducing laborious tuning: a larger range is challenging for the policy to fit all physical parameters (*i.e.*, fail to learn), and a smaller range does not cover the full spectrum of parameters that can occur in the real physical world (*i.e.*, fail to transfer).

In addition to adopting a diverse set of parameters in DR, System Identification (SI) is another popular approach to enhancing model fidelity by approximating the system's input-output behavior from real-world data. Real-to-sim techniques use optimization [285] or search [286] to obtain simulation parameters that can best explain the real robot trajectories collected from policy execution. However, it is challenging to collect high-quality, real-world data covering the full space of states and actions, particularly for versatile, safety-critical humanoid tasks.

Different from SI, which uses real-world data to obtain an accurate model, Domain Adaptation (DA) uses real-world data directly to fine-tune a simulator-trained policy. In DA, the parameter distribution in simulation is defined as the source domain, and parameter distribution in the real world is defined as the target domain. The fine-tuning effectively transfers the policy from the source domain to the target domain. For example, Sim-to-Lab-to-Real [287] develops a two-stage transfer: pre-training in simulation and fine-tuning in the real world. Although only limited hardware data is needed for fine-tuning, safety is still a major concern. Safety filters are often deployed to prevent dangerous movements when collecting real-world data [288].

Despite these efforts to address the sim-to-real gap, a systematic solution remains elusive, as the aforementioned approaches are often ad-hoc and case-specific. Against this backdrop, advancing in humanoid hardware deployment and developing physics engines that facilitate real-to-sim construction and sim-to-real transfer will be crucial. Simultaneously, we must rethink the role of RL to utilize its strengths and avoid its weaknesses for humanoid loco-manipulation. An in-depth discussion on how to integrate RL with modern IL is presented in Sec. VII-B and Sec. VII-C.

Conclusion: RL provides an effective way to learn novel behaviors for humanoid loco-manipulation. However, in practice, the success of RL often relies on informative representations for both observation and action, extensive reward engineering, curriculum learning design, and a vast amount of trial-and-error experiences to estimate gradients. Consequently, using RL to train robots is almost never practical in the real world, at least for the current stage of development. Therefore, RL policies are predominantly trained in simulations. This makes the sim-to-real gap the Achilles' heel of RL, significantly dampening its initial promise. Compared with quadruped robots, the sim-to-real gap is particularly challenging for humanoid robots with high DoFs executing complex loco-manipulation tasks. This is why IL, leveraging limited but in-domain real-world data, has gained popularity over pure RL without demonstration data. For further reading in RL, we recommend the survey on learning-based legged locomotion [277] and the practical lessons for training robotic RL agent [289].

B. *Skill Learning: Imitation from Robot Experience*

Imitation Learning (IL) is an umbrella term that represents a class of algorithms, including supervised, unsupervised, and reinforcement learning, that train policies from expert demonstrations. IL is particularly effective for complex tasks that are difficult to specify explicitly. Three essential steps exist in IL [299]. The first step is to capture the expert demonstration. The next step involves retargeting, where these demonstrations are mapped to the robot motions. The final step is policy training using the retargeted data. If the captured motion comes from the same robot, such as from teleoperation, the retargeting step is unnecessary.

We discuss four possible sources of demonstrations for humanoid robots: (i) policy execution, (ii) teleoperation, (iii) motion capture, and (iv) human videos, as illustrated in Fig. 10 and Table III. We group these data sources into two categories: The first is robot experience data, representing those directly obtained from the robots through policy execution or teleoperation; The second is human data, which includes human motion captures and videos of human activities obtained from the Internet. Robot experiences exhibit smaller morphological discrepancies and are directly applicable to policy learning but are typically scarce. Conversely, human data are more abundant, but they present significant morphological differences to humanoid robots. This section discusses robot experience data, and the next subsection discusses the human data.

TABLE III
SKILL LEARNING METHODS BASED ON DATA SOURCE

Methods and Data	Pros and Cons	Algorithms
RL Without Reference	✓novel behavior ✗sim-to-real gap ✗reward tuning	PPO [278], SAC [279]
IL Robot Execution	✓annotated data ✓dynamically feasible ✗scarce ✗limited diversity	Diffusion [276], IRL [290]
IL Teleoperation	✓multimodal behavior ✗rare full-body motion	BC-RNN [80], ACT [272, 291]
IL Motion Capture	✓accurate kinematics ✗small dataset ✗limited outdoor data ✗proprioception-only	RL motion imitation [292], GAIL [293], AMP [294, 295]
IL Human Video	✓diverse abundant data ✗non-physical motion ✗proprioception-only	RL motion imitation [296], GAIL [297], OKAMI [298]

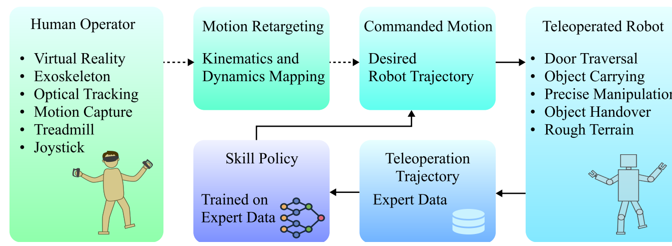

Fig. 11. Control flow for learning from teleoperated demonstrations. Expert data is created from teleoperated trajectories (dashed lines), which in turn is used to train and deploy an autonomous skill policy (solid lines).

1) Obtaining Robot Experience Data: A reliable way to obtain robot experience data is to execute existing expert policy, either model-based or learning-based. However, collecting data on a physical robot requires a laborious setup of the environment and raises significant safety concerns. Therefore, conducting these executions in simulation is a more efficient approach, although the fidelity of the simulator will inevitably cause a sim-to-real gap.

Teleoperation is one of the most common ways to directly capture robot data commanded by human experts. A main advantage of teleoperation is its ability to provide smooth, natural, and precise trajectories for a wide range of tasks. Fig. 11 outlines the control flow of teleoperation data used as a source of policy training. The first step of this process is generating the demonstration through teleoperation, represented by the top path of the control flow (dashed lines). Motion retargeting maps human measurements from the teleoperation device to the desired trajectories in the robot domain. Robot execution data collected from teleoperation can be used to train autonomous policies that directly command the robot's motion without human intervention (solid lines). In this case, the retargeting process is not needed.

However, teleoperation for the *full-body* of a humanoid has a number of limitations. Firstly, a majority of teleoperation systems capture only manipulation skills [8]. Generally, Virtual Reality (VR)-based teleoperation schemes cannot sense the operator's gait and are restricted to simply commanding walking speeds and directions via joysticks [246, 300, 301]. Full-body sensing, including human gaits, often requires additional equipment such as IMU suits [244, 302] or exoskeletons [249]. These devices may be prohibitively expensive, bulky, complicated to maintain, and lack transparency and user-friendliness. Secondly, while teleoperation can generate versatile training data for a wide range of tasks, the utility of this data may be limited if the robot's kinematics do not enable seamless retargeting of reference human motion. Additionally, retargeting dynamic tasks such as walking or pushing an object is sensitive to the dynamic model of the human demonstrator [244] and requires meeting high synchronicity [302] and rich sensory feedback.

Although both teleoperation data and policy execution data are recorded from robots, they exhibit distinct characteristics. During teleoperation, human instructors tend to provide diverse demonstrations even for the same task. Therefore, teleoperation data are often multimodal, *i.e.*, given a specific task, there exists a distribution of plausible ways to accomplish the task. In contrast, data from executing a single policy are often unimodal, *i.e.*, given an input, the output is often fixed. Different policy learning approaches have been proposed to address these multimodal and unimodal data features.

2) Approaches to Learning from Robot Experience Data: From unimodal policy execution data, which contains paired observations and actions, IL approaches are often used for policy distillation. Behavior Cloning (BC) casts IL as a supervised learning problem, which remains one of the most straightforward approaches for robot skill learning [303, 304]. Another IL technique is Inverse Reinforcement Learning (IRL), which reconstructs rewards from the data in addition to training an RL policy. The IRL study in [290] infers a generalizable reward of the expert demonstration for bipedal locomotion and then uses this reward to train an RL policy in unseen terrains.

To capture the data multimodality and produce diverse future actions, Action Chunking Transformer (ACT) [272, 291] is adopted to handle distribution shifts due to the compounding error inherent in naive BC. Recently, diffusion policy [276], a BC method, shows the ability to acquire multimodal locomotion skills by learning from a large dataset collected from multiple expert policies. However, obtaining these skills requires large-scale versatile data, which motivates the scaling of data collection via teleoperation in industrial companies, *e.g.*, Tesla and Toyota Research [8].

Conclusion: Although collecting high-quality data demands considerable effort and resources, IL from robot experience remains a reliable method for attaining skills with expert-level performance. Industrial companies and research labs are increasingly focusing on scaling data collection to develop a broader range of diverse policies through IL. Especially, teleoperation is one of the most popular ways to collect humanoid robot experiences nowadays. For further reading on collecting robot experience data, we recommend the survey on humanoid robot teleoperation [305]. We also find the survey on imitation learning of humanoid bipedal locomotion [299] a decent summary.

C. Skill Learning: Imitation from Human Data

While robot experiences can serve as a reliable data source, collecting loco-manipulation data directly from robots remains a formidable challenge. Collecting teleoperation data, even though it is one of the most commonly used approaches, is costly and time-consuming to scale. Besides, gathering robot data by deploying existing model-based methods or trained policies presents additional difficulties. These methods raise safety concerns on hardware or suffer from significant sim-to-real gaps. Furthermore, model-based methods based on human knowledge (*e.g.*, dynamics models, heuristic trajectories) tend to generate consistent but similar behaviors, leading to limited data diversity.

Learning from a large, diverse corpus of human data mitigates these challenges. Humans use loco-manipulation skills in their daily lives almost reflexively. Therefore, recording human data is more accessible and scalable. Training policies to imitate human data can greatly simplify the synthesis of loco-manipulation behaviors. Recent research efforts in 3D human motion data archival have surged in the vision and computer graphics communities. As shown in Fig. 12, there are currently two primary approaches to acquire 3D human motion data: (i) recording directly from motion capture systems and (ii) reconstructing from 2D videos.

1) Obtaining Human Data: Various tracking systems are used to obtain human motion data. As shown in Fig. 13, [179, 306] captures humans interacting with various objects while moving around. The following datasets, CMU [307], SFU [308], LAFAAN [309], and AMASS [310], are commonly used because they provide a wide variety of human motions. However, motion capture data often require heavily instrumented environments and actors, making them expensive to scale. Besides, indoor lab settings provide little exposure to outdoor activities.

Alternatively, videos and images obtained from the Internet offer a rich and diverse source of human motion data, including athletic performances, artistic dances, or daily chores. However, compared to the aforementioned data sources, motion extracted from internet data is usually of lower quality, containing noise, jittery, and non-physical artifacts due to occlusion and motion blurs. Therefore, the reconstruction of accurate 3D human poses from 2D data remains an active research topic in the computer vision community.

Animation is also a widely explored approach to obtaining human motion data. Although animation is effective in designing expressive motions for virtual human characters, the process often requires the use of sophisticated animation tools by professional animators [311], which makes it less scalable than motion capture or Internet videos. To address this limitation, researchers have been pursuing *motion generation*, leveraging

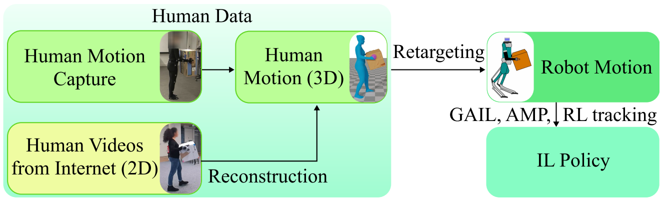

Fig. 12. A pipeline for learning from human data. The 3D human motion data can be recorded from motion capture systems or reconstructed from 2D human videos. Robot motion is retargeted from 3D human motion for imitation learning.

Fig. 13. Motion capture of human data. (a) The human interacts with household items [179]. (b) The human interacts with items with whole-body manipulation [306].

human data to generate diverse and realistic motions; see a comprehensive survey in [312]. Our focus here is on training IL policies to generate *physically plausible* actions that achieve the motions demonstrated in human data. The training pipeline is shown in Fig. 12.

2) Challenges in Learning from Human Data: Using offline human motion data (from any source) to train humanoids inevitably creates an embodiment gap both in observation and action spaces due to different body proportions, joint configurations, and mass distributions between most humanoids and humans. Closing this embodiment gap requires retargeting, which involves mapping the motion collected from a source skeletal model to a target robot model. Previous work in computer graphics and robotics has explored various retargeting strategies, such as joint correspondence [244, 272, 313], task-space correspondence [291], contact points [221], fingertips [314], gait synchronization [249, 302], and motion feasibility filter [156, 271]. Developing systematic solutions for retargeting the entire human body, including dexterous hands, remains a critical topic for advancing humanoids.

Another correspondence problem is that these human data are only proprioception-based, which lacks sensory input and action output. Notably, these human data lack tactile or force measurement from interactions, which limits the capability of learning for loco-manipulation with rich physical interaction. To solve this issue, IL trains control policies that track references within a physical simulator. Specifically, IL control policies accept state-only references instead of state-action pairs and output control signals. The physical simulator plays a key role in providing sensory input and validating the physical feasibility of the policy action.

3) Approaches to Learning from Human Data: Examples of learned human-like motions include walking using Generative Adversarial Imitation Learning (GAIL) [293, 297]. Extending the GAIL framework, Adversarial Motion Prior (AMP) [315] is applied to locomotion tasks in [294] and [295]. Recently, RL-based motion imitation using motion capture data has shown successful transfer to humanoid robots [271, 272, 313, 316]. However, most of these works achieve only relatively conservative loco-manipulation behaviors. Highly agile behaviors, as shown in DeepMimic [317], still exist only in simulators, and similar capabilities have yet to be replicated with real robots.

Human motion imitation can also achieve robust policies capable of rich interactions with objects in unstructured environments. For example, [296, 318] demonstrates the learning of full-body gymnastic skills for humanoids in physics simulation, utilizing video reconstruction data and RL-based motion imitation. [319, 320] learns loco-manipulation policies enabling simulated humanoid characters to carry boxes. Furthermore, [292] mimics motion capture data to achieve playing basketball and grasping objects. However, many of these approaches still rely on privileged information, such as the ground truth of object and ego poses, from the simulator, which limits their extension to real-world hardware.

Conclusion: Transferring skills from humans, especially through Internet-scale datasets, unlocks a broad range of loco-manipulation capabilities for humanoid robots. Although learning from human data holds great promise, a large body of what has been achieved in simulation has yet to be realized in real-world robots. Developing affordable and capable humanoid robots and high-fidelity simulators of real-world loco-manipulation scenarios can accelerate progress in this research direction. As we witness an increasing accessibility of humanoid robots in the market, we foresee that imitation from human data will enable humanoid robots to acquire a vast and diverse skill set. This skill set is fundamental to building humanoid foundation models discussed in Sec. VIII.

D. Skill Learning: Hybrid Methods

Approaches that combine learning-based methods (IL and RL) and model-based methods are illustrated in Fig. 14.

1) Combining Pure RL and IL: The combination of IL and pure RL without demonstration data has led to effective sim-to-real transfer. A two-stage teacher-student paradigm is widely adopted [37, 39, 321]. In these works, a teacher policy is first trained from simulated privileged observation using pure RL. Then, a student policy clones the behavior of the teacher, achieving a similar performance using only partial observations. The trained student policy is readily deployable on hardware with onboard observations. Another two-stage paradigm [322] reverses the order of the two policies. It uses IL first to pre-train an imitation policy from expert data. Then, an RL policy fine-tunes the imitation policy for further improvement. This RL allows achieving performance beyond the IL expert and adapting to different environments or tasks [323].

2) Learning to Track Trajectory Reference: Combining model-based methods with learning-based methods is extensively explored. Numerous works on quadruped robots [324, 325] use MPC to generate reference motions and use them as imitation rewards for RL-based motion imitation. However, calculating MPC online can prolong the training time and MPC may occasionally fail to find a feasible solution. Online RL that tracks *offline-generated* trajectories avoids this problem and has achieved effective RL policies for versatile bipedal locomotion [35, 326, 327]. Supervised learning is also used to mimic TO-generated offline motions. For example, [328] allows humanoid robots to achieve brachiation on monkey bars. In addition to enhancing learning methods with model-informed trajectories, a learned policy can also suggest good warm starts or hyperparameters for model-based methods, thus significantly reducing the iterations required for convergence to an optimal trajectory.

3) Learning to Augment Trajectory Reference: Rather than tracking the reference trajectory, augmenting the reference with a residual is another popular approach. Early work on dynamic movement primitives [329] modifies the reference trajectory by learning a task-specific force output, which achieves a humanoid racket swing. A milestone in trajectory augmentation is the demonstration of bipedal locomotion in [330]. Since then, many works on trajectory augmentation have achieved dynamic locomotion [331, 332]. Recently, loco-manipulation skills are also achieved through augmenting TO-based reference trajectory [333]. Beyond joint-level reference, a policy can also augment the task-space reference. For example, [334] learn a locomotion policy to adapt the foot placement reference derived from inverted pendulum models.

Both imitation and augmentation of the reference trajectory share benefits and drawbacks. As a benefit, using references expedites the learning process and provides an effective way of learning complex skills. However, both methods rely on predefined trajectories and, therefore, have limited potential to learn emergent, diverse behaviors.

Conclusion: Learning-based methods, especially pure RL without demonstration data, present robust and emergent behaviors, while IL enables effective learning of complex behaviors. Model-based methods take advantage of human knowledge and the power of numerical optimization to provide references for efficient learning. Overall, combining model-based and learning-based approaches has achieved efficient, versatile, and high-performing humanoid tasks that outperform single methods alone. Many existing works have shown successful humanoid hardware deployments using hybrid methods.

E. Representation and Composition for Versatile Skills

A good representation of skills makes it easy to compose tasks. In general, a skill can be represented explicitly as a state-action trajectory that accomplishes a task or implicitly as a

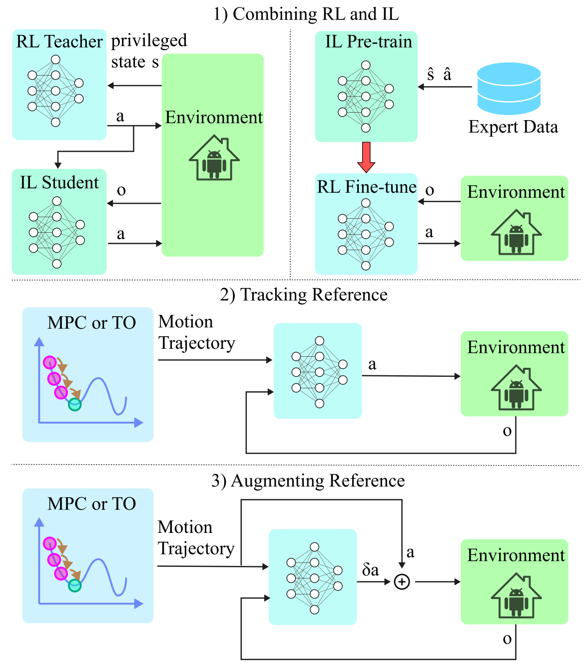

Fig. 14. The frameworks of combining model-based methods and model-free methods for skill learning.

network structure and its learned weights. In this subsection, we explore implicit representations for skill composition to achieve versatile, multi-skill tasks.

1) Skill Composition via Mixture of Experts: Recent learning-based approaches enable smooth transitions between multiple skills. Among them, Mixture of Experts (MOE) is widely used. MOE employs a hierarchical architecture; it first trains multiple distinct skills, implicitly encoded in low-level expert policies, and then learns a high-level policy to select [335] or blend [336] these expert networks. This architecture allows for smooth transitions between skills and facilitates the completion of diverse tasks. However, MOE encounters expert imbalance issues favoring certain experts while degrading others; which could diminish the diversity provided by the experts. Instead of obtaining and then blending *multiple* policies, structured representations improve memory efficiency and allow a *single* policy to achieve multiple tasks. Next, we introduce three well-received structured representations: motion representation, goal representation, and state transition representation, all shown in Fig. 15.

2) Motion Representation: Motion representation extracts the essential features and temporal dependencies of high-dimensional long-horizon motions [337]. Specifically, motion representation encodes high-dimensional motions in a low-dimensional latent space. Such latent-space representations are commonly learned in an unsupervised manner using generative models such as Variational Autoencoders (VAEs) [338] and Generative Adversarial Networks (GANs) [339]. Compared to VAEs, GANs have greater potential to generate realistic motions following the reference data distribution, but they are often difficult to train. The result of learning motion representation is often a model that can generate versatile motions given latent codes. Therefore, the generative model can be easily reused to achieve new downstream tasks by pairing it with a high-level task-specific policy. For example, several studies [340, 341, 342] learn a high-level RL policy to efficiently use a reduced-dimensional latent space motion representation and allow simulated humanoid robots to follow a set of user-commanded tasks.

3) Goal Representation: Besides motion representation, another approach to learning a *single* policy for multiple tasks is through the representation of goals. The goal is typically represented as a feature vector, which can be encoded from an image of the scene in its final state, a natural language instruction, or a desired state from observing human demonstrations. This goal representation is often paired with Goal-Conditioned Policies (GCPs) [343]. Unlike standard RL policies that achieve only one task, GCPs achieve multiple tasks within a single general policy conditioned on different goals. GCPs have achieved versatile humanoid skills using IL such as diffusion-model based BC [276] and RL with imitation objectives [271, 313, 344].

4) State Transition Representation: The latent space can also represent the transition dynamics of a Markov Decision Process (MDP). In this representation, data collected from the MDP are used to train a dynamics model that predicts the transition probability between abstract, compressed representations of MDP states. This learned dynamics model is often referred to as a world model [345]. Sampling from a world model yields imaginary data and can be achieved efficiently in massive parallel. By leveraging the imaginary data, Model-Based RL (MBRL) achieves greater efficiency compared to a typical model-free setting, where interaction data must be obtained from a simulated or real environment. MBRL has shown success in agile motor skills on humanoids [346, 347]. Another approach, TD-MPC2 [348], uses the world model in an MPC fashion, planning actions that lead to imaginary trajectories with high scores. Beyond data efficiency, the world model can mitigate the sim-to-real gap by fine-tuning a small batch of real-world data [349].

Conclusion: Enabling robots to accomplish versatile skills and multiple tasks is one of the main trends in robot skill learning. Whereas obtaining and blending single-skill policies is widely explored, more recent methods put efforts into achieving multiple tasks in a *single* policy. This requires a more structured representation of the skill motion, the task goal, and/or the environment dynamics. Latent space models, goal-conditioned policies, and world models are promising approaches toward this objective. However, many of these methods are still limited to the computer graphics community and yet to be implemented on humanoid hardware.

F. Learning for Humanoid Loco-manipulation

Loco-manipulation skills are challenging for learning-based methods as they often struggle with achieving physically stable contact or precise contact forces.

While many learning-based approaches, such as CooHOI [350], demonstrate humanoid loco-manipulation skills in simulation, the physical interactions with external environments or objects are often oversimplified. As a

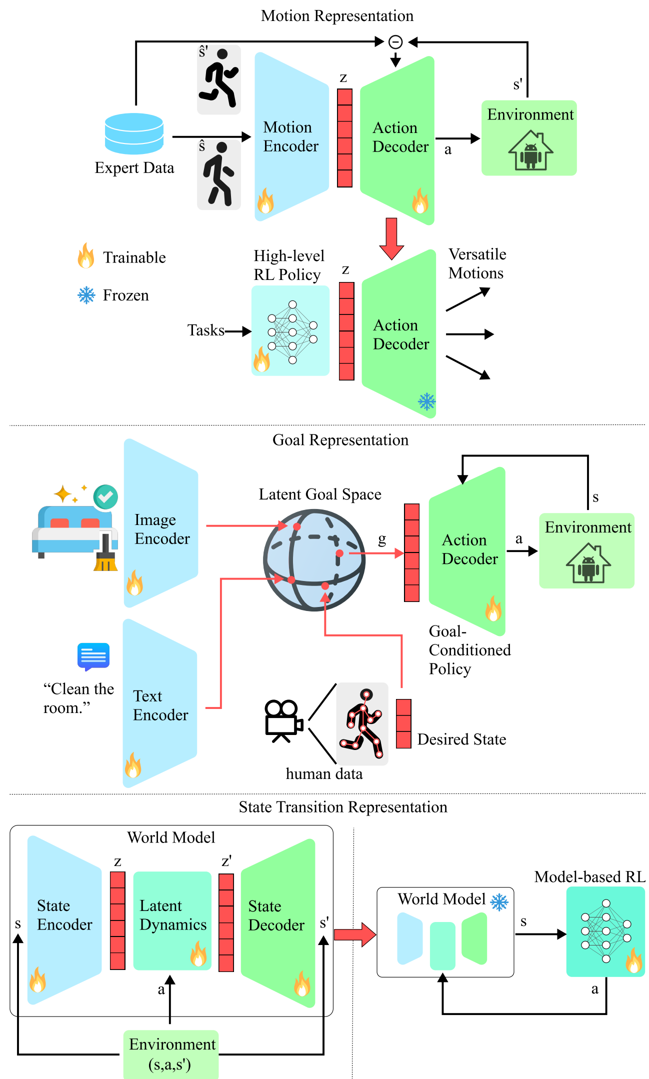

Fig. 15. Implicit skill representations. (a) Represent motions in latent space. (b) Represent goals in latent space and instruct a goal-conditioned policy for execution. (c) Represent state transitions with a world model and then use the learned world model for sample efficient training.

result, only a few studies demonstrate sim-to-real transfer for loco-manipulation skills. This subsection overviews a comprehensive list of studies on learning humanoid loco-manipulation with hardware implementations. A large part of these studies rely on RL, with a few examples shown in Fig. 16. However, RL for loco-manipulation typically involves complicated reward designs that are fine-tuned for specific environments and tasks [351, 352], see Sec. VII-A. To enable loco-manipulation tasks, these methods define the contact sequence either implicitly using reference trajectory [333, 351] or explicitly via reward design [274], thus increasing the success rate of sim-to-real transfer. To address the uncertainty of the mass and other properties of the manipulated object, most RL approaches rely on domain randomization to provide robustness to object parameters [39].

To achieve various loco-manipulation tasks such as playing soccer that involves ball kicking and falling recovery using hands [275], employing a hierarchical RL structure that manages distinctly trained skills is a viable strategy. However,

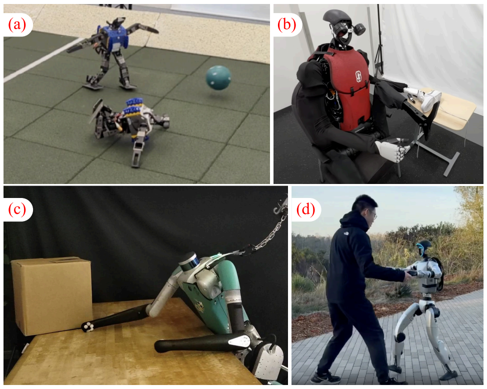

Fig. 16. Learning-based methods for humanoid loco-manipulation skills. (a) Getting up and chasing a ball [275]. (b) Tying shoelace [272]. (c) Multi-contact box manipulation [333]. (d) Dancing with a human [270].

hierarchical RL has scalability issues, see Sec. VII-E. On the other hand, IL methods, particularly those employing RL with motion imitation, have enabled humanoid loco-manipulation via teleoperation, as outlined in Sec. VII-B. Although teleoperation is not autonomous, it is a crucial intermediate step to collect humanoid data. Such humanoid data has led to promising developments in *autonomous* loco-manipulation skills [271, 272], with the potential for further expansion to more diverse loco-manipulation tasks.

Conclusion: Although learning-based methods for humanoid loco-manipulation are less developed than model-based methods, their significance should not be overlooked. Learning-based methods are potentially more robust, as they can adapt to unstructured scenarios that model-based methods struggle to explicitly address, such as recovering from a fall in an arbitrary configuration [353]. Moreover, learning-based methods can find emergent behaviors that are challenging for model-based methods [282]. The recent success of quadrupedal loco-manipulation [72, 76, 77] shows significant promise for humanoids. However, transferring these algorithms from quadruped to humanoid is challenging because of the complex dynamics of humanoids, which require enhanced safety measures and precise balance control.

VIII. Foundation Models for Humanoid Robots

Foundation Models (FMs) are large pre-trained models using Internet-scale data [354]. Recent progress in FMs such as Large Language Models (LLMs) and Vision-Language Models (VLMs) has demonstrated groundbreaking capabilities in solving a wide range of downstream tasks (through in-context learning or fine-tuning), such as code generation, visual question answer, and video understanding [355]. The common sense reasoning capabilities of FMs have inspired many explorations of their applications in robotics [9, 10]. Despite this growing interest, research on FMs specifically for humanoid robots remains sparse. In this section, we first provide an overview of FMs in the context of general robotics (*e.g.*, mobile manipulation, instead of humanoids) and then explore their potential applications to humanoid robots.

Strategies to leverage FMs for robotics can generally be categorized into two, as shown in Fig. 17. The first strategy (Sec. VIII-A) elicits actionable knowledge from pre-trained LLMs/VLMs for robotic tasks, without additional model fine-tuning. The second strategy (Sec. VIII-B) collects abundant robotic data to fine-tune or co-train a *Robot Foundation Model* (RFM) that generalizes to control tasks with common sense reasoning capability [356, 357, 358, 359].

A. Applying LLMs/VLMs to Humanoid Robots

Applying LLMs/VLMs to humanoids is still a nascent field. Many works have shown successful deployment of LLMs/VLMs on various robot embodiments such as dexterous hands [360], manipulators [361], mobile manipulators [362], quadrupedal robots [363], and bipedal robots [364].

Among these works, a majority way of using LLMs/VLMs is to leverage pre-trained models without robot data. Although these pre-trained models have semantic understanding capability and context awareness, they often lack embodied knowledge and can prescribe actions that are ambiguous or non-admissible. Therefore, considerable research efforts have focused on task-planning mechanisms to enable the generation of admissible action plans. For example, SayCan [362] ranks available actions based on value functions obtained during the training of corresponding action policies for mobile manipulators. VLM-PC [365] restricts GPT-4o to output plans with skills available only for quadruped navigation.

The task planning capability of FMs has advanced the complexity of tasks that a humanoid can accomplish. For instance, Figure AI demonstrates fast, dexterous manipulation skills selected by a VLM that interprets natural language commands and the surrounding environment. In [366] and [367], pre-trained LLMs are used to select skills and task goals for animated humanoid characters. OmniH2O [271] employs GPT-4 [355] to select autonomous skills such as greeting a human. HYPERmotion [368] applies an LLM to construct task graphs that enable a hybrid wheeled-leg robot to execute complex loco-manipulation tasks. However, using FMs to plan with a fixed skill set is limited in skill versatility. In addition, for complex behaviors such as those in humanoid loco-manipulation tasks, it is essential to allow FMs to author the detailed motions of low-level skills, instead of selecting from existing, relatively-abstract low-level skills.

Thus, many research efforts have focused on identifying the best bridge between FMs and low-level robot skills. For example, researchers have proposed to generate code [361, 369] and reward functions [363, 364, 370] as intermediate representations for bipedal and quadrupedal robots. Compared to selecting existing skills, these intermediate representations provide additional flexibility in adjusting the generated motion. Furthermore, FMs can generate whole-body poses [371, 372] and whole-body contacts [373, 374] for humanoid robots. These techniques allow users to intuitively direct a robot's behavior through expressive inputs such as natural language, images, or even gestures.

B. Building Humanoid Foundation Models

While most FMs are developed in the vision or language domain, building FMs in the robotics domain for embodied

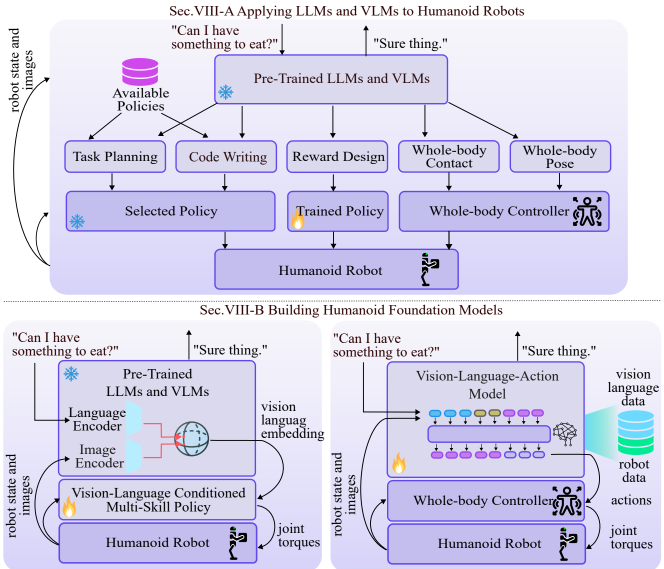

Fig. 17. Sec. VIII-A details different approaches to applying LLMs and VLMs in robotics tasks. These approaches prompt pre-trained LLMs and VLMs to generate task-relevant intermediate representations that can be executed by low-level policies or controllers. Sec. VIII-B presents two approaches to building humanoid foundation models. The first approach uses robot data to train multi-skill policy, and the second approach fine-tunes an existing VLM. Both approaches directly output actions for low-level humanoid control.

intelligence is a natural extension. Similar to LLM and VLM, robot foundation models (RFMs) are large models trained from Internet-scale robotic datasets. The RFMs often process multi-modal inputs (*e.g.*, egocentric images, and natural language as task description) and directly interact with the physical world through robot actions. Leveraging the Internet-scale multi-modal dataset, RFMs hold the promise of generalization across diverse tasks and provide a natural interface for human-robot interaction, both essential for real-world robot applications.

However, building large RFMs presents significant challenges. Successful implementations are limited to robots that have stable dynamics and a large amount of high-quality data collected with significant resources [357, 359, 375, 376]. Recent works have extended such RFMs to floating-base robots such as drones and quadruped robots [377]. However, building an RFM for humanoid loco-manipulation remains a challenging endeavor: the inherent instability in locomotion and high-dimensional action space in dexterous hands makes it extremely difficult to collect high-quality data efficiently. In addition, humanoid robots have critical safety constraints that often limit the exploration of their full behavioral capabilities, resulting in a lack of humanoid datasets.

One popular approach to building RFMs is to create a multi-task sensorimotor control policy using a high-capacity model that can consume large amounts of robot data. The trained policy can perform a wide variety of low-level skills, even for multiple robot embodiments. To enable high-level reasoning/planning, this approach often employs a hierarchical framework combining a pre-trained LLM or VLM with the low-level control policy, initialized from scratch. During training, this setup aligns the semantic knowledge of the LLM and VLM with the physical behavior of the control policy, enabling cross-modal capabilities such as language-to-action. Transformer [378] is a common choice for low-level policy due to its scalability. To enable interactive user commands, the low-level policy is conditioned on language and/or image inputs, often tokenized with pre-trained text or image encoders from LLMs or VLMs. For example, RT-1 [356] and VIMA [358] both train a language-conditioned visuomotor policy with a large amount of manipulation data and have demonstrated the ability to perform a wide range of skills. Despite significant research efforts in RFMs, applying them to humanoid robots remains an unexplored research area with limited existing work. Notable examples include HumanVLA [303] and SuperPADL [304], which train a humanoid-specific policy aligned with the latent space of pre-trained VLMs, enabling skills based on image and language inputs.

To leverage prior knowledge in FMs, another popular approach is to build a vision-language-action (VLA) model, as exemplified by RT-2 [357], OpenVLA [359], and Gato [379]. This approach treats robot data (*i.e.*, observations and actions) as tokens in the language model's vocabulary, allowing direct fine-tuning or co-training with existing VLMs. Unlike the previous approach, VLA outputs actions as tokens directly without relying on trainable low-level policies. The VLA model not only generates robot actions for diverse skills but also retains semantic reasoning abilities in the language and vision domain, enhancing its generalization capacity compared to models trained in single domains. For example, RT-2 [357] represents the actions as a string of numbers similar to the tokens from the pre-trained vision and language tokenizer of the base VLMs. However, representing actions with stringified numbers can be token-inefficient with high degrees-of-freedom robots such as humanoids. Despite the potential of this approach, no existing work has built VLA for humanoid robots. Recently, NVIDIA announced their Project GR00T initiative to develop general-purpose FMs for humanoid robots. The GR00T foundation model aims to leverage diverse data sources, from internet data and simulation data to real-robot data, for scalable training.

A key research question in building RFMs is the design of effective algorithms and model architectures. Although most of today's RFMs are based on autoregressive transformer models [378], their computational inefficiency over long sequences poses a significant challenge for both training and inference. This has driven exploration of alternative models that are both efficient and high-capacity, such as state-space models [380].

The key to the success of training an RFM, especially in the case of VLA, heavily depends on the choice of input and output representations. Most RFMs take as input a combination of task descriptions in language, visual observations of the surrounding environment, and the history of robot states. Outputs typically consist of robot actions, derived either from a multi-task policy (the first approach) or a VLA model (the second approach). There are variations in the VLA model where its token outputs specify more than just actions. For example, Octo [381] and RDT-1B [382] use the token output for the diffusion denoising process. π_0 [375] maps a learned token to robot actions through a diffusion head, enabling high-frequency control (up to 50 Hz for a bimanual manipulator with a wheelbase). GR-2 [383] predicts tokens that represent future images and actions; thus it functions as both a world model and a visuomotor policy. For humanoid robots, input and output are not yet well defined. For tasks involving rich physical interactions, the force feedback is as crucial as egocentric visual input. Given the unstable dynamics of humanoid robots, a more practical approach is to use end-effector and body poses as action outputs from the RFM and adopt additional low-level policies to ensure balance and safety via high-frequency feedback control. Incorporating robotic data as a new modality into state-of-the-art FMs would require significantly more data. Hence, designing effective input/output representation for humanoid loco-manipulation tasks still remains an open research question.

Conclusion: With rapid progress in FMs and humanoid robots, a plethora of research work on embodied intelligence in humanoid robots is anticipated. In the near term, we expect research to lean toward methods outlined in Sec. VIII-A as a more accessible way to leverage the capabilities of LLMs and VLMs. Meanwhile, we anticipate that the strategy of training a humanoid FM in Sec. VIII-B will become the mainstream in the long term as researchers develop a deeper understanding of incorporating additional modalities in FMs and with more humanoid robots deployed and data collected. For further reading of FMs for robotics, we recommend the survey in [9, 10]. Since most of the FMs are built with the Transformer backbones, please refer to [378] for a comprehensive mathematical foundation.

IX. Future Challenges and Opportunities

A. Challenges in Numerical Optimization

Robotic planning and control techniques that are formalized as numerical optimization problems heavily rely on advances in applied discrete mathematics and optimization theory. These advancements address challenges such as non-convexity, numerical robustness, and real-time resolution performance. However, a plateau may have been reached in the transfer of these techniques to the field of robotics at large – humanoids specifically – despite exploiting the unique properties of robotic models. These properties can enhance the efficiency of optimization problem formulation and its resolution by tailoring them to specific applications. However, as evidenced by the formulation OCP, including WBC and MPC, inherent physical uncertainties can disrupt closed-loop performance. Extending these formulations to loco-manipulation primarily involves (i) augmenting models to incorporate loco-manipulated counterparts and (ii) refining contact models formulations to account for various interactions (*e.g.,* impact [384], rolling, deforming). However, these extensions risk overcomplicating the problem, potentially hindering effective formalization, even if the resulting formulations are sparse.

Contact-explicit optimization formulations [6] are generally preferred due to their faster convergence and simplified formulation. However, they still suffer from the *curse of dimensionality*. Moreover, these formulations have the significant limitation of requiring the user to determine the contact mode sequence for the problem, which generally limits the ability to generate complex motions. Alternative contact-implicit formulations introduce complementarity conditions to eliminate the strict dependence on the contact mode sequence [160, 165, 385]. However, contact complementarity conditions are nonsmooth, introducing severe computational challenges. Generally, this is tackled via regularizing the complementarity problem, *e.g.*, [168], which approximates the constraint with a continuous affine function. Even with this linearized approximation, contact-implicit approaches struggle to scale to the high dimensionality of humanoid robots due to excessive computation and numerical difficulty.

All these approaches, however, still have only *local* optimality guarantees—if the structure of the problem requires deviations from the local candidate contact conditions, a feasible solution, even one that is only locally optimal, may never be found. Additionally, they are almost always deterministic in nature, failing to capture the stochasticity in the state estimates and future contact events. Addressing this uncertainty and lack of global optimality has led to the combination of search techniques with traditional trajectory optimization. For example, Model Predictive Path Integral (MPPI) [212] samples a variety of random control signals and their resulting state trajectories to determine the best action to take. Alternative contacts and objectives can also be sampled with contact-implicit approaches to help avoid local minima and find the globally optimal solution to accomplish a task [386]. Although both of these approaches heavily leverage computational parallelization for expediency, parallelizing the underlying optimization algorithms explicitly designed for trajectory optimization is gaining increasing prevalence, both on the CPU [387] and GPU [210, 388], as discussed in Sec. V.

Despite the gains in these algorithms for considering the full system dynamics, the robustness of the mathematical solution when performing numerical optimization has been a concern due to the infeasibility of complex optimization problems, regardless of the computation speed improvement. As discussed in WBC Sec. VI, arbitrating techniques address infeasibility by (i) relaxing the hard constraint to the soft constraint by combining them in the cost with a weighted sum and (ii) prioritizing the constraints by achieving the important ones first. However, how to design a smart solver to automatically resolve this issue and provide numerical robustness is still an open question. In addition, weight-tuning in high-dimensional problems with complex objectives is nontrivial, highly task-dependent, and can lead to instability [263]. Researchers have made initial steps to apply auto-tuning techniques to streamline the tuning process in Optimal Control Problem (OCP) designs for humanoid robots [389, 390]. Until these are solved, assigning definitive but non-violating constraints and designing objective functions while maintaining global versatility still depend on expert knowledge.

B. Challenge: Lack of Benchmarks for Loco-manipulation

Humanoid loco-manipulation skills are at their infancy compared to other tasks such as humanoid locomotion [391] and tabletop manipulation [392]. Therefore, many simulators, such as Isaac Lab [216] or MuJoCo [215], lack large-scale and systematic benchmarks dedicated to humanoid loco-manipulation tasks. Developing well-designed tasks and evaluation metrics can significantly accelerate research in this field. Recently, HumanoidBench [280] and Mimicking-Bench [393] offer a list of loco-manipulation tasks. They provide a standardized benchmark for evaluating the performance of humanoid algorithms and help verify the reproducibility within MuJoCo and Isaac Gym. SMPLOlympics [394] presents a collection of sports as benchmarks for simulated humanoids and shows that leveraging human-motion demonstrations leads to human-like behaviors in these sports.

In addition to defining loco-manipulation tasks, the development of affordable and capable humanoid robots as standardized platforms for hardware evaluation can significantly accelerate the research. Research efforts on open-source humanoid hardware and software, such as Hector [2], the MIT Humanoid [181], the Berkeley Humanoid [395], and the Duke Humanoid [396] represent valuable contributions. In addition, an ecosystem in rapid prototyping and production of humanoid robots also accelerates hardware development, such as the Robotic Grand Factory [397]. The Robotic Grand Factory has incubated the Q-series humanoid robots [397] with the state-of-the-art capability of fast walking, multi-terrain adaptation, and explosive motions, enabling tasks such as organizing, storing, and reception.

C. Challenge: Data Scarcity

As discussed in Sec. VII-B, the four data sources present a trade-off between quality and availability. The lack of high-quality large-scale robot data becomes a bottleneck for robot skill learning. To solve the bottleneck, much effort has been put into data scaling. It is a heated debate in the community whether scaling is the road toward generalist humanoid robots.

The central question we must answer is which aspect of human motion we want robots to learn. Some humanoid tasks can be achieved simply by mimicking 3D human pose trajectories [271, 272, 298, 302, 313], but a true general-purpose robot emerges from purposive learning: the ability to identify meaningful intentions from human data and adapt past experiences to new tasks or environments [398]. Therefore, human data must teach the robot not only *what* humans are doing, but also *how* and *why* they are doing it. Current data acquisition methods that capture human joint poses only enable learning what humans are doing. In this regard, imitation of human data at the trajectory level is not fundamentally generalizable due to the inevitable gap in morphology and in the surrounding environment.

We argue that generalization in loco-manipulation is achieved by including the motion of the manipulated objects, enhanced with a greater variety of sensing modalities instead of data quantity scaling. To develop truly versatile and adaptive humanoids, human data should also include that of the manipulated objects, cognitive actions (*e.g.*, trust, compete, collaborate) paired with multimodal observations (*e.g.*, whole-body haptic sensing, egocentric images), so that humanoids can learn the 'how' and 'why' from human data. However, instrumenting the environment and the manipulated objects with force and tactile sensing might be extremely complex. Therefore, research toward inferring force information from vision [399] and human-captured data [400] can be an intermediary solution to the problem of whole actors instrumentation. Recent work on collecting human multimodal observations [401, 402] and human kinetics [403] are a few examples that aim to bridge the gap between human animation and humanoid applications. Together with the rapid advancement in humanoid hardware, purposive learning with more informative human data will become the mainstream approach to achieve versatile and general-purpose humanoids.

D. Opportunities and Challenges in Foundation Models

Integrating Foundation Models (FMs) into humanoid robots offers distinct opportunities and challenges. On the opportunity side, since the majority of data used to train FMs is collected by humans, the knowledge embedded in these models is inherently biased towards human-like embodiments. Consequently, humanoid robots could potentially utilize existing knowledge in FMs more effectively due to a smaller embodiment gap. This advantage extends beyond planning and control capabilities to include interactions with humans using natural modalities such as language and gestures. However, challenges arise from the humanoid form itself. First, the bipedal platform poses additional challenges in control and safety due to its inherent instability. Furthermore, it elevates expectations for naturalness in their movements and interactions, necessary to avoid the *uncanny valley* effect.

Another challenge in applying FMs to humanoids arises from the high inference cost. Running large foundation models using only onboard computing is not feasible due to the limited power and computation, which hampers real-time hardware control. To address this challenge, several solutions have been proposed. One effective strategy involves adopting a decentralized hierarchy, where FMs operate over the cloud and provide only high-level decisions at a lower frequency, while another controller remains onboard and manages real-time task execution. However, inference delay and internet latency might impede the control performance. Another approach is to enhance the speed of the computing platform and the efficiency of FMs. For instance, NVIDIA introduced Jetson Thor, an on-board computing platform designed for humanoid robots. Google proposed SARA-RT [404], which accelerates the model speed without compromising its quality.

The training of FM is also resource and time consuming. For example, training the LLaMA model took 34 days on 992 NVIDIA A100-80B GPUs [405], which incurs high cost, high energy consumption, as well as carbon dioxide emission. As FMs scale up further, the training cost would increase further. A promising approach to maintain a reasonable cost for training robotics FMs is to leverage parameter-efficient fine-tuning techniques. For example, OpenVLA leverages the LoRA technique to fine-tune an FM with a robotics dataset [359].

A critical component of the humanoid foundation model that has yet to be developed is a scaling law, similar to the training of large language models [406]. The scaling law provides guidance on how we should scale up model, compute, and data, to meet the desired performance in the most efficient way. A major research effort focuses on scaling the robotics dataset. Open X-Embodiment extends the idea to a much larger robotics dataset across various robot embodiments and tasks [376]. Recent work has already explored a data scaling law for robot manipulation, with a focus on generalization capabilities [407], as well as model scaling behaviors for zero-shot capabilities in action selection [408], which marks important initial steps towards this direction.

X. Conclusion

Humanoid robotics is advancing at an unprecedented pace, as seen in recent groundbreaking innovations from both industry and academia. Although humanoid robots still face significant technical challenges, their agility, safety, reliability, and versatility have improved significantly through both model-based and learning-based methods. More opportunities are emerging through the exploration of new paradigms. Physically, advanced observers (vision and whole-body tactile sensing) and estimators are emerging for contact-rich whole-body loco-manipulation. Cognitively, foundation models grounded on humanoid robots have great potential to unlock the ability of open-world understanding and the development of generalized intelligent agents. More importantly, how to seamlessly integrate multimodal sensing and foundation models with the existing planning and control frameworks presents promising and challenging research questions. In the foreseeable future, the cost of humanoid robots will continue to decrease, making them more accessible; their physical capability (hardware intelligence) and cognitive intelligence will significantly advance. We look forward to humanoid robots that are responsive, purposeful, and fully capable of human-like loco-manipulation tasks in the upcoming decade.

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