Reinforcement Learning of Robotic Legged Locomotion

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1 Motivation

Humans and animals show a remarkable level of proficiency in their ways of locomotion. They exploit the dynamics of the whole body to perform a variety of motions such as jumping and running. Hereby, the elasticity in the muscles and tendons carries a key role in enabling robust, dynamic and energy efficient locomotion [1]. At the Autonomous Systems Lab, we have developed the robotic leg *ScarlETH* [2] as a test bed to study the mechanism that can be observed in nature. The bio-inspired articulated leg is electrically driven by highly compliant Series Elastic Actuators (SEA) [3] in the hip and knee joints. The properties of the springs in the joints can be compared to the elasticity of the tissue in nature. Our goal is to maximize ScarlETH's maneuver performance and locomotion efficiency by developing controllers that excite the robot in step with the dynamics of the system.

2 State of the Art

Optimal control of legged robots is challenging due to the high degrees of freedom and highly nonlinear non-smooth dynamics of the systems. We have seen many different approaches, e.g. neural networks [4], however, most of which are restricted to simulations. In a closely related work [5], a genetic algorithm is used to evolve a guided vertical jump for a simulated leg with a compliant knee joint. Directly applying the simulation-based trajectories to the physical system is usually unsuitable as modeling errors can typically not be prevented. As a result, a feedback controller is necessary which leads to suboptimal performance as an artificial pattern is forced on the system. As an alternative, reinforcement learning can be applied online on a real robot and promising results have been presented, e.g. in [6]. While classic reinforcement learning algorithms do not scale suitably to high dimensions, recent developments have overcome this limitation with direct learning of a control policy from trajectory rollouts [7].

3 Own Approach

We generate the control policies with reinforcement learning based on the direct policy learning method *Policy Improvement with Path Integrals* (PI^2) [8]. This algorithm has shown to perform well in high-dimensional continuous state spaces and does not rely on the computation of gradients which are sensitive to noise. The control policy is parameterized with gaussian basis functions which are updated in the learning procedure using random exploration rollouts.

We extend the application of PI^2 to highly dynamic maneuvers and find actuator trajectories that exploit the inherent mechanical properties of the system. For periodic hopping, we introduce a time-independent policy with which the algorithm can find an optimal execution frequency. In order to overcome the model discrepancies, we deploy a combination of simulation and hardware based learning. The simulation allows to quickly converge to a trajectory suitable for the dominating dynamics of the system while the optimization on the real robot compensates for the model inaccuracies.

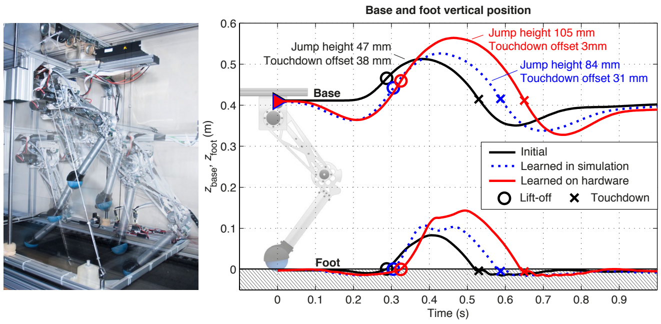

Figure 1: Learning progress of the vertical jump

4 Current Results

We have implemented our approach for different learning tasks. In a first task, the goal is to learn single jumps from a resting posture with maximal height while keeping the touchdown offset (jump distance) to a minimum. The control policy consists of the parameterized desired motor velocity trajectories for hip and knee motor with a total of open 10 parameters. Figure 1 shows the progress of the two step learning framework starting from a manually tuned initial policy (black). While the simulation based policy determined the main form of the trajectory (blue), the optimization on the hardware shows a further significant improvement (red). The algorithm has converged to a characteristic countermovement jump in which the actuators are pre-activated and the body is first lowered to temporarily store energy in the joint springs. This energy is then released during an explosive upwards motion before lift-off. In exercise physiology, this process has been shown the be the underlying mechanisms for maximal jump performance [9].

We have extended the purely vertical jump to learn jumps with a defined height and different distances. By punishing slip of the foot during the thrust phase in the cost function, ScarlETH learns to increase the vertical force on the foot in order to achieve a higher horizontal forces that propel the system to maximal jump lengths. We have created a motion library with different jump lengths and interpolation allows us to reach intermediate lengths with high precision. We observe a different jump capability in forward and backward direction which can be attributed to the segmented leg design.

In another task, the control parameters of a robust periodic hopping controller are learned to maximize energy efficiency. Based on a time-independent control policy, the algorithm is shaping a non-linear virtual spring characteristic while maintaining the robustness of the controller.

We have summarized the experiments and the learning progress in a video: `http://youtu.be/xw6pSal-OgI`

5 Best Possible Outcome

In the future, we will use the presented framework to learn jumping, hopping and running maneuvers on our quadruped robot Starl*ETH* [10].

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