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Stable and continuous vertical jumping control of hydraulic legged robots through reinforcement learning

Key words: Legged robot; Deep reinforcement learning; Quasi-realistic modelling; Hydraulic system; Jumping control

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Introduction

1. Hydraulic legged robots have been a popular research focus in robotics due to their ability to execute high-dynamic and agile motions. Meanwhile, the strong nonlinearities of hydraulic systems lead to increased complexities in their associated control methods.

2. The limb leg unit (LLU) of legged robots plays a decisive role in determining the overall locomotion performance of the system. Current research has primarily focused on improving jumping performance through foot-end trajectory generators and motion tracking controllers.

3. For high-dynamic motion tasks, the parameters of both the trajectory generator and the motion tracking controller jointly influence system performance. Therefore, designing them independently fails to capture their coupled dynamics, often resulting in suboptimal parameter combinations.

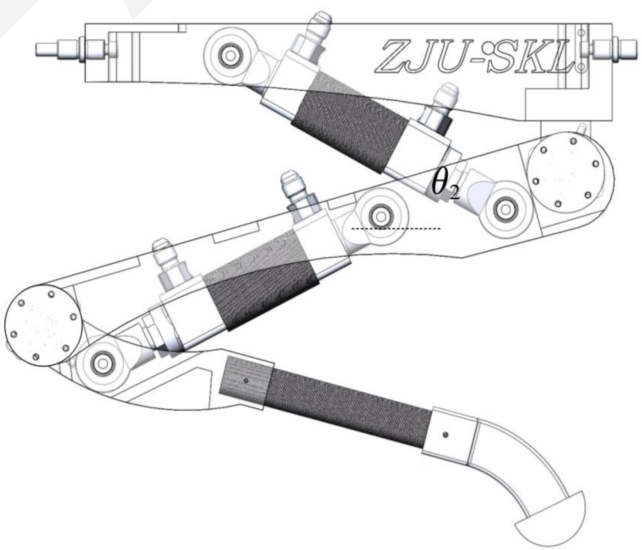

Fig. 1 Structure of the LLU

Main Contributions

1. A quasi-realistic model incorporating physical feasibility constraints for the hydraulic system is established, reflecting the performance of the physical prototype and providing a reliable foundation for simulation training and deployment of DRL.
2. A DRL-based jumping motion control framework for legged robots is proposed, in which the DRL algorithm jointly optimizes the trajectory generator and the motion tracking controller to achieve stable continuous jumping motion in simulation training.
3. The DRL-trained policy is deployed on a physical prototype using the proposed control framework, and the target-height tracking and landing compliance in continuous jumping are compared to a commonly used optimization method.

Method

■ Quasi-realistic LLU model

To facilitate successful simulation training and deployment on the physical prototype, a quasi-realistic model is developed. The trajectory generator provides the desired foot-end trajectory to the motion tracking controller, which computes the desired forces for the two joint hydraulic actuators. The forces are then input to the direct adaptive robust controller (DARC), which outputs the corresponding servo valve current signals to achieve the expected motion control of the LLU.

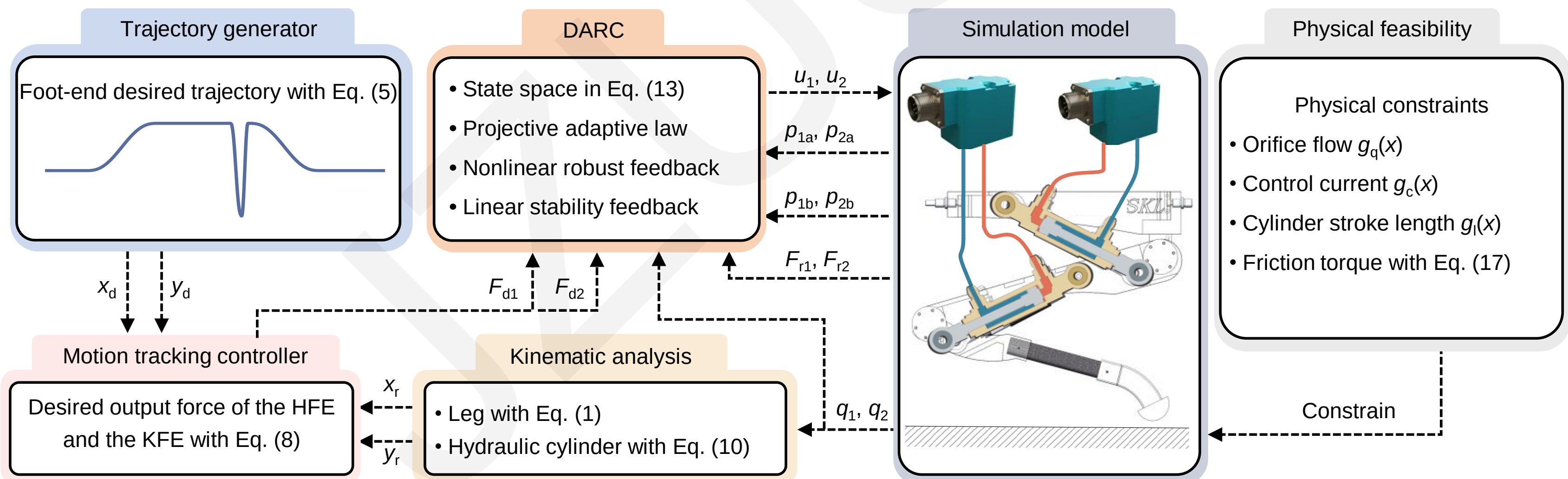

Fig. 2 Quasi-realistic model of the LLU.

Method

■ Motion learning control framework

The DRL algorithm is introduced to jointly optimize the primary parameters of the trajectory generator and motion tracking controller. The control policy is trained in a simulation environment to achieve stable, continuous jumps at the target height and enhance landing compliance.

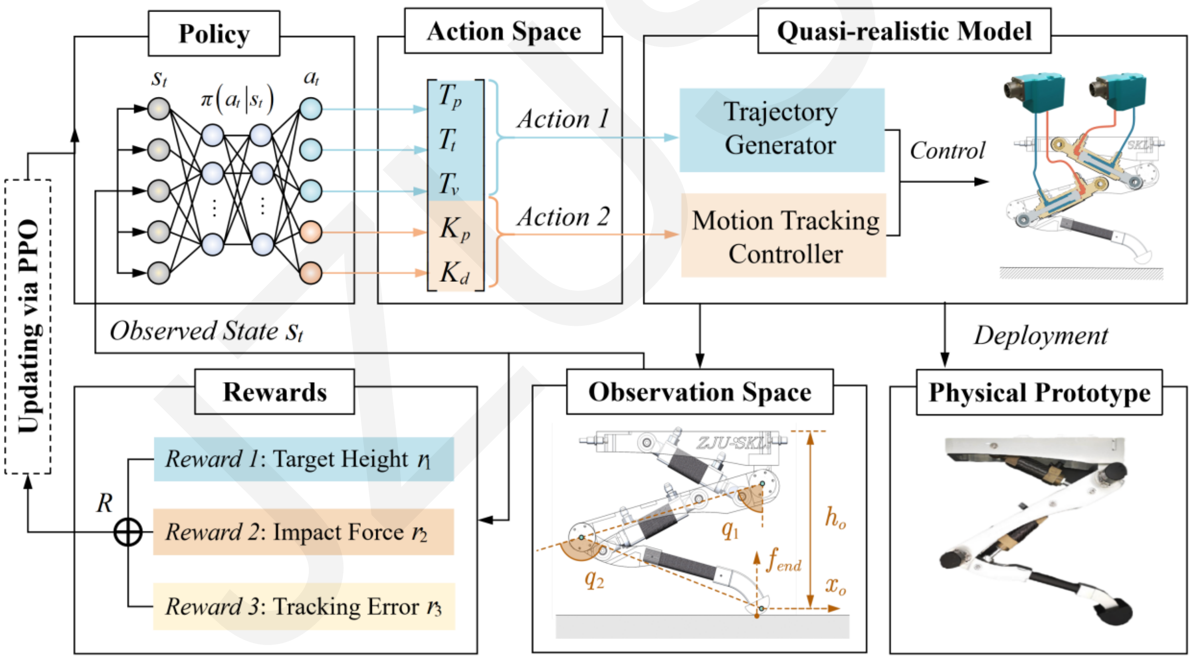

Fig. 3 Jumping motion learning control framework.

Method

■ Simulation to reality transfer

The trained policy is deployed on the experimental platform depicted in Fig. 4, which includes a hydraulic pump station, an LLU platform, internal sensors, a control board, and external sensors.

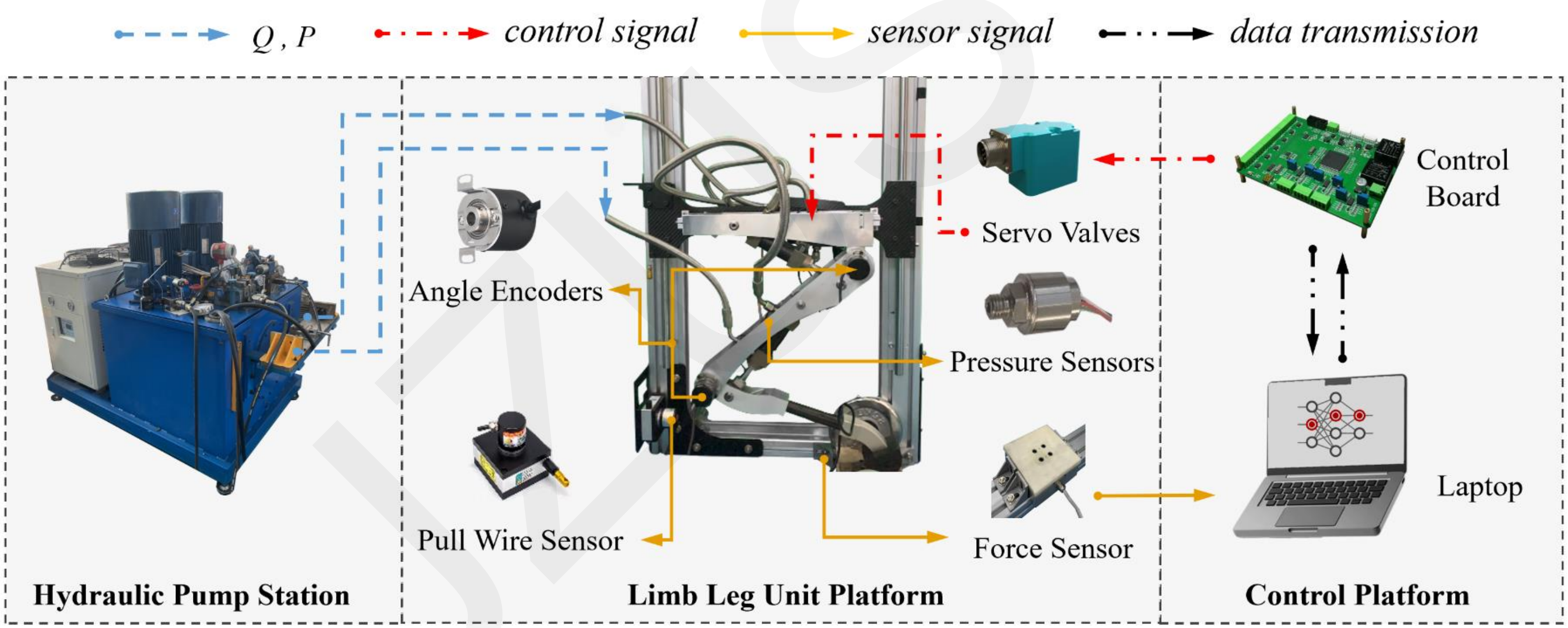

Fig. 4 LLU jumping test platform.

Conclusions

- 1. The proposed quasi-physical model accurately reflects the performance of the physical prototype, and enables the successful deployment of DRL-trained policies from simulations to real-world systems.
- 2. The DRL algorithm jointly optimizes the parameters of the trajectory generator and the motion tracking controller, enabling the LLU model to achieve continuous and stable jumping in the simulations following training.
- 3. The trained policy is successfully deployed on the physical prototype, achieving continuous jumping motions at the target height. In comparison to the NSGA-II algorithm, the height tracking error is reduced by over 60%, and the landing compliance is improved by up to 7.7%.