Hybrid and dynamic policy gradient optimization for bipedal robot locomotion

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Abstract

Controlling a non-statically bipedal robot is challenging due to the complex dynamics and multi-criterion optimization involved. Recent works have demonstrated the effectiveness of deep reinforcement learning (DRL) for simulation and physically implemented bipeds. In these methods, the rewards from different criteria are normally summed to learn a single value function. However, this may cause the loss of dependency information between hybrid rewards and lead to a sub-optimal policy. In this work, we propose a novel policy gradient reinforcement learning for biped locomotion, allowing the control policy to be simultaneously optimized by multiple criteria using a dynamic mechanism. Our proposed method applies a multi-head critic to learn a separate value function for each component reward function. This also leads to hybrid policy gradients. We further propose dynamic weight for hybrid policy gradients to optimize the policy with different priorities. This hybrid and dynamic policy gradient (HDPG) design makes the agent learn more efficiently. We showed that the proposed method outperforms summed-up-reward approaches and is able to transfer to physical robots. The MuJoCo results further demonstrate the effectiveness and generalization of our HDPG.

1 Introduction

Bipedal locomotion for walking robots [9] is about controlling a robot to move on different surfaces with stable walking gaits. This task is challenging because of the complex dynamics involved especially where undulated surfaces or obstacles are present. Traditional hand-crafted control policies, such as zero moment point (ZMP) [11], hybrid zero dynamics (HZD) [1] and divergent component of motion (DCM) [19], often suffer from limited adaptation to various environments.

Recently, reinforcement learning (RL) has made significant progress in solving complex biped locomotion problems [21, 26, 4, 15]. The core of RL is training robots to take actions that maximize the expected cumulative rewards. A reward function usually consists of multiple components [23, 25], each of which quantitatively describes an aspect of the quality for the walking task, such as body balance maintenance, limb-alteration gait, conservative motor torques and so on. Most existing approaches simply add up the component rewards to learn a single value function [21, 25], which may break the correlation between different rewards and therefore limit learning efficiency [22].

In this work, we propose a hybrid and dynamic policy gradient (HDPG) optimization method to address the above-mentioned issues. Specifically, we construct a multi-head critic in the deep deterministic policy gradient (DDPG) [16] framework to capture the gradients separately obtained
from multiple rewards. Each head exclusively learns from corresponding reward feedback (see Figure 1). Meanwhile, the branch gradients are merged during back-propagation with dynamically updating weights, which aims to guide the policy network to first learn from the “easy” components before the “challenging” ones. The motivation for this dynamic mechanism is that we tentatively guide the robot to give higher priority to learn from components that show fast reward accumulation. For example, the agent should learn to maintain body balance before learning to move forward. Thus, the body balance component should have a higher priority than moving forward in the initial learning stage. To achieve this goal, we introduce dynamic weights to allow each component gradient to optimize the policy with a different priority. The contributions of this work are summaries as following:

- We introduce a multi-head critic to learn a separate value function for each component reward. The experimental results show that our proposed multi-head design outperforms the traditional reward-sum method in the biped locomotion tasks.
- We propose dynamic weights for hybrid policy gradients to improve learning efficiency. In this way, the control policy is optimized by hybrid policy gradients in a dynamic manner.
- We build our biped robot in the gazebo simulator and release 3 challenges, which are push recovery challenge, obstacle challenge and slope terrain challenge. We train the proposed HDPG policy with simple dynamics randomization in the simulator. The policy is successfully transferred to the physical robot without further tuning.
- We further conduct experiments on OpenAI gym [3] to verify the generalization of HDPG. Experimental results demonstrate that the proposed method can be applied to more general continuous control tasks to improve learning efficiency.

2 Related work

Bipedal locomotion problems were mostly targeted by manually designed polices using methods such as zero moment point (ZMP) [12, 11], hybrid zero dynamics (HZD) [5, 12, 8], divergent component of motion (DCM) [6, 19] and so on. ZMP-based methods [12, 11] use the simplified models, e.g., linear inverted pendulum (LIP) dynamics, to generate walking patterns with the constraints that ZMP should be maintained in the support polygon. DCM-based methods [6, 19] simplify gait generation using the divergent component of center of mass (CoM) which enlarges the support polygon and allows the robot recover from external perturbations by step adjustment. HZD approaches [1, 2] impose virtual constraints to put the biped into zero dynamics surface via feedback linearization. However, the flexibility of these manually designed polices is limited, therefore, it is challenging to handle difficult situations where obstacles and inclined surfaces are present. To generalize the walking capability for bipeds to such challenging situations, imitation-learning-based approaches aim to train neural network models supervised by expert policies [26, 20, 14, 21]. But these methods rely on human experts to manually design a control policy as reference, which can be laborious.

Reinforcement learning system optimizes the policy in a reasonable way by exploration and interaction with a simulation environment. It encourages favorable movements and punishes improper ones to learn an optimal policy. In order to address the aforementioned issues of traditional controller and imitation learning, many researches attempt to learn bipedal locomotion policies following a reinforcement learning framework [18, 27]. However, they did not demonstrate the effectiveness on physical robots. Recently, Xie et al. [25] formulates a feedback control problem as finding the optimal policy for a Markov Decision Process to learn robust walking controllers that imitate a reference motion with DRL. This proved to be effective on Cassie simulation. Subsequently, they use an iterative training method and Deterministic Action Stochastic State (DASS) tuples to learn a more robust policy [26]. Siekmann et al. [21] introduce recurrent neural networks (RNNs) to learn memory features that reflect physical properties. However, all of these approaches use the sum of rewards to learn a single value function [21, 25], which may cause the loss of the dependency information between different rewards and limit the learning efficiency of value function [22].

In this paper, we aim to make full use of the dependency between different reward components to improve learning efficiency. We first proposed a multi-head critic to learn a separate value function for each component reward function, which is similar to Hybrid Reward Architecture (HRA) [22] and Decomposed Reward Q-Learning (drQ) [10]. They first decompose the reward function of the environment into \( n \) different reward functions. Then they aim to learn a separate value function, each of them is assigned a reward component. Learning a separate value function is proved to enable more
3 Preliminaries

In this section, we will briefly introduce the background and annotations of RL and the theory of deep deterministic policy gradient (DDPG) [16], which is the base model of the proposed method.

3.1 Markov Decision Process (MDP)

Specifically, biped locomotion is formulated as a Markov Decision Process problem. A standard reinforcement learning includes an agent interacting with an environment \( E \) and receiving a reward \( r \) at every time step \( t \) in MDP. MDP can be denoted as the tuple \((S,A,P,R,\gamma)\), where \( S \) is the state space, \( A \) is the action space, blue \( P: S \times A \rightarrow S \) is the transition probability function, and \( R \) is the reward function, \( \gamma \in (0,1) \) is the discount factor.

At every time step \( t \), the robot observes current state \( s_t \in S \), and takes an action \( a_t \) according to a policy \( \pi: a_t = \pi(s_t) \). Then, the agent transits to the next state \( s_{t+1} = P(s_{t+1} | s_t, a_t) \) and receives a reward \( r_t = R(s_t, a_t) \) as well as a new state \( s_{t+1} \in S \) from the environment. The return from a state \( s_t \) as the cumulative \( \gamma \)-discounted reward: \( \sum_{k=t}^{T} \gamma^{k-t} R(s_k, a_k) \). The objective of RL is to optimize the policy \( \pi \) by maximizing the expected return from the initial state. According to the Bellman Equation, the expected return starts from state \( s_t \), takes action \( a_t \), and follows policy \( \pi \), which is denoted as action-value function \( Q_{\pi}(s_t, a_t) \), i.e., Q-function:

\[
Q_{\pi}(s_t, a_t) = E_{r_t, s_{t+1} \sim E}[r(s_t, a_t) + \gamma Q_{\pi}(s_{t+1}, \pi(s_{t+1}))]
\]  

3.2 Deep Deterministic Policy Gradient

Deep Deterministic Policy Gradient (DDPG) [16] is a representative model-free RL method. Considering its remarkable performance for the continuous control problem, DDPG is utilized as our basic model. It consists of a Q-function (the critic) and a policy function (the actor) to learn a deterministic continuous policy. The actor \( \pi \) and the critic \( Q \) are learnt with deep function optimization, which is parameterized by \( \theta^\pi \) and \( \theta^Q \), respectively.

To avoid the agents falling into a local optimum and further improve the exploration efficiency, an Ornstein-Uhlenbeck (OU) noise is introduced to the policy. The output action can be expresses as: \( a_t = \pi(s_t) + \mathcal{N}_t \), where \( \mathcal{N}_t \sim \mathcal{N}_{OU} \). It utilizes the experience replay strategy which collects the experience tuples \((s_t, a_t, r_t, s_{t+1})\) stored in a replay buffer \( B \) during exploration. In training stage, the training data are sampled from the replay buffer to optimize the policy. DDPG approximates Q-function by a critic network, which is updated by minimizing the Bellman loss:

\[
L(\theta^Q) = E_{s_t, a_t, r_t, s_{t+1} \sim B}(y_t - Q(s_t, a_t | \theta^Q)),
\]  

where \( y_t = r_t + \gamma Q(s_{t+1}, \pi(s_{t+1}) | \theta^Q) \) is the target value. Then the actor learns a Q-optimal policy:

\[
\pi(s) = \arg \max_a Q(s,a | \theta^Q)
\]

and optimizes the policy by using the sampled policy gradient:

\[
\nabla_{\theta^\pi} J \approx E_{s_t, a_t, r_t, s_{t+1} \sim B} [\nabla_a Q(s,a | \theta^Q)]_{s=s_t,a=\pi(s_t)} \nabla_{\theta^\pi} \pi(s|\theta^\pi)]_{s=s_t}.
\]  

For stabilize training, DDPG introduced a target actor network \( \theta^{\pi'} \) and a target critic network \( \theta^{Q'} \) respectively, which are used for calculating the target values. The target network is updated through “soft” update [16]: \( \theta^\prime = \tau \theta + (1 - \tau) \theta^\prime \), where \( \tau \) is the update rate.

4 Hybrid and dynamic policy gradient RL for biped locomotion

The framework of our method is given in Fig[1]. The robot observes the current state \( s_t \) from Gazebo environment, which contains the data from the inertial measurement unit (IMU) and angular positions...
Figure 1: Overview. The biped robot interacts with the simulation environment and obtains experience transitions \((s_t, a_t, s_{t+1}, r_t)\). HDPG contains an actor and a multi-head critic. The multi-head critic learns a separate Q-value function for each reward component. We then assign the dynamic weight for the hybrid policy gradient to adjust the learning priority of each policy gradient component. With dynamics randomization in the simulator, the policy is successfully transferred to the physical robot.

of all joints. Inspired by “memory-based control” [21, 28], we use state sequence \((s_{t-2}, s_{t-1}, s_t)\) as the input of the actor to contain temporal information. In total, the input dimension of the policy networks is 69. The predict action \(a_t\) from the actor contains the control signal about the angular position of joints. It is sent to a minimum jerk planning module [13] to generate their smooth transition trajectories. A low level PD controller is applied to track these joint position trajectories. After that, the agent will receive a reward \(r_t\) from the environment. This process is iterative until termination.

Learning biped locomotion is a complex task due to multiple constraints involved [7, 24, 23]. When walking forward, the robot needs to maintain the balance of the pelvis and avoid the abnormal states, such as falling down, over-torque and strange posture. This usually results in multi-dimensional rewards, each of which corresponds to a constraint. Existing methods usually use the weighted sum of rewards to learn a single value [28, 26, 21]:

\[ r_t = K \sum_{k=1}^{K} w_k r_{t,k} \]

where \(K\) is the number of rewards and \(w_k\) is the weight parameter of each reward. However, simply summing the rewards will lose the dependencies information between different rewards. Two sets of very different rewards may get the same sum, which results in Q-value not giving insight into factors contributing to policy. For example, when the biped robot receives a negative reward, it cannot understand whether it is due to the unnatural pose or the over-torque of steering engine.

4.1 Multi-head Critic for multiple values learning

Inspired by “hybrid reward architecture (HRA)” [4], we conduct a multi-head critic to learn a separate value function for each component reward function. As shown in Fig. 1. Therefore, the reward is decomposed and can be expressed as a vector: \(r_t = [r_{t1}, r_{t2}, ..., r_{tK}]\). Each head of the critic learns an action-value corresponding to a specific sub-reward. In this way, the overall Q-value is also expressed as a vector:

\[ Q(s_t, a_t|\theta^Q) = [Q_{t,1}, Q_{t,2}, ..., Q_{t,K}] \]

HRA [22] estimate the Q-value based on Deep Q Network (DQN) [17]:

\[ Q_k(s_t, a_t) \leftarrow r_k + \max_{a_{t+1}} Q_k(s_{t+1}, a_{t+1}) \]

which ignores the influence of other components to the overall Q-function. Our HDPG is built on the DDPG algorithm [16], which allows the policy to produce continuous control. Different from HRA, HDPG estimates each value with overall action:

\[ a_{t+1} = \pi(s_{t+1}|\theta^\pi) \]

Thus, the Q-value of each component is estimated as:

\[ Q_k(s_t, a_t) \leftarrow r_k + Q_k(s_{t+1}, a_{t+1}) \]

Intuitively, this leads \(Q_k\) to converge toward the value (w.r.t. \(k\)th component) of the consistent policy. According to Equation 2 the loss function associated with the multi-head critic is:

\[ L(\theta^Q) = \mathbb{E}_{s_t, a_t, r_t \sim B} \sum_{k=1}^{K} \left[ (y_{t,k} - Q_k(s_t, a_t|\theta^Q))^2 \right] \]
where \( y_{t,k} = r_{t,k} + \gamma Q_k(s_{t+1}, \pi(s_{t+1})|\theta_k^Q) \). Note that we use \( \theta_k^Q \) to differentiate the parameters of different \( Q_k \). In practical, different \( \theta_k^Q \) have share multiple lower-level layers of a critic network. Only the last layer is independent of each other. The architecture details of multi-head critic are presented in the Appendix. Then, the overall Q-value is defined as the sum of each \( Q_k \): 
\[
Q(s_t, a_t) = \sum_{k=1}^K Q_k(s_t, a_t).
\]

### 4.2 Dynamic policy gradient

According to equation [3] the policy gradient can be re-expressed as:
\[
\nabla_\theta J \approx E_{s_t, a_t \sim B} [\nabla_{\theta} \sum_{k=1}^K Q_k(s_t, \pi(s_t)|\theta_k^Q) \nabla_\theta \pi(s_t|\theta^\pi)]
\]
\[
= \sum_{k=1}^K E_{s_t, a_t \sim B} [\nabla_{\theta} Q_k(s_t, \pi(s_t)|\theta_k^Q) \nabla_\theta \pi(s_t|\theta^\pi)]
\]
\[
= \sum_{k=1}^K \nabla J_k
\]

where \( \nabla J_k = E_{s_t, a_t \sim B} [\nabla_{\theta} Q_k(s_t, \pi(s_t)|\theta_k^Q) \nabla_\theta \pi(s_t|\theta^\pi)] \). This formula indicates that all Q-values update the policy with the same weight. In other words, the agent learns all skills in parallel with the same learning rate. However, if there are potential dependencies between reward components, then learning all components with the same learning rate can be challenging and inefficient. At the same time, some components are much easier to learn than others.

Therefore, we propose to learn each skill orderly according to the priority. We then determine the priority based on the difficulty of each component relative to the current policy. We hope the agent to learn the easier components first, and then gradually learn the more complex components.

The agent utilizes current policy \( \pi_T \) to interact with the environment and obtains \( N \) experience samples, which contains \( N \) one-step rewards: \( r^n = [r^n_1, r^n_2, ..., r^n_K], n \in [1, N] \). All component rewards are normalized to the same value range (e.g., \( (0, 1) \)). The mean and the variance of reward samples are calculated as \( \mu = [\mu_1, \mu_2, ..., \mu_K] \) and \( \sigma = [\sigma_1, \sigma_2, ..., \sigma_K] \), respectively.

A larger \( \mu_k \) means that the component is easier to get a larger reward, so it is easier to learn for the current policy, and vice versa.

The variance reflects the dispersion of each reward’s distribution. Stable walking will produce uniform rewards for biped robot, which leads to a small variance \( \sigma \). In contrast, the larger variance \( \sigma_k \) indicates that the policy is more unstable in component \( k \). Intuitively, in order to make the policy more stable, we would like to increase the learning rate of the unstable components. We define the priority weight \( m_k \) of each policy gradient component to mathematically formulate these rules:
\[
m_k = \frac{\mu_k + e^{\sigma_k^2}}{\sum_{k=1}^K (\mu_k + e^{\sigma_k^2})}
\]

Therefore, the total policy gradient is dynamic updated every \( T \) episodes according to: 
\[
\nabla_\theta J = \sum_{k=1}^K m_k \nabla J_k.
\]
In this way, the priority weights will be updated every \( T \) episodes. Our HDPG can be used for algorithms with the form of actor-critic.

### 5 Experiments

To verify the effectiveness of the proposed method, we conduct our simulator, named AIDA, to support development, training, and validation of biped locomotion. AIDA is built on Robot Operating System (ROS) framework[4] and Gazebo simulation environment. The biped robot and the terrain are

[4] https://www.ros.org/
Figure 2: Illustrations of biped locomotion tasks: (a) walking under random push disturbance; (b) walking cross obstacles; (c) walking on the slope.

modelled with SolidWorks as shown in Figure 2. The robot contains 10 degrees of freedom (DoF), and each leg has 5 DoF. The center of mass of the pelvis is maintained at the center of the pelvis, which is similar to humans.

We first describe the experiment setting and a biped locomotion benchmark in Sec. 5.1. Then, the simulation results and sim-to-real results of biped walking experiments are illustrated in Sec. 5.2 and 5.3, respectively. Experimental results from both simulation and transfer-to-real robots are presented in this video. We finally conduct the experiments on MuJoCo of OpenAI gym in Sec 5.4 to further demonstrate the generalization of the proposed HDPG.

5.1 Experiment settings

In this section, the experiment setting and implementation details of the proposed method will be elaborated. The robot state $s_t$, as shown in Figure 1, contains the IMU data and the angular position of each joint. In order to extract temporal features, 3 state frames $(s_{t-2}, s_{t-1}, s_t)$ are concatenated and fed into the policy network to predict an action. The combined states yield 69-dimensional state space (23D for each state). The predicted action is the angular position of each joint, which is a 10-dimensional vector. See the Appendix for the rest of the implementation details.

To make comprehensive evaluation of the proposed method, we further define a biped locomotion benchmark that contains 3 walking tasks, which simulate 3 corresponding real-world challenging problems: walking under random disturbances, walking cross obstacle, and walking on the undulated ground. The details of 3 tasks are described as follows:

- Walking under random disturbance: The robot walks under disturbances from different directions, as shown in Figure 2(a). The disturbance range is from 6N to 14N, and the duration is 0.2s. The directions contain forward, backward and sideward (either on the left or right side). We measure the success rate that the robot recovers from push disturbances.
- Walking cross obstacles: We randomly placed static obstacles of different heights on the ground, as shown in Fig. 2(b). We separately measure the success rate of the robot crossing obstacles of different heights.
- Walking on the slope: We build a slope with different angles to evaluate the terrain adaptability of the robot, as shown in Figure 2(c). We separately measure the success rate of the robot climbing slopes of different angles.

5.2 Simulation results

In this section, we will qualitatively and quantitatively analyze the performance of the proposed HDPG with ZMP method and DDPG [16], which is the baseline of the proposed method.

- ZMP: ZMP-based algorithm [12][11] is a kind of traditional classical control method. It has been proven effective in many bipedal walking tasks.

https://www.solidworks.com/
https://1drv.ms/v/s!Ak4kXYOGgb3ucX3ZEL-kja_1GJw?e=qrfIBi
Figure 3: Comparison of DDPG, MHDDPG and HDPG training curves. (a) is the Comparison of DDPG, MHDDPG and HDPG. Our HDPG achieves a much higher reward than MHDDPG and DDPG. It performs the highest learning efficiency at the same time. (b) is the training curve of each reward of MHDDPG. (c) is the training curve of each reward of HDPG.

Figure 4: Comparison of the success rate in “walking under random disturbance” task. The robot is commanded to walk forward, and random push force will be applied to the robot’s pelvis from different directions. We conducted 100 trials for each test. A trial is considered successful if the robot recovers stable walking from push disturbance.

• DDPG: DDPG [16] is a advanced actor-critic model-free RL algorithm. It is also considered as the basic model with single-head critic.

• MHDDPG: MHDDPG represents the DDPG [16] model equipped the proposed multi-head critic. We keep the experimental settings and parameter settings consistent with DDPG. The only difference is that we learn hybrid policy gradients with multi-head critic, and each policy gradient is assigned with the same static weight to optimize the policy (e.g., $m_1 = m_2 = \ldots = m_K = 1$).

• HDPG: HDPG is the complete version of the proposed method. It can be regarded as MHDDPG incorporate with dynamic weight for each policy gradient.

We train the biped robot in AIDA with DDPG [16], MHDDPG and HDPG, respectively. The training curves are shown in Figure 3(a). The accumulative reward of HDPG starts to rise after training $2k$ episodes while MHDDPG and DDPG require $4k$ and $6k$ episodes, respectively. The performance of MHDDPG is much better than vanilla DDPG [16]. Since vanilla DDPG simply sums the rewards up to a single value, it is unable to explicitly express the value of each component. This results in single Q-value not giving insight into factors contributing to policy, as mentioned in Sec. 4. Some value functions are much easier to learn than others [22], then learning a separate value function is more effective. Obviously, the proposed HDPG outperforms DDPG and MHDDPG. With the utility of dynamic weight, HDPG can adjust the learning priorities of each gradient component and learn in a more efficient way.

5.2.1 Walking under random disturbance

To evaluate the robustness of the above several methods, the robot is asked to walk under various push disturbances from different directions, as mentioned in Sec. 5.1. The success rate results are shown in Fig 4. For 6N disturbances from 3 directions, all algorithms show good resilience. In 8N disturbance 8N from sideward tasks, only HDPG can maintain a success rate of over 90%. In comparison, the
success rate of DDPG and MHDDPG dropped sharply to about 80%. As the disturbance increases, the success rate of the ZMP-based method drops the fastest and exhibits the worst robustness. For example, when the disturbance increases to 10N, the success rate of ZMP in 3 directions is only 38%, 38% and 24% respectively. While the other RL-based methods can maintain a success rate of over 50%. As the disturbance increases to 12N and 14N, HDPG shows greater stability. It is at least about 10% higher than other methods in forward tasks. In general, the proposed MHDDPG and HDPG outperform DDPG on all walking under random disturbance tasks, and HDPG achieves the best performance.

5.2.2 walking cross obstacle

We simulate the obstacle on the ground to further evaluate the robustness of different algorithms. In our experiment, obstacles are randomly placed on the ground. The success rate curve is shown in the left of Fig. 5. Since ZMP agent can hardly walk across obstacles, no comparison is made here. RL-based methods show better adaptability. In this task, HDPG performs the best robustness in crossing obstacles of all heights, while MHDDPG achieves the second performance. For 0.6cm obstacles, HDPG and MHDDPG are able to maintain a 100% success rate of recovery. For 1.2cm obstacles, only HDPG achieves a success rate over 60%, while MHDDPG and DDPG 50% drop to about 50%. For 1.4cm obstacles, although HDPG has the best performance, it is only about 40%. This is due to the limitation of the height of the robot’s leg lift.

5.2.3 Walking on the slope

Walking on the undulating terrain is another challenging task for a biped robot. We test the success rate of robots walking on the slope for 10 seconds, as shown in the right of Fig. 5. It can be seen that the performance of DDPG and MHDDPG is close. In other words, multi-head critic doesn’t have a strong effect in the slope setting. HDPG also has the best performance. When the slope angle is 12 degrees, HDPG shows more robust performance, and the success rate is nearly 20% higher than the other two algorithms.
5.2.4 The effectiveness of dynamic weight

To further reveal the effectiveness of dynamic weights, we recorded the cumulative reward of each reward during training, as shown in Fig. 3(b) and (c). For MHDDPG, as shown in the Fig. 3(b), the height reward and orientation reward learning is relatively stable. However, the step reward and gait reward are very unstable, which indicates that there is dependency between different reward components, and different components will influence each other during training. On the contrary, HDPG exhibits a stable training process of all 4 sub-rewards, as shown in the Fig. 3(c). It is worth noting that the height reward and orientation reward first rises at about 2k episodes, while the gait reward and step reward then rise at about 6k episodes. This means that the robot first learns how to keep body balance, and then learns to walk forward. It implies that priority weight allows the robot to learn different components in a more orderly manner.

5.3 Sim-to-real results

In this section, we show that the policies trained with dynamics randomization in simulation are successfully transferred to physical robot. For dynamics randomization, we only randomize the pelvis center of mass, which is introduced in [21]. As shown in Fig. 6, the biped robot was disturbed by push force at 13.1s. Subsequently, The pelvis tilted at 13.5s. As the policy adjusts the actions, the robot recovers to stable gait at 13.9s. This demonstrates that the policy trained with HDPG in the simulation is robust enough to handle the shift from simulation to reality.

5.4 MuJoCo results

To further verify the generalization of the proposed method, we evaluate HDPG on 3 locomotion tasks on MuJoCo continuous control environment of OpenAI Gym [3], i.e., Walker2d, HalfCheetah and Hopper. Following the same experiment settings, we compare the performances of DDPG, MHDDPG, and HDPG. As shown in the Fig. 7, MHDDPG and HDPG outperform DDPG baselines on all tasks within 1M environment steps, and HDPG achieves the best performance on all tasks. It implies that the proposed “learning a separate value function” and “dynamic policy gradient” can be applied to more general continuous control tasks. More results are presented in the Appendix.

6 Conclusion

In this work, we propose hybrid and dynamic policy gradient (HDPG) method for biped locomotion tasks. It decomposes the commonly adopted holistic polynomial reward function and achieves improvement on all reward terms as well as the overall accumulative reward. Experimental evaluation illustrates the effectiveness of our HDPG framework by showing better performance on Gazebo simulation in perturbation walking challenges, walking cross obstacles challenges and walking on undulating terrain challenges. With dynamics randomization, the policy trained in simulation is successfully transferred to a physical robot. In addition, we further verify the generalization of HDPG on 3 continuous control tasks from MuJoCo. Our future work is to transfer the policy trained in simulation into real physical robots in walking across obstacle challenges and undulating terrain challenges.
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A  HDPG setup

The HDPG agent training following typical off-policy reinforcement learning. The agent interacts with the environment and collects experience for policy training. The difference is that we collect the hybrid reward \( r_t = [r_{t,1}, r_{t,2}, ..., r_{t,K}] \) for learning a separate \( Q \)-value function, which is more explicit than single \( Q \)-value. For priority weight, we update it every \( T \) episodes. The complete HDPG algorithm is depicted in Alg. 1.

Algorithm 1  Hybrid and dynamic policy gradient optimization

| Initialize actor network \( \pi \left( a \mid \theta^\pi \right) \) and multi-head critic network \( Q \left( s, a \mid \theta^Q \right) \) with weights \( \theta^Q \) and \( \theta^\pi \). Initialize target network \( Q' \) and \( \pi' \) with \( \theta^{Q'} = \theta^Q \), \( \theta^{\pi'} = \theta^\pi \). Initialize replay buffer \( B \), Initialize priority weight \( M = [m_1, ..., m_k, ..., m_K] \).
| repeat |
| Receive initial state \( s_1 \); |
| for \( t = 1 \) to \( L \) do |
| Select action \( a_t = \pi(s_t \mid \theta^\pi) + N_t \); |
| Observe new state \( s_{t+1} \), reward \( r_t = [r_{t,1}, r_{t,2}, ..., r_{t,K}] \); |
| Store transition \( (s_t, a_t, r_t, s_{t+1}) \) in \( B \); |
| Sample \( N \) transition \( (s_i, a_i, r_i, s_{i+1}) \) from \( B \) as a minibatch, |
| Calculate \( y_i: y_{i,k} = r_{i,k} + \gamma Q_k(s_{i+1}, \pi(s_{i+1}) \mid \theta^Q_k) \); |
| Update multi-head critic by minimizing the loss calculated through: Eq. 5; |
| Update the policy using the hybrid and dynamic policy gradient: \( \nabla_{\theta^\pi} J = K \sum_{k=1}^{K} m_k \nabla J_k; \) |
| Update the target networks through "soft" update method; |
| end for |
| if it's time to update the priority weight then |
| Sample set of recent experience rewards from \( B \); |
| Calculate the mean and the variance of reward samples; |
| Update the priority weight through Eq. 7 |
| end if |
| until convergence |

B  Bipedal robot experiment setup

B.1 AIDA robot

Simulation. We built our AIDA bipedal robot on Robot Operating System (ROS) framework and Gazebo simulation environment. The biped robot is modelled with SolidWork, as shown in Fig. 8. It contains 10 degrees of freedom (DoF), and each leg has 5 DoF. We will release the AIDA simulator and the code of HDPG later.

Physical robot We equip the physical robot with a mini computer (Intel NUC8i7BEH), an IMU (YIS100-A-DK), 10 servo motors for joint control (DYNAMIXEL XH430-W210-T actuator) and a USB communication converter (U2D2). At testing time, the trained model is evaluated on NUC in real time. It receives IMU data and joint angles of 10 motors. The policy network predicts appropriate controls based on only the current joint angles and IMU data. The U2D2 receives controls from NUC and transfers them to the motor controller of the robot.

B.2 Rewards design

HDPG does not rely on manually designed reference trajectories to guide the learning process. Existing no-reference methods mainly require careful engineering of the reward function. In other words, the reward function may contain many components (e.g., there are 10 reward components involved in (28)). In this work, only some principles of human gait are utilized to design the reward function. It consists of six sub-rewards with regards to the biped performance of forward distance,
gait and stability. The multi-head critic learns the value function with the reward vector, which is defined as:

$$ r_t = [r^g_t, r^s_t, r^f_t, r^h_t, r^d_t] $$ (8)

Gait reward $r^g_t$: The gait walking is the ultimate goal of the biped robot. The gait occurs when the single support period and double support period arise in time sequence. We formulate this principle as following:

$$ r^g_t = \begin{cases} w_1 d^g_t \cos \theta^g, & \text{if a gait occur} \\ 0, & \text{otherwise} \end{cases} $$ (9)

where $d^g_t$ is the length of the gait, and $w_1$ is a weight parameter. Assuming $T$ is the time’s length of a gait occurs at $s$ time step. $\theta^g$ is the angle between the direction of the robot at $(t - T)$ and $t$. The intention is to encourage the robot to walk forward instead of the other directions.

Step reward $r^s_t$: We also introduce a step reward $r^s_t$ to encourage the robot to move forward at each time step. The step reward function is defined as:

$$ r^s_t = w_2 d^s_t \cos \theta^s $$ (10)

where $d^s_t$ is the move distance at $t$ time step, and $w_2$ is a weight parameter of step reward. $\theta^s$ is the angle between the direction of the robot at $(t - 1)$ and $t$.

Torque reward $r^f_t$: The torque reward is inverse proportional to the torque of the joint motors. This punishes the robot when the joint angle approaches the limit or the self collision happens.

$$ r^f_t = -w_3 \sum_{i=1}^{I} f^i_t $$ (11)

where $I$ is the number of joints, $f^i_t$ is the torque on the $i$-th joint. Meanwhile, the pose of the robot is one of the important indicators for assessing whether the robot is walking normally, which is evaluated with the height and the orientation of the pelvis.

$$ r^h_t = -w_4 |h_t - h_0| $$ (12)

$$ r^\alpha_t = -w_5 (|\alpha^r_t| + |\alpha^p_t|) $$ (13)

where $h_t$ is the current height of pelvis and $h_0$ is the desired height. In Equation (13), $\alpha^r_t$ is the roll angle and $\alpha^p_t$ is the pitch angle of the pelvis. Finally, the fall down reward $r^d_t$ is set as -50 for the robot fell to the ground.

**B.3 Implementation details**

**Actor.** The actor network consists of 3 fully connected layers. The concatenating state $(s_{t-2}, s_{t-1}, s_t)$ passes through 3 fully connected layers of size (69, 128), (128, 256) and (256, 10) to predict an action.
Figure 9: Multi-head critic architecture. The multi-head critic learns multiple values, each value corresponding one reward component. Different Q-values share the low-level layers parameters.

**Multi-head critic.** The multi-head critic network is shown in the figure. The action $a_t$ and the state $s_t$ are passed through one fully connected layer of size (10,128) and (69, 128), respectively. They are then concatenated and pass through two fully connected layers of size (256,256) and (256,6) to produce predicted 6 Q-values, each value corresponding one reward component.

**Training.** In the training process, the discount factor is set as 0.99. The learning rate of actor network and critic network are set as $1e^{-5}$ and $1e^{-4}$, respectively. And the training batch size is set as 64. The priority-based dynamic weight for hybrid policy gradient is updated every $T=20$ episodes.

**Reward normalization.** We use simple max-min normalization for each component. To clarify how to normalize rewards, gait reward is given as an example. Firstly, the maximum achievable gait length $d_{g_{\text{max}}}$ is calculated according to the physical limitations. So the maximum and minimum gait rewards are $r_{g_{\text{max}}}^g = w_1 d_{g_{\text{max}}}^g$ and $r_{g_{\text{min}}}^g = -w_1 d_{g_{\text{max}}}^g$, respectively (according to Eq. 9). Hence, any gait reward $r^g$ can be normalized to (0,1) by $(r^g - r_{g_{\text{min}}}^g)/(r_{g_{\text{max}}}^g - r_{g_{\text{min}}}^g)$. It is the same for other rewards.

Table 1: Performance on OpenAI Gym at 1M environment steps. The results show the mean and standard deviation across 10 runs. The best results are highlighted in bold.

| Methods  | Hopper-v3 | Walker2d-v3 | HalfCheetah-v3 |
|----------|-----------|-------------|----------------|
| DDPG     | 3476.452 ± 97.998 | 2398.483 ± 1169.66 | 12422.9 ± 620.36 |
| MHDDPG   | 3539.288 ± 23.918 | 3162.01 ± 1263.83 | 12748.93 ± 501.81 |
| HDPG     | **3600.422 ± 30.484** | **3217.48 ± 1144.81** | **12895.29 ± 528.06** |
| PPO      | 2609.3 ± 700.8 | 3588.5 ± 756.6 | 5783.9 ± 1244.0 |
| HD-PPO   | 3263.46 ± 367.792 | **4687.975 ± 220.1** | 6165.17 ± 150.39 |

### C MuJoCo experiments

**Training.** We conduct MuJoCo experiment using the publicly released implementation repository [4] as baseline. For reward normalization, we use the maximum reward and minimum value of each reward in the experience data for max-min normalization. Except for multi-head critic and dynamic policy gradient, the other experiment settings are consistent with tianshou [4].

**Experiment results.** To verify the generalization of HDPG, we further equip it with proximal policy optimization algorithms (PPO), which is denoted as HD-PPO. Experiment results are shown in Table [1] Hopper and Walker tasks contain 3 reward components, while HalfCheetah contains 2 reward components. Obviously, hybrid and dynamic policy gradient method is able to improve the performance of DDPG and PPO on all tasks. It is worth noting that HD-PPO has achieved a breakthrough of more than 25% on Hopper and Walker tasks, while it has nearly increased by about 6.6% on HalfCheetah task. This demonstrates that HDPG is more effective for more complex (more constraints involved) tasks.

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[4] https://github.com/thu-ml/tianshou