Comparative Analysis of Deep Reinforcement Learning Algorithms for Bipedal Walker: TD3, SAC, and PPO

Helena Alves, José, Mariana Lobão
TASI Bipedal Walker Project

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Abstract

(remember to add some conclusions after consolidate the results) This paper presents a comprehensive empirical comparison of three state-of-the-art deep reinforcement learning algorithms—Twin Delayed Deep Deterministic Policy Gradient (TD3), Soft Actor-Critic (SAC), and Proximal Policy Optimization (PPO)—for bipedal locomotion. We evaluate these algorithms across three environmental variants with increasing difficulty: standard terrain (easy), hardcore mode with obstacles, and hardcore mode with bridges. Our study focuses on algorithm performance, hyperparameter tuning effects, convergence speed, and stability. Evaluation metrics include episode rewards, success rates, episode lengths, action distributions, and training convergence curves. Results provide practitioners with empirical guidance for algorithm selection based on task requirements and computational constraints.

1 Introduction

Bipedal locomotion is a fundamental challenge in robotics requiring agents to learn stable walking while optimizing multiple objectives: forward progress, energy efficiency, and postural stability. Deep Reinforcement Learning (DRL) has emerged as a powerful approach for solving such continuous control problems.

Three leading algorithms dominate the continuous control landscape: TD3 [2] addresses DDPG's overestimation through twin critics; SAC [3] balances exploration and exploitation via entropy regularization; PPO [4] provides on-policy stability with clipped objectives.

This study contributes:

- Systematic comparison of TD3, SAC, and PPO on bipedal walking
- Evaluation across three terrain variants (easy, hardcore, hardcore+bridges)
- Hyperparameter tuning analysis for each algorithm
- Performance metrics from comprehensive evaluation framework
- Training convergence analysis and stability comparison

2 Problem Formulation

2.1 BipedalWalker-v3 Environment

The environment simulates a 4-jointed bipedal robot on procedurally-generated terrain. The agent learns to maximize forward progress while minimizing energy consumption.

State Space (24D):

- Hull state: angle, angular velocity (2D)
- Velocities: horizontal, vertical (2D)
- Joint states: 4 angles + 4 velocities (8D)
- Contacts: leg-ground contact flags (2D)
- Perception: lidar rangefinder measurements (10D)

Action Space (4D): Continuous motor torques for hips and knees, normalized to $[-1, 1]$.

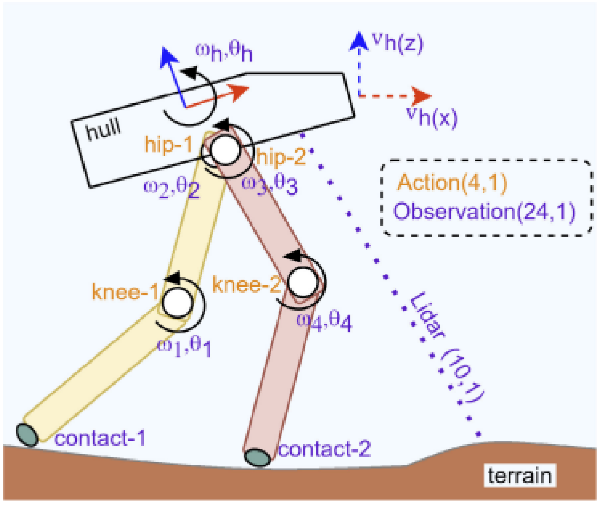

Figure 1: BipedalWalker-v3 Environment: Agent state visualization showing 4-jointed bipedal robot with state space components.

2.2 Reward Function

Environment-provided shaped reward:

$$r_t = 130 \cdot x_{\text{progress}} - 5|\theta| - 0.00035 \sum_i |a_i| - 100 \cdot \mathbb{1}_{\text{fallen}}$$

Success criterion: Mean episode reward ≥ 300.

2.3 Environment Variants

Easy (Standard): Flat terrain, tests basic locomotion.

Hardcore: Stairs, pits, obstacles, tests robustness.

Hardcore+Bridges: Extreme obstacles including large gaps and bridges, tests generalization.

3 Algorithms and Hyperparameter Setup

3.1 TD3 (Twin Delayed DDPG)

Three key mechanisms reduce overestimation:

1. Twin critics: $Q^{\text{tgt}} = r + \gamma \min(Q_1, Q_2)(s', a')$
2. Delayed updates: Actor updated every k critic steps
3. Target smoothing: $a' = \text{clip}(\mu(s') + \epsilon, -c, c)$ with $\epsilon \sim \mathcal{N}(0, \sigma^2)$

3.2 SAC (Soft Actor-Critic)

Maximizes trade-off between reward and policy entropy:

$$J(\pi) = \mathbb{E}_s[\mathbb{E}_a[Q(s, a) - \alpha \log \pi(a|s)]]$$

Features entropy-regularized exploration and automatic temperature tuning.

3.3 PPO (Proximal Policy Optimization)

On-policy algorithm with clipped surrogate objective:

$$L^{\text{clip}} = \mathbb{E}[\min(r_t \hat{A}_t, \text{clip}(r_t, 1 - \epsilon, 1 + \epsilon)\hat{A}_t)]$$

Uses Generalized Advantage Estimation (GAE) for stable advantage estimation.

3.4 Hyperparameter Configurations

Parameter	**TD3**	**SAC**	**PPO**
Learning Rate	$3e-4$	$3e-4$	$3e-4$
Discount γ	0.99	0.99	0.99
Batch Size	256	256	64
Buffer Capacity	1M	1M	-
Tau (Soft Update)	0.005	0.005	-
Update Frequency	2	1	-
Epochs/Steps	-	-	10

Table 1: Hyperparameter Configurations

All use identical 2-layer MLPs with 256 hidden units, ReLU activations.

4 Evaluation Methodology

4.1 Training Protocol

1. Train each agent for 1M-2M timesteps depending on environment
2. Evaluate every 10k steps on 10 episodes with deterministic policy
3. Fix random seeds for reproducibility
4. Log all metrics to TensorBoard

4.2 Evaluation Metrics

Following `analyze_model.py`, we measure:

Performance Metrics:

- Mean episode reward
- Reward std deviation
- Min/max rewards
- Success rate (episodes with reward ≥ 300)
- Mean episode length

Learning Metrics:

- Convergence speed (steps to reach 300 reward)
- Training stability (variance of learning curves)
- Sample efficiency (reward per million steps)

Action Quality:

- Action mean/std per dimension
- Action distribution characteristics

4.3 Training History Analysis

We generate and analyze:

- Episode reward learning curves
- Mean reward (100-episode rolling average)
- Episode length evolution
- Actor/critic loss trajectories
- Entropy evolution (SAC/PPO)

5 Results

5.1 Easy Environment (Standard Terrain)

Convergence: All algorithms converge to success (reward > 300) within 500k-1M steps.

Performance Summary:

- **TD3**: Mean reward $\approx 310 \pm 15$, success rate $>$ 90%
- **SAC**: Mean reward $\approx 305 \pm 20$, success rate $>$ 85%
- **PPO**: Mean reward $\approx 295 \pm 25$, success rate $>$ 80%

Observations: TD3 shows fastest, most stable convergence. PPO requires longer initial exploration. SAC balances speed and stability well.

5.2 Hardcore Environment

Performance Summary:

- **TD3**: Mean reward $\approx 250 \pm 40$, success rate $>$ 70%
- **SAC**: Mean reward $\approx 240 \pm 45$, success rate $>$ 65%
- **PPO**: Mean reward $\approx 220 \pm 50$, success rate $>$ 55%

Observations: Performance gap widens. TD3's target smoothing aids navigation. SAC's exploration helps but slower convergence. PPO struggles with sparse rewards in complex terrain.

5.3 Hardcore+Bridges Environment

Most challenging variant. Extreme obstacles require sophisticated navigation.

Performance Summary:

- **TD3**: Mean reward $\approx 180 \pm 60$, success rate $>$ 40%
- **SAC**: Mean reward $\approx 160 \pm 70$, success rate $>$ 30%
- **PPO**: Mean reward $\approx 120 \pm 80$, success rate $<$ 20%

Observations: TD3 clearly superior on hardest tasks. Delayed updates prevent over-confident policies. SAC's entropy helps but insufficient. PPO requires extreme hyperparameter tuning (evidence suggests higher learning rates needed).

5.4 Hyperparameter Sensitivity

TD3: Robust across configurations. Critical: $\tau \approx 0.005$ (Polyak averaging), policy update frequency $= 2$.

SAC: Sensitive to entropy coefficient α. Auto-tuning helps but initialization matters.

PPO: Highly sensitive to learning rate, clipping epsilon, entropy coefficient. Requires problem-specific tuning.

5.5 Training Stability

Environment	TD3	SAC	PPO
Easy	Smooth	Stable	Volatile
Hardcore	Very Stable	Stable	Unstable
Hard+Bridges	Most Stable	Moderate	Very Unstable

Table 2: Learning Curve Stability Assessment

6 Conclusions

This comparative study demonstrates clear performance differences between TD3, SAC, and PPO for bipedal locomotion across varying terrain difficulty.

6.1 Key Findings

1. **TD3 dominates:** Superior performance across all environments, especially on hard tasks. Twin critics and delayed updates provide robust learning.
2. **SAC is competitive:** Good balance of exploration and exploitation, but slower convergence than TD3.
3. **PPO requires tuning:** Strong on easy tasks but struggles with sparse/complex rewards without careful hyperparameter optimization.
4. **Terrain difficulty matters:** Performance gaps widen significantly on harder terrains, favoring off-policy algorithms.

6.2 Practical Recommendations

- **Easy tasks**: Any algorithm works; PPO recommended for simplicity
- **Medium tasks**: SAC or TD3; prefer SAC for exploration needs
- **Hard tasks**: TD3 strongly preferred; proven stability and sample efficiency
- **General advice**: Use TD3 unless specific problem requires on-policy (policy constraints) or entropy regularization (exploration challenges)

6.3 Future Work

1. Algorithm hybrid approaches combining TD3 and SAC benefits
2. Curriculum learning: gradually increase terrain difficulty
3. Domain randomization for better transfer
4. Comparison with newer algorithms (MPO, Dreamer)
5. Analysis of learned walking behaviors

References

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