Learning Bipedal Walking for Humanoids with Current Feedback

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Abstract— Recent advances in deep reinforcement learning (RL) based techniques combined with training in simulation have offered a new approach to developing control policies for legged robots. However, the application of such approaches to real hardware has largely been limited to quadrupedal robots with direct-drive actuators and light-weight bipedal robots with low gear-ratio transmission systems. Application to life-sized humanoid robots has been elusive due to the large *sim-to-real* gap arising from their large size, heavier limbs, and a high gear-ratio transmission systems.

In this paper, we present an approach for effectively overcoming the *sim-to-real* gap issue for humanoid robots arising from inaccurate torque tracking at the actuator level. Our key idea is to utilize the current feedback from the motors on the real robot, after training the policy in a simulation environment artificially degraded with poor torque tracking. Our approach successfully trains an end-to-end policy in simulation that can be deployed on a real HRP-5P humanoid robot for bipedal locomotion on challenging terrain. We also perform robustness tests on the RL policy and compare its performance against a conventional model-based controller for walking on uneven terrain.

I. INTRODUCTION

As conventional model-based approaches for humanoid locomotion continue to improve, such as those based on preview control [1] or model predictive control (MPC) [2], their robustness against unexpected disturbances and inaccurate modeling is still an elusive research goal. On the other hand, rapid advancements in RL-based control methods for legged locomotion have shown outstanding performance in unstructured, and uncontrolled environments for quadrupedal robots [3], [4], [5], [6] and even bipedal robots [7], [8], [9]. It would be appealing to apply similar methods to develop walking controllers for larger and heavier humanoid robots too.

Training a capable policy using deep RL is data intensive and can be damaging to the hardware. Physics simulation environments offer a safe way to collect a large amount of data, so policies are typically trained in simulation and then transferred to the real system. However, the simulated environment can fail to capture the richness of real-world dynamics. This gives rise to the "reality gap", more commonly known as the *sim2real* gap. The *sim2real* gap can cause the performance of a policy trained in simulation to drop drastically when deployed on the real hardware. In the case of life-sized humanoid robots such as the HRP-series humanoids, this gap can have a more critical effect

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Fig. 1: **HRP-5P humanoid robot** trained to perform bipedal locomotion via model-free reinforcement learning in MuJoCo (top); RL policy transferred to the real robot (bottom). We make use of the feedback from measured actuator current to account for the poor torque tracking on the real system.

on the robot's stability during walking, compared to the quadrupedal robots or lightweight bipedal robots that are used in most of the recent works. Furthermore, these robots have heavy limbs to support a heavy upper body, which requires a high gear-ratio transmission system with a large output torque range. Consequently, the actuators used have relatively large armature (also known as rotor inertia) and low backdrivable joints. High gear-ratio also induces other hard-to-model but non-trivial effects such as joint friction and back-EMF. This makes the *sim2real* gap for a robot such as HRP-5P (Figure 1) much larger than the lighter and more backdrivable bipedal systems like Cassie and Digit. Hence, the suitability or relevance of recent *sim2real* successes in the literature for this robot is a matter of investigation.

In this paper, we develop a system to train bipedal walking controllers in simulation and deploy them on a HRP-5P humanoid robot. HRP-5P is a high-power, electrically-actuated, 53 degrees of freedom (DoF) humanoid robot weighing over

100kg, with a height of $182cm$ [10]. Our key insight is that the *sim2real* gap is mainly a result of poor torque tracking due to the effect of back-EMF. We simulate the back-EMF effect during training and develop a policy that incorporates current feedback from the motors. The resulting policy learns to actively use the current feedback signal and compensate for the inaccurate torque-tracking within the motor drivers. We then successfully deploy this policy on a real HRP-5P robot. Notably, our experiments show that it is possible to bridge the "reality gap" without relying on memory-based policy architectures or resorting to unreasonably wide randomization of dynamics parameters.

To the best of our knowledge, this is the **first demonstration of an end-to-end policy for controlling a life-size humanoid robot** to achieve dynamic stability. We demonstrate locomotion over uneven and compliant surfaces. The policy runs onboard the robot; and can receive user commands via a joystick. We also compare the qualitative performance of the RL policy to an open-source model-based walking controller over the same surfaces.

II. RELATED WORK

A. *Reinforcement Learning and Sim-to-Real for Legged Robots.*

Reinforcement Learning has become a powerful approach for synthesizing controllers for legged robots. Control policies are typically trained in simulation and then transferred to the hardware, i.e., sim-to-real. A large number of such works focus on quadrupedal robots, e.g., ANYmal[4], Laikago[11], A1[5], Jueying[12] and Mini-Cheetah[3]. There are also successes in applying the same approach for bipedal robots, e.g., on the Cassie [7], [13], [14], Digit[15], [16] and NimbRo-OP2X[17]. DeepWalk [17] demonstrates a single learned policy for a real humanoid robot that can achieve omnidirectional walking on a flat floor. However, it is unclear whether the robot can achieve a dynamically stable walk. The robot platform also appears to have relatively large feet which may help the robot to avoid falls even under a fragile RL policy.

Important ingredients for successful sim-to-real include (1) careful system identification, e.g, a learned actuator model is incorporated in the simulator to account for hard-to-model actuator dynamics [4], [18], (2) dynamics randomization[19], where simulation parameters such as mass and inertia are randomized to improve robustness of the policy (3) domain adaptation, where the policy learns to adapt based on the history of observations and actions, e.g, [6], [5], [13]. While successful on several legged robot platforms, we are yet to see such approaches being successfully applied to life-size (e.g., more than 170cm) humanoid robots with heavy limbs. This is not due to lack of attempt, prior work has explored how to apply reinforcement learning to the NASA Valkyrie robot, e.g., [20], but so far no *sim2real* is demonstrated. In this work, we demonstrated the first *sim2real* success on such a platform, with a focus on how the choice of input to the policy and accurate modeling of the system play important roles.

Again, implementing learned policies on the hardware of a bulky humanoid robot, such as Valkyrie and the HRP-series robots, presents significantly greater challenges than lighter bipedal robots, such as Cassie. Safety risks are also amplified in the case of a bigger robot with powerful actuators.

B. *Control for Humanoid robots.*

Conventional model-based approaches for humanoid bipedal locomotion consist of local feedback controllers to track Zero-Moment-Point (ZMP) or Center-of-Mass (CoM) trajectories precomputed in an offline process. Stabilization control through the use of divergent component of motion (DCM) has been extensively studied in prior works [21], [22] and applied to real robots. It relies on the linear inverted pendulum model [23] of bipedal walking. Other recent works such as [1], on the other hand, do not rely on biped-specific dynamics and instead perform online generation of centroidal trajectory based on preview control for impressive multi-contact motion. The method uses a preview control scheme to generate a centroidal trajectory and a stabilization scheme to correct errors in tracking the trajectory. Since the trajectory is generated online the robot can react robustly to environmental disturbances.

Generally, the output of such controllers is in the form of desired ZMP, CoM, and/or contact wrenches, which are then fed to Quadratic programming (QP) solver to compute desired joint positions. The desired joint positions are then tracked by a local proportional-derivative (PD) controller for stiff position control. This is in sharp contrast to RL approaches mentioned above that use low PD gains to achieve compliant tracking.

III. BACKGROUND

The motor control system on the HRP-5P robot (and generally, on most robot transmission systems) is shown in Figure 2. The block structure consists of a PD controller which computes the desired torque command given the reference position from a higher-level controller and measured position from the joint encoder. The desired torque command - or equivalently, the current command (assuming a proportional relationship between torque and current for a brushed-DC motor) is then sent to a proportional-integral (PI) controller. The PI controller tries to track the current command given the measured current from the current sensor in the motor. The output of the PI controller is fed to the motor power amplifier, which in turn drives the motor.

The key observation here is that the PI controller is unable to precisely track the torque commands, as desired by the higher-level controller or policy, often leading to significant torque tracking errors. We suspect that such tracking errors could be caused largely due to the effect of the back electro-motive force (EMF). When the motor rotates, the back-EMF creates a counter-voltage that opposes the applied voltage, reducing the current flowing through the armature, leading to tracking errors. This makes the real system vastly different from simulation environments where the desired torque command is applied *exactly* to the actuator without
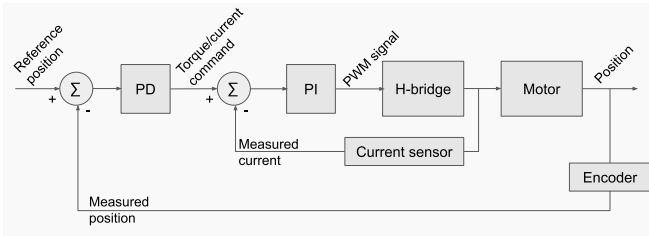
Fig. 2: **Block diagram of the motor control system in HRP-5P.** The torque computed by the PD controller is tracked by a PI current controller, albeit, with significant tracking errors. These tracking errors form a crucial component of the *sim2real* gap.

errors. Other factors such as the battery voltage, resistance of the transmission cables, changes in load, or poorly tuned gains of the PI controller may also contribute to poor current tracking.

IV. APPROACH

In this section, we detail each component involved in training the RL policy. The training is performed in the MuJoCo simulator [24]. In particular, we describe how we overcome the poor torque-tracking on the real robot by simulating Back-EMF effect and using current feedback for the policy. Since the current and torque on the robot's actuators are assumed to be proportional, we use the terms interchangeably through the paper.

A. Observations and actions.

Similar to prior work in simulation [25], the input to our policy consists of the robot state, the external state, and a clock signal. The robot state includes the joint positions and joint velocities of each actuated joint (6 in each leg), roll and pitch orientation and angular velocity of the root (pelvis). And, more relevant to the contributions of this work, we include the motor-level torque signal for each actuator in the robot state. In simulation, this signal is equal to the actual torque applied to the actuators in the previous timestep. On the real robot, it needs to be derived from the raw current measurements, as explained in V-B. The external state vector comprises of a $3D$ one-hot encoding to denote the walking mode — $[0, 0, 1]$ for standing and $[0, 1, 0]$ for stepping in-place and $[1, 0, 0]$ for walking forward. It also includes a $1D$ scalar which acts as a reference value depending on the mode: If the active mode is *Stepping*, the reference value denotes the turning speed; for *Walking* it denotes forward walking speed; and is ignored for the *Standing* mode.

The policy also observes a clock signal that depends on a cyclic phase variable ϕ. This variable is also used to define a periodic reward term in our reward function to generate walking behaviors. As in [25], we do a bijective projection of ϕ to a $2D$ unit cycle:

$$\text{Clock} = \left\{ \sin\left(\frac{2\pi\phi}{L}\right), \cos\left(\frac{2\pi\phi}{L}\right) \right\}, \quad (1)$$

where L is the cycle period. ϕ increments from 0 to 1 at each control timestep and reset to 0 after every L timesteps. Clock is then used as input to the policy.

The policy outputs desired positions of the actuated joints in the robot's legs. These predictions from the network are added to fixed motor offsets corresponding to the robot's half-sitting posture. The desired positions are tracked using a low-gain PD controller, which computes the desired joint torque as follows:

$$\text{tau}_{pd} = K_p(q_{des} - q) + K_d(0 - \dot{q}), \quad (2)$$

where K_p and K_d denote the proprotional and derivate gain factors respectively. q_{des} is the policy prediction summed with the fixed motor offsets. q and $\dot{q}$ denote the current joint position and velocity.

B. Reward function.

Our reward design ensures that a reference motion is not needed. Instead, we rely on several hand-crafted reward terms that promote the desired robot behavior in 3 modes: stand in place, step in-place (including turning) and walk forward given a reference speed. This requires the robot to develop a periodic bipedal gait, follow the mode and reference velocity command and maintain a fixed height. Further, we introduce terms to develop a more realistic motion that will allow *sim2real* transfer in a realistic and safe manner.

Bipedal Walking. We introduce reward terms for promoting a symmetrical bipedal walking gait characterized by a periodic motion of the legs, alternating between double-support (DS) phases, and the single-support (SS) phases. Depending on the phase variable ϕ and the desired mode (*standing* or *walking*), the rewards for feet ground reaction forces (GRF) and body speeds are computed.

For example, when ϕ lies in the first single-support region of the gait cycle (the left foot is in the swing phase and the right foot is in the support phase), larger values of GRF on the left foot are rewarded negatively while larger values of GRF on right foot lead to positive reward. Simultaneously, higher speeds for the left foot are incentivized but penalized for the right foot.

The definition of the bipedal walking terms — ground reaction forces at the feet r_{grf} and the feet body speeds r_{spd} — are adopted exactly from [25]:

$$r_{\text{grf}} = I_{left}^{grf}(\phi) \cdot F_{left} + I_{right}^{grf}(\phi) \cdot F_{right} \quad (3)$$

$$r_{\text{spd}} = I_{left}^{spd}(\phi) \cdot S_{left} + I_{right}^{spd}(\phi) \cdot S_{right} \quad (4)$$

where F_{left} and F_{right} denote the GRF and S_{left} and S_{right} denote the body speeds on the left and right foot respectively. We refer the reader to [25] for a detailed explaination of the "phase indicator" functions I_*^{grf} and I_*^{spd} for modulating the reward coefficients for ground reaction forces and feet speeds.

For *standing*, the DS phase is expanded to span the entire gait cycle, and the policy is rewarded to maximize ground reaction forces on both feet while minimizing the feet speeds.

Root Velocity, Orientation and Height. The root linear velocity reward term is a simple cost on global speed $^x v_{root}$ of the root link of the robot in the x-direction.

$$r_{\text{rv}} = \exp(-10 \cdot \|\,^x v_{root} - \,^x \hat{v}_{root}\|^2) \qquad (5)$$

The root yaw velocity term encourages the angular velocity of the root ω_{root} to be close to the desired velocity $\hat{\omega}_{root}$.

$$r_{\text{av}} = \exp(-10 \cdot \|\omega_{root} - \hat{\omega}_{root}\|^2) \qquad (6)$$

During training, the active mode is randomly selected between *Standing*, *Stepping*, and *Walking* at the start of an episode. Depending on the active mode, the scalar input for the reference value is sampled from a uniform distribution, i.e., $^x \hat{v}_{root}$ from a range of $[0, 0.4]\,\text{m s}^{-1}$ if mode is *Walking* and $\hat{\omega}_{root}$ from a range of $[-0.5, 0.5]\,\text{rad/ sec}$ if mode is *Standing*.

We also reward the policy to maintain the root height h_{root} at a desired value $\hat{h}_{root} = 0.79\,\text{m}$:

$$r_{\text{height}} = \exp(-40 \cdot (h_{root} - \hat{h}_{root})^2). \qquad (7)$$

Safe and realistic motion. In addition to the above terms, we also try to create a motion that remains close to the nominal posture of the robot to avoid unnecessary sways. This is critical for safe deployment on the real robot, which has a wide range of motion and significantly strong actuators.

To encourage the robot to maintain an upright posture, we use a reward term to minimize the distance between the floor projection of the head position $^{x,y}\mathbf{p}_{head}$ and the root position $^{x,y}\mathbf{p}_{root}$. This prevents the robot from developing a leaned-back behavior and excessively swaying the upper body:

$$r_{\text{upper}} = \exp(-10 \cdot \|\,^{x,y}\mathbf{p}_{head} - \,^{x,y}\mathbf{p}_{root}\|^2). \qquad (8)$$

We use a term to penalize the distance of the current joint positions $\mathbf{q}$ from the nominal "half-sitting posture", $\mathbf{q_{nominal}}$:

$$r_{\text{posture}} = \exp(-\|\mathbf{q} - \mathbf{q_{nominal}}\|^2). \qquad (9)$$

We also place a penalty on joint velocities $\dot{\mathbf{q}}$ above 50% of the maximum joint velocity $\dot{\mathbf{q}_{\mathbf{lim}}}$.

$$r_{\text{jv}} = \exp\left(-5 \times 10^{-6} \sum_{\dot{\mathbf{q}} > k \cdot \dot{\mathbf{q}_{\mathbf{lim}}}} \|\dot{\mathbf{q}}\|^2\right). \qquad (10)$$

The full reward function is given by:

$$r = w_1 r_{\text{grf}} + w_2 r_{\text{spd}} + w_3 r_{\text{rv}} + \dots$$
$$w_4 r_{\text{av}} + w_5 r_{\text{height}} + w_6 r_{\text{upper}} + \dots$$
$$w_7 r_{\text{posture}} + w_8 r_{\text{jv}}, \qquad (11)$$

where, the weights w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8 are set to 0.225, 0.225, 0.100, 0.100, 050, 0.100, 0.100, 0.100, respectively.

C. Dynamics Randomization.

Since policies trained in simulation interact with an imperfect representation of the world, they are prone to overfitting and show brittleness on the hardware. A common approach to overcome this is to randomize various robot model and environment parameters, such as mass, intertia, motor strength, latency, ground friction, etc [13], [5].

In our work, we carefully select the variables that are needed to be randomized for a better transfer. Firstly, we can expect the mass and position of the center of mass (CoM) of each link to be different on the real system than in the simulation, due to the distribution of electronics and mechanical parts within a link. We randomize the mass of each link by 5% and randomize the CoM positions by $5cm$ at the start of each episode during training.

Secondly, prior work shows there exists a significant amount of friction between the motor and the load [26] in geared transmision systems. This frictional torque is difficult to identify or even model in simulation. MuJoCo allows the simulation of static friction and viscous friction. Hence, we randomize the static friction magnitude in the uniform range of $(2, 8)\,\text{N m}$ and coefficient for viscous friction in the uniform range of $(0.5, 5)\,\text{Nm/rad s}^{-1}$, based on coarse identification performed in [26].

Besides the mass, CoM positions, joint friction, we do not randomize any other robot dynamics parameters during training.

D. Terrain Randomization.

In order to enable the real robot to walk robustly over uneven terrain, we expose the policy to randomized terrains during training. In MuJoCo, the terrains are represented using a height fields - a $2D$ matrix comprising of elevation data. As generating new height fields online during the training may cause slowness during training, instead, we generate one random height field at the start of the training and then randomize its relative position to the flat floor in each episode. The flat ground plane and the height map are simulated simultenously, so that the floor resembles a terrain with obstacles of varying heights scattered randomly. In this way the robot is explosed to unevennes of maximum height of $3.5\,\text{cm}$. The introduction of terrain randomization in this work is done uniformly through the training; but it could also be done gradually according to a curriculum to promote smoother learning.

E. Simulating Back-EMF.

In order to simulate the phenomenon of poor torque tracking (observed on the real system), during the training phase, we introduce a modification to the applied torque for each joint at each simulation timestep. The modification is implemented by injecting a counter-torque that scales with the joint velocity, specifically, by using the following equation:

$$\text{tau}_{applied} = \text{tau}_{pd} - \text{k}_{bemf} \times \dot{q}, \qquad (12)$$

where, tau_{pd} denotes the torque at the output of the PD controller, and $\dot{q}$ represents the joint velocity. The damping coefficient, k_{bemf}, is unknown for the real system. During training, we randomize k_{bemf} to simulate different tracking behavior. The coefficient for each joint is sampled uniformly within $[5, 40]$ at every $100\,ms$.

V. EXPERIMENTS

A. RL Policy

Training Details. As in [25], both the actor and critic policies are represented by MLP architectures to parameterize the policy and the value function in PPO. Both MLP networks have 2 hidden layers of size 256 each and use *ReLU* activations. Each episode rollout spans a maximum of 400 control timesteps (equivalent to $10\,s$ of simulated time), and may reset if a terminal condition is met. Each training batch holds 64 of such rollouts. The learning rate was set to 0.0001. We use the *LOSS* method [8] , which adds an auxiliary loss term (in addition to the original PPO loss term) to enforce symmetry. Training the policy takes around 12 hours to collect a total of 120 million samples for learning all modes, on a AMD Ryzen Threadripper PRO 5975WX CPU with 32 cores.

B. Implementation on Real Robot.

We propose to include the actual applied torque in the observation vector to our RL policy. As mentioned previously, the applied torque on the real robot is extracted from the measurements of the current sensors in the motor drivers. The measured current is multiplied by the torque constant and the gear ratio corresponding to the joint and fed to the policy. It is important to note that the applied torque here refers to the torque applied at the level of the actuator. The torque applied to the load (i.e. the robot link) cannot be measured on the HRP-5P robot due to absence of joint torque sensor. The difference between the actuator-level torque and the joint-level torque can in fact be quite significant due to the presence of static friction and viscous friction.

The policy is executed on the control PC of the robot (specifications: Intel NUC5i7RYH i7-5557U CPU with 2 cores, Ubuntu 18.04 LTS PREEMPT-RT kernel), and is implemented as an *mc-rtc*[1], controller in C++. The inference is done at $40\,Hz$ with the PD controller running at $1000\,Hz$. Policy inference is quite fast, taking only around $0.2\,ms$. The global run of the controller is around $1\,ms$.

C. Sim-to-sim Validation.

While we use MuJoCo as the training environment, we perform thorough evaluations also in the Choreonoid simulator before real robot deployment. Choreonoid is traditionally a more popular choice for simulating humanoid robot controllers [27]. We use the *mc-rtc* control framework for executing the policy onboard the control PC of the robot.

This allows us to evaluate the same controller code transparently in 3 different environment: (1) in MuJoCo using
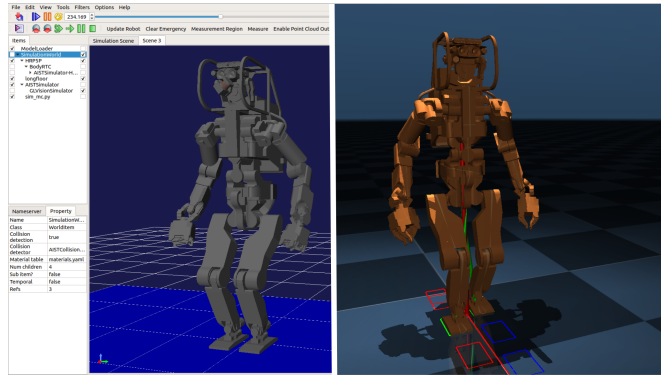
[1] https://jrl-umi3218.github.io/mc_rtc/index.html

Fig. 3: **Sim-to-sim validation.** Simulating HRP-5P in Choreonoid (left) and MuJoCo (right) using the mc-openrtm and mc-mujoco interfaces respectively.
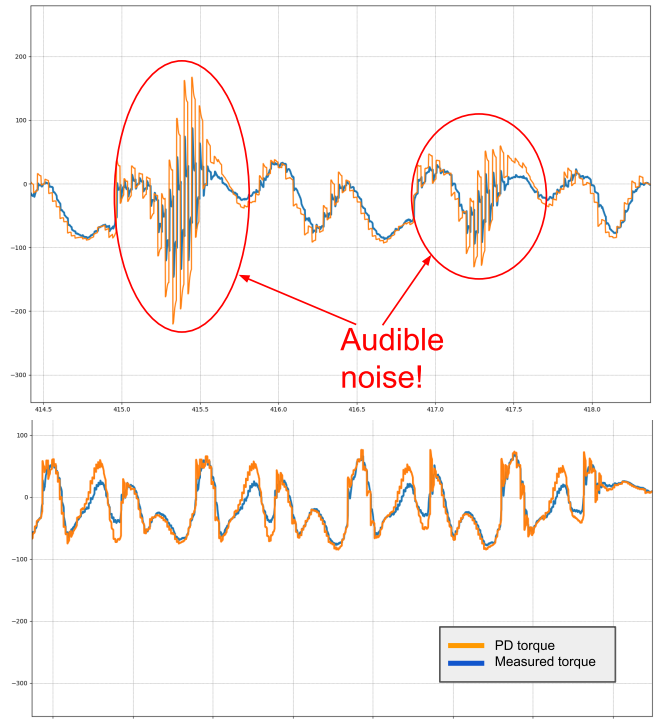

Fig. 4: **Real experiment logs for torque tracking on the right hip roll joint** for the baseline policy (top) and the policy trained with our proposed approach (bottom). We observe that the torque tracking becomes unstable for the baseline policy (circled), when the robot is turning and an audible noise can be heard from the joint. Such effects are not observed with the proposed approach, and the robot behaviour looks much more stable.

the *mc-mujoco* interface [28], (2) in Choreonoid and (3) on the real robot, both using the *mc-openrtm* interface for communicating with OpenRTM middleware [29] used in the HRP robots and Choreonoid simulator.

We found the contact modelling in Choreonoid to be more stable than the contact modelling for height fields in MuJoCo. Hence, Choreonoid forms an important part of our pipeline for evaluating policies on uneven terrain before real robot deployment. Nevertheless, besides some small differences, we did not observe any major discrepancies in the policies behavior between MuJoCo and Choreonoid

during evaluation.

D. Ablation study.

We perform ablation on the two main ingredients proposed in this work for *sim2real* success - (1) training with simulated poor torque-tracking and (2) providing torque feedback to the policy.

Although real robot experiments are expensive and testing of policies that are prone to failure can be dangerous, developing a test environment in simulation is not a credible alternative. We found that policies that succeed in simulation even in very challenging circumstances (like degraded torque tracking, uneven terrain, external perturbations), can still behave undesirably when deployed on the real robot; indicative of a large and critical reality gap. Hence, it is important to study the behaviour of the policies on the real system. We train 3 different policies to analyze the impact of the proposed approach:

1) **Policy A** forms the baseline policy. It is trained without simulated poor torque-tracking and without observing the current feedback from the actuators. When deployed on the real robot, this policy gives the worst peformance. The robot is prone to self-collision between the feet when the swing leg lands on the ground. This points to the difficulty faced by the policy in controlling the real robot's leg swing motion. This is because the policy is trained with perfect tracking in the simulation environment but is exposed to degraded tracking on the real robot. Further, we attempt to train another policy with an additional termination condition on the feet distance ($d < 0.2\,\mathrm{m}$) to promote a wider stance. In this case, self-collision is prevented on the real robot but we can observe that the torque-tracking becomes unstable in some regions of the motion with an audible noise heard from the joints (see Figure 4).

2) **Policy B** is trained with poor torque-tracking but without torque feedback. We replace the inputs corresponding to the torque-feedback with the **0** vector during training and evaluation, while keeping all other parameters the same. This policy appears robust in the simulation environment. However, when deployed on the real robot, we again observe the self-collision between the feet. The speed of the swing leg is also considerably higher, meaning that the policy finds it harder to compensate for the changing discrepancy between command and applied torque. From this observation, we conclude that providing the torque feedback (from the measured current) is vital for the policy to adapt to the degraded torque tracking environment.

3) **Policy C** is trained using the proposed approach of simulating poor torque-tracking plus providing feedback from current measurements to the policy. This policy appears significantly more stable on the real robot. Self-collision is not observed and there is no audible noise during any part of the motion. The robot could successfully walk upto several meters, including turning, stepping in-place and standing. The robot
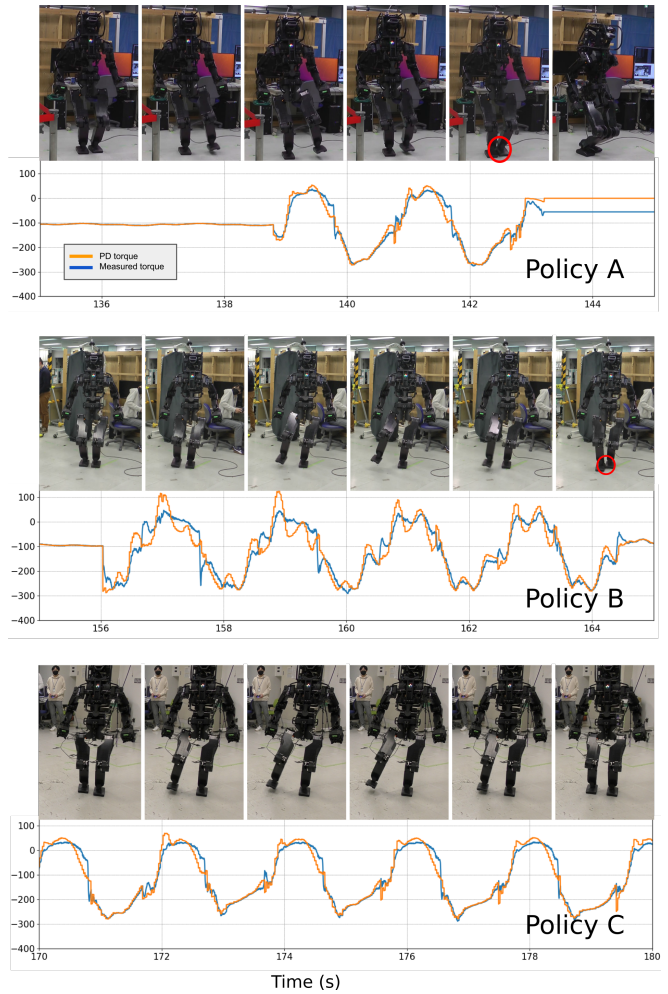

Fig. 5: **Torque-tracking performance on the RKP joint** for 3 policies. Policy A is trained without back-emf effect in sim and without feedback. Policy B is trained with back-emf but without feedback. Policy C is trained with back-emf and with the torque (current) feedback. Policy A and B both lead to self-collision between the feet (circled in red) while C is able to perform stable walking. An important observation leading to the developments in this work, is that even though the output of the RL policy is in the form of "desired joint positions", the robot can make environmental interaction only by applying torques on the links. Since there is mismatch between the PD torque exerted by the policy and the actual torque applied at the motor on the real systems, the policy needs to be trained to account for this discrepancy for improved *sim2real* transfer.

could also walk over uneven terrain consisting of rigid and soft obstacles upto $2\,\mathrm{cm}$ high.

We further analyze the real robot experiment logs corresponding to the 3 policies in Figure 5 for torque-tracking on the "RKP" (right knee pitch) joint. The "RKP" joint is chosen because the tracking errors are more noticeable for this joint. And also because the knee joint is expected to have a more consequential impact on the walking behavior (than compared to the hip yaw joint, say). We observed self-collision between the feet in case of Policy A and Policy B, while Policy C can perform stable walking and handle uneven terrain well. The tracking for the "RKP" joint for A and C looks somewhat similar, however, in case of Policy C, the feedback allows the policy to react to the tracking error

in the previous timestep and achieve better control on the swing motion. For B, the tracking is observed to be much worse. Tracking for "RCR" (right hip roll) joint for Policy A (retrained for wider feet distance) and C are also showng in Figure 4.

Notably, providing the torque feedback will not eliminate tracking errors because it is difficult for the policy to anticipate the errors in the future. We believe that incorporating history data in the observation space will also be beneficial.

E. Comparison to model-based controller.

We compare the robustness of our policy for locomotion on uneven terrain to an existing model-based controller for humanoid locomotion. For the test, we use the open-source *BaselineWalkingController*, which provides an implementation of walking control based on linear inverted pendulum mode (LIPM). This method combines online CoM trajectory generation based on preview control, ZMP feedback based on the divergent component of motion (DCM) of LIPM, and foot contact force control based on the damping control law [30], [23].

Our test environment consists of a stack of padded carpet tiles, each of thickness $0.6\,\text{cm}$, placed on a flat floor. The robot starts from some distance ahead of the stack and needs to go across while stepping on top of the stack. Since the tiles are made from a soft material, the obstacle forms a compliant support surface - which is more challenging from a balance perspective. The *BaselineWalkingController* could succeed on a stack of 3 tiles but failed on a stack of 4 tiles (nearly $2.4\,\text{cm}$ in height) — the robot loses balance and falls when the support leg is on the stacked carpets. On the other hand, the RL policy trained with our approach could succeed on a stack of 5 carpets ($= 3\,\text{cm}$ high) on 2 of 2 trials. The policy also succeeds in making several partial contacts on the obstacle, where the foot is placed partially on the stack. (The tests are shown in the supplementary video.)

While there exist newer model-based approaches for humanoid locomotion that may provide greater robustness [1], [2], our test still provides valuable insights into the robustness of model-free RL polcies against LIPM-based bipedal locomotion controllers. The critical factors responsible for the higher robustness in the case of controllers based on deep RL is subject to debate, but we believe the low PD gains, feedback nature of the policy, and the absence of strict constraints on feet trajectories, may play an important role.

VI. Conclusion

In this work, we developed a system to train control policies for a life-sized humanoid robot HRP-5P. We identified that the main *sim2real* gap for these types of large robots arises from poor torque tracking of the motor control systems due to high gear-ratio. We simulated back-EMF and applied torque feedback to the policy to combat the *sim2real* gap. Policies were trained in simulation and directly transferred to the hardware.

Our experiments show that providing the current feedback is a key ingredient for reliable *sim2real* transfer. Without the proposed feedback signal, the policy is prone to failure in controlling the leg swing motion, often causing self-collision between the legs. We could not achieve *sim2real* success without simulating poor torque tracking during training. For robots with joint-level torque sensors, we believe our proposed approach can yield better performance by accounting for the frictional torque in the joints.

An important aspect of our findings was that we did not need to perform tedious manual tuning of the reward function or randomizing dynamics variables to wide, unreasonable ranges (an often omitted part from the literature). It points to the potential effectiveness of an accurate robot model for training as well as careful identification of key factors responsible in overcoming the *reality gap*.

We compared the RL policy to a conventional model-based approach for bipedal locomotion on the real humanoid platform and obtained encouraging results. The RL policy could handle obstacles over $3\,\text{cm}$ while the robot lost balance and falls with the model-based controller for obstacles over $2\,\text{cm}$. We release the source code for RL training and evaluation in MuJoCo for reproducibility [2]. The model-based controller is also public [3].

In the future, we plan to expand the framework for developing a policy for *backwards* locomotion and tackle even more challenging terrain. We also hope to identify and overcome other factors inhibiting better *sim2real* transfer.

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