Creating a Dynamic Quadrupedal Robotic Goalkeeper with Reinforcement Learning

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***Abstract*— We present a reinforcement learning (RL) framework that enables quadrupedal robots to perform soccer goalkeeping tasks in the real world. Soccer goalkeeping with quadrupeds is a challenging problem, that combines highly dynamic locomotion with precise and fast non-prehensile object (ball) manipulation. The robot needs to react to and intercept a potentially flying ball using dynamic locomotion maneuvers in a very short amount of time, usually less than one second. In this paper, we propose to address this problem using a hierarchical model-free RL framework. The first component of the framework contains multiple control policies for distinct locomotion skills, which can be used to cover different regions of the goal. Each control policy enables the robot to track random parametric end-effector trajectories while performing one specific locomotion skill, such as jump, dive, and sidestep. These skills are then utilized by the second part of the framework which is a high-level planner to determine a desired skill and end-effector trajectory in order to intercept a ball flying to different regions of the goal. We deploy the proposed framework on a Mini Cheetah quadrupedal robot and demonstrate the effectiveness of our framework for various agile interceptions of a fast-moving ball in the real world.**

I. Introduction

Developing a robotic goalkeeper is an appealing but challenging problem. This task requires the robot to perform highly agile maneuvers such as jumps and dives in order to accurately intercept a fast moving ball in a short amount of time. Solving this problem is attractive because it can offer solutions for combining dynamic legged locomotion with fast and precise non-prehensile manipulation. Recent developments in quadrupedal robots have resulted in hardware platforms that enable agile and versatile maneuvers, making them suitable for tackling this task. Furthermore, recent advances in model-free reinforcement learning (RL) has shown promising results on developing controllers for dynamic motor skills on quadrupedal robots [1]–[3]. However, previous efforts on applying RL on quadrupedal robots mainly focus on low-level locomotion control, such as tracking a desired walking velocity [3] or mimicking a reference motion [1], without extending the learned locomotion skills to a higher level task, such as precisely intercepting a fast-moving soccer ball using agile maneuvers. This is challenging because it is a combination of highly dynamic locomotion and accurate non-prehensile manipulation of a fast moving object, each of which is already a difficult task on its own. Therefore, there have been few prior attempts on developing goalkeeping controllers with agile maneuvers using quadrupeds.

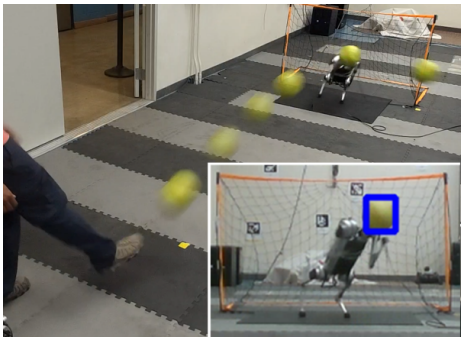

Fig. 1: A quadrupedal robot goalkeeper, Mini Cheetah, intercepts a soccer ball flying towards the goal using the proposed hierarchical RL framework with multiple locomotion control policies and a motion planning policy. The flight time of the ball is only around 0.5 second. Video is at `https://youtu.be/iX6OgG67-ZQ`.

In this work, we propose to address the goalkeeping task using a hierarchical model-free RL framework. This framework decomposes the goalkeeping task into two sub-problems: 1) low-level locomotion control to enable the robot to perform various agile and highly-dynamic locomotion skills, and 2) high-level planning to decide an optimal skill and motion to perform in order to intercept the ball.

A. Related Work

The soccer goalkeeping problem using quadrupedal robots can be viewed as a combination of three domains of robotics research: robotic manipulation to intercept a fast moving object, locomotion control to enable a quadruped to perform highly dynamic maneuvers, and robot soccer.

1) Robotic Catching / Hitting of Fast Moving Objects: Enabling robots to catch or hit fast moving objects, such as a ball, has been studied extensively in the robotic manipulation field. Typically, robotic arms, with a fixed base [4] or a mobile base [5], and even a quadcopter [6] have been used for these tasks. A common approach to tackling catching tasks is to separate it into two sub-tasks: prediction of the ball's trajectory based on the estimated ball position and velocity using models of the ball's dynamics [4], [7], [8], and generation of a trajectory for the robot's end-effector based on robot's dynamics model [6], [7], [9] or model-free RL [10], [11] to catch the ball at the predicted interception point. An alternative approach [12] is to learn an end-to-end policy in simulation that directly takes the camera's RGB image as input, followed by fine-tuning in the real world [13],

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[14]. Applying these previous ball-catching/hitting methods to quadrupeds is challenging. Model-based approaches require accurate dynamic modelling of the ball, robot, and contact with the ground, making it complex. Model-free reinforcement learning methods have not been used to control legged robots for such dynamic manipulation tasks.

2) Dynamic Locomotion Control for Quadrupeds: In recent years, there have been considerable advances in legged robot hardware and control algorithms that enable quadrupedal robots to perform highly dynamic locomotion maneuvers, such as jumping [1], [15]–[19] or running [2], [3], [20], in the real world. One approach is to use an optimal control framework with the robot's dynamics models, which can either be the robot's full-order models optimized offline [15], [16], [18], or simplified models deployed online [17], [20]. Another approach is to leverage model-free deep RL to train control through trial-and-error in simulation and then transfer to real robots [1]–[3], [19], [21]. However, most previous work only focuses on a specific dynamic locomotion skill without attaining a more diverse repertoire of maneuvers based on learned skills to achieve a longer horizon task, such as jumping while intercepting a ball.

3) Legged Robot Soccer: Developing robots that can one day compete with humans in soccer games has been an overarching goal in the robotics community. RoboCup [22], a notable robot soccer game was created to enable researchers to work towards this goal. Related to the goalkeeping problem of this work, there are some efforts to develop an intelligent goalkeeper using holonomic wheeled robots [23]–[25]. However, most previous work only considers the robot moving in a 2D plane to intercept the ball rolling on the ground at low speeds [23], [24]. Intercepting balls in a 3D and at high speeds, like a flying ball with a speeds up to 8 m/s, as in this work, has not been studied in robot soccer. Legged robots, such as humanoid robots and quadrupedal robots, are also used in RoboCup, but most presented soccer skills by legged robots, such as shooting [26], kicking [27], and goalkeeping [28], are based on rule-based motion primitives due to their challenging dynamics. Most recently, by leveraging deep RL, a quadrupedal robot demonstrates the capacity to dribble a soccer ball to a target at a low walking speed [29], as well as precisely shooting a soccer ball to a random given target while the robot is standing with a single shooting skill [30]. However, enabling legged robots to play soccer while performing multiple highly dynamic locomotion skills, such as using jump and dive skills, and precise ball manipulation has not yet been demonstrated.

B. Contributions

This work presents one of the first solutions that combines both multiple highly dynamic locomotion skills and precise object interception (manipulation) on real quadrupedal robots by using a hierarchical reinforcement learning framework. Compared to our prior work on quadrupedal soccer shooting [30], which is limited to using a single manipulation skill while standing and without locomotion, this work aims to combine dynamic locomotion and non-prehensile manipulation to accomplish a long-horizon complex task such as goalkeeping. The proposed method allows quadrupeds to track parametric trajectories with its end-effector(s) while engaging in dynamic locomotion maneuvers to intercept a fast-moving (and potentially flying) ball. We show that our system can be used to directly transfer dynamic maneuvers and goalkeeping skills learned in simulation to a real quadrupedal robot, with an 87.5% successful interception rate of random shots in the real world. Through an ablation study, we show that such a performance cannot be obtained using just a single locomotion skill. We hope this paper takes us one step closer to enabling robotic soccer players to compete with humans in the future.

II. Hierarchical RL Framework for Goalkeeping Task with Multi-Skills

In this section, we introduce the Mini Cheetah robot as our experimental platform and give a brief overview of the framework for developing goalkeeping skills shown in Fig. 2.

A. The Mini Cheetah Quadrupedal Robot

As shown in Fig. 1, Mini Cheetah [20] is a quadrupedal robot having a weight of 9 kg and height of 0.4 m when it is fully standing. It has 12 actuated motors $q_m \in \mathbb{R}^{12}$ with a 6 degree-of-freedoms (DoFs) floating base, representing its translational $q_{x,y,z}$ (sagittal, lateral, and vertical) positions and orientation $q_{\psi,\theta,\phi}$ (roll, pitch, yaw), respectively.

B. Locomotion Skills for Goalkeeping

Inspired by human goalkeepers, we propose a collection of skills for intercepting a ball flying to different regions of the goal, as illustrated in Fig. 3. One challenge underlying the design of goalkeeping locomotion skills is that the robot needs to react very quickly, since the total timespan of a ball's ballistic trajectory is typically under 1 sec. Therefore, from an initial standing pose in the middle of the goal, the robot needs to perform very dynamic maneuvers to intercept the ball. To accomplish this, our system uses three skills: *sidestep*, *dive*, and *jump* to cover different goal regions.

1) Sidestep: During a sidestep, the robot takes a quick step in the lateral direction to intercept the ball when it is rolling on the ground or flying toward the goal at a low attitude. For larger steps, this skill may involve a small sideways hop. However, this skill may not be effective in covering the lower corners or upper regions of the goal.

2) Dive: The dive skill is based on quadrupedal jumping behaviors [16], which allows the robot to cover a larger area of the goal. During a dive, the robot pitches the body up, turns to the side while pushing off with the rear legs, and extends the swing legs sideways to quickly block the ball moving towards the lower corners of the goal. The rear legs may or may not leave the ground during the dive, depending on the distance needed to catch the ball.

3) Jump: The jump skill, although similar to the dive skill, demands the robot to pitch up steeper and swing its front legs upwards faster. The rear legs need to stretch out to almost their maximum limits and potentially lift off from the ground

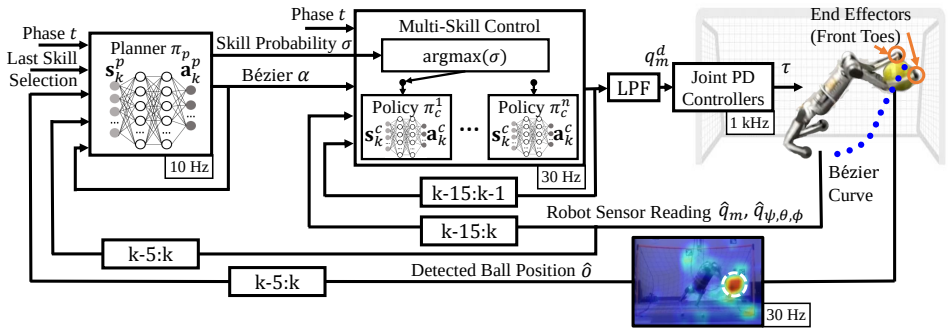


Fig. 2: Proposed hierarchical reinforcement learning framework for creating a quadrupedal robotic goalkeeper. We firstly develop a set of locomotion control policies for multiple skills, such as sidestep, dive, and jump. The locomotion control policies are designed to follow a random parametric Bézier curve using the robot end-effectors (swing front toes). The controller outputs PD targets at 30 Hz to generate motor torques, after passing through a Low Pass Filter (LPF) [1], [31]. A motion planner running at 10 Hz is developed on top of the multiple skill-specific controllers to select the specific skill to perform, as well as the desired end-effector trajectory for the controller to track. The planner's objective is to enable the robot to intercept the ball via its end-effectors or body before the ball enters the goal. The controllers and planner are trained by RL and the ball position is detected by a deep neural network using a RGB-Depth camera (30 Hz).

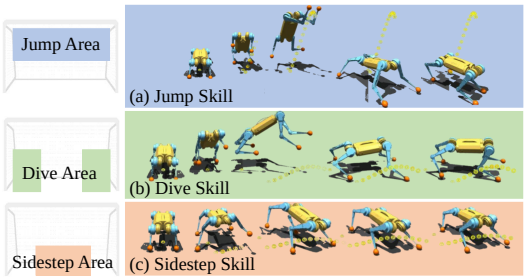


Fig. 3: Three different locomotion skills for goalkeeping. The robot can use different skills to cover different regions of the goal.

to gain enough height for the swing legs to reach the flying ball. In the flight phase, the robot also needs to reconfigure itself in the air to a more stable landing pose. This skill requires a higher level of agility.

For each of these three skills, a nominal reference motion for the robot is manually authored using an animation tool [32]. Each motion starts with the same standing pose.

C. Parameterizing Multiple Skills using Bézier Curves

Our robot leverages the above-mentioned three locomotion skills to reach different commanded locations in front of the goal in order to intercept the ball. Inspired by previous work [30], [31], we use Bézier curves to parameterize the desired robot motion. A Bézier curve parameterized by Bézier coefficients α is defined as a function of phase t, $B_\alpha(t)$ [30, Sec.II-C] where $t \in [0, 1]$ is the normalized time with respect to a total duration T of the entire trajectory. Similar to [30], the Bézier curve represents the desired trajectory for the robot's end-effectors, which is designated to be the toes. In the *sidestep* skill, the end-effector is designated to be the toe of the robot's swing leg, either the front right or left toe. However, for the skills that need to use two swing legs to catch the ball, like *jump* and *dive*, the Bézier curve specifies a trajectory for the center of the two end-effectors (two front swing toes). In this work, we choose to use 5 control points in $3D$ space, therefore, $\alpha \in \mathbb{R}^{5\times3}$. The duration T of each skill is set to be 0.5 seconds. In this way, we can parameterize and represent different robot's end effector trajectory to reach different locations by using different Bézier coefficients.

D. Hierarchical Reinforcement Learning Framework

We now present our hierarchical RL framework (Fig. 2) for controlling a quadrupedal robotic goalkeeper. For each goalkeeping locomotion skill, we train a control policy to specify joint-level commands for the robot using model-free RL. This enables the robot to mimic the nominal reference motion while tracking a large range of randomized end-effector trajectories represented by parametric Bézier curves. This process produces multiple control policies ($\pi_c^1 \dots \pi_c^n$) for different goalkeeping skills. In this work, we trained three control policies for each of the *sidestep*, *dive*, and *jump* skills. Each policy runs at 30 Hz. Since each policy performs a distinct behavior, training individual skill-specific control policies avoids the challenge of training a single multi-task policy for all skills. We train a high-level planning policy π_p using model-free RL to select an appropriate skill corresponding to ball travelling towards different regions of the goal, based on the detected ball position and robot's current states, which runs at 10 Hz. It also specifies the desired Bézier curve for the chosen controller to track in order to intercept the ball. The ball position is obtained by an external camera and detection algorithm YOLO [33].

We first train each control policy in simulation, and test them extensively on the real robot with zero-shot transfer. After obtaining reliable controllers in the real world, we use the same control policies to train the planning policy in simulation and then directly deploy the entire pipeline in the real world. This approach decouples the complex goalkeeping task into the locomotion control and manipulation planning problems, and solves each problem separately.

III. Dynamic Locomotion Control using Deep RL

In this section, we detail our framework for training control policies for each goalkeeping skill.

A. Training Environment

The control policies are trained using a simulation of the Mini Cheetah in Isaac Gym [34], a GPU-accelerated

dynamics simulator. For a skill-specific controller c, at each timestep k of an episode, the robot takes an action $\mathbf{a}_k^c$ based on its current observations $\mathbf{s}_k^c$, and the environment transitions to the next state and provides the agent with a reward $r_{c,k}$. The RL is used to maximize the expected accumulated reward over the course of an episode.

1) Action Space: The skill-specific control policy outputs a 12-dimensional action that specifies target motor positions for each joint q_m^d and is used by joint-level PD controllers to compute motor torques τ.

2) Observation Space: As shown in Fig. 2, the policy's observations consist of three components. The first component is the desired end-effector trajectory for the robot to track, represented by a set of Bézier coefficients and normalized phase t with respect to the 0.5-sec-timespan of the motion. The second component is the robot's raw sensor reading, which consists of the measured motor positions $\hat{q}_m$ and base rotation $\hat{q}_{\psi,\theta,\phi}$. We also include a history of the sensor readings $(\hat{q}_m, \hat{q}_{\psi,\theta,\phi})$ and policy's outputs (q_m^d) in the past 15 timesteps, which corresponds to a time window of around 0.5 seconds. This history provides the policy with information necessary for inferring the dynamics of the system, which can be vital for sim-to-real transfer [31].

B. Reward Formulation

The reward $r_{c,k}$, for skill-specific controller c, at timestep k is designed to encourage the control policy to track the given Bézier curve for the robot's end-effector and smoothly mimic the skill-specific reference motion while maintaining gait stability. The reward function contains three parts:

$$r_{c,k} = 0.5\, r_{c,k}^E + 0.3\, r_{c,k}^I + 0.2\, r_{c,k}^S, \tag{1}$$

where $r_{c,k}^E$ represents the robot's end-effector tracking term, $r_{c,k}^I$ is the imitation term, and $r_{c,k}^S$ is a smoothing term. The end-effector tracking term has the highest weight to prioritize tracking the desired Bézier curve while imitating (but not being restricted to) the reference motion, which has a lower weight. Next, we define an abstract reward function

$$r(u, v) = \exp(-\rho||u - v||_2^2), \tag{2}$$

which calculates the normalized distance between vector u and v, with $\rho > 0$ being a hyperparameter. With this, the $r_{c,k}^E$ term can be decomposed into:

$$r_{c,k}^E = 0.8\, r(B_\alpha(t), x_{e,k}) + 0.2\, r(\dot{B}_\alpha(t), \dot{x}_{e,k}), \tag{3}$$

where the Bézier curve $B_\alpha(t)$ is the desired end-effector position evaluated at phase t at current timestep k and $\dot{B}_\alpha(t)$ is the derivative of the curve at phase t representing the desired end-effector velocity. The term $x_{e,k}$ is robot's end-effector position in Cartesian space while $\dot{x}_{e,k}$ is its velocity. We empirically found that adding the end-effector velocity tracking term improves the smoothness of the trajectory.

Similarly, the imitation reward $r_{c,t}^I$ encourages the robot to mimic the skill-specific reference motion, and consists of 3 terms: the motor tracking reward $r(q_m, q_m^r)$, robot base height following reward $r(q_z, q_z^r)$, and base orientation tracing reward $r(q_{\psi,\theta,\phi}, q_{\psi,\theta,\phi}^r)$, by calculating the distance between robot's current values and the one from reference motion $(q_{m,z,\psi,\theta,\phi}^r)$ at each timestep. Note that the reference motion is just a kinematically feasible animation and a reward formulation with a small weight on this term allows the robot to deviate from the reference motion to perform dynamically feasible maneuvers. Moreover, $r_{c,k}^S$ is the smoothing reward and consists of $r(\dot{q}_{\psi,\theta,\phi}, 0)$, $r(\ddot{q}_{\psi,\theta,\phi}, 0)$, and $r(\tau, 0)$ to minimize the robot base rotational velocity, rotational acceleration, and torque consumption, respectively. By incorporating the smoothing reward, we can effectively minimize nonessential angular movement that hampers robot stability, and energy consumption throughout the motion.

C. Motion and Dynamics Randomization

With the skill-specific nominal reference motion unchanged, the desired end-effector trajectory is randomized by adding a random change $\tilde{\alpha}$ to a nominal set of Bézier coefficients $\bar{\alpha}$, *i.e.*, $\alpha = \bar{\alpha} + \tilde{\alpha}$. The coefficients change $\tilde{\alpha}$ of each control point is uniformly sampled from a large range, especially in the lateral direction to cover farther sides of the goal. This then allows each policy to track a large variety of end-effector trajectories defined by the randomized α.

During training in simulation, dynamic parameters are randomized to facilitate transfer from simulation to the real world. Similar to previous work [30], we randomize the link mass, inertia, center of mass, and the PD gains of the motors to reduce modeling error of the robot and the motors. Sensor noise and delay are also simulated similar to [30]. Ground friction and restitution plays a critical role in skills such as jumping and diving. Therefore, they are randomized within a large range of $[0.5, 4.5]$ for friction coefficient and $[0.5, 4.5]$ for restitution coefficient to facilitate adaptation to various ground surfaces. Finally, a random 6 DoFs wrench (force from -1 to 1 N and torque, except roll, from -3 to 3 Nm) is applied to the robot base to improve the policy robustness. We have a large perturbation in the roll direction (± 12.5Nm), which is found to be effective in preventing the robot from rolling over when jumping sideways.

D. Episode Design and Training

Each episode lasts for 300 timesteps max, corresponding to 10 seconds, and consists of three stages: (1) starting in a nominal standing pose for a random span of time, (2) tracking the desired end-effector trajectory parameterized by a set of randomized Bézier coefficients while imitating the reference motion of the specific skill, and (3) returning to a nominal standing motion after completing the goalkeeping maneuver. During training, two early termination conditions are considered: unsafe behavior and large deviation from the commanded curve for end-effectors. We find that early termination leads to faster training and more precise tracking of end-effector trajectories. Proximal Policy Optimization (PPO) [35] is used to train all policies, with actor and critic networks modeled by separate MLPs using ELU activation functions with hidden layers of 512, 256, and 128 units. We train each skill with one billion simulation timesteps.

IV. Multi-Skill Motion Planning using Deep RL

Each obtained skill-specific locomotion control policy is first tested thoroughly on the robot hardware. After the sim-to-real test, these control policies can then be used to train a planning policy that enables the robot to intercept the ball by performing dynamic locomotion maneuvers after examining the detected ball position and the current robot states.

A. Training Environment

The planning policy is also trained in Isaac Gym with the Mini Cheetah driven by its controller and a rigid ball. The goal in the simulation is sized 1.5 m wide and 0.9 m high, and the robot is placed 0.2 m in front of the goal line.

1) Action Space: As shown in Fig. 2, the planning policy outputs the desired skill type to perform, and the desired end-effector trajectory for the selected controller to track. Therefore, the action of the planner $\mathbf{a}_p$ contains two parts: the skill type and desired Bézier coefficients α^d. For n skills, the planner outputs skill selection probabilities $\sigma \in \mathbb{R}^{n+1}$, and the desired skill type can be determined by finding the argmax of σ. The extra skill utilizes a time-invariant standing pose with a PD controller. In this work, $n = 3$. Although there are 5 control points to construct the Bézier curve used by the control policy, the planner outputs only 4 points, excluding the first control point, *i.e.*, $\alpha^d \in \mathbb{R}^{4\times 3}$. The first control point is always set to a nominal initial position of the robot's toes to reduce the dimension of the action space.

2) Observation Space: The observation of the planning policy $\mathbf{s}_k^p$ consists of four components. First, we provide the current (at timestep k) detected ball position in global frame $\hat{o}_k$ along with a history of the ball positions so that the policy can implicitly filter noisy camera readings, estimate velocity, and infer the ball's future trajectory. Second, the current robot sensor reading, including motor angles $\hat{q}_m$ and base orientation $\hat{q}_{\psi,\theta,\phi}$, along with a history of the sensor readings and actions are provided to the planning policy to implicitly learn to estimate dynamics. Note that although the planner runs at 10 Hz, all the history observations are 6 timesteps long and are sampled at 30 Hz (the controller's frequency). Third, by inputting previous skill and motion selection, the planner needs to avoid making sudden infeasible skill changes that may cause the robot falling over. Finally, the phase t of the performed skill is also included.

B. Reward Formulation

The reward for the planning policy is designed to perform a "save" by intercepting the flying ball with the robot's end-effectors, body, or trunk. To facilitate this, the reward is specified as:

$$r_{p,k} = b_k(r^{\dot{o}}_{p,k} + 0.6r^{x_e}_{p,k} + 0.2r^{x_e^d}_{p,k} + 0.2r^{\alpha^d}_{p,k}), \quad (4)$$

where

$$b_k = \begin{cases} 1, & \text{if } ||o_k - x_{e,k}|| \leq 0.3 \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

is a binary variable indicating if the current ball position o_k is close enough to robot's current end-effector position $x_{e,k}$. In this way, the reward is only nonzero when the ball is close to the robot. Since the robot is only allowed to perform one save in each episode, such a design encourages the robot to preserve its skill for a good interception opportunity.

The dominant reward term $r^{\dot{o}}_{p,k}$ represents the reward for the ball velocity. It is set to 1 if the ball speed $||\dot{o}||_2$ is zero and to 0 otherwise. By this term, we encourage the robot to stop the ball, which is the primary objective of goalkeeping. Furthermore, the reward $r^{x_e}_{p,k}$ stimulates the robot to minimize the distance between the robot's end-effector position x_e to the ball by $r(x_{e,k}, o_k)$ where $r(\cdot,\cdot)$ is defined via (2). Similarly, $r^{x_e^d}_{p,k}$ incentivizes the policy to plan a desired end-effector trajectory that tracks the ball by $r(B_{\alpha^d}(t), o_k)$. Given that the dominating term is to stop the ball ($r^{\dot{o}}_{p,k}$), the robot can still receive a reasonably good return if it uses other parts of the body to save the ball.

Finally, the smoothing term $r^{\alpha^d}_{p,k} = r(\alpha^d, 0)$ is introduced to encourage the planner to regularize the desired Bézier coefficients α^d to prevent having fluctuating curves.

Please note that the reward for minimizing energy consumption is not directly included due to the high variance in motor torques between skills. This also makes sure the reward doesn't favor using low-energy skills, like sidestep, over the main task of goal saving.

C. Early Termination Condition

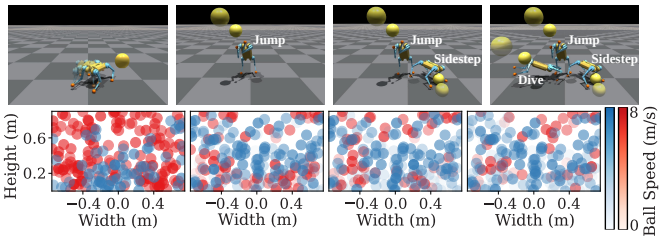
Besides the reward design, the termination conditions to end the episode earlier are critical to enable the robot to save the ball in front of the soccer goal. We terminate the episode to prevent the agent from having a future return if the ball flies into the goal area. This can stimulate the robot to try its best to save the ball instead of adopting conservative behaviors like just standing where the robot can still receive some rewards such as the smoothing reward. Further, the episode will be terminated if the robot falls over. This can prevent the planning policy from outputting infeasible end-effector trajectories or commanding wrong skills, like selecting a sidestep skill while the robot is in the air, because these will cause the controllers to fail.

D. Episode Design, Domain Randomization, and Training

Each episode lasts for 90 timesteps (3 seconds) in total, which is sufficient for a goal save that typically lasts less than one second. Upon reset, the ball's initial $3D$ position and velocity in the transverse plane is randomly sampled. The target position for the ball is sampled within the goal area, and the initial vertical speed is obtained accordingly.

We again leverage domain randomization to improve the robustness of the policy. In addition to those during training the control policy, we also applied Gaussian noise with zero mean and 0.05m standard deviation and constant delay randomized from $[80, 100]$ms for the ball positions as measured on the camera, which is crucial for the sim-to-real transfer.

The planning policy uses separate and identical actor and critic networks, both with a 2-layer MLP with 256 and 128 hidden dimensions with ELU activation. The last layer of the actor network is followed by two action heads, one



(a) End-to-end (b) 1-Skill (c) 2-Skill (d) 3-Skill

Fig. 4: Snapshots and shot interception map in simulation. (a) depicts the end-to-end baseline trained without proposed hierarchy, while (b)(c)(d) represent hierarchical policies with different number of skills learned. The map represents the goal region. Blue records a goal save while red is a goal (miss). Darker colors indicates faster ball speeds. The snapshots visualize how the planner leverages the new skills, and the shot interception map quantitatively illustrates the benefits of adding each skill. Note that the failing corner cases are noticeably reduced by adding the second sidestep skill in 4c, and further reduced by the third dive skill in 4d. The goal saving rates are 30.84%, 65.09%, 72.46%, and 78.11%, respectively.

for continuous Bezier coefficients, and one for categorical skill selection action. A $tanh$ and a $softmax$ activation are applied to the continuous and discrete heads respectively. The planning policy is also optimized by PPO with 10 million timesteps. Unlike [30], our simulation-trained planning policy can be directly deployed in the real world without fine-tuning.

V. Results

After developing all components of the proposed framework (Fig. 2), we now validate the proposed framework in simulation and real-world experiments (video is at `https://youtu.be/iX6OgG67-ZQ`.)

A. Simulation Validation

We first evaluate the performance of the proposed multi-skill framework in simulation. We compare four policies: (1) *end-to-end* policy, and hierarchical policies with (2) *1-skill*, (3) *2-skill*, and (4) *3-skill* (ours). The *end-to-end* baseline combines planning and control into one policy and does not use reference motions during training. This is because learning a single policy from multiple reference motions [36] involves multi-task RL and is challenging. If we use only one reference motion, the end-to-end policy becomes similar to a *1-skill* policy. The three hierarchical policies use the proposed hierarchical framework with different numbers of skills. Specifically, the *1-skill* baseline only has one jumping controller, *2-skill* has both jump and sidestep skills, and our *3-skill* contains all jump, sidestep, and dive skills. The *end-to-end* policy and the high-level planners of the three hierarchical models are trained using the same method introduced in Sec. IV. Each method is tested with 200 randomized scenarios as specified in Sec. IV-D, and results are recorded in Fig. 4.

The *end-to-end* policy shows the worst success rate of 30.84%. The results in Fig. 4a show that while the end-to-end policy can save some slow-rolling balls, it misses most of the fast flying balls. This is because the robot may need to leave its nominal pose and utilize different skills in order to intercept the ball flying at different heights. Developing a single policy to explore different skills using RL on its own is a challenging problem. This showcases the importance of the proposed hierarchy method which divides the complex task into relatively easy-to-solve sub-problems.

Next, we evaluate the performance of the hierarchical models with different number of locomotion skills. The *1-skill* planner achieves a comparable saving rate with flying balls, but misses almost all of the balls that roll on the ground, resulting in a 65.09% saving rate (Fig. 4b). Such a result demonstrates that using a single skill is not sufficient for the diverse scenarios present in the goalkeeping task. While the *2-skill* planner can catch most of the balls (72.46%), there are two notable corner cases on the lower left and right that often leads to failures. We discovered that in these cases, a majority of the balls travel underneath the robot when it jumps, and can not be reached by the sidestep skill. This problem highlights the necessity of the dive skill to intercept balls flying to these regions. When the dive skill is added, the proposed *3-skill* planner shows the best success rate of 78.11%. Please note that our proposed method is not limited to the three specific skills presented in this work. The hierarchical framework in Fig. 2 provides flexibility to incorporate more locomotion skills by simply retraining the planning policy to utilize a larger repertoire of skills.

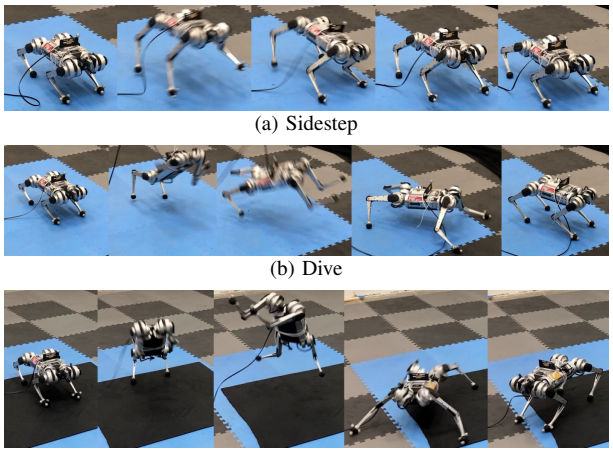
B. Experiments

We now deploy the proposed framework on the Mini Cheetah robot to save soccer goals in the real world.

1) Experiment Setup: We set up a mini penalty field to conduct the experiments, as shown in Fig 1, with a $1.5m \times 0.9m$ goal. The robot is placed at the center with its rear feet 0.1 m in front of the goal line. A size 3 soccer ball is either kicked or thrown from roughly 4 m in front of the robot with a random initial speed towards a random target in the goal. We set an external RGB-Depth camera (Intel RealSense D435i) placed 6 m away from the goal line. The global frame is set to the robot's initial frame. We also setup a Motion Caption System (MoCap) with markers on the robot's trunk and front toes to evaluate the tracking performance of the locomotion controllers. Note that our system does not require accurate measurement from the external MoCap.

2) Performance of Skill-specific Locomotion Controllers: The performance of the low-level controllers on the robot hardware is firstly validated, as demonstrated in Fig. 5. The control policies are able to produce similar maneuvers in real world (Fig. 5) as in the simulation (Fig. 3) without any training in the real world. Furthermore, given a random set of Bézier coefficients, all three policies are able to track the desired trajectories for the robot's end-effector to the best of its physical limitations, as shown in Fig. 6, with an average tracking error of 0.11 m (measured by MoCap) over all trials.

3) Goalkeeping Performance: As demonstrated in Fig. 7, the proposed framework that utilizes three different goalkeeping skills is able to enable Mini Cheetah to save goals in



(a) Sidestep

(b) Dive

(c) Jump

Fig. 5: Experiments with control policies for different skills. The policy is able to directly transfer to the hardware. As designed in Sec. II-B, we can observe that the dive skill 5b is able to reach a significantly larger range horizontally than sidestep 5a, while the jump skill 5c can produce a notable period of flight time, swing the front legs to cover higher regions of the goal, and land safely.

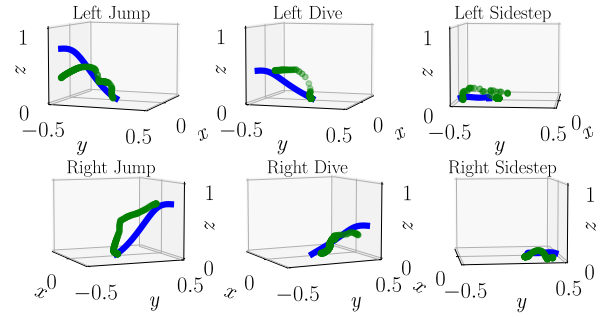
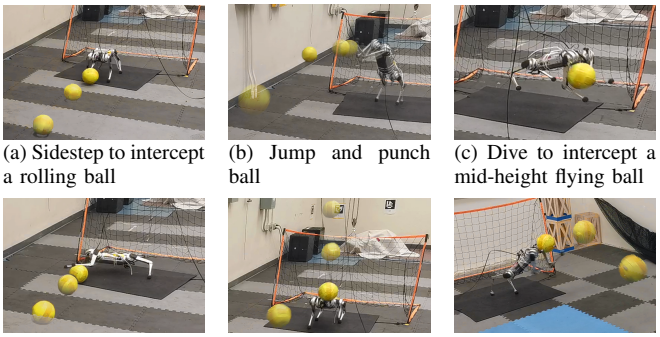


Fig. 6: Comparison between robot's desired (blue) and actual (green) end-effector trajectories. The desired end-effector trajectory is randomly specified and the resulting actual trajectory is obtained through MoCap. The average tracking error for left jumping, left diving, and left sidestepping are 0.10, 0.15, 0.08 m, and those for right sides are 0.12, 0.13, 0.05 m, respectively.

different scenarios. For easier ones (Fig 7a), the most energy-efficient way (taking a sidestep) is leveraged, while in harder cases such as in Fig 7b,7f, the robot takes a large jump and punches out the ball in the air intentionally. In most shots, the soccer ball interception time is within 0.9 second and the robot is able to quickly react to it. Note that another advantage of our planner is that it may leverage the existing skills to infer other skills, such as the header in Fig. 7e, which prevents the ball from slipping through its feet.

To further evaluate the performance in the goalkeeping task using the proposed framework, we conducted extensive ablation study on three methods: 1) a *model-based* planner, 2) the *2-skill* planner with jump and sidestep skills, and the proposed planner which utilizes *3-skill*. The *model-based* planner runs an optimization online to determine the desired Bézier coefficients. Like most prior work using model-based methods [4], we use a Kalman Filter to estimate the ball velocity from measurements of the ball position and dynamical model of the ball (assuming there is only gravitational force acting on the ball). The planner finds a Bézier curve that intercepts the ball along its predicted path



(a) Sidestep to intercept a rolling ball

(b) Jump and punch ball

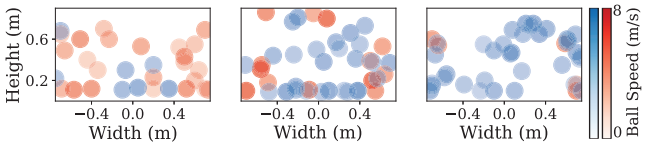
(c) Dive to intercept a mid-height flying ball

(d) Dive for corners

(e) Emergent header

(f) Save within 0.5s

Fig. 7: Snapshots of the real-world experiments showing the Mini Cheetah robot goalkeeper handling various scenarios. In 7a, the robot chooses sidestep when the ball is nearby, whereas in 7d a dive save is selected as the ball is rolling towards the corner. When the ball comes high as in 7b, the robot jumps and intentionally pushes the ball away, while dive is chosen for balls in the lower half, as in 7c. Shown in 7e, the planner generalizes to leverage other parts of the body to complete the task. These experiments are conducted with a RGB-Depth camera, while the robot responded to a fast ball in less than 0.5 second supported by MoCap in 7f.



(a) Model-based (b) 2-Skill (c) 3-Skill

Fig. 8: Shot interception maps in real-world experiments. The model-based method yields a very low saving rate due to imprecise ball prediction. The lower-corner failures in 8c are significantly reduced compared to 8b, coherent with the result in simulation. The saving rates are 23.3%, 66.7%, and 87.5%, respectively. These experiments are conducted using a RGB-Depth camera.

and the locomotion skill is selected based on the ball height at the predicted interception point. The shot interception maps with these three methods are recorded in Fig. 8.

The *model-based* planner results in the worst performance with only a saving rate of 23.3% over 30 trials. This is likely due to the unreliable ball velocity estimation, which is a crucial element for this method, and the limited ability to consider robot's full-order dynamics. Since the robot often fell over while catching the flying ball with this method, we stopped at 30 tests to prevent potential hardware damage. On the other hand, the learning-based *2-skill* and *3-skill* planners do not require knowlege of the ball's velocity, leading to a significant improvement in saving rates. Both *2-skill* and *3-skill* planners are tested consecutively for 40 trials, and the shot interception maps are shown in Figs. 8b,8c. The most frequent failure spots for the *2-skill* planner occurs noticeably on the lower corners, which is innately difficult for the robot without learning the dive skill. In contrast, the proposed *3-skill* planner (87.5% saving rate) with all three skills noticeably alleviates these corner cases and outperforms the *2-skill* planner by 20.9%.

However, one limitation of the proposed framework is that the robot often fails to save balls whose with flight times less than 0.5s. This is due to the minimum timespan of the robot's motion and ball detection delays from the camera.

4) Penalty Kicks with Humans and a Quadrupedal Robot: We further showcase the capacity of the proposed framework by inviting human soccer players, and a quadrupedal robot soccer ball shooter developed in [30] to conduct penalty shots with the proposed robot goalkeeper. These experiments are recorded in the video.

VI. Conclusion and Future Work

In conclusion, we proposed a multi-skill reinforcement learning framework that enables quadrupedal robots to function as soccer goalkeepers with precise and highly dynamic maneuvers. We developed a RL-based framework in simulation and demonstrated its performance with zero-shot transfer to the real world. The framework consists of multiple locomotion controllers specialized for specific skills (sidestep, dive, and jump) and a multi-skill manipulation planner to find the optimal skill and desired trajectory for robot's end-effector to intercept the incoming ball. We have shown that the multi-skill RL framework outperformed a model-based planner under delayed and noisy measurements, and was able to adequately leverage the specialty of each skill. In this work, we focused solely on the goalkeeping task, but the proposed framework can be extended to other scenarios, such as soccer ball dribbling.

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