

# FastMimic: Model-based Motion Imitation for Agile, Diverse and Generalizable Quadrupedal Locomotion

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**Abstract**—Robots operating in human environments need various skills, like slow and fast walking, turning, side-stepping, and many more. However, building robot controllers that can exhibit such a large range of behaviors is a challenging problem that requires tedious investigation for every task. We present a unified model-based control algorithm for imitating different animal gaits without expensive simulation training or real-world fine-tuning. Our method consists of stance and swing leg controllers using a centroidal dynamics model augmented with online adaptation techniques. We also develop a whole-body trajectory optimization procedure to fix the kinematic infeasibility of the reference animal motions. We demonstrate that our universal data-driven model-based controller can seamlessly imitate various motor skills, including trotting, pacing, turning, and side-stepping. It also shows better tracking capabilities in simulation and the real world against several baselines, including another model-based imitation controller and a learning-based motion imitation technique.

## I. INTRODUCTION

Animals are capable of performing diverse and agile locomotion behaviors in nature, but transferring such behaviors on robots remains a challenge. Robots operating in human environments should be equipped with diverse skills like trot and pace when walking slowly or speeding up, turn around corners, and side-step around obstacles. However, building a universal controller that is robust enough to perform such a wide range of skills is still an unsolved problem.

Motion imitation [1], [2] holds the promise of learning diverse natural movements by imitating reference motions captured from real humans or animals. Traditional model-based control algorithms [3], [4], [5] in locomotion literature have demonstrated impressive agility and robustness, but they often require extensive effort in developing the proper mathematical models and control strategies tailored to the given task. On the other hand, many works in physically simulated agent control [1], [6], [7], [8], [9] have demonstrated that motion imitation offers a framework to learn a wide range of skills, including walking, running, jumping, and dancing; it can also easily be combined with existing motion planners such as data-driven kinematic controllers [10]. This approach does not assume any prior knowledge about input motions, and its repertoire is only limited by the given motion dataset and the learning capacity of the policy network, making it ideal for teaching robots a wide range motions. However, learning-based motion imitation is often computationally expensive and its performance could deteriorate during real-



Fig. 1: We present a unified model-based motion imitation algorithm to mimic multiple animal motion trajectories on the A1 robot. We follow animal motions of trotting, pacing, turning, side-stepping using a *single* model-based controller.

world deployment due to sim-to-real gaps unless expensive adaptation processes are performed [2].

Our key insight is that we can combine the motion imitation paradigm with model-based control to take advantages of both approaches. In the context of model-based control, this data-driven imitation approach provides a unified framework for achieving various motor skills without the burden of task-specific modeling and tuning. From the motion imitation perspective, model-based control can play a role of tracking controllers which do not require training cost per motion unlike learning-based methods. In addition, our controller inherits all the strengths of model-based control, such as better sim-to-real transferability.

We develop a novel model-based control algorithm to imitate a given reference motion. More specifically, our method includes two main components: a stance controller using a low-dimensional centroidal model for the CoM from Di et al. [5], along with an online adaptation that commands desired joint positions to improve motion imitation, and a swing controller using inverse-kinematics to follow swing leg trajectories augmented by a feedback term, similar to a Raibert footstep [11]. We also develop an algorithm to adapt input animal motions that are kinematically infeasible on target robots, while maintaining the overall style of the motion. We fit a rhythmic dynamic movement primitive (DMP) [12] to the input motion and optimize a subset of its parameters using CMA-ES [13] to improve imitation performance.

The contributions of our work are: (1) a universal data-driven model-based controller that can follow any reference motion trajectory and (2) a trajectory optimization algorithm to fix the kinematic infeasibility of the reference motions. We demonstrate that our approach can seamlessly perform various motor skills, including trotting, pacing, turning, and sidestepping, using a *single* controller in simulation and on hardware of an A1 robot [14]. Our controller shows much better tracking capabilities compared to other state-of-the-art model-based imitation control schemes [15] and a model-free

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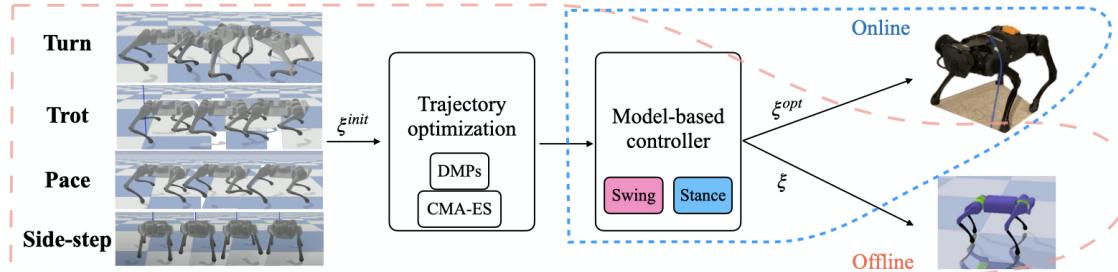


Fig. 2: An overview of our approach. We start with retargeted animal motions and use them as reference motions in a model-based controller. In simulation, we run trajectory optimization to update the reference motion and send the optimized trajectory to hardware. The optimization pipeline is used on four animal motions - turn, trot, pace, and side-step. The same hardware controller tracks these motions, resulting in diverse, agile gaits on hardware with no real-world fine-tuning.

imitation learning algorithm [2].

## II. RELATED WORK

### A. Motion Imitation

Designing controllers that generate natural-looking motions is challenging on robots and animated characters. Imitating reference motions (usually recorded by motion capture equipment), using learning based approaches has shown a lot of promise in simulation for bipeds [1], [7], [6], [16], [8], [17], [18], [19], and quadrupeds [1], [16], [20]. In some cases where it is hard or impossible to get those real reference motions, manually created motions could also be used [1], [16]. However, learned imitation policies are often vulnerable to the sim-to-real gap even after a long learning process [19], which can be mitigated by domain randomization [21] or online adaptation [2]. However, fine-tuning per motion in the real world is quite expensive. Instead, we present a unified controller capable of producing varied gaits, without fine-tuning on hardware.

### B. Model-based Legged Locomotion Control

Model-based approaches use a dynamics model to optimize actions with respect to a given cost/reward function. Several reduced-order dynamic models have been developed for legged robot control due to its complex dynamics. For bipedal robots, the inverted pendulum model and its variants have been widely used [22], [23], [24], [25]. For quadrupedal robots, simplifying the robot into a single rigid body that is driven by the sum of external forces from stance legs is one of the reliable approaches to control [4], [26], [5]. However, these low-dimensional models depending on hand-designed reference motions generate gaits of which styles are robotic and not lifelike. There have been other previous work that combined model-based controllers with reinforcement learning [27], [28] to generate desired CoM acceleration, or adopted learned dynamics models [29] for planning. In this work, we adapt the model-based controller from [5] and use animal motion trajectories as the reference motion to generate diverse, agile, natural motions on an A1 quadrupedal robot. Instead of using RL like [27], we use trajectory optimization to improve the performance of the model-based controller in simulation, and transfer optimized reference trajectory to the real robot.

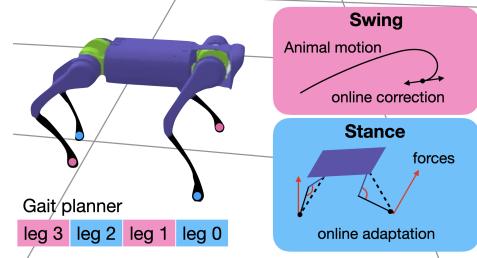


Fig. 3: An overview of our model-based controller which uses animal motions as desired trajectory input.

Closely related to our work, recently Kang et al. [15] present a model-based controller that uses animal motions to create reference CoM trajectories for quadrupedal robots. However, their swing motion is not inspired from animals, they rather use a Raibert [11] stepping policy with hand-designed foot trajectories. Moreover, all the results are shown in simulation, which include trotting-like walking behaviors only. In contrast, we present four dynamic gaits – trot, pace, turn and side-step on an A1 robot in the real-world, using the swing trajectories recorded from animals, resulting in more natural looking motions. To achieve this challenging result, we present online adaptation techniques, as well as trajectory optimization to improve reference motion.

### C. Dynamic Movement Primitives (DMPs)

Dynamic Movement Primitives (DMPs) are powerful and well-studied tools for motion imitation. In manipulation problems, DMPs have been widely explored for imitation learning [30], [31], [32], [33], hierarchical learning [34], [35], motion optimization [36], [37] and reinforcement learning [38]. In legged robots, pattern generators, a subset of rhythmic DMPs, have been long used for modeling trajectories for locomotion [39], [40], [41]. However, central pattern generators [42] and other limit cycle approaches are not easily applicable to imitation learning scenarios. On the other hand, rhythmic DMPs can be learned from demonstrations and applied to locomotion [43]. We learn the parameters of rhythmic DMPs from animal motion, followed by optimizing a subset of the parameters to improve imitation performance.

## III. MODEL-BASED CONTROL FOR MOTION IMITATION

We present a motion imitation framework based on a model-based low-level controller that can generalize to dif-

ferent target motions. We assume that the reference motions are generated using kinematic motion retargeting with hand-designed keypoints that maps animal motions to the robot. Then our framework consists of two steps. (1) Trajectory optimization using a simulated robot equipped with a model-based controller. (2) Transfer of the optimized trajectory to a real-world robot using a model-based low-level controller. The trajectory optimization is performed offline in simulation, and the optimized trajectory is zero-shot transferred to the robot, without fine-tuning. Figure 2 gives an overview.

## A. Motion Retargeting

We use the retargeting technique described in Peng et al. [2] to map animal motions to an A1 robot. We select key-point pairs between animal and robot, followed by inverse-kinematics and manual scaling.

## B. Model-based Controller

Our model-based controller consists of three components: (1) A stance controller that commands desired joint angles and torques on the stance legs, (2) a swing controller that commands desired joint angles on the swing legs, and (3) a gait planner switching the legs between swing and stance. The stance and swing controllers take retargeted trajectories as reference and produce outputs based on the current and desired robot states. The gait planner takes into account the current and desired contact states to determine either swing or stance control per leg. Additionally, we develop an online adaptation scheme to enhance stability by modulating the reference motion according to the current state of the robot. Figure 3 gives an overview of our model-based controller.

**1) Gait Planner:** The gait planner switches the control between swing and stance for each leg, based on the desired contact state, and the current contact state of the robot. The desired contact state is measured from the animal motion demonstration whereas the current contact state is measured by foot sensors on the simulated/real A1 robot. If the measured vertical ground reaction force  $f_i > f_{\text{thresh}}$  for leg  $i$ , where  $f_{\text{thresh}}$  is the contact threshold, the leg is considered to be in stance. Figure 4 shows the finite state machine (i.e. logic) used by our gait planner to determine the appropriate control mode for each leg. When the desired contact state deviates from the measured contact state, the gait planner initiates a transition from swing control to stance control or vice versa. For example, if the desired contact for leg  $i$  switches to swing from stance, the measured contact state would remain stance for a short time. The gait planner detects this mismatched contact states and initiates swing on leg  $i$ . In situations like early contact and early take-off, the current contact state can also deviate from the desired contact state. If the measured force  $f$  on a swing leg is above the contact threshold while the desired state is swing, we detect early contact and start stance control on the leg. Similarly, if a stance leg leaves contact ( $f_i < f_{\text{thresh}}$ ) when the desired state is in contact, we detect early take-off and switch the leg to swing control. Additionally, we add a minimum time of 100ms between consecutive state switches to avoid

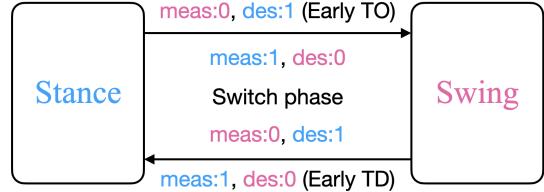


Fig. 4: Finite state machine used by the gait planner to switch leg control from swing (0) to stance (1) and vice versa. When the measured contact state deviates from the desired contact state, depending on the previous state of the leg, the gait planner initiates a switch from stance to swing, or vice versa. This also takes into account early touch down (TD) and take off (TO). We additionally add a minimum time limit of 100ms between consecutive switches to avoid instability due to measurement noise.

instability caused by noisy foot force measurements. This results in a robust gait planner, which generalizes across different quadrupedal gaits like trotting, pacing and turning.

2) *Stance controller*: The stance controller uses a linearized centroidal dynamics model to reason about robot CoM motion, similar to [5]:  $\ddot{\mathbf{x}} = \mathbf{M}^{-1}\mathbf{f} - \tilde{\mathbf{g}}$ , where  $\mathbf{M}^{-1}$  is the inverse inertia matrix of the robot (calculated from the robot's model),  $\mathbf{f}$  is the measured contact force on the stance legs, and  $\tilde{\mathbf{g}}$  is the gravity vector. We use  $\ddot{\mathbf{x}}$  to denote the 6-dimensional CoM acceleration, consisting of both position and orientation terms in the world frame.

First, we calculate a desired CoM acceleration  $\ddot{\bar{x}}$  as  $\ddot{\bar{x}} = k_p(\bar{x} - x) + k_d(\dot{\bar{x}} - \dot{x})$ , where  $\bar{x}, \dot{\bar{x}}$  are the desired CoM position and velocity from the reference motion that the robot is following, respectively,  $x, \dot{x}$  are the measured CoM position and velocity, and  $k_p, k_d$  are feedback gains, which are tuned in advance and kept fixed for all reference motions. Next, we formulate a Quadratic Program (QP) to solve for the desired instantaneous contact forces  $\bar{f}$  that can achieve  $\ddot{\bar{x}}$  subject to friction constraints, and the current contact state of the robot:

$$\begin{aligned} \bar{\mathbf{f}} = \arg \min_{\mathbf{f}} & \quad \|\mathbf{M}^{-1}\mathbf{f} - \tilde{\mathbf{g}} - \ddot{\mathbf{x}}\|_Q + \|\mathbf{f}\|_R \\ \text{s.t. } & f_{z,i} \geq f_{z,min}, \text{ if Stance, } \quad f_{z,i} = 0, \text{ if Swing} \quad (1) \\ & -\mu f_{z,i} \leq f_{x,i} \leq \mu f_{z,i}, \quad -\mu f_{z,i} \leq f_{y,i} \leq \mu f_{z,i}, \end{aligned}$$

where,  $Q, R$  are weight matrices, kept fixed for all motions.  $\mathbf{f}_i = [f_{x,i}, f_{y,i}, f_{z,i}]$  is the contact force on leg  $i = \{0, 1, 2, 3\}$  in world coordinates.  $\mu$  is an assumed friction coefficient, and the last two constraints ensure that the robot does not violate a friction cone when in contact with the ground.  $f_z$  is zero for legs in swing, and higher than a contact threshold for legs in stance. The QP returns desired contact forces  $\bar{\mathbf{f}}$  that are converted to desired leg torques for stance legs using the leg Jacobian:  $\tau_i = J_i^T \cdot \mathbf{R}^T \cdot \bar{\mathbf{f}}_i$ , where  $\mathbf{R}$  is the rotation matrix that transforms from body to world.

**Online adaptation:** The above model-based controller is borrowed from [5]. During our experiments, we observed that this controller does not robustly track a wide range of target motions, especially when the target motion is dynamic or violates linearized centroidal model assumptions, which could happen frequently for motions obtained from real animals. In such cases, the controller parameters need to be

tuned per reference motion to avoid instabilities. This requires expert intervention and is not scalable to large varieties of motions. Instead, we augment the stance controller with online adaptation to improve the overall robustness of the model-based controller, allowing the *same* parameters to generalize to different motions.

A common failure case for the robot is caused by poor CoM tracking. For example, if the CoM height is lower than desired, the swing legs might hit the ground early, causing instability. However, ‘tolerance’ to CoM tracking error is highly motion dependant, making feedback gains on CoM acceleration hard to design. To improve CoM height tracking across all motions, without requiring motion-specific tuning, we add low-gain joint position feedback to the stance legs. Specifically, at each time step  $t$ , we first estimate the foot position of stance leg  $i$  at the next time step  $t+1$ , given the desired CoM velocity:

$$\hat{\mathbf{x}}_{t+1,i}^f = \mathbf{x}_{t,i}^f - \dot{\bar{\mathbf{x}}}^{\text{robot}}_t \cdot \delta t. \quad (2)$$

Here,  $\mathbf{x}_{t,i}^f$  is the stance foot location of the  $i$ -th leg at time  $t$  in the robot frame,  $\dot{\bar{\mathbf{x}}}^{\text{robot}}_t$  is the desired CoM velocity in the robot frame,  $\hat{\mathbf{x}}_{t+1,i}^f$  is the estimated foot location at the next time, and  $\delta t$  is the control frequency. In the robot frame, the stance foot moves with inverse of the local CoM velocity, hence the velocity of the stance foot is  $-\dot{\bar{\mathbf{x}}}^{\text{robot}}_t$ ; euler integration results in Eq. 2. Next, we use inverse kinematics to find the corresponding joint angles per stance leg, and use low-gain position feedback on these desired positions.

Intuitively, Eq. 2 estimates the future joint angles that the robot would end up in, if it followed the desired CoM velocity at the current time step. An alternative approach for determining desired joint angles for stance legs could be to use the joint angles from the reference motion directly. However, these might not be feasible on the robot at execution time. For example, if the foot configuration at the start of stance is different from the reference due to early touch down, leg angles throughout the stance phase will be different from reference motion. Accurately following the joint angles from the reference would require a leg to break contact and re-position the foot. Instead, by using Eq. 2 we can follow the CoM trajectory in stance without requiring very close correspondence between the reference and actual leg joint angles in stance. This online adaptation improves the robustness of the model-based controller, and allows it to follow different animal motions using the same parameters.

**3) Swing Controller:** Swing foot trajectory is an important part determining the motion ‘style’ and has been shown to be distinct for different animal gaits [44]. Hence, following the swing foot motion as close as possible is crucial for realistic motion imitation of different animal gaits.

**Online adaptation:** The reference motion trajectory basically does not change when the robot operates. However, feedback during swing foot placement can be important for disturbance rejection and increasing stability of legged robots [45]. Therefore, we also add online adaptation to the swing foot position to increases robot stability, especially against real-world disturbances like early touch down, while

mimicking the original style of the animal motion as close as possible.

The target foot position  $\mathbf{x}_i^{f,\text{ref}}$  of swing leg  $i$  consists of the reference motion  $\bar{\mathbf{x}}_i^f$  and a feedback on the desired CoM velocity  $\dot{\bar{\mathbf{x}}}^{\text{robot}}$  in the robot frame:

$$\mathbf{x}_i^{f,\text{ref}} = \bar{\mathbf{x}}_i^f - K(\dot{\bar{\mathbf{x}}}^{\text{robot}} - \dot{\mathbf{x}}^{\text{robot}}) \quad (3)$$

Here,  $K$  is a constant gain term. The feedback term resembles a Raibert [11] stepping policy, and adds a disturbance rejection mechanism to the purely feed-forward animal reference motion. For example, if the CoM velocity goes higher than in the demonstration due to a disturbance, the swing trajectory compensates by stepping outwards and stabilizing the robot, while maintaining the overall style of the animal motion through  $\bar{\mathbf{x}}_i^f$ . Finally, we use inverse kinematics per leg to convert the desired foot position from robot frame to joint angles and follow this joint trajectory using position control.

### C. Trajectory optimization with DMPs

Reference trajectories from animal motions might not be dynamically feasible for the robot, or might violate some assumptions of our model-based controller. For example, our controller assumes that the stance foot does not slip, but some animal motions might include feet sliding on the ground, making them infeasible for our model. Additionally, naively mimicking animal motion might not result in high-performing motion, due to dynamical mismatch between robots and animals. Changing (i.e. optimizing) input reference motions in a way to resolve this inconsistency would provide better robot performance. The question arises: what is an ideal way to represent input motions and how can we modify them efficiently while maintaining the style of the original demonstration?

We choose a dynamic movement primitive (DMP) parametrization to represent swing trajectories. DMPs are trajectory generators that combine linear fixed-point attractors with function approximators whose parameters can be learned from demonstrations. We refer to Ijspeert et al. [12] for an overview on DMPs; a demonstration  $\xi$ , which comes from the retargeted animal motion in our case, is represented by learning parameters  $(w^1, w^2, \dots, g, a)$ :  $DMP(w^1, w^2, \dots, g, a) \rightarrow \xi$ . Weights  $\mathbf{w} = (w^1, w^2, \dots)$  are weights of the non-linear function approximator and encode the overall style of the motion, while  $g$  represents the start point of the DMP and  $a$  is its amplitude. Specifically, we use rhythmic DMPs which encode cyclic motions whose time period, amplitude, and start point can be modulated by changing the parameters of the DMP. We learn separate  $DMP_i$  for each dimension of the reference trajectory  $\xi_i$ , using 100 basis functions per DMP. Reference motions include the CoM position in 6-dimensions, CoM linear and angular velocity, and swing foot trajectory in 3-dimensions for 4 legs (a total of 24 DMPs). DMPs are initialized to mimic the animal motion, and then sent as reference motion to a model-based controller in simulation.

Once DMPs are learned, their parameters are optimized to improve robot performance. More specifically, we maximize

the cumulative reward of the resultant trajectory in simulation (reward described in Section IV-A). Note that we optimize  $g, a$  only while keeping  $w$  fixed to maintain the original style of the animal motion during trajectory optimization. Figure 7b shows an example of a swing foot trajectory modified by the optimization. We use a gradient-free optimization method CMA-ES [13] to optimize the  $g, a$  of the DMPs that represent the z-motion of swing trajectories of all 4 legs. This leads to an 8-dimensional optimization where the swing retraction ( $g$ ), and amplitude ( $a$ ) is optimized to maximize episodic reward:  $g_{i=1\dots 8}, a_{i=1\dots 8} = \arg \min_{g_i, a_i} \sum_{t=1}^T r_t$ , where  $T$  is the total length of an episode, and  $r_t$  is the step reward, detailed in Section IV-A. We optimize the DMP parameters over 200 iterations of CMA-ES taking about 50 minutes in simulation.

Because our offline whole-body trajectory optimization procedure takes the full dynamics of the robot, including contacts, into account to improve the reference motion, the optimized trajectory can successfully be transferred to hardware without any fine-tuning. Including domain randomization techniques can further improve the robustness of the optimized trajectory, but we leave this for future work.

#### IV. EXPERIMENT

We evaluate our method by imitating four animal motions – trot, pace, turn, and side-step. The motion data, found publicly from Zhang et al. [46], is pre-processed using the retargeting procedure (Section III-A) to map the animal motion to an A1 robot. The target motions can be seen in Figure 2 and the supplemental video. Our experiments are conducted in a PyBullet simulation [47] and on hardware, with an A1 quadruped from Unitree Robotics [14] (Fig. 2). A1 is a four-legged robot with 3 servos on each leg. It has 4 force sensors placed on each foot that can measure ground reaction forces, along with joint position, velocity, torque sensors. Robot position is estimated using onboard IMU and kinematic filtering, adapted from open-source code [2].

Our experiments show that our method can mimic the desired animal motions in simulation and the optimized trajectory can be zero-shot transferred to hardware. We also present comparisons to RL-based approaches from literature, which learn one policy per motion, and compare performance in both simulation and on hardware. Additionally, we compare against variants of model-based control [15] without trajectory optimization. These experiments help to understand how the different components in our method contribute to the robustness that we achieved.

##### A. Reward Function

We use the same reward function as Peng et al. [2] when training baseline RL policies and measuring overall performance. The per-step reward  $r_t \in [0, 1]$  is

$$r_t = w^p r_t^p + w^v r_t^v + w^e r_t^e + w^{rp} r_t^{rp} + w^{rv} r_t^{rv} \quad (4)$$

$$[w^p, w^v, w^e, w^{rp}, w^{rv}] = [0.25, 0.05, 0.1, 0.3, 0.3].$$

Individual components are:

- Joint pose reward  $r_t^p = \exp[-5 \sum_j \|\bar{\mathbf{q}}_t^j - \mathbf{q}_t^j\|^2]$ ,

- Joint velocity reward  $r_t^v = \exp[-0.1 \sum_j \|\dot{\bar{\mathbf{q}}}_t^j - \dot{\mathbf{q}}_t^j\|^2]$ ,
- End-effector reward  $r_t^e = \exp[-40 \sum_i \|\bar{\mathbf{x}}_{t,i}^f - \mathbf{x}_{t,i}^f\|^2]$ ,
- CoM position reward  $r_t^{rp} = \exp[-20 \|\bar{\mathbf{x}}_{pos,t}^{robot} - \mathbf{x}_{pos,t}^{robot}\|^2 - 10 \|\bar{\mathbf{x}}_{ori,t}^{robot} - \mathbf{x}_{ori,t}^{robot}\|^2]$ ,
- CoM velocity reward  $r_t^{rv} = \exp[-2 \|\dot{\bar{\mathbf{x}}}_{pos,t}^{robot} - \dot{\mathbf{x}}_{pos,t}^{robot}\|^2 - \|\dot{\bar{\mathbf{x}}}_{ori,t}^{robot} - \dot{\mathbf{x}}_{ori,t}^{robot}\|^2]$ .

Here,  $\bar{\mathbf{q}}_t^j$  and  $\mathbf{q}_t^j$  stand for the desired and current joint positions,  $\dot{\bar{\mathbf{q}}}_t^j$  and  $\dot{\mathbf{q}}_t^j$  are the desired and current joint velocities,  $\mathbf{x}_{t,i}^f$  represents the current foot position,  $\mathbf{x}_{pos,t}^{robot}$  and  $\dot{\mathbf{x}}_{pos,t}^{robot}$  denote the CoM linear position and velocity,  $\mathbf{x}_{ori,t}^{robot}$  and  $\dot{\mathbf{x}}_{ori,t}^{robot}$  are the CoM angular position and velocity. The higher the reward, the closer the robot motion is to the demonstration.

##### B. Comparison experiments

Here, we describe the different approaches compared in our paper. The baselines are chosen to highlight the robustness of a unified model-based controller, and the efficacy of our approach (**MBC-DMP**) at mimicking animal motions. Note that all model-based controller baselines also use the online adaptations described in Section III-B, which was essential to get robust performance across the 4 motions considered in our experiments.

- **DeepMimic (RL):** We compare our approach against DeepMimic [1], a learning-based approach that learns an RL policy per reference motion. We use the reward function described in Section IV-A, train each policy for 100 million simulation steps using Proximal Policy Optimization [48]. We use the open-source implementation to train policies for trot, pace, turn, and side-step motions. For each target motion, we train 2 RL policies with different random seeds and report average performance in Figure 5. We apply policies learned in simulation to hardware with no fine-tuning, to make the comparison fair to our approach.
- **Model-based Controller with Raibert Swing (Raibert):** Next, we compare our method against a model-based method from Kang et al. [15] which uses animal reference for CoM motion, but uses linear swing trajectories of fixed time length  $T_s$  that reach a footstep calculated using the Raibert heuristic:  $\mathbf{x}_i^{f,ref} = 0.5T_s \dot{\mathbf{x}}^{robot} - K(\dot{\bar{\mathbf{x}}}^{robot} - \dot{\mathbf{x}}^{robot})$ . Compared to Eq. 3, we note that this method does not take the animal motion into account, while our approach augments the animal motion with a stabilizing feedback mechanism. Because each gait has unique swing foot motion style, using pre-defined swing trajectories could have difficulties in reproducing natural and diverse motion styles.
- **Model-based Controller (MBC) :** In this baseline, we send the animal motion trajectories to our model-based controller without any trajectory optimization. This experiment highlights the importance of whole-body trajectory optimization in simulation.
- **Model-based Controller with DMP Optimization (MBC-DMP, ours):** Our approach which uses offline trajectory optimization to adapt the reference motion sent to the model-based controller.

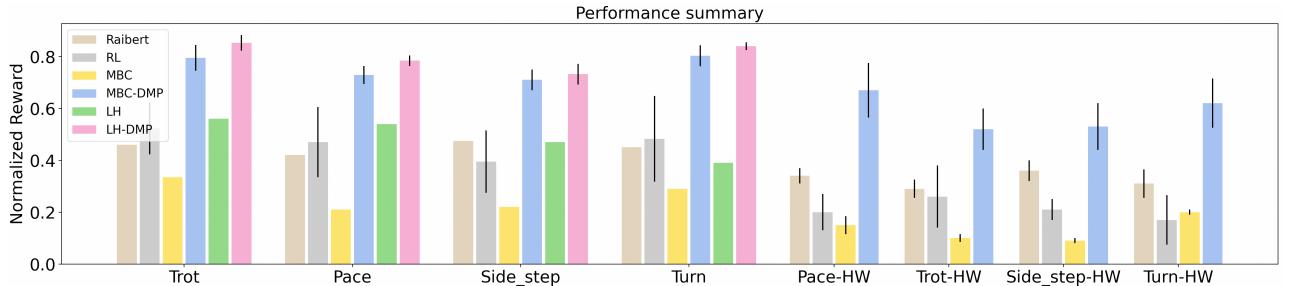


Fig. 5: Comparison against other baselines. Our method (MBC-DMP) outperforms other learning-based (RL) or model-based (Raibert, RL, MBC, LH) in simulation and on hardware, except for LH-DMP. Note that methods with long-horizon predictions, LH and LH-DMP, cannot easily be deployed to hardware due to their computational costs.

- **Long horizon Model-predictive control (LH):**

Whole-body control of quadrupedal robots can be improved by using a receding-horizon model predictive control approach that plans over multiple time steps, instead of instantaneous forces, as in Eq. 1. We utilize the approach from Di et al. [5] to solve a higher-order QP to plan actions over a horizon of 10 steps, instead of a single step. During stance, this long-horizon convex MPC controller uses the linearized centroidal model to predict future states, and plans a sequence of contact forces that lead to a desired CoM trajectory. For swing control, we use the same setup as ours. This experiment is aimed to test if online MPC can replace offline trajectory optimization.

- **Long horizon MPC with DMP Optimization (LH-DMP):**

Lastly, we augment the long horizon model-predictive control (LH) with our DMP-based trajectory optimization (LH-DMP). We expect that this method outperforms our method because it reasons over a longer horizon of the reference motion. However, both long-horizon predictive control methods, LH and LH-DMP, cannot easily be deployed to hardware due to their expensive computational costs. Therefore, we only conduct simulation experiments for analysis.

Figure 5 shows comparison experiments between the different baseline approaches and our approach (MBC-DMP). In simulation, we observe that DeepMimic (RL) is able to replicate all target motions well. However, when transferred to hardware, we see a significant drop in performance, owing to the sim-to-real gap (e.g.  $0.483 \pm 0.195$  in sim vs.  $0.17 \pm 0.095$  on hardware for turn). We observe that RL policies tend to be very conservative, and do not lift the robot legs sufficiently during swing. This causes early-contact on hardware which degrades the performance on the real robot. Peng et al. [2] show that online adaptation can improve the performance of RL on hardware. In contrast, our method can generalize to hardware with no real-world adaptation.

Model-based control with no trajectory optimization (MBC) achieves good performance in pace and trot, but poor performance in side-step and turn in simulation (e.g. 0.223 using MBC vs.  $0.715 \pm 0.012$  using our approach for turn). In side-step and turn, the robot falls over due to low swing leg retraction, and early contact, increasing the disturbance on the system. When applied to the real robot, the pace and

trot motions also deteriorate in performance. As an example, Figure 7b shows the tracking of the left back leg during a pace motion in simulation. The x-tracking of the foot deviates from the reference during swing, made worse on hardware due to tracking errors. Although online adaptation of the model-based controller manages to maintain robot stability, the overall imitation reward is very low. On the other hand, our approach learns to optimize the swing leg retraction in simulation, also improving performance on hardware.

The model-based baseline Raibert achieves lower performance than our approach on all gaits, with turning motion seeing the largest drop in simulation ( $0.453$  vs.  $0.803 \pm 0.008$ ). Turning is a challenging motion, with robot legs stretching outwards, more in the rear legs and lesser in the front legs. If the swing leg trajectories are designed to be symmetric across all legs, as in [15], not only is the swing motion not natural, but also the CoM turning motion does not follow the reference. This experiment highlights the importance of following both reference (animal) swing and stance motions to generate natural motions. Due to the robustness of Raibert swing trajectories combined with our model-based controller, Raibert does not experience a significant performance drop between sim and real, but the overall performance is still lower than our approach.

Our approach (MBC-DMP) outperforms all RL- and model-based baselines that plan instantaneous actions in simulation and on hardware. The DMP optimization improves motion tracking in simulation, and also generalizes to hardware with little performance deterioration in most gaits (Fig. 5). Fig. 7a compares the optimized vertical foot motion with the original trajectory of the back left leg in a pace gait, where the optimization increases the leg clearance for swing trajectory, improving tracking and stability. Figure 6 shows that the optimized DMP reference trajectory achieves good hardware performance on challenging motions like turning ( $0.803 \pm 0.012$  in sim vs.  $0.627 \pm 0.096$  on hardware). In the side-step motion, we observe deterioration in performance on hardware due to slipping. Side-step requires a wide robot stance which makes the leg configuration at the edge of the friction cone, making it easy for the robot to slip. Since we do not do any system identification on the actual friction of the floor, the model-based controller is unable to compensate for the slippery floor. We believe that this behavior can be improved by real-world fine-tuning, which can be very

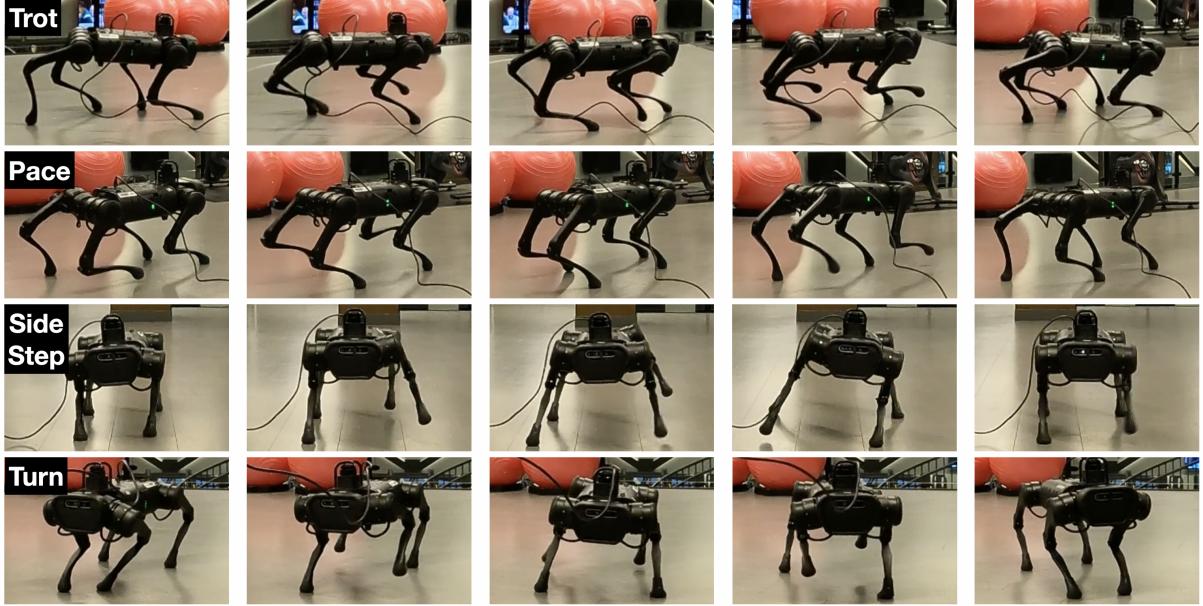
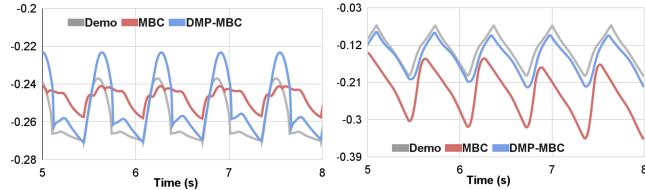


Fig. 6: Snapshots of our approach in action on the A1 robot - Turn, Trot, Pace and Side-stepping motions. A *single* model-based controller with online adaptation achieves all the motions, with no fine-tuning.



(a) Foot position in z-axis (m) (b) Foot position in x-axis (m)

Fig. 7: (a) Tracking in z-axis. DMP optimization increased the amplitude of the trajectory, tracking error was decreased by 24%. (b) Tracking in x-axis. With optimization, the constant drift was reduced, tracking error was decreased by 92%.

efficient as once the friction coefficient is identified, it can be used for all motions.

The hypothesis that offline trajectory optimization is not needed if planning over a long horizon is disproved in our experiments. Despite using a longer horizon, and online adaptation, long-horizon MPC (LH) performs worse than our approach on all simulated tasks (0.39 using LH vs.  $0.803 \pm 0.012$  using our approach on turn). On the other hand, when the reference trajectory sent to long-horizon MPC is optimized using our DMP parametrization (LH-DMP), we see that there is a rise in performance. This further reinforces that even with long horizon planning, offline trajectory optimization is crucial for robust mimicking of varied animal motions. As compared to long-horizon MPC (LH-DMP), we observe that the loss in performance is minor when using instantaneous optimization ( $0.831 \pm 0.004$  using LH-DMP versus  $0.803 \pm 0.012$  using MBC-DMP on turn.) This motivated our decision to perform hardware experiments using an instantaneous QP, and leave real-world evaluation of costly LH-DMP for future work.

### C. Motion stitching

We create new motions by stitching different motion trajectories to verify that our method can be used for imitating very long motions. The stitched motions are created by directly concatenating individual reference motions  $\xi_{st} = \xi_1 \oplus \xi_2$ , for example by concatenating pacing and trotting trajectories. However, these stitched trajectories cannot be directly tracked by the model-based controller since the transition between the motions is not smooth. Therefore, we first fit each elementary motion  $\xi_i$  independently with DMPs. Then, we optimize all DMPs together w.r.t the reward function mentioned in Sec IV-A. To warm start the optimization, we initialize the DMPs with the parameters for individual optimized motion. Our method successfully imitates four stitched motions: (1) Pace + Trot, (2) Trot + Turn + Trot, (3) Side Step + Trot + Turn, and (4) Trot + Side Step + Reverse trot. Real-world results can be seen in the supplementary video.

## V. CONCLUSION

In this work, we propose a unified framework for transferring agile animal motions to real-world robots. Our framework uses trajectory optimization and a model-based controller with online adaptation. Experiments show that our model-based controller can imitate reference motions robustly, and the quality of imitation can be further improved by trajectory optimization. We validate our framework by applying our model-based controller to four motions in simulation and hardware. We compare our approach with learning-based and model-based baselines. We show that our method outperforms the baseline methods in simulation and on the real-world A1 robot. Although our method currently does not include any sim2real adaptation, incorporating it into our method would bring further capabilities such as enhanced robustness to external perturbation. We are also

interested in combining our method with other learning-based methods to learn more dynamics motions, for example, back flip and jumping motions.

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