DeepQ Stepper: A framework for reactive dynamic walking on uneven terrain

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I. Background

Developing fast contact planning algorithms has been an important goal in legged locomotion for several years because they enable to quickly decide where robots should interact with their environment to move in the desired manner or react to external pushes. Currently, fast contact planners that can handle push recovery for biped robots are often restricted to flat and convex terrains [3] because of the difficulty in computing capture regions for non linear dynamical systems [2]. On the other hand, contact planners that can handle complex scenarios use nonlinear or mixed-integer optimization frameworks which despite recent advances in computation speed, are still not fast enough to be used in real-time. In this work, we address this limitation by proposing a novel 3D reactive stepper, the DeepQ stepper. It can approximately learn the 3D capture regions of both simplified and full robot dynamic models using reinforcement learning and can then be used to find optimal steps in complicated scenarios [1].

II. Method

The main idea of the DeepQ stepper is to formulate the problem of choosing step locations as a continuous-state discrete-action Markov Decision Problem (MDP). Subsequently, the action value of a step is defined as the capability of the robot to either bring itself to rest or track the desired velocity after taking that it. Consequently, by learning a Q function associated with each feasible stepping action for a given robot state, the set of possible steps with low Q values provide an approximation of the capture region. Since the approach is model-free, it can directly be used to approximate the capture region of the full robot dynamics. During run time the learned state-action value function is then used to plan footsteps online at a constant computational cost.

III. Results & Discussion

Empirical evidence shows that the DeepQ stepper learns a good approximation of both 2D & 3D capture regions for linear and nonlinear dynamic models. Extensive walking simulations with a biped robot demonstrate that the DeepQ stepper is able to plan contacts on nonconvex terrain with obstacles, walk on restricted surfaces like stepping stones while tracking different velocities, and recover from external

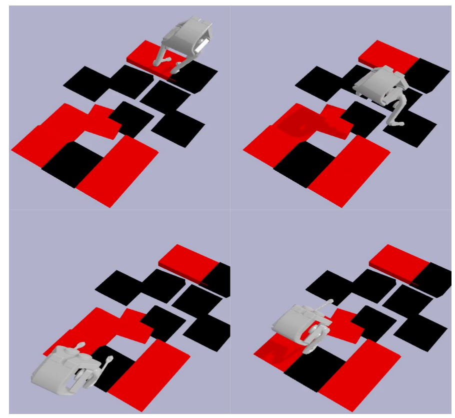

Fig. 1: DeepQ stepper navigating stepping stones in real time.

disturbances for a constant low computational cost and in real-time. Further, improved walking performance is achieved by accounting for full robot dynamics - swing foot dynamics, acceleration limits, and joint friction, which are often ignored in existing reactive steppers [1].

IV. Conclusion

In this work, we propose a novel reactive stepping framework that can approximately learn the 3D capture regions for non-linear dynamic models and step reactively with it. Further, the capability of the framework to handle complex terrains is demonstrated in simulation with a biped robot.

In the future, the aim is to extend the DeepQ stepper to learn capture regions for more dynamic motions like running, jumping on complex terrain with contact time adaptation and handle multicontact scenarios.

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References

[1] Meduri, Avadesh, Majid Khadiv, and Ludovic Righetti. "DeepQ Stepper: A framework for reactive dynamic walking on uneven terrain." arXiv preprint arXiv:2010.14834 (2020).

[2] Koolen, Twan, et al. "Capturability-based analysis and control of legged locomotion, Part 1: Theory and application to three simple gait models." The international journal of robotics research 31.9 (2012): 1094-1113.

[3] Khadiv, Majid, et al. "Walking control based on step timing adaptation." IEEE Transactions on Robotics 36.3 (2020): 629-643.