Report on PIE: Parkour with Implicit-Explicit Learning Framework for Legged Robots

Raman Kumar Jha
New York University
Net ID: N13866145

I. Summary of the Paper

A. Summary:

This paper analyzes the PIE (Parkour with Implicit-Explicit Learning) framework, a novel approach for enabling quadruped robots to perform parkour-like maneuvers. PIE utilizes a one-stage end-to-end reinforcement learning approach with dual-level implicit-explicit estimation, significantly enhancing robots' parkour capabilities and demonstrating robust sim-to-real transfer. Even though the paper used simulation for training, however, their zero-shot deployment of their framework for parkour performance on difficult situations, validates their performance in real-time. This analysis provides PIE's methodology, its relation to course algorithms, and critically discusses its strengths and limitations.

B. What was done?

PIE represents a significant advancement in quadruped robot locomotion, enabling robots to perform parkour-like maneuvers with remarkable agility. The key contributions include:

- A one-stage end-to-end reinforcement learning approach using dual-level implicit-explicit estimation.
- Significant improvements in parkour capabilities, allowing robots to traverse obstacles up to 3x their height/length.
- Demonstration of robust sim-to-real transfer and generalization to challenging outdoor environments.

C. How was it done?

The authors implemented the PIE framework using a one-stage end-to-end reinforcement learning approach within the Isaac Gym simulation environment. The training involved: The authors implemented the PIE framework using a one-stage end-to-end reinforcement learning approach in the Isaac Gym simulation environment. Key aspects of the implementation include:

- Domain randomization to enhance robustness and sim-to-real transfer
- Dual-level implicit-explicit estimation integrating proprioceptive and exteroceptive data
- Parallel training of 4096 environments using NVIDIA Warp, completing 10,000 iterations in under 20 hours
- Real-world validation on a DEEP Robotics Lite3 quadruped robot

D. Why was it worth doing?

1) Advancement in Robotics: It pushes the boundaries of quadruped robots' capabilities in parkour-like maneuvers, enabling them to traverse obstacles that are up to three times their height or length. It advanced quadruped robot capabilities, enabling traversal of obstacles up to 3x the robot's height/length
2) Robust Performance: The PIE framework demonstrated impressive sim-to-real transferability without extensive fine-tuning, achieving consistent performance across challenging terrains, in the real-world.

E. What are the results?

The results showed that PIE enabled the quadruped robot to achieved impressive results, including:

- Climbing 0.75m high steps (3x robot height)
- Leaping 1m wide gaps (3x robot length)
- Navigating 0.25m high stairs (1x robot height)

Overall, PIE outperformed previous methods by at least 50%, showcasing its effectiveness in enhancing parkour capabilities for legged robots.

In the real world outdoor scenes, the PIE netowrk, covered the whole trail in 40 minutes without any stops. Additionally in the low light outdoor conditions, the robot was capable of continuous jumping over high steps, and rocks.

II. Relation to Course Algorithms:

A. Which Algorithms:

The PIE framework primarily relates to policy optimization algorithms covered in the course:

- Actor-Critic Architecture: PIE utilizes an asymmetric actor-critic setup, similar to those discussed in Lecture 11 on actor-critic algorithms.
- Proximal Policy Optimization (PPO): The framework optimizes the actor-critic using PPO, which was covered in Lecture 11.
- Deep Q-Learning Concepts: While not directly using DQN, the estimator network in PIE shares similarities with value function approximation techniques from Lecture 10 on Deep Q-learning.

B. *Key Differences from Course Algorithms*

The main innovations of PIE that extend beyond the basic algorithms covered in class include:

- Dual-level implicit-explicit estimation: PIE combines implicit estimation of the robot's state and surroundings (by predicting the successor state) with explicit estimation of terrain features. This goes beyond the standard state estimation techniques covered in class.
- Multi-modal integration: The framework uses a transformer encoder to facilitate cross-modal reasoning between visual and proprioceptive features. This advanced integration of multiple sensory inputs was not covered in the basic course algorithms.
- One-stage end-to-end learning: PIE optimizes all components simultaneously in a single stage, potentially reducing information loss. This differs from the separate training of actor and critic networks typically covered in class.
- Complex estimator network: PIE employs a more sophisticated estimator network to enhance the actor's understanding of the robot's state and environment, extending beyond the basic network architectures discussed in class.
- Application to robotics: While the course likely focused on simpler environments, PIE applies these algorithms to complex robotic parkour scenarios, demonstrating capabilities far beyond typical class examples.

These innovations allow PIE to achieve superior performance in challenging parkour scenarios, showcasing applications of reinforcement learning algorithms that surpass the basic implementations covered in the course curriculum.

III. Critical Discussion

A. *Strengths:*

- Impressive real-world results, significantly advancing quadruped parkour capabilities.
- Robust sim-to-real transfer without extensive fine-tuning, demonstrating the framework's generalizability.
- Generalization to unseen terrains and conditions (e.g., outdoor environments, low light), showcasing adaptability, and efficiency.
- Unified policy for various parkour maneuvers, simplifying the control architecture.
- Efficient training process using a relatively simple reward function.

B. *Limitations:*

- Lacks 3D terrain understanding, limiting certain maneuvers (e.g., crouching under obstacles).
- Relies solely on depth images, missing potential benefits of RGB information for richer semantic understanding.
- Training limited to static environments, potentially limiting adaptability to dynamic scenes with moving obstacles.
- Possible challenges in extreme scenarios where visual perception significantly contradicts perception.

C. *Convincing Aspects:*

The PIE framework demonstrates several convincing aspects in the paper:

- Impressive real-world performance: The robot can traverse obstacles up to 3x its height/length, significantly outperforming previous methods.
- Robust sim-to-real transfer: PIE shows consistent performance between simulation and real-world deployment without extensive fine-tuning.
- Generalization capabilities: The framework enables the robot to navigate unseen terrains and conditions, including outdoor environments and low-light scenarios.
- Efficient training process: PIE uses a relatively simple reward function and one-stage end-to-end learning approach.
- Adaptive behavior: The robot demonstrates the ability to recover from unexpected situations during intense maneuvers.

D. *Issues with Limitations:*

However, there are some issues with the limitations:

- Lack of 3D terrain understanding: The robot cannot perform certain maneuvers like crouching under obstacles.
- Reliance on depth images only: The framework misses potential benefits of RGB information for richer semantic understanding.
- Limited to static environments: Training is confined to static scenes, potentially limiting adaptability to dynamic environments.

E. *What could be done better?*

To improve the PIE framework and advance quadrupedal robot capabilities further, these areas could be addressed:

- Incorporate 3D terrain understanding to enable more complex maneuvers like crouching under obstacles.
- Integrate RGB information alongside depth data for richer semantic understanding of the environment.
- Extend training to dynamic environments to improve adaptability to real-world scenarios with moving obstacles or changing terrains.
- Explore multi-modal sensory integration beyond depth cameras to enhance robustness and environmental awareness.

F. *What should be done next?*

Future work should focus on:

- Develop a unified learning-based sensorimotor integration framework that extracts 3D terrain information from depth images and obtains rich semantic data from RGB images.
- Enhance real-time adaptation capabilities to quickly adjust to unexpected situations or perception errors during intense maneuvers.
- Investigate techniques to enable more complex behaviors like crouching under obstacles, expanding the robot's parkour maneuvers.