Imitation Methods for Bipedal Locomotion of Humanoid Robots: A Survey

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***Abstract*—Motion imitation techniques offer a promising approach to the bipedal locomotion problem by leveraging human expertise. This survey provides an overview of the diverse methods employed for this task and introduces two taxonomies. The first one is based on motion transfer approaches for mapping expert motions to the learner, and the second one is based on the techniques utilized for ensuring robot stability. Furthermore, we include a comprehensive summary table that categorizes some relevant works on whole-body imitation and highlights their contributions and limitations. Our review aims to present a roadmap for future research in bipedal locomotion for aiding the advancement of more stable and efficient humanoid robots.**

***Index Terms*—Bipedal locomotion, center of mass, center of pressure, correspondence problem, dynamic stability, humanoid robots, imitation learning, motion imitation, motion mapping, zero moment point.**

I. Introduction

Imitation is a fundamental ability that allows humans and some other animals to learn behaviors from peers by witnessing their ways of completing a task or achieving a certain goal. It is perhaps our principal manner for acquiring skills and knowledge in our everyday lives, especially in our early years of existence. Due to its importance and properties, it receives attention from broad interdisciplinary research. From the robotics perspective, it allows robots to learn and be programmed in a "human-like" style without the necessity for the user to be a robotics expert for a successful interaction. Hence it is considered as a key path for the advancement of social and humanoid robots, designed to continuously interact with humans and their surroundings.

Bipedal locomotion is an essential aspect of such robots as they found numerous applications across diverse domains [1]. However, achieving stable and efficient walking patterns is a challenge that demands significant computational resources and time [2]–[4]. The search space for this problem is enormous, and finding a solution that satisfies all the constraints can be a daunting task. Moreover, it has many low-quality local minima, potentially leading the agent to unstable or inefficient gaits. Therefore, there is a need for techniques capable of narrowing down the search space while enhancing search efficiency. A machine learning set of data-driven techniques for addressing this complex task is known as *Imitation Learning* (IL), which enables an agent to learn from an expert's behavior by observing its actions and the corresponding state transitions.

This work aims to review the existing literature on the use of imitation techniques for bipedal locomotion. There are three main contributions. First, we assess the suitability of the current state-of-the-art taxonomies for categorizing the research regarding the imitation of locomotion by humanoids. Second, we identify relevant design choices for bipedal motion imitation and balance control frameworks, including two new categorizations for achieving these tasks. Third, research directions are suggested through the review of relevant works and their classification by using the exposed taxonomies.

Accordingly, the article is organized as follows. Section II introduces the common framework for imitation techniques and *Imitation Learning* (IL) algorithms. Section III presents the main classical taxonomies from literature. Section IV proposes two new taxonomies based on relevant considerations and design choices, including an overview of some works on the area. In Section V the discussed taxonomies are used to classify all the reviewed works. Finally, Section VI offers some conclusions, possible future work, and research directions.

II. Imitation problem statement

The imitation process involves three general steps to be taken by the imitator: *perception* of demonstrated motions or states, *mapping* these to its states, and *learning* the actions to be performed under a given state. First, the human demonstrations are recorded and stored as motion capture (MoCap) data. These are then mapped to the imitator by using a control policy and by taking into account its kinematic and dynamic properties. Finally, the imitator learns these motions to achieve a desired behavior or goal. In this work, we will focus our attention on the last two tasks.

A mapping function or control policy defines the sequence of actions that must be taken to achieve a given task or exhibit a desired behavior, i.e. how to perform the task. This is done by mapping the current state of a movement system and its environment into a convenient action that induces a shifting from one state to another [2]. Note that both states and actions normally represent a vector rather than a single value, meaning that the policy can execute multiple decisions at once. Therefore, imitation can be seen as an optimization process where a fitness function may be used to assess the imitation quality and can penalize deviations from the demonstration.

This process becomes not so trivial when the kinematic and dynamic properties of both the demonstrator and the imitator differ considerably; this issue is known as the *correspondence problem* [5]. Additionally, defining a policy by hand is not a straightforward task, hence various artificial intelligence techniques are developed to overcome this kind of issues. It is of particular interest the IL set of techniques, as they leverage the knowledge of an expert to guide the policy learning process. By observing an expert's behavior, the agent can extract valuable information such as geometrical properties of the gait. This information can accelerate the identification of viable solutions and can even yield closed solutions. IL can be used at any degree in the interval from pure imitation to initialization of a different learning procedure.

III. State-of-the-art imitation taxonomies

Some taxonomies were proposed to classify the solution alternatives for the overall imitation problem described previously. The first classical taxonomy reviewed here is focused on answering the question of *how* to learn, while the second is focused on the abstraction level of the task that must be imitated. We will describe these two main taxonomies with a brief explanation for each of their categories and examples of how they are applied to bipedal locomotion control.

A. Imitation Learning Algorithms

The first classical taxonomy of imitation methods focuses on the learning approach, i.e. the way the control policy is learned. This is addressed by the well-known IL set of techniques, which gathers three main categories identified in review works such as [6], [7]. We present briefly the foundational theory for each category, and straight away we evaluate to what extent it applies to the special case of bipedal locomotion and whole-body imitation.

1) Behavioral Cloning (BC): It is a straightforward approach that draws inspiration from supervised learning techniques where the expert's states are treated as input or feature vectors, and their corresponding actions are treated as output or label vectors [7], [8]. The goal is to minimize the differences between the learned policy and the expert's demonstrations by employing a specific cost function. Ultimately, the resulting model should be capable of predicting the appropriate action for a given state, whether it is part of a discrete decision set or a continuous control signal.

Some challenges arise when applying BC techniques to bipedal locomotion due to two main factors. First, the *correspondence problem* hinders direct mapping of demonstrations. Works as [9]–[11] point out that directly applying the reference joint positions to the imitator may not yield satisfactory performance. Second, BC relies on supervised learning from sampled state-action pairs [7], but in the context of bipedal locomotion the reference motions are typically represented solely through the state space of the expert, while the corresponding actions remain unknown. BC approaches applied to humanoid robots as [12] often focus on upper-body imitation, simplifying the problem by treating it as a robotic manipulation task while the lower body remains still or exhibits little motion without lifting any foot.

2) Inverse Reinforcement Learning (IRL): At times also identified as *Apprenticeship Learning* (AL), this set of techniques involves the inference of a reward function for representing the desired behavior. Instead of mapping states to actions, the model is iteratively recovering a function that describes the expert demonstrations. In other words, the reference data are used to learn the unknown reward function that the expert optimizes to generate its actions so that this function is then used for training the learning model. This reward function provides a scalar value for qualifying a performed action in a given state or situation. As an advantage, such an approach avoids the great number of demonstrations that BC methods require and allows the agent to adapt when changes in the environment occur.

Features from the demonstrated locomotion are extracted into the reward function for learning the imitation controller. Such features may include the desired CoM trajectory or the end-effectors' position. For instance, [13] minimizes the difference between the reward from human demonstrations and the robot reward defined by a trajectory generator. In [14], a Deep RL framework defines the overall reward as a weighted sum of a task reward and an imitation reward, enhancing a more natural locomotion on a humanoid by tracking joint positions and the support phase. Similarly, [15] used demonstrated motions to add an imitation reward term, employing space-time bounds for the exploration of diverse motion styles instead of tracking a reference feature.

3) Generative Adversarial IL (GAIL): This learning method employs *Generative Adversarial Networks* (GANs), which consist of two neural networks: the *generator* and the *discriminator*. The *generator* creates new instances of the required movement from random data or certain references, while the *discriminator* classifies these instances as generated or as part of the reference motion. Both engage in a competitive Zero-Sum game: the *discriminator* aims to correctly classify instances, while the *generator* aims to deceive it. This reward-penalty system enables the adjustment of the network parameters during training. Both networks improve with each iteration, resulting in generated instances that closely resemble the expert demonstrations.

This sort of techniques has also been explored in bipedal locomotion research. In [10], a stochastic policy is trained to imitate state-only walking demonstrations, although the simulated human model exhibited an unnatural gait. To address this issue, additional proprioceptive information from software sensors and relative position vectors were provided to the discriminator. In [16], pose features from video clips were compared against generated samples. Then, the discriminator outputs a probability as the reward signal for updating the controller's parameters. In a different approach, [17] combined demonstrations from MoCap data and video clips, employing two discriminators to handle each format of reference data. The generator policy learned primary base motions from the MoCap data and advanced motions depicted in the video clips.

B. Task Abstraction Level

Another usual classification for imitation methods considers the abstraction level of the task defined by the control policy, which can be generally categorized as *Low-level Tasks* and *High-level Tasks*. Although they are not uniformly defined across the related research as in [7], [8], [18], due to the high applicability of imitation methods, we can outline the main idea of such categorization and examine its application to whole-body control.

1) Low-level Tasks: This level involves continuous space policies that translate states into control signals or actions, focusing on specific movements from the demonstration like walking forward, jumping, or reaching an object. For instance, [19] generated a walk plus a turn according to the demonstrated locomotion, while considering a balance criterion, the floor contacts, and the joint limits. Works like [20] imitate a reference pose while maintaining static stability, in either single or double support mode. Alternatively, [21] and [15] imitate the demonstrated motion while adding diverse new styles, conceding attention to how the imitation of a specific skill is done rather than the motives for effectuating it.

2) High-level Tasks: On the other hand, high-level tasks not only imitate specific skills but also integrate several base motions into complex routines for solving problems not present in the reference data. For instance, in [13] the goal task of the robot is segmented into four behaviors; i.e. approaching a door, grasping the doorknob, opening the door, and releasing the knob. This is an example of locomotion with a manipulation task. Alternatively, [22] use MoCap data and neural networks to recreate complex behaviors with altered motion styles, such as gaits with fluctuating trajectories and velocity profiles. Similarly in [10], GANs are applied to learn movement primitives such as walking, kicking, turning, and jumping, integrating them to tackle challenges like traversing obstacle courses or shooting penalty kicks.

IV. Taxonomies for whole-body motion imitation

To advance the design of a successful imitation framework, five key preliminary questions have been identified in [23]–[25] regarding the fundamental imitation problem: *who* to imitate, *when* to imitate, *what* to imitate, *how* to imitate, and *how to evaluate* the imitation. By answering these questions, a clearer pathway may arise for adopting a decision amongst various design alternatives, under the available resources and the final goal of the imitation exercise. Such design choices are identified in Table I. The decisions to take will vary for each specific study case, hence posing a set of possible combinations for an imitation approach.

In addition to these design choices, the other two features are relevant for the specific case of whole-body imitation by humanoids, as the reviewed works expose when designing and applying the imitation procedure. These identified features shape the foundation of the proposed taxonomies, and each one can be seen as an additional design choice for this specific task. They aim to classify the methods used for addressing two main concerns regarding bipedal locomotion: the expert motions mapping or transference to the body of the imitator, and the control strategy for accomplishing dynamic stability throughout the imitator's performance.

TABLE I
Categorization of design choices for whole-body motion imitation frameworks.

Taxonomies for state-of-the-art features of motion imitation:	
Learning Technique	◇ Behavioral Cloning ◇ Inverse Reinforcement Learning ◇ Generative-Adversarial IL
Task Level Abstraction	◇ Low-Level Tasks ◇ High-Level Tasks
Access to System Dynamics	◇ Model-Based ◇ Model-Free
Expert-Agent Communication	◇ Online Imitation ◇ Offline Imitation
Policy Type	◇ Deterministic ◇ Stochastic
Proposed taxonomies for additional features of whole-body imitation:	
Motion Transfer Technique	◇ Geometric Approaches ◇ Optimization Methods ◇ Using a Reward Function
Stability Control Strategy	◇ CoM Projection ◇ ZMP Criterion ◇ Implicit Optimization

A. Motion Transference Technique

It is not simple to directly use MoCap data for imitation due to the so-called *correspondence problem* [5], as the kinematics and dynamics of the humanoid imitator differ significantly from those of the human demonstrator. The methods categorized here attempt to address this issue by dealing with the task of mapping the demonstrated motion from the human expert to the humanoid robot. Therefore, this taxonomy focuses on answering the following two questions when categorizing an imitation method: *What* will be imitated? And, more important, *how* will it be imitated? Due to their importance when designing an imitation framework, these questions represent a relevant starting point for determining the nature of the imitation technique needed to overcome such structural disparities. The solution to these questions leads to one of the following categories, whose methods are ultimately implemented for mapping the human motions (states) into the actuator data (actions) of the robot.

1) Transference by a Geometric Approach: These techniques convert task space trajectories into the humanoid robot joint space by considering the end effectors (i.e. hands and feet) rather than the joint angles. Later, these angles are found through inverse kinematics (IK) for motor control. Diverse methods involve vector-space transformations, length scaling, rotation matrices, and analytic geometry. This approach includes advantages like direct motion mapping across bodies with different DoF while exhibiting an explainable process. On the downside, this explicit process requires also an explicit balance control strategy, whose solution alternatives have been developed along the bipedal locomotion theory.

For example, in [19] specific human joint angles are computed from MoCap data by using rotation matrices and then applied to the robot. However, this mapping approach requires further processing to adjust the feet orientation and keep the robot's balance. A teleoperation setup in [20] applies vector scaling to find hands and feet positions relative to shoulders and hips, for mapping the posture of a human demonstrator onto the humanoid robot in real-time. Similarly, an exhaustive geometric analysis is done in [11] for an analytical motion mapping of joints and locomotion. This work also considers the human body's initial and final global displacement and rotation through the motion capture process.

2) Transference by Optimization Techniques: This set of methods focuses on minimizing the motion differences between the expert and learner. Common methods for achieving this task are based on IK for obtaining the internal states of the imitator, geometric approaches as described in the previous category, or even by directly applying representative joint angular values to the robot. After this preliminary imitation, the idea of applying an optimization method is to further bring closer the robot's trajectories towards those of the human, while considering physical constraints and overcoming kinematic differences.

In [26] a preliminary mapping of the relevant joint angles is done straightforwardly, before utilizing an optimization process to adjust the robot's joint angles according to those of the human. A dynamics filter in [27] is created for receiving the reference joint angles as input and includes a non-linear optimizer for finding the optimal joint trajectories in the presence of predefined physical constraints. A different approach is developed in [28], where an LSTM-based gait generator is optimized by using extracted features from the acquired demonstrations for mapping and learning gait patterns.

3) Transference by using a Reward Function: Among the three alternatives presented, this is the most implicit manner for solving the retargeting problem. This task is accomplished by employing a reward function for approximating the robot states to the demonstrations. Usually, the works categorized as IRL like [13]–[15] belong within this category, yet some works that leverage other IL techniques may also fit into this category. This means that a reward function can be used to effectuate a transformation from the human dynamics to those of the robot, but not necessarily used for learning the goal task or behavior. This is the case of GAIL techniques, which often employ a reward function for this end as reviewed in [10], [16] and [17] previously.

B. Stability Control Strategy

As the dynamic properties of a bipedal robot are naturally unstable, the stabilization method is a relevant aspect that draws a clear distinction from other robotics and control-related works. Therefore, a categorization based on the criteria and techniques for achieving dynamic stability is presented. This provides insights into the progress made and possible research directions for attaining both stable standing and locomotion in humanoid robots.

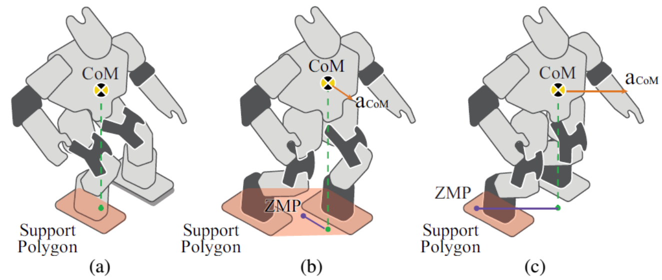

Fig. 1. Stable conditions according to CoM and ZMP criterion. If the CoM acceleration (orange) is small, the robot is stable as long as the CoM projection onto the ground (green) lies within the SP (red), as depicted in (a) and (b). For larger CoM accelerations, the robot is also considered stable as long as the ZMP (purple) lies within the SP, even if the CoM projection does not, as depicted in (c).

1) Center of Mass (CoM) Projection: This technique controls the CoM displacement of the humanoid so that its projection onto the floor remains inside of the support polygon (SP) during the entire motion while following the reference trajectory. Figure 1.(a) and (b) illustrate the essence of this method. This criterion is mainly used for assessing and accomplishing static stability in humanoids, as it depends on accelerations of the CoM trajectory close to zero.

For tracking the CoM trajectory while complying with the SP restriction, the robot's motion is often modified by adjusting its posture throughout the gait. This is done in [20] to accomplish steady postures by relocating the robot's feet according to its current support mode. This strategy can be sequenced to ensure a rather dynamic balance through key locomotion frames as in [11], where the static balance is still the main concern. On the other hand, different learning methods were also employed in works like [31] to control the CoM projection trajectory.

2) Zero Moment Point (ZMP) Criterion: This strategy considers the robot as a Linear Inverted Pendulum Model (LIPM) for simplifying the analysis through its centroidal dynamics. As long as the ZMP lies within the robot's SP, it will not fall [32], as shown in Figure 1.(b) and (c). ZMP is also referred to as the center of pressure (CoP) under certain conditions and is evaluated according to (1), which quantifies the relation between the CoM and the ZMP of the robot.

$$X_{\text{ZMP}} - X_{\text{CoM}} = \frac{Z_{\text{CoM}}\ddot{X}_{\text{CoM}} - I\ddot{\theta}}{m\ddot{Z}_{\text{CoM}} + mg} \quad (1)$$

Where X_{ZMP} is the position on the ground of the ZMP, X_{CoM} the position of the robot's CoM, $\ddot{X}_{\text{CoM}}$ is the acceleration of the robot's CoM in the forward direction, Z_{CoM} represents the height of the robot's CoM, $\ddot{Z}_{\text{CoM}}$ the acceleration of the robot's CoM in the vertical direction, I represents the centroidal rotational inertia of the robot, $\ddot{\theta}$ the angular acceleration of the robot, m the robot's mass, and g is

TABLE II

CATEGORIZATION OF SOME REVIEWED WORKS ON WHOLE-BODY IMITATION TECHNIQUES OF BIPEDAL ROBOTS.

Year	Ref	Motion Transfer Method			Stability Criterion			High-level Task	Learning Method			Humanoid Robot
		Geometric Approach	Optimization Technique	Reward Function	CoM	ZMP	Implicit Optimization		BC	IRL	GAIL	
2010	[9]		✓				✓					✓
2011	[19]	✓				✓						✓
2011	[26]		✓				✓					✓
2012	[29]	✓				✓						✓
2014	[20]	✓			✓							✓
2015	[13]			✓		✓		✓		✓		✓
2016	[27]		✓			✓						✓
2016	[22]		✓				✓	✓				
2016	[30]		✓			✓						✓
2017	[31]	✓			✓							✓
2017	[10]			✓			✓	✓			✓	
2018	[21]		✓				✓					
2018	[11]	✓			✓							✓
2019	[16]			✓			✓				✓	
2020	[14]			✓			✓			✓		✓
2021	[15]			✓			✓			✓		
2022	[28]		✓				✓					✓
2022	[17]			✓			✓				✓	

the gravity acceleration constant. This model can be further simplified by considering the height of the CoM as a constant h and the angular acceleration as negligible. In this way, we obtain (2), the well-known ZMP general equation.

$$X_{\text{ZMP}} = X_{\text{CoM}} - \frac{h}{g}\ \ddot{X}_{\text{CoM}} \tag{2}$$

Note that as the CoM acceleration goes to zero, the ZMP position tends to be the same as the CoM projection, showing that as long as the accelerations are small enough the CoM projection criterion does apply. ZMP allows the assessment of the dynamic stability throughout locomotion, but it can also be applied for static posture stability and push recovery as in [29]. For the control of dynamic balance, in [13] a cart-table model is used to explain the LIPM and (2) is used to find the appropriate CoM trajectory in the two horizontal axes of motion. In addition to the optical MoCap system, [30] uses a force platform for recording the CoP from a ”robot-like” human gait, so that it can be properly processed and passed as a reference to the robot's controllers.

3) Implicit Optimization: This category refers to stability reached implicitly through the learning process, where a falling penalization is applied within a reward function or some balance parameters are optimized during the imitation process. Therefore, methods that apply a reward function for either motion mapping or learning benefit from this strategy. The imitator learns the parameters for steady motions through a trial and error process, although initialized by expert demonstrations. For example, the walking controller designed in [21] calculates the joint torques from extracted features for keeping balance while imitating the style of the reference motions.

Some approaches include additional sensor data for quantifying the agent's internal states other than joint angles, e.g. by using gyroscopes in the torso or pressure sensors on the feet. These data are then used in the optimization process itself as in [9] or solely for stability evaluation as in [26], where the main imitation technique is expected to provide sufficient gait stabilization. The learning method in [28] generates gait trajectories that were verified through phase plots and cyclograms as a stability analysis alternative.

V. EXAMPLES OF CATEGORIZATION

Considering the main aspects of an imitation framework presented previously, we gather a set of articles that design, implement, and assess a certain imitation technique for the specific task of attaining a human gait in a humanoid. Each one is then categorized as shown in Table II within the described taxonomies. Their approach is implemented into a simulated human model or a humanoid robot, either simulated or real; this property is specified in the last column, where the absence of a checkmark indicates the use of a humanoid dummy model instead of a specific humanoid robot.

Furthermore, some works did not find an adequate category for the learning technique, for they lack the main elements that define any of these IL categories. Such works often leverage other strategies suited for the bipedal locomotion problem as illustrated in this summary table. These alternative strategies shape most of the research and exhibit relevant results, suggesting the need for recognizing new areas within motion imitation and stability control research.

VI. CONCLUSIONS AND FUTURE WORK

The bipedal locomotion is a complex dynamic task, as well as the categorization of the diverse techniques and features for accomplishing it. Such categories are defined by the design choices presented in this review and must be taken into account beforehand to achieve a successful imitation framework. Additionally, one may consider other issues such as information from the environment or additional proprioceptive sensors.

Regarding imitation methods, these can involve geometric approaches, optimization methods, or reward functions for mapping the human motion data to actuator data in the robot.

Additional directions for future research work, obtained from the categorization exercise done, include methods from both classical and proposed taxonomies. First, consensus on terminology should be reached when referring to IL techniques, as different terms could be either a variation or a synonym according to different state-of-the-art works. Besides, more work could be performed to explore how the BC methods can be leveraged for bipedal locomotion imitation. Similarly, the GAIL approach can be further explored, as normally the work around this kind of technique is focused on creating complex motions in physics-based human characters. By doing this, the transferability issues of learned motions from simulation to reality could be better addressed.

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