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SURVEY PAPER

Humanoid Robot Motion Planning Approaches: a Survey

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Abstract
Humanoid robots are complex, dynamic systems. Any humanoid robotic application starts with determining a sequence of optimal paths to perform a given task in a known or unknown environment. This paper critically reviews and rates available literature on the three key areas of multi-level motion and task planning for humanoid robots. First is efficiency while navigating and manipulating objects in environments designed for humans. Here, the research has broadly been summarized as behavior cloning approaches. Second is robustness to perturbations and collisions caused by operation in dynamic and unpredictable environments. Here, the modeling approaches integrated into motion planning algorithms have been the focus of many researchers studying humanoid motion's balance and dynamic stability aspects. Last is real-time performance, wherein the robot must adjust its motion based on the most recent sensory data to achieve the required degree of interaction and responsiveness. Here, the focus has been on the kinematic constraints imposed by the robot's mechanical structure and joint movements. The iterative nature of solving constrained optimization problems, the computational complexity of forward and inverse kinematics, and the requirement to adjust to a rapidly changing environment all pose challenges to real-time performance. The study has identified current trends and, more importantly, research gaps while pointing to areas needing further investigation.

Keywords Humanoid robots · Motion planning · Motion control

1 Introduction

Since the first industrial revolution in 1760, technology has evolved significantly, which has changed our lifestyle enormously. Especially the current industrial revolution, 4.0, has dramatically increased the use of information technology in our daily lives. A variety of smart devices has become part of our households. People spend hours on these devices, which has an impact (both positive and negative) on our society and culture. Our dependence on these smart devices is increasing day by day. The information technology revolution has also made robots more and more capable, and now robots can do complex tasks and procedures that were unimaginable twenty years ago.

In humans, the brain is the most important part of decision-making, reasoning, and controlling movements of various body parts. Humans normally do not need to make an effort to move their arms or legs. However, for a humanoid robot to have capabilities similar to humans, it is a complex or even impossible task in many cases. The humanoid robot may have to read many inputs from the sensors monitoring its surroundings and body and respond appropriately. A simple task for humans, for example, riding a bike or driving a motorcycle, can be very challenging for a humanoid robot. Robots must learn how to accelerate, brake, and recognize obstacles, people in the street, traffic lights, etc. For a robot to be capable of this, it must deal with a lot of information and have proper robot motion planning.

Imagine another task where a humanoid robot needs to pick a glass of water from a table and move it to another place or hand it over to a human (Fig. 1). The robot needs to recognize the cup, move its arm until it reaches it, grab it, hold it, move with it in its hand, and then put it on the other surface or hand it over to a human. To accomplish this task, we must plan for all the body motions. We must deal with the kinematics and the center of mass for walking and plan the motions for the upper body. Everything must be synchronized and coordinated.

Humanoid robots still have to learn much to live in a social environment. They should be capable of doing common tasks

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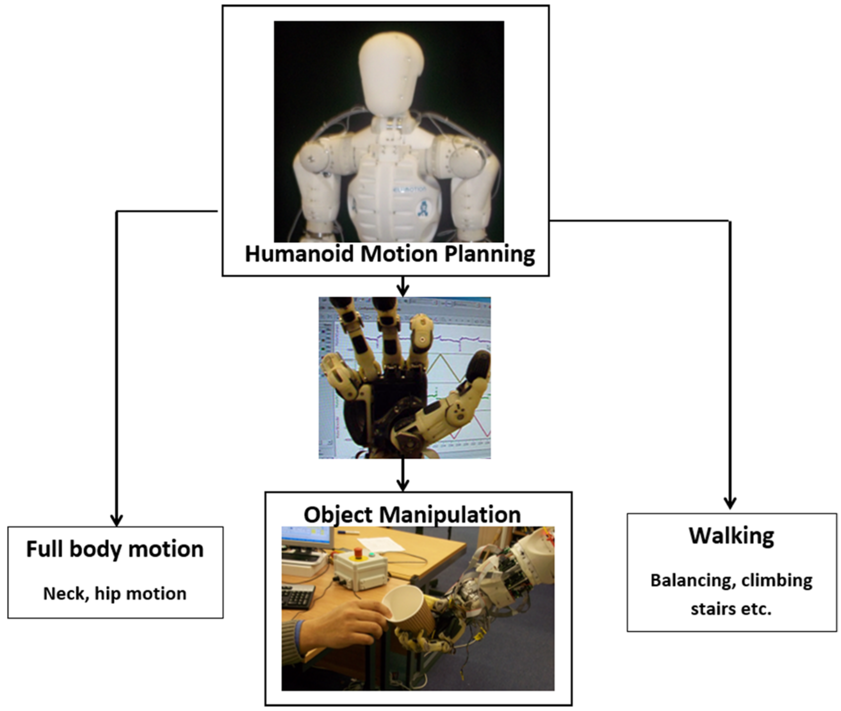

Fig. 1 Humanoid Motion planning classification

similar to human beings, like driving a car, riding a bike or a scooter, or doing housekeeping. In short, most of the common activities in the social environment are still open problems in humanoid robotics [57]. In this paper, we aim to explore the current state of the art by exploring the published research work in recent years. As mentioned before, technologies have evolved exponentially over the last few decades. This review paper analyzes many papers highlighting different aspects of humanoid robot motion planning. In addition, we investigate how these techniques have been used to deal with unsolved and challenging problems. This review should also serve as a guide for new researchers in the humanoid robot motion planning field.

The rest of the paper is divided into various sections. Section 2 presents a background of humanoid robot motion. Cloning approaches have been discussed in Sect. 3. Inverted pendulum-type schemes are discussed in Sect. 4. Section 5 presents a kinematics constraints-based approach. Section 6 introduces AI (Artificial intelligence) techniques. The paper is summarised and concluded in Sect. 7.

2 Background of Humanoid Robot Motion Planning

This section defines the issue of motion planning and control for humanoid robots and establishes a framework for analyzing the literature. Figure 2 presents a humanoid motion planning and control framework. Other similar frameworks include those reported in [50] and [51]. Notice that although a clear demarcation has been made between the three modules, an integrated approach is more common in the literature and also in practice, e.g., see [52], and [53]. In robotic motion planning, robot motion is divided into discrete steps while dealing with the constraints imposed by the robot workspace. In addition, some aspect of the motion is optimized.

The area of robot motion planning and control has gained substantial attention, especially with the increasing emphasis on humanoid robots. This area addresses how these robots can autonomously navigate their environments while interacting seamlessly with their surroundings and humans. This topic becomes even more crucial when considering the inherent complexities of humanoid robot structures, which are often less robust than industrial manipulators and must prioritize safety due to their direct interactions with humans.

The landscape of robotic motion planning encompasses several methods and approaches. For instance, Wang et al. [64] provide an in-depth review of learning-based motion-planning techniques. The paper emphasizes their application in navigating intricate settings without any collisions. These methods, which have garnered considerable success in high-dimensional spaces, span across supervised, unsupervised, and reinforcement learning paradigms. Depending on the adopted approach, these techniques rely on predefined reward functions or adjust based on successful motion planning experiences. This insightful piece shines a light on conventional and learning-focused perspectives on motion-

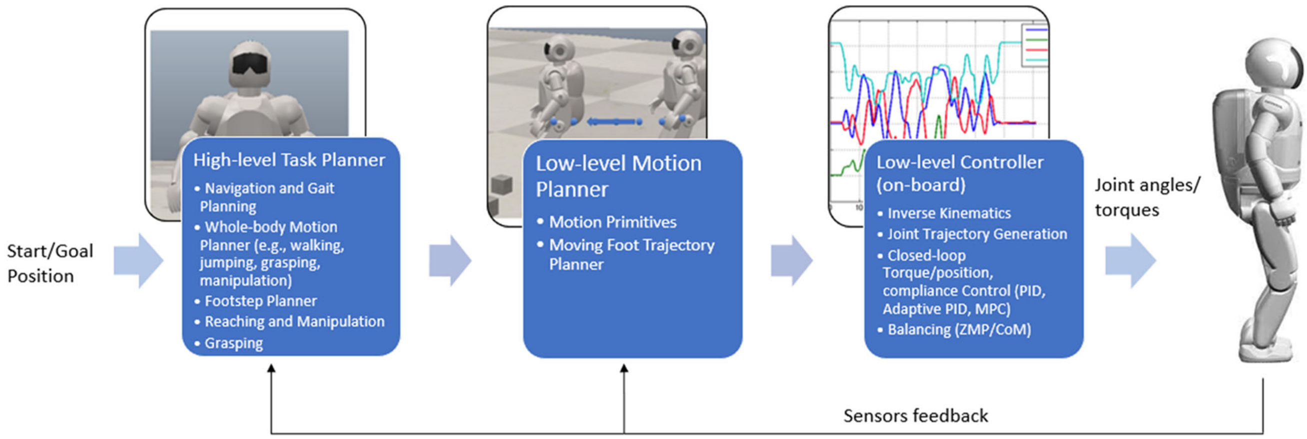

Fig. 2 Framework for humanoid robot motion planning

planning issues and delves into an array of learning-based motion-planning algorithms. Moreover, it highlights the integration of classical techniques with contemporary learning methodologies.

According to Sciavicco and Siciliano [40], a path is the location of the points the manipulator/robot needs to follow to execute the assigned motion. It is fundamentally a geometric description of motion as highlighted in Fig. 3. However, a trajectory is a path on which a timing law is applied. We consider the velocities and/or accelerations at each point.

A trajectory planning algorithm generates an end-effector position and orientation time sequence while satisfying the set constraints. Since the control action is conducted in the joint space, a well-defined inverse kinematics solution will be employed to reconstruct the time sequence of joint variables, giving the desired result in the operational space.

Trajectory planning enables intrinsic computation for path limitations resulting from workspace regions that the robot is prohibited from entering, such as the presence of barriers. Due to the difficulty in calculating their corresponding points in the joint space, such restrictions are often better stated in the operational space.

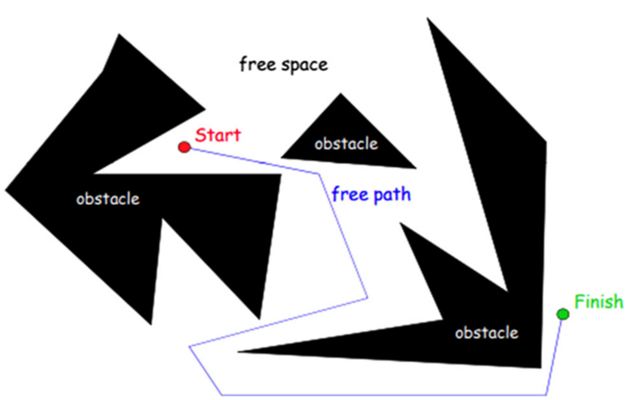

Fig. 3 Motion planning to walk through obstacles

In [40], trajectory planning is defined as an interpolating function *q(t)* that computes joint variables at each point within the set restrictions. Essentially, a joint space trajectory planning algorithm must have the following characteristics:

- Generate trajectories should not be significantly challenging from a computational perspective;
- The joint position, speed, and acceleration functions should not have any discontinuity;
- Non-smooth trajectories are corrected by interpolating a sequence of points on a path.

Humanoids perform their tasks autonomously with minimal to no instruction. Task and motion planning is, therefore, done separately and independently. Task planning includes finding a sequence of high-level actions (e.g., pick, place, move, press, walking, climbing, standing-up, etc.), motion planning plans, and joint motions based on the motion primitives ("templates") to achieve the desired tasks. Unlike wheeled mobile robots, humanoid robots perform footstep planning all the time due to their bipedal nature [48],[54].

Industrial articulated robots are quite different from humanoid robots and their applications. Hence, in their case, motion planning should also be viewed from a different perspective [41, 42]. For example, industrial robots are resilient and robust and usually have specific tasks to perform. For instance, objects picking and placing, polishing [43], etc., the motion of these robots does not include a wide range of options. Hence, with conventional robotic control approaches, motion planning is based on direct and indirect kinematics. In addition, human safety is not of high concern due to their confined workspace environment [44, 45]. On the other hand, the motion planning of a humanoid robot is highly challenging, and in most cases, these robots are less robust than industrial manipulators. Furthermore, since humanoid robots directly interact with humans, safety is a key problem in dealing with these robots [46]. Hence, it is critical to comprehend the level of complexity and how we can perform motion control planning for these robots. The continuous development of humanoid robots will enhance their capability to perform new and diverse tasks. Therefore, new motion planning approaches may be needed to address the new challenges. Motion planning aims to determine a feasible and optimized path for a moving entity from a start to a target destination, avoiding obstacles and adhering to various constraints, including physical, environmental, and task-specific requirements, across applications like robotics, autonomous vehicles, and computer animation. Humanoid motion planning can be divided into subcategories, as shown in Fig. 1.

Motion planning allows autonomous robots to compute their motions to achieve high-level goals such as going from point A to B while avoiding obstacles, assembling a product, building an environment map, climbing a ladder, and manipulating objects. Computing motions means computing the geometric paths (in configuration space) and time-parameterized trajectories (in time-space) and generating motion commands for the robot. The theoretical basis for the motion planning problem is the configuration space (C-space), which is a set of all possible configurations that a robot mechanism can attain. A continuous space is discretized and then searched for an optimum collision-free path. Discretization is either sampling-based or criticality-based. The method works both for articulated robots and mobile robots. Challenges one has to face during path planning include dealing with moving obstacles, respecting the nonholonomic, dynamic, and stability constraints, and dealing with uncertainties in modeling, control, and sensing. Example algorithms include the Rapidly Exploring Random tree (RRT), Probabilistic Roadmaps (PRM), and Vertical Cell Decomposition (VCD), as their variants [47]. Although motion planning for mobile robots in C-space seems easy due to its two-dimensional nature, a primary requirement here is that the robot must have a predictive model of its actions. This requires perfect control of robot actions and an accurate geometric model of the environment (layout, boundaries, and obstacles).

The pioneering work in motion planning for humanoid robots was carried out in the early 90 s [24]. Path planning was used, which searches for the graph to connect the local minima of a potential function defined over the robot's configuration space. The studies involved manipulator arms with 8, 10, and 31 DOFs and rigid objects with 3 DOFs in the 2D workspace and 6 DOFs in the 3D workspace.

Robot motion planning has attracted more researchers since the early 2000 s, when more powerful computers were widely and easily available, and robotics technology was advancing at a rapid pace. A technique for path planning for humanoid robots that calculates dynamically stable, collision-free trajectories using whole-body posture goals was introduced in [25]. It searches the robot's configuration space for a collision-free path that fulfills dynamic balancing conditions using a geometric representation of the environment and a statically stable selected posture.

A non-gaited motion planner for humanoid robots crossing extremely unlevel and sloping terrain was reported in another early 2000 s study by [26]. Simulated tests were conducted on hypothetical humanoid robot HRP-2 motion examples. The authors in [27] have investigated dynamically stable full-body motions, object gripping and manipulation, motion planning for navigation, and footstep placement. They specifically investigated full-body motions, object manipulation, and robot footstep planning on the humanoid robot SDR-4X.

A current trend in motion planning is to exploit more computationally intensive schemes such as artificial intelligence techniques. For instance, deep learning, reinforcement learning, and other similar neural network-based schemes are gaining popularity. Authors in [2] have developed a Deep Reinforcement Learning (DRL) based control framework to teach humanoid robots the complex motor abilities of push recovery. To explore and understand similar research work, we divide them into 1) Human-Inspired Approaches, 2) Inverted Pendulum Approaches, 3) Kinematics Constraints Approaches, and 4) Motion Planning Using AI Techniques for Humanoid robot motion planning. These categories will be discussed in detail on the following pages. In the end, a small section has been included on the motion planning of non-humanoid robots.

Besides that, we have also included a review table with four important metrics. They will be categorized as “High," “Medium," and “Low." These metrics are:

1) Efficiency: Time and computational resources required to compute a path;
2) Robustness: Ability to handle uncertainties in the environment or the robot's model;
3) Scalability: Performance in varying environments, from simple to complex terrains;
4) Adaptability: Capability to adjust to dynamic changes in real time.

3 Human-Inspired Approaches

This section presents research by mimicking or cloning human behavior. Most of these approaches employ Artificial Intelligence (AI) techniques with the data acquired to solve the robot's whole body motion and the motion of the individual elements.

In the work by [4], the robot learns many environment-aware locomotion skills with minimal prior knowledge. The framework used encompasses two distinct tiers: the low-level and high-level controllers. The high-level controllers are trained to strategically determine the timing of actions, suggesting specific step targets for the low-level controller. At this juncture, decisions are made in real-time, influenced by high-dimensional inputs, like terrain maps or other pertinent environmental representations. The authors emphasized how this operates at a finer timescale, executing stable walking patterns that satisfy both stepping-target and style requirements. Both control layers were trained on a 3D biped using deep reinforcement learning.

Another significant contribution, presented in [60], introduces a humanoid motion planning technique for robotic arms to bolster their reliability and safety, especially in scenarios like assisting the elderly or vulnerable. Drawing parallels with human arm physics, the methodology starts by collecting data related to human arm motions through the VICON optical motion capture system. This dataset is pivotal in decoding humanoid motion rules. With these rules as the foundation, fitting reward functions are sculpted, and the robotic arm is subjected to humanoid motion training using the Deep Deterministic Policy Gradient (DDPG) and Hindsight experience replay (HER) algorithms. Experimental assessments reinforced the method's effectiveness, specifically in curating humanoid-like motions for robotic arms.

The work by Kanjar et al. [1] offers a novel procedure for a humanoid robot to traverse a significant obstacle. The approach leans heavily on multi-body contact motion planning from genuine human demonstrations. It unfolds with a multi-contact search algorithm rooted in a whole-body control technique. This algorithm works with human motion data to streamline the search for the optimal outcome based on human data representations. The sheer brilliance of this method is that it hinges solely on recorded observational data, giving the robot the flexibility to engage with the obstacle using any body part.

Gulletta et al. [61] have explored Human-like Upper-limb Motion Planner, a groundbreaking algorithm tailored for anthropomorphic robots. It is adept at crafting human-like, collision-evading trajectories for the upper limbs. At its core lies the amalgamation of human motor control theories. Depending on the task, the algorithm modulates spatial and postural constraints, modeling them into cost functions. Subject to various tests, ranging from simple reaching maneuvers to intricate object manipulation, the algorithm unfailingly exhibited its prowess in orchestrating naturalistic arm movements. A testament to its success, it leverages smoothness measures borrowed from human motor control studies, reflecting its efficacy in delivering human-like kinematic robot movements. This indeed sets the stage for more fluid human-robot collaborations.

Reference [2] presents a unique approach for directing humanoid robot arms, amalgamating deep reinforcement learning (DRL) and the nascent digital twin technology. Central to this method is a data aggregation system meticulously designed to gather and furnish data to the twin synchro-control (TSC) scheme optimized for motion control planning. The strategy accelerates the DRL agent training by harnessing pre-existing knowledge from the data collection system. The culmination of this research sees a comparative simulation involving a planar 3-DOF manipulator and a model of the BHR robot, employing the DDPG algorithm, both with and without the TSC scheme.

In biped robots, Balakrishana et al. [69] delve into their increasing relevance, attributed to their uncanny resemblance to human structure and joint mechanisms. Despite their intricate designs and multiple degrees of freedom, these robots rely heavily on meticulous gait planning to guarantee stable locomotion. The study meticulously chronicles the evolutionary trajectory of dual-legged robots and their pursuits for energy-efficient motion planning. It also comments on the design of gait trajectories, propelled by optimization techniques, culminating in pioneering assistive devices such as exo-suits or exoskeletons. These inventions hold promise in revolutionizing support for injured individuals and facilitating daily chores. However, the study does not abandon critiquing bipeds' somewhat mechanical gait cycles, emphasizing their shortcomings in mirroring fluid human movements adaptively. This critique lays the groundwork for potential advancements in biped robot design, underlining future challenges and goals.

Khazoom et al. [73] embark on a fascinating exploration into the auxiliary benefits of arm movements in robots. Drawing parallels with the natural arm swinging observed in humans, which is instrumental for balance and movement, the study presents an innovative approach. Recognizing the limitations of existing robotic controllers that employ arm movements-predominantly feedback-driven and unable to preempt disturbances-it proposes a model hierarchy predictive control (MHPC) approach. This is geared towards planning arm motions, catering to predicted and unforeseen disturbances. Empirical evaluations on the MIT Humanoid in simulated balance scenarios revealed an optimal MHPC formulation that operates at a staggering 40 Hz frequency. This optimization endowed the robot with rapid momentum dissipation and the agility to independently adjust its center of mass, thus ensuring efficient ground interactions and maintaining stability. The added advantage of preemptively accounting for disturbances using MHPC further enhances these merits.

Zhao et al. [77] pivot towards robots imitating human actions, which are undeniably useful in human-robot physical interactions. However, it is not just the appearance that counts; human-like movement is quintessential in boosting efficiency and ensuring safety. The study unveils a motion planner molded on human arm motion patterns (HAMPs), tailored for seamless robot-human object transfers. Handover tasks are dissected into pick-up and delivery phases, with unique HAMPs extrapolated for each. A selection protocol is introduced to cherry-pick the most representative HAMPs, complementing a thorough analysis of factors influencing motion duration. Drawing on these insights, a motion-planning framework for robotic arms ensures anthropomorphic movements. Validation exercises involving a KUKA IIWA robot vouch for the method's precision, with the trajectories closely emulating natural human arm movements. Comparative evaluations further underscore the human-like nuances of this innovative technique.

Lastly, Yan et al. [3] delve into the stability of humanoid robots constructed using cutting-edge machine learning and AI techniques. A deep reinforcement learning-based control framework, meticulously crafted to empower humanoid robots with the dexterity needed for push recovery, takes center stage. Complex challenges emerge, such as multi-contact coordination relying on multi-sensory inputs, the interplay between fully and under-actuated conditions, fine-tuning policies, and the ability to adapt to disturbances affecting any body part. These intricate facets often elude traditional designers. However, the study meticulously addresses these concerns. Constructing novel control mechanisms manually and the inception of a reliable switching mechanism in such scenarios necessitates a harmonious blend of labor, analytical prowess, and computational might.

The efficiency of robot path planning has been explored and addressed in various research. In [4], the robot learns to navigate its environment using a two-tiered system. The high-level controller determines the optimal timing for actions, while the low-level controller ensures the movement matches style requirements, emphasizing an environment-aware approach. Similarly, Yang et al. [60] center on humanoid robotic arms that emulate human motion. The data collected decodes humanoid motion rules to ensure more reliable and safe interactions, especially in vulnerable scenarios. Researchers in [61] have developed the Human-like Upper-limb Motion Planner, which is proficient in creating human-like trajectories for anthropomorphic robots. Using theories from human motor control, the algorithm can adjust to different constraints based on the task. Another work, [69], offers another perspective on path planning, which provides an overview of biped robots and their challenges in gait planning.

Ensuring that robots can make decisions and act in real-time is essential for practical applications. In [4], the high-level controller makes real-time decisions influenced by complex inputs such as terrain maps. Zhao et al. [77] focuses on robots that look human and move like one, particularly in handover tasks. By breaking down the handover into phases and studying motion patterns, the research ensures that the robot's actions closely emulate natural human movements in real-time scenarios. Table 1 summarizes the papers reviewed in this article.

Table 2 comprehensively analyzes various research works exploring human behavior replication in robots using Behavior Cloning techniques. This evaluation is based on four critical metrics: efficiency, robustness, scalability, and adaptability, briefly defined previously. These metrics are instrumental in gauging the effectiveness, reliability, and practical applicability of the proposed AI methodologies in humanoid robotics. Here is a closer look at these metrics and their implications:

Efficiency: This metric evaluates how effectively the proposed methods enable robots to learn and mimic human behaviors, considering both the computational resources required and the learning speed. High efficiency indicates that the method can quickly and effectively train robots to perform tasks with minimal computational cost.

Robustness: Robustness measures the ability of the method to cope with environmental changes, uncertainties, and disturbances. A high rating in robustness signifies that the approach ensures consistent robot performance despite variations in its operational environment.

Scalability: Scalability assesses the method's applicability across tasks, robot models, and complexities. Medium scalability indicates that while the method shows promise, it might need adjustments or further development to be applied broadly across various scenarios or to handle more complex behaviors.

Adaptability: This metric gauges the method's flexibility in learning new tasks or adjusting to new environments. High adaptability reflects the approach's capacity to enable robots to adjust their behavior based on new information or changes in their surroundings, which is essential for dynamic and unpredictable environments.

Table 2 showcases a range of research works, such as:

- [4]: Demonstrates high efficiency and robustness in teaching robots environment-aware locomotion skills using a two-tiered deep reinforcement learning system. Its medium scalability suggests potential limitations in application breadth without further adaptation;
- [60]: Exhibits high efficiency in training robotic arms for tasks requiring human-like dexterity, using motion capture data to learn from human arm movements;
- [1]: Offers a unique approach to obstacle traversal with medium efficiency, highlighting challenges in scaling and adapting the method for various obstacles;
- [61] and [77]: Both achieve high marks across efficiency, robustness, and adaptability, underscoring their success

Table 1 Humanoid Robot Review Papers: Behavior Cloning Approaches

Paper Name	Main Problem	Main Approach to Solve It	Simulation	Real Robot Application	Robot's Name
[4]	Robot locomotion in various environments	Two-tiered system with High-level controllers determining action timings and low-level controllers executing walking patterns	Yes	No	DeepLoco
[60]	Humanoid motion planning for robotic arms, especially in vulnerable scenarios	Data collection through VICON system, decoding humanoid motion rules, training robotic arm using DDPG and HER algorithms	Yes	Yes	Not Available
[1]	Traverse significant obstacles for humanoid robots	Multi-body contact motion planning based on human demonstrations using a whole-body control technique	Yes	No	Not Available
[61]	Human-like trajectories for anthropomorphic robots' upper limbs	Human-like Upper-limb Motion Planner algorithm that integrates human motor control theories adjusting spatial and postural constraints based on tasks	Yes	Yes	HUMP
[2]	Directing humanoid robot arms	Combination of DRL and digital twin technology with a data aggregation system tailored for motion control planning	Yes	No	Model BHR-6
[69]	Gait planning for biped robots	Detailed overview of biped robots and evolutionary trajectory focusing on gait trajectory designs, optimization techniques, and assistive devices	Yes	No	Not Available
[73]	Benefits of arm movements in robots for balance and movement	Model Hierarchy Predictive Control (MHPC) approach to plan arm motions considering both predicted and unforeseen disturbances	Yes	Yes	Not Available
[77]	Human-like movement in robot-human object transfers	Motion planner based on human arm motion patterns (HAMPs) for pick-up and delivery tasks with a selection protocol to choose representative HAMPs	Yes	Yes	Model KUKA IIWA
[3]	Stability of humanoid robots	DRL-based control framework addressing challenges like multi-contact coordination, adaptation to disturbances, policy fine-tuning, and interplay between actuation conditions	Yes	Yes	Not Available

in creating human-like movements for robotic arms and enhancing human-robot interaction, respectively;

- [2] and [3]: Illustrate the integration of cutting-edge technologies like digital twins and deep reinforcement learning to enhance motion control and stability in humanoid robots, showing promising scalability and adaptability.
- [73] develops a Model Hierarchy Predictive Control (MHPC) for humanoid robots, enhancing balance through planned arm motions. Efficiency is demonstrated by the controller's ability to handle unexpected and anticipated disturbances, optimizing whole-body dynamics while maintaining real-time operability. Robustness is shown in the system's increased disturbance withstandability, benefiting from arm usage to maintain balance. Scalability and adaptability are implied through its potential for real-time application on actual hardware and its foundational design for locomotion, suggesting its applicability to varied tasks and conditions.

Table 2 Evaluation of Behavior Cloning Approaches

Paper Name	Efficiency	Robustness	Scalability	Adaptability
[4]	High	High	Medium	High
[60]	High	High	Medium	High
[1]	Medium	High	Low to Medium	Medium
[61]	High	High	Medium	High
[2]	High	High	Medium to High	High
[69]	High	Medium	Medium	Medium
[73]	High	High	Medium	High
[77]	High	High	Medium	High
[3]	High	High	Medium to High	High

This evaluation provides insights into behavior cloning approaches' current state and potential in humanoid robotics. While the research exhibits significant advancements in mimicking human behavior, varying degrees of scalability highlight the need for ongoing efforts to generalize these methods across various tasks and environments. The high adaptability scores across most studies reflect the evolving capability of AI-driven robots to adapt to new challenges, promising more sophisticated, versatile, and lifelike humanoid robots in the future.

4 Inverted Pendulum Approaches

In this section, both dynamics and kinematics-based approaches are highlighted. In most cases, full body and individual limb motion are considered, which also relies on the physical parameters. Researchers have presented methods for path planning for humanoid robots that calculate dynamically stable, collision-free trajectories for full-body posture. The biped robot's posture is investigated in the joint space for a collision-free path that also complies with dynamic balancing restrictions using a geometric model of the environment and a statically stable goal posture. They modify current randomized path planning techniques to ensure the final path's overall dynamic stability by balancing limits on incremental search moves. A dynamic filtering function is used as a post-processing step to transform static collision-free pathways into dynamic collision-free trajectories by constraining the Zero Moment Point (ZMP) trajectory.

In humanoid robotics, modeling approaches extend far beyond the traditional inverted pendulum model, encompassing a variety of methods that offer unique insights into robot balance, stability, and motion. The Zero-Moment Point (ZMP) and Linear Inverted Pendulum Model (LIPM) stand out for their significant contributions to dynamic walking and balance control. The ZMP model, pioneered by Vukobratović and Juricić [101], has been instrumental in developing robots capable of maintaining stability while moving. The LIPM, further developed by Kajita et al. [102], simplifies the control of walking robots by focusing on the linear dynamics between the center of mass and foot placements, offering a practical approach to gait planning.

Another critical advancement in humanoid robotics modeling is the Centroidal Momentum Dynamics (CMD) approach. Introduced by Orin et al. [103], CMD considers the robot's total mass distribution and its effects on motion, offering a more nuanced understanding of how different body segments contribute to overall momentum and stability. This model has allowed researchers to explore more sophisticated control strategies that account for the intricate interactions between a robot's limbs and torso, leading to more adaptable and capable robotic systems.

These models represent the collaborative efforts of the robotics research community to tackle the challenges of bipedal locomotion. By integrating insights from ZMP, LIPM, and CMD, researchers can develop humanoid robots with enhanced balance, agility, and interaction capabilities. Each model brings a unique perspective to humanoid robotics, emphasizing the importance of diverse approaches to solving complex problems in robot motion planning and control.

As we continue to explore and integrate these models, the field of humanoid robotics is poised for significant advancements. The contributions of pioneers like [101] and Orin [103] have laid a solid foundation for future research, inspiring new generations of engineers and scientists to push the boundaries of what is possible in robotics. By acknowledging and building upon these foundational models, the research community can look forward to creating increasingly sophisticated and lifelike humanoid robots capable of navigating the complexities of the human environment.

The strategies discussed in this section, such as the center of mass and the zero-moment point, are related to the dynamic stability of humanoid robots. Using these techniques, the robot may instantly and effectively modify its body posture and walking patterns in the presence of unknown disturbances, improving the robustness of its walking.

The work reported in [33] offers a navigation and manipulation problem-solving planning algorithm for a humanoid robot and its environment. The path was approximated by a series of dynamic walking trajectories, which involved 1) computing a collision-free path in the space of quasi-statically balanced configurations and 2) a sequence of dynamic walking trajectories. The algorithm's accuracy-approximating any non-necessarily admissible path by a sequence of acceptable trajectories-is demonstrated using the small-space controllability principle. Because the planner is developed for structured indoor spaces with horizontal and flat floors and does not explicitly compute footprint positions during the planning phase, it is easy to demonstrate that dynamic walking makes humanoid robots' small spaces controllable. However, it is not meant for actions where the robot steps over obstacles.

A categorization of methods for resolving multi-contact motion planning in humanoid robots has been reviewed in Tazaki et al. [17]. This study offers motion planning techniques for bipedal movement planning in humanoid robots based on low-dimensional dynamical models and multi-contact issues that employ non-coplanar and spontaneous contact.

Griffin et al. [18] suggest a new swing speed-up algorithm to change the timing of the step, allowing the robot to put its foot down faster to recuperate from errors in the direction of the current capture point dynamics, as well as a new algorithm to adapt the selected footstep, extending the base of support to use the center of pressure (CoP) founded ankle strategy for balance. The momentum rate of change for the inverse-dynamics-based full-body controller is then estimated using the estimated centroidal moment pivot (CMP).

A nonlinear optimization problem based on continuous and discontinuous dynamics was used by Hu et al. [22] to study bipedal movement in their work. The linear inverted pendulum serves as the motion model, capturing the dynamics of the center of mass, and its low dimensionality makes the issue more controllable. For them, the primary step was to create a comprehensive methodology to investigate optimality in the three-dimensional parametric space and use these findings as a starting point.

By taking into account the capabilities of step position adjustment and Center of Mass (CoM) height modification, the work published as [21] has proposed a revolutionary nonlinear model predictive Control (NMPC) framework for full-bodied locomotion. The nonlinear inverted pendulum plus flywheel model is used to analyze the effects of upper-body rotation and vertical height motion. Because of this, the NMPC is formulated as a quadratically constrained quadratic problem, which sequential quadratic programming can solve efficiently. A walking pattern generator for robust locomotion based on NMPC is proposed in contrast to the above mentioned work. The proposed method can produce stable walking patterns by only employing walking parameter references and considering the dynamic effects of the roll and pitch angular momentum change and the CoM height variation. Instead of strictly tracking the pre-defined parameters, this optimizer can modify the CoM height trajectory and body inclination angle in real time based on state feedback.

The authors in [20] have presented a human-like balance recovery controller and examined the resilience and energy usage of the device. To predict the optimal strategy to maintain balance in the face of various disturbances, they presented a numerical model of predictive control (N-MPC). They constructed a three-link model and simulated balance recovery using the upper body, a foot with unilateral limitations, and the bottom body to achieve this. Then, it was obtained and linearized from the model's dynamical equations. Based on human balance abilities, the authors develop binding limits on the model, along with angles and balancing torques of the ankle and hip.

Without explicit control of the robot's center of mass or its feet' center of pressure (CoP), it might be difficult to determine the appropriate foot location and time for footstep adaptation. Khadiv et al. [23] focus on improving step adjustment (CoM). It enables the relaxation of the CoP control requirements related to more conventional receding horizon techniques. These methods are appropriate for biped robots with little or no controlling authority over their CoP.

The collection of research papers presented in this section revolves around enhancing the dynamic stability and adaptability of humanoid robots during navigation and walking tasks. While path planning efficiency is not the central focus in these papers, the authors prioritize robustness to perturbations and real-time or near-real-time performance.

Robustness to perturbations is a common theme, with several papers employing advanced control techniques like numerical model predictive control (N-MPC) and nonlinear model predictive control (NMPC) to predict and respond to disturbances effectively. These strategies empower humanoid robots to maintain balance and recover from unexpected external forces or errors in real-world scenarios. The emphasis on robustness ensures that the robots can operate safely and effectively in dynamic and uncertain environments.

Real-time performance is also addressed, albeit with varying degrees of computational complexity in the proposed methods. Achieving real-time or near-real-time motion planning and control is crucial for practical applications of humanoid robots. While some papers demonstrate computationally efficient solutions, others may require further optimization to meet real-time performance requirements. These papers contribute to developing cutting-edge techniques that enhance humanoid robots' agility, stability, and adaptability, paving the way for their broader utilization in various tasks and environments. Some of the papers reviewed in this section are listed in Table 3.

Table 4 serves as a concise evaluation of selected research papers that delve into motion planning and control strategies for humanoid robots, focusing on approaches that leverage the principles of the inverted pendulum model. This evaluation is structured around four pivotal metrics: efficiency, robustness, scalability, and adaptability. These metrics are paramount in assessing the practicality and applicability of the discussed approaches in real-world humanoid robotics applications.

The table encapsulates the performance of each discussed research work across these metrics, providing a snapshot of their strengths and areas for improvement:

- Efficiency: Most approaches are evaluated as medium to high, indicating a balance between computational demand and the ability to produce timely motion plans. For instance, the Nonlinear Model Predictive Control (NMPC) framework in [21] showcases high efficiency by efficiently generating dynamic motion plans;
- Robustness: The high robustness rating across several papers reflects the importance of stability and reliability in humanoid motion planning, particularly in dynamic and uncertain environments. Techniques like the swing speed-up algorithm in [18] enhance the robot's ability to recover from disturbances;
- Scalability: With generally medium ratings, scalability highlights the challenges in extending these approaches to more complex scenarios or different robot models without significant modifications. This underscores the need for further research to enhance the generalizability of these methods;
- Adaptability: High adaptability in methods such as the one proposed in [23] indicates a strong capacity for real-time adjustments based on feedback, crucial for navigating complex environments and performing diverse tasks;

This table not only evaluates the contributions of each paper within the context of humanoid robotics but also sheds light on the collective progress and remaining challenges in the field. It underscores the ongoing need for research that pushes the boundaries of efficiency, robustness, scalability, and adaptability in motion planning strategies to achieve more sophisticated, reliable, and versatile humanoid robots capable of operating autonomously in human-centric environments.

5 Kinematic Constraints Approaches

In this section, both dynamics and kinematics-based approaches are highlighted. In most cases, full body motion and individual limb motion are considered, which also relies on the physical parameters.

Researchers in [25] have presented a method for path planning for humanoid robots that calculate dynamically stable, collision-free trajectories for full-body posture. The biped robot's posture is investigated in the joint space for a collision-free path that also complies with dynamic balancing restrictions using a geometric model of the environment and a statically stable goal posture. They modify current ran-

Table 3 Humanoid Robot Review Papers: Inverted Pendulum Approaches

Paper name	Main problem	Main approach to solve it	Simulation	Real robot application	Robot's name
[17]	Motion planning	Multi-contact motion planning involving noncoplanar and acyclic contact	Yes	No	Not Available
[18]	Stable walking speed	Wing speed up algorithm an algorithm to adjust the desired footstep	Yes	No	Model Atlas
[20]	Balance recovery controller	Numerical model predictive control (N-MPC) by predicting the best way to maintain balance against disturbance	Yes	No	Not Available
[21]	Robust locomotion humanoid robot	Nonlinear Model Predictive Control (NMPC) framework	Yes	No	Not Available
[22]	Bipedal locomotion	Non-linear optimization for continuous and discrete dynamics	No	No	Not Available
[23]	Step adjustment improvement	Optimal footstep location and timing adaptation without direct controlling the feet CoP or either the robot's CoM	Yes	No	Not Available

Table 4 Evaluation of Inverted Pendulum Approaches

Paper Name	Efficiency	Robustness	Scalability	Adaptability
[17]	Medium	High	Medium	Medium
[18]	High	High	Medium	Medium
[20]	Medium	High	Medium	Medium
[21]	High	High	Medium	High
[22]	Medium	Medium	Low to Medium	Low to Medium
[23]	Medium	High	Medium	High

domized path planning techniques to ensure the final path's overall dynamic stability by balancing limits on incremental search moves. Finally, a dynamic filtering function is used as a post-processing step to transform static, collision-free pathways into dynamic, collision-free trajectories by constraining the Zero Moment Point (ZMP) trajectory.

In the paper [59], researchers present a humanoid robot capable of executing acrobatic behaviors like flips and spinning jumps. The achievement results from integrated hardware design, motion planning, and control advancements. Two newly developed proprioceptive actuators are critical to these dynamic movements, whose parameters feed into an actuator-aware kino-dynamic motion planner. This planner considers the actuators' torque, velocity, and power limits, approximating the reaction force limits based on the robot's configuration. Landing control merges model-predictive control with whole-body impulse control, ensuring optimal performance over extended periods and rapid, full-body feedback dynamics. These innovations successfully enable the robot to execute acrobatic feats in realistic dynamic simulations.

Yoshida et al. [32] offer a two-stage solution for humanoid motion planning for dynamic activities. It consists of two basic steps: 1) The kinematic and geometric motion planner generates the trajectory for the humanoid body and its object; 2) The dynamic walking pattern generator produces an appropriate dynamically stable walking motion that enables the robot to carry the object. As a result, until a dynamically attainable motion is gained, the intended motion is partially or fully adjusted if the projected trajectory is not practical. By employing a dynamic pattern generator and the final planner, the planning is constructed in a powerful way to handle numerous physical parameters of the object and dynamic effect.

Muni et al. [63] propose a scheme for improving the maritime strategy of humanoid robots in intricate environments using a controller that combines fuzzy logic, neural networks, and Petri nets. The robot gauges distances to obstacles from its present location, defining them as front, right, and left obstacle distances. These measurements are inputs to a neural network model that generates a target angle. A Mamdani fuzzy system then processes this angle and obstacle distances to refine the robot's target direction. A Petri-net controller is incorporated to facilitate dynamic path analysis. Both singular and multiple humanoid robots are tested using the devised neuro-fuzzy-petri-net controller in V-REP simulated environments, and corresponding physical tests are conducted in lab settings. The findings from the simulation and real-world tests align closely. The developed controller's efficiency is further illustrated through surface and contour plots, revealing its ability to optimize motion planning. Compared to existing techniques, notably Improved Q-Learning (IDQ), the new controller exhibited a 16.66% improvement in path length efficiency.

A humanoid robot is shown navigating over a steep and uneven surface in work reported in [26], where walking is impossible due to the terrain. Robots crawl according to their design, making contact with the surface to analyze it before taking a step. An authentic real-time re-planning method and architecture for humanoid robot reactive walking are experimentally shown in [14]. This is accomplished by implementing a software architecture that enables real-time planning and re-planning using the humanoid robot *HRP-2* in a setting where obstacles are detected through motion capture.

Some humanoid robots are created to help people in their daily activities, e.g., in [15]. Unlike industrial applications, the environment is structured to the robot's needs, and humanoids must be able to work automatically. Moreover, one example of a fundamental task in this environment is to grasp a known object that the robot already has information about its shape, weight, or associated actions. Also, the robot does not have a full internal representation because of inaccurate perceptions or uncertainties. However, it must be able to deal with these problems that do not belong to its internal knowledge base.

Designing a series of stances and postures is the main goal of [10]. The algorithm incorporates a best-first strategy on top of the inverse kinematics-and-statics solver developed to produce static equilibrium setups. The objective is to design multi-contact sequences of postures and poses for humanoid robots. The output sequence also describes the contact transitions that help the robot learn new skills like dexterous handling and biped mobility. As a result, the best-first algorithm acts as the framework for planning the main building block. It investigates the contacts that should be added or subtracted at each stage, uses a manual input path free of collisions, and generates calls to an optimization-based inverse kinematics solver while abiding by static equilibrium restrictions.

Meduri et al. [72] propose the BiConMP, a nonlinear model predictive control (MPC) framework designed for online whole-body motion planning in legged robots. By efficiently leveraging robot dynamics, the framework can produce varied cyclic gaits, demonstrated on a real quadruped robot across different terrains, push responses, and gait transitions. Additionally, BiConMP showcased its capability to create complex, non-repetitive dynamic motions. Its adaptability was further tested on a humanoid robot and another quadruped robot in virtual simulations. The research concludes with a comprehensive analysis of the impact of planning horizon and frequency on the nonlinear MPC approach.

Hubo-II+ is a ladder-climbing abilities humanoid robot [12]. It offers a planning method that produces multi-limb locomotion patterns automatically that adhere to contact, collision, and torque limit constraints for a specified ladder specification. This process simulates climbing techniques on several ladders and automatically tests them. This enables extensive simulations to quickly build, test, and show new climbing techniques and how potential hardware alterations would affect the robot's ladder-climbing abilities.

The development of path planning, optimum control, and an algorithmic basis to address optimal control issues in cluttered environments have been discussed in [13]. They break down how they handle this issue into the following categories: 1) use a simple method to automatically generate minimum bounding capsules around the precise robot body geometries expressed by meshes; 2) use bounding capsules to get the distance restrictions for optimal control problem solver and implement self-collision avoidance; 3) finish a two-stage framework for flawless motion planning on complex robots.

An algorithm that chooses the motion sequence for an appropriate motion to deal with obstacles is proposed by [9]. They use bumper sensors and a monocular camera to detect obstacles. The framework enables the robot to carry out strong full-body balancing sequences of motions, including stepping over and ascending/descending simple staircases and barriers in a 3D space.

An optimization technique for dynamic planning, control, and state computation for a bipedal robot that operates dependably in challenging environments is elaborated in [11]. Additionally, it describes a simple transcription algorithm that uses the robot's whole kinematics and centroidal dynamics to create dynamically-feasible paths.

A motion planning of the humanoid's full-body trajectory is proposed in [16]. It proposes a humanoid gesture planner based on key pose generation that satisfies various constraints. The center-of-mass feasible region (CFR) method was employed, which consists of three steps: (a) designing roughly the balance constraints of statics and dynamics into CFR; (b) generating the pose qualified regarding the swing and support phase to meet asymptotically CFR condition while fulfilling kinematics constraints; (c) interpolating executed key pose to obtain a whole-body trajectory.

The efficiency of path planning is central to ensuring that a robot can navigate and execute tasks smoothly. Research by [25] emphasizes a method that modifies current randomized path planning techniques to ensure the overall dynamic stability of the generated paths. The dynamic filtering function then converts static paths into dynamic ones. Similarly, the work by [59] features an actuator-aware kino-dynamic motion planner that considers torque, velocity, and power limits, underpinning the robot's acrobatic capabilities. [63] introduces a controller that combines multiple methodologies, notably fuzzy logic and neural networks, which has proven to enhance the path length efficiency by 16.66% compared to existing techniques. This efficiency in planning is further seen in [10], which utilizes a best-first strategy layered over an inverse kinematics solver to design sequences of postures and poses, and [72], which implements the BiConMP framework for online whole-body motion planning in legged robots.

Robustness is crucial when robots are navigating in intricate, dynamic, or uncertain environments. The approach of Yoshida et al. [32] is particularly noteworthy as it offers a two-stage solution that initially plans a trajectory and then adjusts it until a dynamically attainable motion is achieved. Hauser et al. [26] focuses on robots navigating steep terrains, emphasizing the robot's ability to crawl when walking is unfeasible. Baudouin et al. [14] demonstrates real-time re-planning in the presence of obstacles, while [15] stresses humanoid robots' adaptability in structured environments. Zhao et al. [12] introduces the Hubo-U+ humanoid's ladder-climbing capabilities, stressing the importance of contact, collision, and torque constraints. The approach by El et al.[13] discusses optimal control in cluttered environments and offers a systematic approach to handle various constraints efficiently. Finally, the framework in [9] enables robots to perform robust full-body balancing sequences of motions in 3D spaces.

Ensuring real-time performance is essential for robots to operate seamlessly, especially in dynamic environments. Kuffner et al. [25]'s dynamic filtering function stands out as it transforms static paths to dynamic ones post-path generation. The acrobatic capabilities enabled by Chignoli et al. [59]'s integrated hardware design and motion planning showcase effective real-time execution of complex tasks. Baudouin et al. [14]'s study demonstrates authentic real-time re-planning and control in a setting where obstacles are dynamically detected. The real-world experiments conducted by Muni et al. [63] are aligned closely with simulation findings, indicating the consistency of their neuro-fuzzy-petri-net controller. Moreover, Kuindersma et al. [11] focuses on the bipedal robot's real-time dynamic planning and control, and Nozawa et al. [16] underscores a gesture planner based on key pose generation that meets various constraints to ensure real-time trajectory execution.

The research landscape in humanoid robotics is vast and multi-faceted, emphasizing path planning efficiency, robustness against disturbances, and real-time performance. The methodologies and findings from these studies offer critical insights for the next steps in advancing humanoid robotics. Table 5 summarizes the papers reviewed in this chapter.

Table 6 systematically evaluates the performance of various studies focused on kinematic and dynamic approaches in humanoid robotics based on four key metrics: efficiency, robustness, scalability, and adaptability. These metrics provide insight into how effectively these approaches can be integrated into real-world applications, addressing the unique challenges of motion planning for humanoid robots. Here is a detailed explanation of the table:

The evaluations in the table reveal a strong emphasis on high efficiency and robustness across most studies, illustrating the research community's focus on developing motion planning strategies that are both practical and reliable for humanoid robots. For instance, papers such as [25, 59], and [72] demonstrate high marks in these areas, showcasing advanced methodologies that enable dynamic and acrobatic movements, as well as comprehensive motion planning frameworks that consider the full body dynamics and constraints.

However, scalability and adaptability receive mixed evaluations, with most studies achieving medium ratings. This indicates that while the proposed methods are effective within their specific research contexts or robot models, there may be limitations to their direct application to broader scenarios or different robotic systems without further development or customization.

For example, [26] is noted for its medium scalability and adaptability, pointing to specialized applications in navigating steep and uneven surfaces where traditional walking may not be feasible. Similarly, [10]'s approach, which focuses on designing sequences of stances and postures, also receives medium ratings in these metrics, suggesting a targeted application with room for further generalization.

In summary, Table 6 provides a concise overview of the current state of research in motion planning for humanoid robots, highlighting strengths and areas for improvement. While efficiency and robustness are generally high, indicating robust and effective motion planning strategies, scalability and adaptability present opportunities for future research to extend these approaches to more diverse applications and robotic platforms.

6 Motion Planning Using AI Techniques

Motion planning, the process of determining a sequence of movements to accomplish a particular goal, has become an integral part of robotic systems and automation. As robots become more embedded in our daily lives and tasks, their capacity to plan and act autonomously becomes crucial, especially in dynamic and unpredictable environments. The literature cited herein offers a comprehensive look into the latest advancements in motion planning using artificial intelligence (AI) techniques. This section will shed light on the innovations and methodologies presented in these works and bridge their connections.

In [76], the narrative underscores the necessity of motion planning for autonomous mobile robots, especially in unpredictable settings. Recognizing the limitations of traditional hierarchical planners, the exploration leans towards deep reinforcement learning (DRL) based motion planners. Such planners have emerged as a promising alternative due to their ability to operate without reliance on prior structured maps, effectively merging global and local planning techniques.

Similarly, [80] underscores the relevance of Task and Motion Planning (TAMP) in real-world scenarios, such as offices and restaurants. These applications demand a blend of high-level reasoning with low-level geometric considerations, which TAMP effectively integrates. Yet, the paper also underscores the challenges inherent to these methods, especially in the face of real-world uncertainties.

Diving deeper into the practical applications, [83] introduces an incremental training approach for DRL-based path planning. This method ensures phased and efficient training by initially establishing a 2D context and transitioning to more complex 3D environments. The fusion of conventional global path planning methods with DRL algorithms, exemplified by the PRM+TD3 planner, showcases the model's versatility and adaptability.

Taking a similar stance, both [84] and [86] tackle the challenge of DRL agents needing extensive experience in environments rich in obstacles. RL agents can improve their learning efficiency and exploration capabilities by integrating motion planners directly into the action space. This approach addresses the challenges of motion planning in environments laden with obstacles and intricate tasks.

Further enhancing the AI-driven motion planning landscape, [85] presents an online kinodynamic motion planning framework. This framework marries the strengths of traditional techniques, such as the rapidly exploring random

Table 5 Humanoid Robot Review Papers: Kinematic Constraints Approaches

Paper Name	Main Problem	Main Approach to Solve it	Simulation	Real Robot Application	Robot's Name
[25]	Path planning ensuring dynamic stability	Modify randomized path planning techniques and apply dynamic filtering function	Yes	Yes	Not Available
[59]	Humanoid robot executing acrobatic behaviors	Integrated hardware design, motion planning considering actuators' limits	Yes	No	MIT Humanoid Robot
[32]	Dynamic activities of humanoid motion planning	Two-stage solution: kinematic and geometric motion planner followed by dynamic walking pattern generator	Yes	No	Not Available
[63]	Improving maritime strategy of humanoid robots	Controller combining fuzzy logic, neural networks, and Petri nets	Yes	No	Not Available
[26]	Navigation on steep and uneven surfaces	Analysis of surface contact before taking a step	Yes	No	Model Robot HRP-2
[14]	Real-time re-planning for obstacle detection	Software architecture for real-time planning and re-planning	Yes	Yes	Robot Robot HRP-2
[15]	Tasks in structured environments	Robots working autonomously in environments structured to their needs	Yes	Yes	Robot ARMAR-III
[10]	Design of stances and postures	Best-first strategy with inverse kinematics-and-statics solver	Yes	No	Not Available
[72]	Online whole-body motion planning for legged robots	BiConMP: nonlinear MPC framework	Yes	Yes	Not Available
[12]	Ladder-climbing abilities	Planning method adhering to contact, collision, and torque constraints	Yes	No	Hubo-II+
[13]	Optimal control in cluttered environments	Automatic generation of bounding capsules around robot body geometries and distance restrictions	Yes	Yes	Model Robot HRP-2
[9]	Dealing with obstacles with appropriate motion sequences	Use bumper sensors and monocular camera	Yes	Yes	NAO
[11]	Dynamic planning, control in challenging environments	Optimization technique with robot's whole kinematics and centroidal dynamics	Yes	Yes	Robot Atlas
[16]	Humanoid's full-body trajectory planning	Gesture planner based on key pose generation satisfying constraints	Yes	No	Not Available

Table 6 Evaluation of Kinematic Constraints Approaches

Paper Name	Efficiency	Robustness	Scalability	Adaptability
[25]	High	High	Medium	Medium
[59]	High	High	Medium	High
[32]	High	High	Medium	Medium
[63]	High	Medium	Medium	Medium
[26]	Medium	Medium	Low to Medium	Medium
[14]	High	High	Medium	High
[15]	Medium	High	Medium	High
[10]	Medium	Medium	Medium	Medium
[72]	High	High	Medium	High
[12]	Medium to High	High	Medium	Medium
[13]	High	High	Medium	Medium
[9]	High	High	Medium	Medium
[11]	High	High	Medium to High	High
[16]	High	High	Medium	High

tree (RRT*), with the advancements of AI, exemplified by continuous-time Q-learning.

In a collaborative context, [87] Highlights the importance of robots conveying clear intentions when interacting with humans. This is achieved through an actor-critic method that molds robot motions to be comprehensible and anticipatable. Such a methodology underscores the importance of mutual understanding in human-robot collaborations.

The intersection of industry and AI-driven motion planning is captured in [89]. Highlighting the requirements of Industry 4.0, the study introduces an RL-driven industrial robot capable of performing intricate tasks like welding and cutting, emphasizing adaptability and robustness.

On the other hand, Perez-Higueras et al. [91] offers a unique approach to teaching robots social navigation. Leveraging neural networks, the technique transforms path planning into a classification problem, eliminating the need for manual cost map creation. Such an approach presents a paradigm shift in robot training methodologies.

Addressing the challenge of computational complexity, [92] introduces DeepSMP, a neural network-driven sampler designed to enhance the efficiency of sampling-based Motion Planners. This innovation exhibits scalability, especially in Higher-dimensional challenges, marking a significant advancement in the domain.

A pinnacle achievement in AI is presented in [95], where AlphaGo Zero, using only reinforcement learning, demonstrates the capability of surpassing human expertise without prior knowledge. This triumph illustrates the immense potential of AI in mastering complex tasks.

Emphasizing the necessity of harmonious human-AI integration, [96] sheds light on the importance of AI systems being both understandable and explainable. The study accentuates the “theory of mind" concept, advocating for AI systems to plan actions considering both the AI and human perspectives.

Finally, the work by the authors of [100] focuses on the Behavior Trees (BTs), a technique originating from the gaming industry but finding application in robotics. The research in [100] offers insights into the practicalities of BTs, emphasizing their optimization in real-world robotic applications.

The rapidly evolving domain of motion planning, central to robotic systems and automation, has witnessed numerous breakthroughs, especially with the incorporation of artificial intelligence (AI) techniques. This progression, crucial for ensuring the autonomous operation of robots in dynamic environments, is expertly illustrated in the following analysis of recent research.

Path Planning Efficiency: At the heart of effective robot operation lies the need for efficient path planning, a theme consistently echoed in the literature. In [76], the spotlight is on deep reinforcement learning (DRL) based motion planners for autonomous mobile robots in unpredictable settings, a stride away from traditional hierarchical planners. Such models offer the enticing advantage of functioning without relying on pre-constructed maps, seamlessly integrating global and local planning approaches. Further complementing this theme, [83] elucidates an incremental training methodology, starting from a simpler 2D context and progressing to intricate 3D environments, ensuring systematic and efficient learning. Notably, the marriage of conventional planning methods with DRL algorithms, as exhibited by the PRM+TD3 planner, establishes the adaptability of such models.

Robustness to Perturbations: The dynamism and unpredictability of real-world environments necessitate the robustness of motion planning techniques. [80] delves into the intricacies of Task and Motion Planning (TAMP) in real-

Table 7 Motion Planning Using AI Techniques

Paper Name	Main Problem	Main Approach	Robot Name
[76]	Autonomous motion planning in unpredictable environments	DRL-based motion planners	Not Available
[80]	TAMP in real-world scenarios	Integration of High-level reasoning and geometric considerations	Not Available
[83]	Efficient training for DRL-based path planning	Incremental training (2D to 3D)	Robot Turtlebot2
[84, 86]	DRL agents in obstacle-rich environments	Motion planners integrated into action space	Robot Arm Sawyer
[85]	Kinodynamic motion planning	RRT* with continuous-time Q-learning	Not Available
[87]	Conveying clear intentions in human-robot interactions	Actor-critic method	Not Available
[89]	RL-driven industrial robot for Industry 4.0 tasks	RL-driven methods for tasks like welding and cutting	Not Available
[91]	Social navigation for robots	Neural networks for path planning as a classification problem	Not Available
[92]	Computational complexity in sampling-based Motion Planners	DeepSMP neural network-driven sampler	Robot UR6
[95]	AI mastering complex tasks without prior knowledge	Reinforcement learning (AlphaGo Zero)	Not Available
[96]	Understandable and explainable AI	“Theory of mind” in AI systems	Not Available
[100]	Applicability of Behavior Trees in robotics	Behavior Trees	Not Available

world contexts, like restaurants and offices, which demand a harmonious blend of high-level reasoning and geometric specifics. However, the research also candidly addresses the inherent challenges posed by real-world uncertainties. Further echoing the theme of robustness, [89] introduces an RL-driven industrial robot tailored for Industry 4.0, emphasizing the robot's adaptability in tasks like welding. Meanwhile, [91] presents an innovative approach to social navigation, transforming path planning through neural networks into a classification challenge, effectively sidestepping manual cost map design.

Real-Time Performance: Real-time adaptability and performance in motion planning stand as the capstone for successful AI and robotics integration. [85] presents an online kinodynamic motion planning framework, marrying traditional techniques, such as RRT*, with AI-powered continuous-time Q-learning, emphasizing real-time adaptability. In human-robot collaboration contexts, the research in [87] underscores the significance of robots clearly expressing their intentions, achieved through an actor-critic method, ensuring seamless real-time interactions. Addressing the elephant in the room of computational complexity, [92] unveils DeepSMP, a neural network sampler crafted to boost the efficiency of sampling-based Motion Planners, showcasing scalability, especially in high-dimension settings. Moreover, the groundbreaking work in [95], where AlphaGo Zero emerges superior to human expertise, underscores the promise of AI in mastering real-time challenges. Simultaneously, the insights from [96] emphasize AI's understandability and explainability, advocating for incorporating a "theory of mind" in planning, thereby ensuring harmonious human-AI synchronization.

Concluding, the realm of AI-driven motion planning, from efficiency to real-time adaptability, is an ever-expanding frontier, with each cited research offering invaluable contributions. Whether it is the innovative use of Behavior Trees (BTs) in robotics, as elaborated in [100], or other AI techniques, the future of robotic motion planning promises greater efficiency, robustness, and real-time responsiveness. Table 7 is shown as a summary of the papers reviewed in this section.

Table 8 provides a summarized evaluation of various research works in AI-driven motion planning, focusing on four key metrics: efficiency, robustness, scalability, and adaptability. These metrics are crucial in assessing the practicality and applicability of AI techniques in real-world robotic applications. Here is an interpretation of the table and how it relates to the broader context of motion planning in robotics:

The table shows that most cited research works exhibit high efficiency, robustness, and adaptability, with scalability varying slightly across different studies. This indicates a strong overall performance of AI techniques in motion planning, suggesting their potential to address the critical needs of modern robotic systems effectively.

For instance, [76, 83], and [92] show high marks across all four metrics, highlighting the success of deep reinforcement learning (DRL) and neural network-driven approaches in offering versatile, reliable, and efficient solutions for motion planning challenges. These works demonstrate the potential of AI to revolutionize motion planning in robotics by providing robust methods capable of adapting to complex and dynamic environments.

Conversely, papers like [80] and [87] have a medium rating in scalability and adaptability, respectively, underscoring the challenges faced when integrating high-level reasoning with geometric planning (TAMP) and ensuring clear intention conveyance in human-robot interactions. These findings point to areas where further research and development could enhance the overall effectiveness of AI techniques in motion planning.

Overall, the table serves as a concise overview of the current state of AI in motion planning, showcasing the

Table 8 Evaluation of Motion Planning Using AI Techniques

Paper Name	Efficiency	Robustness	Scalability	Adaptability
[76]	High	High	High	High
[80]	Medium	High	Medium	Medium
[83]	High	High	High	High
[84, 86]	High	High	Medium to High	High
[85]	High	High	Medium	High
[87]	Medium	High	Medium	Medium
[89]	High	High	Medium to High	High
[91]	High	High	Medium	High
[92]	High	High	High	High
[95]	High	High	High	High
[96]	Medium	High	High	High
[100]	Medium	High	Medium	High

strengths of various approaches while highlighting areas for future improvement. The evaluations underscore the significant advancements in the field, pointing towards a future where robots can autonomously navigate and perform tasks in increasingly complex and dynamic environments.

7 Conclusion

Motion planning is one of the most crucial features of humanoid robots. Humanoid robot motion planning is complex as walking, body, arms, and hands may have to coordinate to complete a task in a social environment. So far, no universal framework or solution exists for humanoid robot motion planning. Most research focused only on one part of a humanoid robot, such as gait or manipulation tasks.

This review paper attempted to summarize some of the issues and solutions presented in the state-of-the-art examination in the humanoid robot domain. As noted above, the research in the literature demonstrates that working with humanoid robots is arduous due to their high degree of complexity. Various motion planning approaches can be employed to solve specific tasks. One of the most effective and commonly used approaches is the inverse kinematics-based approach for motion planning of humanoid robots. However, this approach has a high degree of complexity. Further work is needed to simplify the inverse kinematic approach and make it more compact and workable. Conversely, AI algorithms and traditional methods show great potential to deal with complex problems and humanoid robot motion planning challenges. Although AI and reinforcement learning-based schemes are the way forward and have great potential, the need for high computational power and complexity is still an issue. Obstacle avoidance during motion tasks is more challenging for humanoid robots in the social environment due to the dynamic nature of the environment. Safety aspects, flexibility, and real-time autonomous or guided motion planning are required. Hence, more intelligent and AI-based schemes are the future of motion planning, as mentioned above.

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