Adaptive Mimic: Deep Reinforcement Learning of Parameterized Bipedal Walking from Infeasible References

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Abstract

Not until recently, robust robot locomotion has been achieved by deep reinforcement learning (DRL). However, for efficient learning of parametrized bipedal walking, developed references are usually required, limiting the performance to that of the references. In this paper, we propose to design an adaptive reward function for imitation learning from the references. The agent is encouraged to mimic the references when its performance is low, while to pursue high performance when it reaches the limit of references. We further demonstrate that developed references can be replaced by low-quality references that are generated without laborious tuning and infeasible to deploy by themselves, as long as they can provide a priori knowledge to expedite the learning process.

Keywords: Deep Reinforcement Learning; Legged Robots; Imitation Learning; Robot Locomotion

1. Introduction

It has been challenging to design a stable gait for bipedal robots to walk due to their complex dynamics, and much has been explored on modeling and control of bipedal robots. Traditional methods are based on dynamic models and use ZMP (Vukobratović and Borovac (2004)) or Capture Point (Englsberger et al. (2011)) as the criteria for stability, which has led to successful control of many humanoid robots (Huang et al. (2001); Hong et al. (2013); Nelson et al. (2012)). However, such methods have inherent defects that they typically rely on model-based strategies which are difficult to obtain. To make matters worse, the region of reasonable foot locations is often limited, which makes the robot show little agility. Designers may also need gait libraries to resist violent perturbations and walk in multiple speeds (Xie et al. (2018)). In addition, the generalization of these methods can be difficult. When designing new motions other than simple walking, new physical models must be put forward, and complex situations of contact points are hard to deal with.

Model-free Deep Reinforcement Learning (DRL) provides a way to design controllers for omnidirectional walking without explicit knowledge of complex robot dynamics. DRL also enables the robot to achieve difficult motions like dribbling a ball or following a rough path (Peng et al. (2017)). It has been proved effective in simulation (Lee et al. (2019); Liu and Hodgins (2018); Castillo et al.
Infeasible Reference Adaptive Mimic

Figure 1: Snapshots of an infeasible reference and the learned gait through our proposed Adaptive Mimic. Although such a reference is unreliable and can not be directly deployed, our method can help the robot learn stable gait from the reference.

A single control policy learned from DRL can be applied for locomotion in all directions and different speeds (Rodriguez and Behnke (2021)), and can be transferred to real robots after certain sim2real operations (Lee et al. (2020); Li et al. (2021)).

Typically, there are two kinds of DRL-based approaches, according to the use of references. Approaches without references train the agent directly through trial-and-error, requiring a large amount of training and tuning, and the quality of motions is not guaranteed (Peng et al. (2018)). An alternative is to track expert motions. While imitation in physics-based model is difficult to implement (Lee et al. (2010)), imitation in DRL has shown much success.

While researches by (Xie et al. (2018)), Peng et al. (2018)), (Peng et al. (2020)) and (Li et al. (2021)) have managed to achieve imitation in DRL, we find that their implementations rely on well-performing references and require motion capture data or laborious tuning of expert controllers. Moreover, in (Li et al. (2021)), the robot could not walk much faster than the maximum speed of the gait library despite the aggressive commands. Therefore, in this paper, we propose an Adaptive Mimic method that can not only decrease tuning efforts but also take advantage of simple and probably unreliable references.

1.1. Related Work

Regarding bipedal walking, there are several implementations. One traditional way is the Zero-Moment Point (ZMP). When the biped is dynamically stable, the ZMP should locate inside the support polygon. Therefore, controllers can be designed to generate the desired ZMP using preview control (Kajita et al. (2003)), convolution sum (Kim (2007)) and other algorithms (Takanishi et al. (1989)). Capture Point (CP) is also used in the design of controllers. Capture Point is the point where another step of the robot can stabilize itself. It was originally used in push recovery but was later introduced to gait generation (Englsberger et al. (2011)). Another approach is to use Hybrid Zero Dynamic (HZD). The main idea of HZD is to use virtual constraints for desired status (Westervelt et al. (2018); Nguyen et al. (2020)). It can be then parameterized by Bezier polynomials and generate a periodic gait. An offline gait library can be generated by HZD and then deployed online (Reher et al. (2016)).

Regarding DRL, (Peng et al. (2018)) proposed DeepMimic, an example-guided DRL framework of complex physics-based skills with which bipeds can do backflips, cartwheels, and rolls. They also proposed a hierarchical DRL approach in (Peng et al. (2017)) to achieve robust gaits and complex locomotion tasks. (Li et al. (2021)) proposed a framework that combines a gait library from HZD
with DRL and implemented it on 3D bipedal locomotion. On the other hand, DRL without references were also brought up. (Rodriguez and Behnke (2021)) proposed the DeepWalk framework that does not require references for omnidirectional locomotion. (Rudin et al. (2021)) proposed a game-inspired curriculum by using massive parallelism on GPU, which effectively shortened the training time.

1.2. Motivation and Our Contribution

In this paper, we aim to find a way to reduce the efforts on tuning for DRL of bipedal walking from references. In our opinion, references should only serve to inspire the agent to achieve a primitive walking pattern, e.g., the robot should lift its foot off the ground and alternate the positions of feet periodically, no matter the velocity or stability achieved. Even infeasible references can be instructive for the agent. Therefore, the process of generating references can be greatly simplified. After learning the primitive walking pattern, the agent should pursue more the performance, but less the imitation. To this end, we propose to automatically adapt the weights of reward terms for performance and imitation during the learning process.

Our contributions in this paper include:

- an Adaptive Mimic formulation to mitigate the contradiction between imitation and performance when learning biped locomotion from unreliable references;
- showing that laborious manual tuning or high cost for references can be eliminated by imitation learning from a casually designed reference with low quality.

With our method, the requirements for the quality of references are greatly reduced, leading to simplification of the reference generation progress. Time consumed on parameter tuning for references and adjustment of reward function is reduced. Better performance and higher efficiency is achieved compared to DeepMimic formulation and direct DRL without reference.

2. Adaptive Mimic

Imitation learning of robot behaviors from references, as is formulated in DeepMimic (Peng et al. (2018)), is based on the reward function. It can be more specifically expressed as

\[ r_t = \omega^I r_I^t + \omega^P r_P^t + \omega^R r_R^t + \omega^O r_O^t, \]  

where \( r_I^t \) is the imitation reward, \( r_P^t \) is the performance reward that is specified for certain tasks, \( r_R^t \) is the regularization reward that encourages realistic movements, \( r_O^t \) is other reward terms that can facilitate learning, and \( \omega^I, \omega^P, \omega^R, \omega^O \) are the weights. Usually, these weights are constants.

However, in the case of low-quality and infeasible references, the imitation reward and the performance reward terms can greatly contradict each other, which can lead to low efficiency and even failures of learning. Yet we expect the robot to learn certain patterns from the references.

To solve this problem, we propose the adaptive mimic (AdaMimic) formulation that can automatically adapt the weights to balance the pursuit of performance and imitation. Specifically, we reformulate Eq. (1) as

\[ r_t = (1 - \omega_P^t) r_I^t + \omega_P^t r_P^t + \omega^R r_R^t + \omega^O r_O^t, \]  

with

\[ \omega_P^t = \omega_P(r_I^t, r_P^t), \]  

3
i.e., the weight $\omega^p_t$ is described as a function of $r^I_t$ and $r^P_t$. For convergence of learning process, we further limit the bounds of $r^I_t$ and $r^P_t$:

$$0 \leq r^I_t \leq R^*, \quad 0 \leq r^P_t \leq R^*,$$

(4)

where $R^*$ is a positive real number. We recommend the relationship below:

$$\max r^I_t = \max r^P_t = R^*,$$

(5)

which is naturally suitable for reward terms in the form of radial basis functions (RBF).

The key of AdaMimic is the definition of $\omega^p_t$ function in Eq. (3). We define it as

$$\omega^p_t = \begin{cases} r^P_t \frac{R^*}{R^*} & \text{if } r^I_t \leq r^P_t, \\ \min \left( (4 \frac{r^I_t}{R^*} - 3 \frac{r^P_t}{R^*})^2, 1.5 \right) & \text{if } r^I_t > r^P_t, \end{cases}$$

(6)

with visualization of $\omega^p_t$ and $r^{I&P}_t = (1 - \omega^P_t) r^I_t + \omega^P_t r^P_t$ in Figure 2. A high performance reward is always encouraged, while the critical point for pursuit of imitation is $\omega^P_t = 1$.

Regarding imitation, there are different cases. If both $r^P_t$ and $r^I_t$ are low, imitation is encouraged, because we assume that imitation can help improve the performance in such case. If $r^P_t$ is low while $r^I_t$ is high, imitation is discouraged, with the assumption that excessive imitation is detrimental to performance. If $r^P_t$ is high, imitation is hardly cared about, but excessive imitation is still discouraged if it cannot bring better performance.

3. Parameterized Bipedal Walking

In this section, we describe our robot platform in 3.1, and the generation of low-quality gait references in 3.2. The DRL framework of parameterized bipedal walking is presented in 3.3.

3.1. Robot Model

Our experiments are conducted on MOS, a self-designed humanoid robot platform. The MOS is 58 cm in height and 5 kg in weight, as is shown in Fig 3. It has 20 DoFs, including 2 for head, 6
Figure 3: The MOS humanoid platform: (a) the real robot, (b) the mesh in simulation, (c) the simplified collision model, and (d) the distribution of 20 DoFs.

| Part | DoF       | Type   | Stall Torque (N·m) | No Load Speed (rev/min) |
|------|-----------|--------|-------------------|-------------------------|
| Head | Head Pitch| MX28   | 2.5               | 55                      |
|      | Head Yaw  | MX28   | 2.5               | 55                      |
| Arm  | Shoulder Pitch | MX28 | 2.5           | 55                      |
|      | Shoulder Roll   | MX28 | 2.5            | 55                      |
|      | Elbow Yaw      | MX28  | 2.5             | 55                      |
| Leg  | Hip Roll      | MX106 | 8.4             | 45                      |
|      | Hip Pitch      | MX64  | 6.0             | 63                      |
|      | Knee Yaw      | MX64  | 6.0             | 63                      |
|      | Knee Pitch     | MX64  | 6.0             | 63                      |
|      | Ankle Pitch   | MX64  | 6.0             | 63                      |
|      | Ankle Roll    | MX106 | 8.4             | 45                      |

Table 1: Hardware Specifications

for each leg and 3 for each arm. DYNAMIXEL MX series servos are used for joint actuators. The hardware specifications are shown in Table 1.

3.2. Gait References

For references, we casually assigned the critical frames and generated the open-loop references by fifth-order Bezier spline interpolation, with joint positions solved by inverse kinematics. We generated gait references of the following parameters for experiments: 1) \( v_x = -0.4 \) m/s, \( v_y = 0 \) m/s, \( \omega_z = 0 \) rad/s, 2) \( v_x = 0.15 \) m/s, \( v_y = 0 \) m/s, \( \omega_z = 0 \) rad/s, 3) \( v_x = 0.4 \) m/s, \( v_y = 0 \) m/s, \( \omega_z = 0 \) rad/s, with x-axis pointing forward, y-axis pointing leftward, and z-axis pointing upward. Figure 4 shows how the references are designed, and the body is assumed to be at a fixed height. These references are all of low quality, i.e., they can not be directly applied to the robot, but are easy to obtain without laborious tuning.

3.3. Learning of Bipedal Walking

For learning, we adopt the massively parallel DRL framework in (Rudin et al. (2021)). The Proximal Policy Optimization (PPO) algorithm (Schulman et al. (2017)) is applied together with generalized advantage estimation (GAE) (Schulman et al. (2016)). We adopt the positional control according
Figure 4: Generated gait references for (a) $v_x = -0.4 \text{ m/s}$, (b) $v_x = 0.15 \text{ m/s}$, and (c) $v_x = 0.4 \text{ m/s}$. The two feet follow symmetric trajectories, thus only one step is shown, and the first step should be a half step. Red points and lines are for the body, blue points and lines are for the left foot, and green points and lines are for the right foot. These references can make the robot fall within 3 steps if directly deployed.

to (Peng and van de Panne (2017)), and the policy outputs target joint positions at 50 Hz. The PD controllers generate torques based on the target joint positions and the measured joint positions at 200 Hz. The simulation environment is Isaac Gym (Makoviychuk et al. (2021)).

4. Experiments

We experimentally validated our method on the MOS robot introduced in 3.1, with the DRL framework in 3.3. In this section, the tasks and settings of our experiments are respectively presented in 4.1 and 4.2, and the results are displayed in 4.3.

4.1. Tasks

As is described in 3.2, we generated three low-quality references, respectively with $v_x = -0.4 \text{ m/s}$, $v_x = 0.15 \text{ m/s}$, and $v_x = 0.4 \text{ m/s}$. All of them have $v_y = 0 \text{ m/s}$, $\omega_z = 0 \text{ rad/s}$.

To show the applicability of our method, we designed different tasks below:

1) From the same reference to different targets

1.1. learning to walk at $v_x = 0.4 \text{ m/s}, v_y = 0 \text{ m/s}, \omega_z = 0 \text{ rad/s}$ from reference $v_x = 0.4 \text{ m/s};$

1.2. learning to walk at $v_x = 0.6 \text{ m/s}, v_y = 0 \text{ m/s}, \omega_z = 0 \text{ rad/s}$ from reference $v_x = 0.4 \text{ m/s};$

1.3. learning to walk at $v_x = 0.5 \text{ m/s}, v_y = 0.2 \text{ m/s}, \omega_z = -1 \text{ rad/s}$ from reference $v_x = 0.4 \text{ m/s}.$

2) From different references to the same target

2.1. learning to walk at $v_x = 0.6 \text{ m/s}, v_y = 0 \text{ m/s}, \omega_z = 0 \text{ rad/s}$ from reference $v_x = 0.4 \text{ m/s};$

2.2. learning to walk at $v_x = 0.6 \text{ m/s}, v_y = 0 \text{ m/s}, \omega_z = 0 \text{ rad/s}$ from reference $v_x = 0.15 \text{ m/s};$

2.3. learning to walk at $v_x = 0.6 \text{ m/s}, v_y = 0 \text{ m/s}, \omega_z = 0 \text{ rad/s}$ from reference $v_x = -0.4 \text{ m/s}.$
### Adaptive Mimic

#### Symbols

| Body height | $h$ |
| Joint positions | $q$ |
| Joint velocities | $\dot{q}$ |
| Joint accelerations | $\ddot{q}$ |
| Joint torques | $\tau$ |
| Target joint positions (action) | $a$ |
| Difference of the action | $\delta a$ |
| Reference joint positions | $\dot{q}^r$ |
| Base linear velocity | $v$ |
| Base angular velocity | $\omega$ |
| Commanded base linear velocity | $v^\ast$ |
| Commanded base angular velocity | $\omega^\ast$ |
| Environment time step | $dt$ |

| Imitation reward $r^i$, $R^i = 1dt$, sum of below |
| --- |
| Imitation reward for joint positions | $1dt \cdot \text{RBF}(q, \dot{q}, 1.5)$ |

| Performance reward $r^p$, $R^p = 1dt$, sum of below |
| --- |
| Linear velocity tracking | $0.75dt \cdot \text{RBF}([v_x, v_y], [v^\ast_x, v^\ast_y], 0.16)$ |
| Angular velocity tracking | $0.25dt \cdot \text{RBF}(\omega_z, \omega^\ast_z, 2.5)$ |

| Regularization reward $r^r$, sum of below |
| --- |
| Torque regularization | $-1 \times 10^{-6} dt \cdot \|\tau\|^2_2$ |
| Joint acceleration regularization | $-2 \times 10^{-8} dt \cdot \|\ddot{q}\|^2_2$ |
| Z-axis linear velocity regularization | $-2 \times 10^{-2} dt \cdot \|v_2\|^2_2$ |
| Roll rate and pitch rate regularization | $-2 \times 10^{-2} dt \cdot (\omega_2^2 + \omega_3^2)$ |
| Action rate regularization | $-1 \times 10^{-4} dt \cdot \|\delta a\|^2_2$ |

| Other reward $r^o$, sum of below |
| Alive reward | $-50$ if $h < 0.33$ m then reset, else 0 |

Table 2: Reward Terms

Note that task 2.1 is the same as task 1.2, so there are 5 tasks and 3 targets in total. It is also worth mentioning that a speed of 0.6 m/s is close to the limit of the MOS robot which is 0.58 m tall and can hardly jump.

#### 4.2. Settings

For learning, we adopted the framework in ([Rudin et al. (2021)]) as is mentioned in 3.3, and kept most of the configurations as original. Changed configurations are: $n_{\text{robots}} = 4096$, $n_{\text{steps}} = 96$, plain terrains without measurements sampled from the grid.

The reward terms are displayed in Table 2. The RBF function applied in the table is

$$\text{RBF}(x, y, \sigma^2) = \exp \left( -\frac{\|x - y\|^2_2}{\sigma^2} \right).$$

And the reward function is the sum of the weighted terms according to Eq. (1), with $\omega^P = \omega^O = 1$.

For comparison, we tried 5 strategies for the other two weights:

1. $\omega^P = 0.2$ and $\omega^I = 1 - \omega^P$, following our AdaMimic formulation, abbreviated to "Ada";
2. Fixed $\omega^P = 0.5$ and $\omega^I = 1 - \omega^P = 0.5$, abbreviated to "DM0.5";
3. Fixed $\omega^P = 0.8$ and $\omega^I = 1 - \omega^P = 0.2$, abbreviated to "DM0.8";
4. Fixed $\omega^P = 1$ and $\omega^I = 1 - \omega^P = 0$, i.e, no imitation, abbreviated to "NI."

For "NI", different tasks are only determined by different targets, so there are only 3 tasks (task 1.1, 1.2, and 1.3) for "NI".
Figure 5: Snapshots of the learned gait patterns without imitation after 1000 iterations. (a) for task 1.1, (b) for task 1.2, and (c) for task 1.3.

Figure 6: Snapshots of the learned gait patterns through AdaMimic after 1000 iterations. Upper body joints are not included in imitation. (a) for task 1.1, (b) for task 1.2, (c) for task 1.3, (d) for task 2.2, and (e) for task 2.3. The patterns are more reasonable and elegant compared to those in Figure 5.

4.3. Results

The essential distinction between "NI" and other strategies is that the robot could not learn reasonable gait patterns. Therefore, for "NI", we only show some snapshots in Figure 5. For comparison, snapshots of gait patterns learned through "Ada" are also displayed in Figure 6.

Learning curves of other strategies are shown in Figure 7 and Figure 8. X-axis and Y-axis of the plots respectively correspond to the "iterations" and the "Episode Reward" in the framework in (Rudin et al. (2021)). The "Performance” reward demonstrates how well the target is achieved, and our proposed AdaMimic successfully outperformed the DeepMimic formulation. For different references and targets, the best DeepMimic weight changes, but the AdaMimic strategy does not require the manual adjustment of weights.
Figure 7: Learning curves for task 1.1, 1.2, and 1.3. Empirically, a “Performance” larger than 0.5 means that the robot is going to achieve the target.

Figure 8: Learning curves for task 2.1, 2.2, and 2.3. Empirically, a “Performance” larger than 0.5 means that the robot is going to achieve the target.

For different tasks, the switch time between pursuit of imitation and performance can be different, but the pattern is similar, as is shown in Figure 9. The imitation is firstly encouraged with a low $\omega^p_t$, but as the performance reward increases, the imitation reward slowly decreases. The “mean” terms in Figure 9 are averaged over steps, instead of over the horizon as in Figure 7 and Figure 8.
5. Conclusion and Future Work

In this paper, we proposed the AdaMimic formulation for imitation learning of robot behaviors from low-quality references. Based on infeasible references, policies of parameterized bipedal walking were learned through AdaMimic for our MOS humanoid robot. We claim that the references were generated without manual tuning, and the weights of imitation and performance can be automatically adjusted during the learning process, which finally serves to pursue better performance.

To obtain ideal references for various locomotion tasks, laborious motion capturing or manual tuning of parameters is usually unavoidable. AdaMimic should change this situation because it only requires simple references without tuning.

In the future, we will further use simple references to help our MOS robot learn omnidirectional bipedal locomotion and achieve the ability to travel across difficult terrains. The learned policy will be tested on the real robot. Extensions to other locomotion tasks such as fall recovery and soccer dribbling will also be explored.

References

Guillermo A Castillo, Bowen Weng, Ayonga Hereid, Zheng Wang, and Wei Zhang. Reinforcement learning meets hybrid zero dynamics: A case study for rabbit. In 2019 International Conference on Robotics and Automation (ICRA), pages 284–290. IEEE, 2019.

Johannes Englsberger, Christian Ott, Máximo A Roa, Alin Albu-Schäffer, and Gerhard Hirzinger. Bipedal walking control based on capture point dynamics. In 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 4420–4427. IEEE, 2011.

Seokmin Hong, Yonghwan Oh, Doik Kim, and Bum-Jae You. Real-time walking pattern generation method for humanoid robots by combining feedback and feedforward controller. IEEE transactions on industrial electronics, 61(1):355–364, 2013.

Qiang Huang, Kazuhiro Yokoi, Shuji Kajita, Kenji Kaneko, Hirohiko Arai, Noriho Koyachi, and Kazuo Tanie. Planning walking patterns for a biped robot. IEEE Transactions on robotics and automation, 17(3):280–289, 2001.

Shuji Kajita, Fumio Kanehiro, Kenji Kaneko, Kiyoshi Fujiwara, Kensuke Harada, Kazuhito Yokoi, and Hirohisa Hirukawa. Biped walking pattern generation by using preview control of zero-moment point. In 2003 IEEE International Conference on Robotics and Automation (Cat. No. 03CH37422), volume 2, pages 1620–1626. IEEE, 2003.
Jung-Hoon Kim. Walking pattern generation of a biped walking robot using convolution sum. In 2007 7th IEEE-RAS International Conference on Humanoid Robots, pages 539–544. IEEE, 2007.

Joonho Lee, Jemin Hwangbo, Lorenz Wellhausen, Vladlen Koltun, and Marco Hutter. Learning quadrupedal locomotion over challenging terrain. Science robotics, 5(47), 2020.

Seunghwan Lee, Moonseok Park, Kyoungmin Lee, and Jehee Lee. Scalable muscle-actuated human simulation and control. ACM Transactions On Graphics (TOG), 38(4):1–13, 2019.

Yoonsang Lee, Sungeun Kim, and Jehee Lee. Data-driven biped control. In ACM SIGGRAPH 2010 papers, pages 1–8. 2010.

Tianyu Li, Hartmut Geyer, Christopher G Atkeson, and Akshara Rai. Using deep reinforcement learning to learn high-level policies on the atrias biped. In 2019 International Conference on Robotics and Automation (ICRA), pages 263–269. IEEE, 2019.

Zhongyu Li, Xuxin Cheng, Xue Bin Peng, Pieter Abbeel, Sergey Levine, Glen Berseth, and Koushil Sreenath. Reinforcement learning for robust parameterized locomotion control of bipedal robots. In IEEE International Conference on Robotics and Automation (ICRA), 2021.

Libin Liu and Jessica Hodgins. Learning basketball dribbling skills using trajectory optimization and deep reinforcement learning. ACM Transactions on Graphics (TOG), 37(4):1–14, 2018.

Viktor Makoviychuk, Lukasz Wawrzyniak, Yunrong Guo, Michelle Lu, Kier Storey, Miles Macklin, David Hoeller, Nikita Rudin, Arthur Allshire, Ankur Handa, and Gavriel State. Isaac gym: High performance gpu-based physics simulation for robot learning, 2021.

Gabe Nelson, Aaron Saunders, Neil Neville, Ben Swilling, Joe Bondaryk, Devin Billings, Chris Lee, Robert Playter, and Marc Raibert. Petman: A humanoid robot for testing chemical protective clothing. Journal of the Robotics Society of Japan, 30(4):372–377, 2012.

Quan Nguyen, Xingye Da, JW Grizzle, and Koushil Sreenath. Dynamic walking on stepping stones with gait library and control barrier functions. In Algorithmic Foundations of Robotics XII, pages 384–399. Springer, 2020.

Xue Bin Peng and Michiel van de Panne. Learning locomotion skills using deeprl: Does the choice of action space matter? In Proceedings of the ACM SIGGRAPH/Eurographics Symposium on Computer Animation, pages 1–13, 2017.

Xue Bin Peng, Glen Berseth, KangKang Yin, and Michiel Van De Panne. Deeploco: Dynamic locomotion skills using hierarchical deep reinforcement learning. ACM Transactions on Graphics (TOG), 36(4):1–13, 2017.

Xue Bin Peng, Pieter Abbeel, Sergey Levine, and Michiel van de Panne. Deepmimic: Example-guided deep reinforcement learning of physics-based character skills. ACM Transactions on Graphics (TOG), 37(4):1–14, 2018.

Xue Bin Peng, Erwin Coumans, Tingnan Zhang, Tsang-Wei Lee, Jie Tan, and Sergey Levine. Learning agile robotic locomotion skills by imitating animals. In Robotics: Science and Systems, 2020.
Jacob Reher, Eric A Cousineau, Ayonga Hereid, Christian M Hubicki, and Aaron D Ames. Re- alizing dynamic and efficient bipedal locomotion on the humanoid robot durus. In 2016 IEEE International Conference on Robotics and Automation (ICRA), pages 1794–1801. IEEE, 2016.

Diego Rodriguez and Sven Behnke. Deepwalk: Omnidirectional bipedal gait by deep reinforcement learning. In IEEE International Conference on Robotics and Automation (ICRA), 2021.

Nikita Rudin, David Hoeller, Philipp Reist, and Marco Hutter. Learning to walk in minutes using massively parallel deep reinforcement learning. In 5th Annual Conference on Robot Learning, 2021.

John Schulman, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. High-dimensional continuous control using generalized advantage estimation. In Proceedings of the International Conference on Learning Representations (ICLR), 2016.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347, 2017.

A Takanishi, M Tochizawa, T Takeya, H Karaki, and I Kato. Realization of dynamic biped walking stabilized with trunk motion under known external force. In Advanced Robotics: 1989, pages 299–310. Springer, 1989.

Miomir Vukobratović and Branislav Borovac. Zero-moment point—thirty five years of its life. International journal of humanoid robotics, 1(01):157–173, 2004.

Eric R Westervelt, Jessy W Grizzle, Christine Chevallereau, Jun Ho Choi, and Benjamin Morris. Feedback control of dynamic bipedal robot locomotion. CRC press, 2018.

Zhaoming Xie, Glen Berseth, Patrick Clary, Jonathan Hurst, and Michiel van de Panne. Feedback control for cassie with deep reinforcement learning. In 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pages 1241–1246. IEEE, 2018.