Terrain RL Simulator

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Abstract

We provide 89 challenging simulation environments that range in difficulty. The difficulty of solving a task is linked not only to the number of dimensions in the action space but also to the size and shape of the distribution of configurations the agent experiences. Therefore, we are releasing a number of simulation *environments* that include randomly generated terrain. The library also provides simple mechanisms to create new environments with different agent morphologies and the option to modify the distribution of generated terrain. We believe using these and other more complex simulations will help push the field closer to creating human-level intelligence.

1   Introduction

Research in Deep Reinforcement Learning (DRL) has grown significantly in recent years, and so to has the demand for simulated environments that can be used to evaluate DRL algorithms. Some environments serve as standard benchmarks to evaluate the performance of DRL algorithms by ensuring the simulation and reward function are the same across papers. More custom environments have also been created as challenges for researchers and practitioners to achieve higher quality results. Although, many *environments* have been created, not enough is truly known about the difficulty of the *environments*. Many aspects of control problems make them challenging to solve: sparse/delayed rewards, large number of dimensions in the control space, complex dynamics, etc. For example, getting a simulated biped to walk and be robust to perturbations could be challenging, however, simple control structures were created to facilitate this problem years ago (Yin *et al.*, 2007; Kajita *et al.*, 2003; Yamaguchi *et al.*, 1999; Kajita *et al.*, 2001). The *environments* included in openAIGym have similar and simpler control problems that have recently been solved using methods less complicated than DRL. These methods include using Radial Basis Function (RBF) (Rajeswaran *et al.*, 2017)[1] and random search in the network parameter space (Salimans *et al.*, 2017; Mania *et al.*, 2018). These papers note that the improvements in DRL methods in the recent years could be focusing on the challenges related to optimization, not exploration and discovery of good actions. Although, this might be possible the authors view the prospects of finding solutions to these problems using less complex methods a sign that the environments used are too simple.

In DRL we not only want to push the boundaries of how efficiently we can solve problems but to also make strides in solving new challenging tasks that benefit from task generalization. What makes a problem challenging is not only related to the control capabilities but also the affordances available in the environment (Gibson, 1979). Therefore, we need to shape the affordances available to the agent as well to affect the difficulty of a task. We provide TerrainRLSIM[2], a library with many difficult control tasks, many that have not been seen before. We provide an easy mechanism to create even more challenging environments, via parameterized terrain generation, and encourage people to create more challenging environments.

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[1]Simple Nearest Neighbor Policy Method for Continuous Control Tasks
[2]https://github.com/UBCMOCCA/TerrainRLSim

2 RELATED WORK

There are a number of similar libraries for evaluating reinforcement learning methods. The Arcade Learning Environment is one of the first sets of *environments* that was used to show the effectiveness of DRL on tasks with high dimensional observations (Bellemare *et al.*, 2012). The OpenAIGym contains a collection of discrete action as well as continuous action tasks (Brockman *et al.*, 2016). OpenAI Roboschool is a version of OpenAIGym where a number of the *environments* have been recreated using Bullet instead of Mujoco [3].DeepMind recently released a new character motion control library (DeepMind Control Suite) that includes control problems similar to openAIGym with additional *environments* for mocap imitation (Tassa *et al.*, 2018). The OpenAI Universe is a different, large set of *environments* created with the goal of it being used to create a general agent that can play a large number of games competitively [4]. The DeepMind-lab is another set of *environments* that focuses on using visual inputs as observations, the visual input provides the agent with partial information of the environment state (Beattie *et al.*, 2016). Expanding upon the partially observable *environments* is ELF that includes a novel RTS game. (Tian *et al.*, 2017)

We provide a set of *environments* that include tasks similar to openAIGym and the DeepMind Control Suite and new more challenging control problems. The simulation *environments* use Bullet (Bullet, 2015) an open source free simulator where many continuous control libraries use Mujoco (Todorov *et al.*, 2012) a non-free, closed source piece of software. Many *environments* include terrain features in the observation. In the *environments* with terrain state features the agent navigates over terrain that is randomly generated between episodes. As a result not only does the agent need to learn to locomote but it also needs to learn how to perceive its environment and avoid obstacles and rough terrain. Some *environments* have been so challenging they could only be solved with Hierarchical Reinforcement Learning (HRL) techniques. We provide these in hopes more will continue work in the area of HRL. Additional extra difficult *environments* are included that have never been solved. Many of these difficult tasks were created while working on other projects but we were not able to produce controllers to solve these problems, or the controllers produced were not of sufficient quality. Last, there are different actuation models to choose from. Most libraries only offer torques as a means to actuate and control the agent's movement. We include a variety of control options such as torques, desired velocities, desired position and muscle-based control.

3 TERRAINRLSIM

The API closely follows the openAI Gym interface. We include a mechanism to set the random seed for the simulation, allowing for reproducible simulations. Many *environments* include state features for the local terrain around an egocentric agent. The observation produced by the simulation always puts these terrain features first, for example, $(< terrain - features > || < agent - features >)$, all as a single vector. The observation can be sliced into multiple parts, allowing only the terrain features to be passed through convolution layers. The software uses the Bullet Physics library (Bullet, 2015) an open source physics simulator. The simulation performance depends primarily on the efficiency of Bullet which is highly optimized. Overall, the simulation is fast and supports different kinds of action parameterizations (torque, velocity, pd and muscle activations). The state features used for an agent are visualized in 1.

We show a simplified code snippet of how to load and simulated a number of trajectories/epochs of the simulation.

```
import terrainRLSim
import numpy as np
import matplotlib.pyplot as plt
import json


if __name__ == '__main__':

    envs_list = terrainRLSim.getEnvsList()
    print ("# of envs: ", len(envs_list))
```

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[3]https://github.com/openai/roboschool
[4]https://blog.openai.com/universe/

(a) Character state features

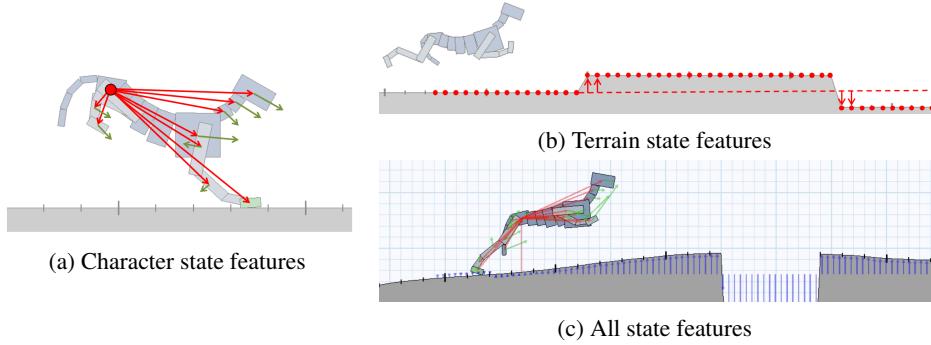(b) Terrain state features

(c) All state features

Figure 1: agent state features from simulation.

```python
print ("Envs:\n", json.dumps(envs_list, sort_keys=True, indent=4))
env = terrainRLSim.getEnv(env_name="PD_Biped3D_FULL_Imitate-Steps-v0", render=True)

env.reset()
actionSpace = env.getActionSpace()
env.setRandomSeed(1234)

actions = []
action = ((actionSpace.getMaximum() - actionSpace.getMinimum()) * np.random.uniform(size=actionSpace.getMinimum().shape[0])  ) + actionSpace.getMinimum()
actions.append(action)

print("observation_space: ", env.observation_space.getMaximum())

for e in range(10):
    env.reset()

    for t in range(100):
        observation, reward,  done, info = env.step(actions)
        print ("Done: ", done)
        if ( done ):
            break

        #### LLC states. If there is an LLC
        # llc_state = env.getLLCState()
        # print ("LLC state:", llc_state.shape)

        ## Get and vis terrain data
        """
            img_ = np.reshape(states[0][:1024], (32,32))
            print("img_ shape", img_.shape)
            plt.imshow(img_)
            plt.show()
        """

        print ("Agent state: ", state)

    env.finish()
    print (env)
```

Listing 1: Example code for loading and simulating an environment.

The terrain in the environment is randomly generated and controlled via a set of parameters that are defined in a *terrain* file. For example, the terrain file contains parameters that determine the random

distance between gaps, the depth of the gap and the width of the gap. There are similar settings for many types of obstacles. Here we give an example of a terrain file.

```
{
"Type": "var2d_slopes_mixed",

"Params": [
  {
    "GapSpacingMin": 3,
    "GapSpacingMax": 4,
    "GapWMin": 0.3,
    "GapWMax": 0.5,
    "GapHMin": -2,
    "GapHMax": -2,

    "WallSpacingMin": 3,
    "WallSpacingMax": 4,
    "WallWMin": 0.2,
    "WallWMax": 0.2,
    "WallHMin": 0.25,
    "WallHMax": 0.4,

    "StepSpacingMin": 3,
    "StepSpacingMax": 4,
    "StepH0Min": 0.1,
    "StepH0Max": 0.3,
    "StepH1Min": -0.3,
    "StepH1Max": -0.1,

    "SlopeDeltaRange": 0.05,
    "SlopeDeltaMin": -0.5,
    "SlopeDeltaMax": 0.5
  }
]
}
```

Listing 2: Example terrain parameter file.

4 ENVIRONMENTS

Here we describe the types of simulation *environments* included in *TerrainRLSim*. In total there are almost 100 environments.

4.1 TERRAINRL

The *TerrainRL environments* are based on the work in (Peng *et al.*, 2016). In this work physics-based characters with Finite State Machine (FSM) controllers are parameterized and trained to traverse complex dynamically generated terrains. Examples of different terrain types and characters are shown in Figure 2 and Figure 3.

On top of what was created for the Terrain Adaptive Locomotion (terrainRL) project we include additional character and terrain types. These include a Simple Biped Controller (SIMBICON) based biped controller and a hopper controller. The new terrain types include *cliffs* and other more challenging versions of the ones used in the paper (Peng *et al.*, 2015).

4.2 IMITATION LEARNING

The goal in these *environments* is to train an agent to imitate particular behaviours described by a motion capture clip, and is based on the work in (Peng and van de Panne, 2017). The provided clip includes sequential character poses that are used in the reward function to instruct the character to match the motion capture pose. For these environments there are three types of characters that

(a) *mixed* terrain

(b) `slopes-mixed` terrain

(c) `narrow-gaps` terrain

(d) `tight-gaps` terrain

(e) `slopes-gaps` terrain

(f) `slopes-steps` terrain
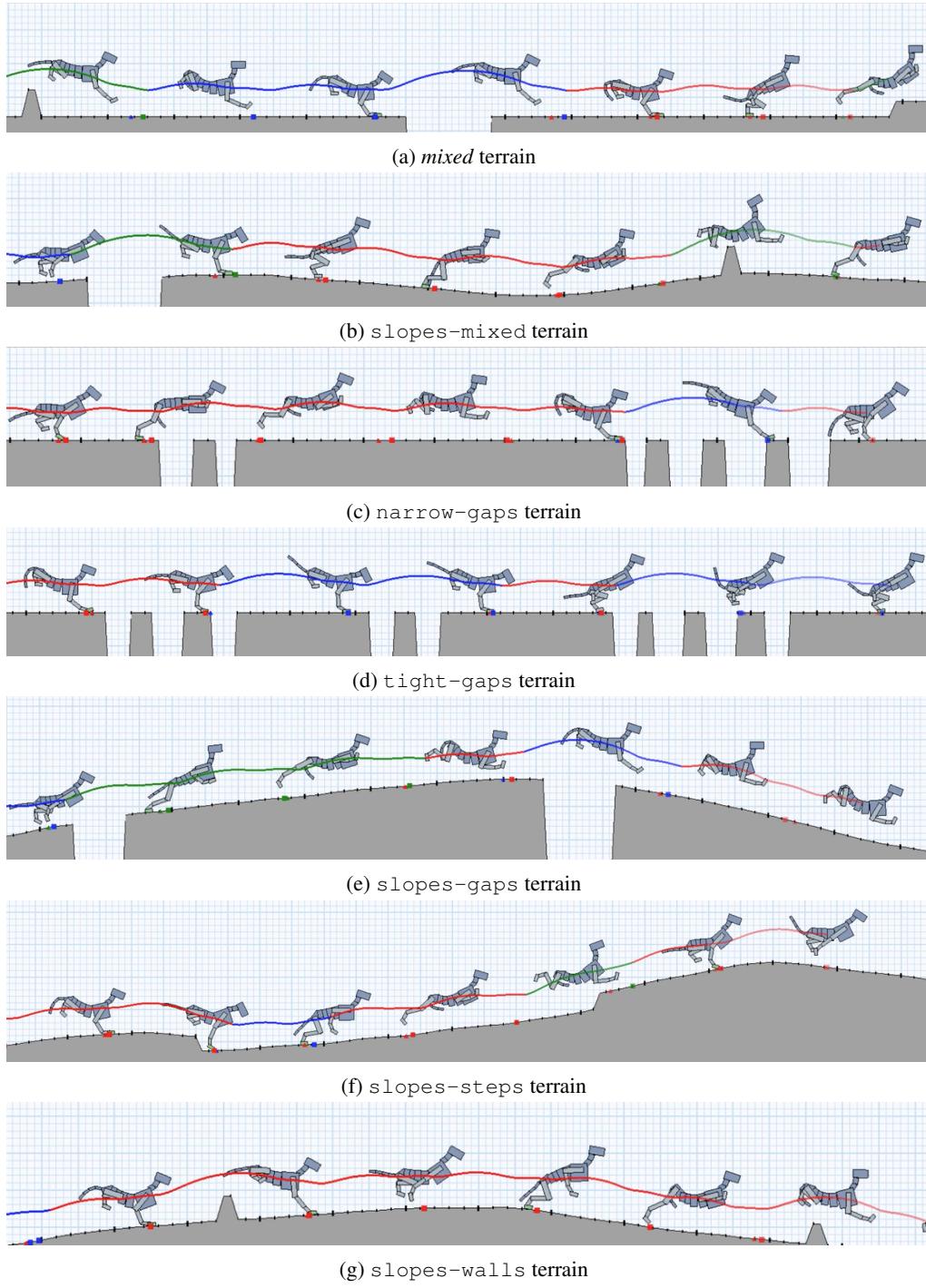

(g) `slopes-walls` terrain

Figure 2: Dog on different terrain types.

are used, a *biped*, *dog* and *dog* (Figure 4). For each of these characters there are 4 different action models available to actuate the joints: torques, desired velocity, desired position and muscle-based control. Example motions learned on these models are shown in Figure 5.

We include additional *environments* for learning walking and running motions for 3D bipeds. There are also a number of terrain types, including *rough* and *steps*, that can be used to add randomly generated terrain into the simulation.
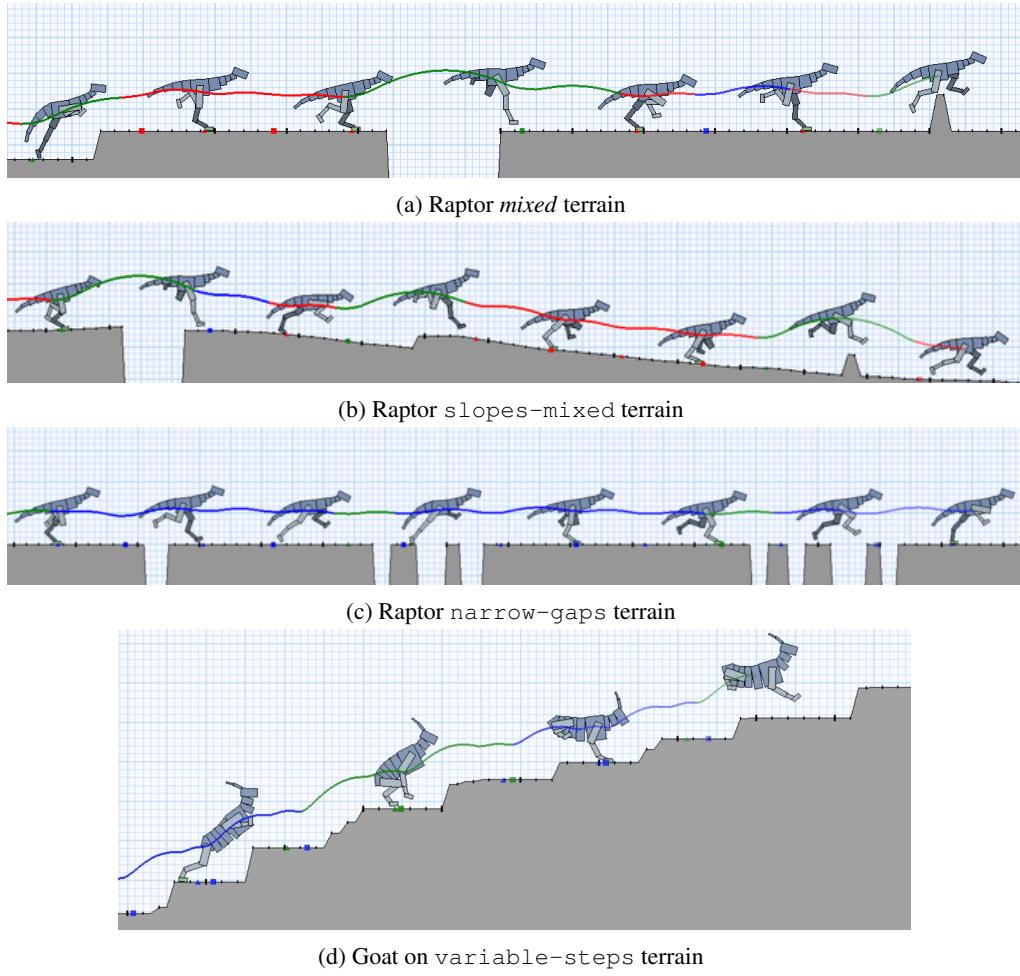
(a) Raptor *mixed* terrain

(b) Raptor `slopes-mixed` terrain

(c) Raptor `narrow-gaps` terrain

(d) Goat on `variable-steps` terrain

Figure 3: Other Control Policies
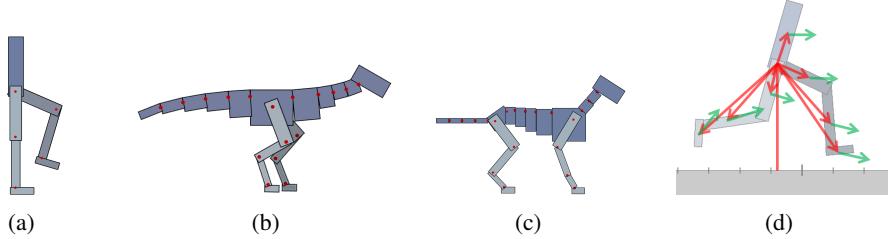

| (a) | (b) | (c) | (d) |

Figure 4: Simulated articulated figures and their state representation. Revolute joints connect all links. From left to right: 7-link *biped*; 19-link *dog*; 21-link *dog*; State features: root height, relative position (red) of each link with respect to the root and their respective linear velocity (green).

4.3 DEEPLOCO

The *DeepLoco environments* are similar to the ones used in (Peng *et al.*, 2017). They include a number of 3D simulations where the goal is to train a biped to walk in complex environments with randomly generated terrain Figure 6.

We include additional environments and configuration that were used for testing and evaluation in the process of completing this project. These include more challenging environments and a version
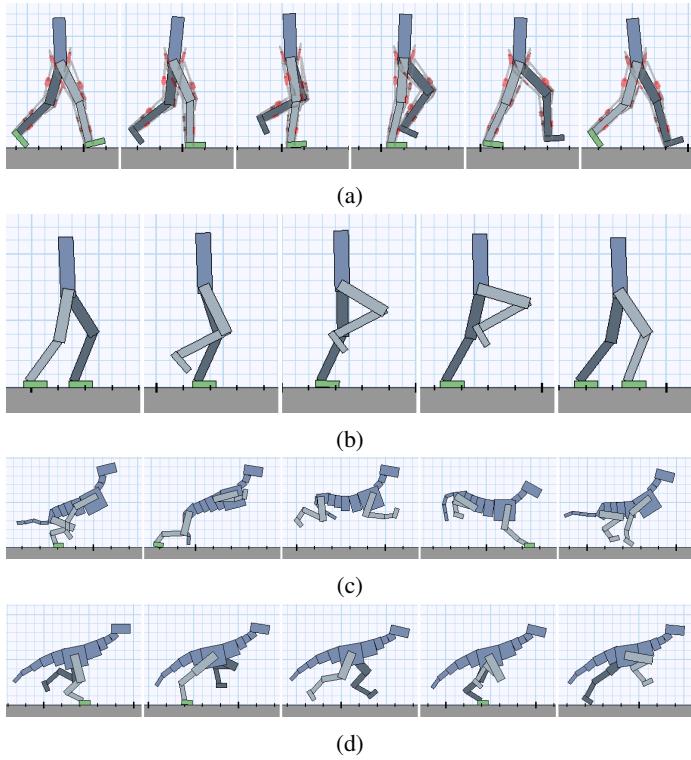
Figure 5: Simulated Motions Using the desired position Action Representation. The top row uses an muscel action space while the remainder are driven by a desired position action space.

of the controller that does not use hierarchical control, such as a controller that includes the terrain input and operates at 30 fps. The code also includes processed versions of mocap clips.

4.4 PLAID

These environments are an extension of the *environments* in Section: 4.2. Here the agent has been modified to have arms and the terrain is randomly generated. With the addition of randomly generated terrain additional state features are added to provide visual perception of the terrain. Part of these environments were used in (Berseth *et al.*, 2018). These are the only available environments that can be used for multi-task and continual learning in the continuous action space domain for Rienforcement Learning (RL). Examples of the *environments* are shown in Figure 7.

On top of the environments used in PLAiD we add additional ones for both the *dog* and *dog* characters. These additional *environments* are for each of the terrain types in Figure 7 and two additional terrain types, *walls* and *slopes-mixed*. New *environments* were also created for a 3D biped with different 3D terrain types. These *environments* contain most of the challenging aspects of interesting problems and are well suited for the use of comparing DRL methods.

5 DISCUSSION

Many of these *environments* have been used to create robust controllers that produce high quality motion. Even with the great progress in this area there is still much work to be done. These *environments* use more realistic joint torque limits that a true biological version of the character might be capable of. Having realistic torque limits is a start but only captures a small portion of the complexities of generating torques. For biological creatures the maximal and minimal possible joint torques can be different depending on the direction of rotation, it can even depend on the joint pose. In many robotics applications you have to cope with the issue of *backlash* that involves the amount of free space between the engineered parts causing the system to move in unintended directions. There is
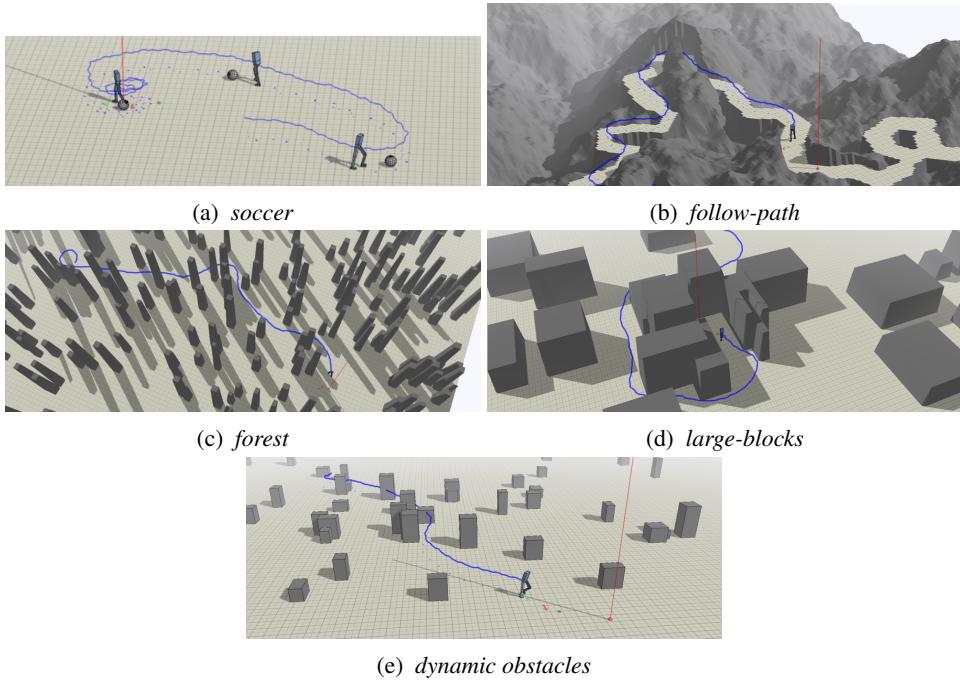
(a) *soccer*

(b) *follow-path*

(c) *forest*

(d) *large-blocks*

(e) *dynamic obstacles*

Figure 6: Snapshots of DeepLoco tasks. The red marker represents the target location and the blue line traces the trajectory of the character's centre of mass. **in order:** soccer dribbling, path following, pillar obstacles, block obstacles, dynamic obstacles.

(a) *flat*

(b) *incline*
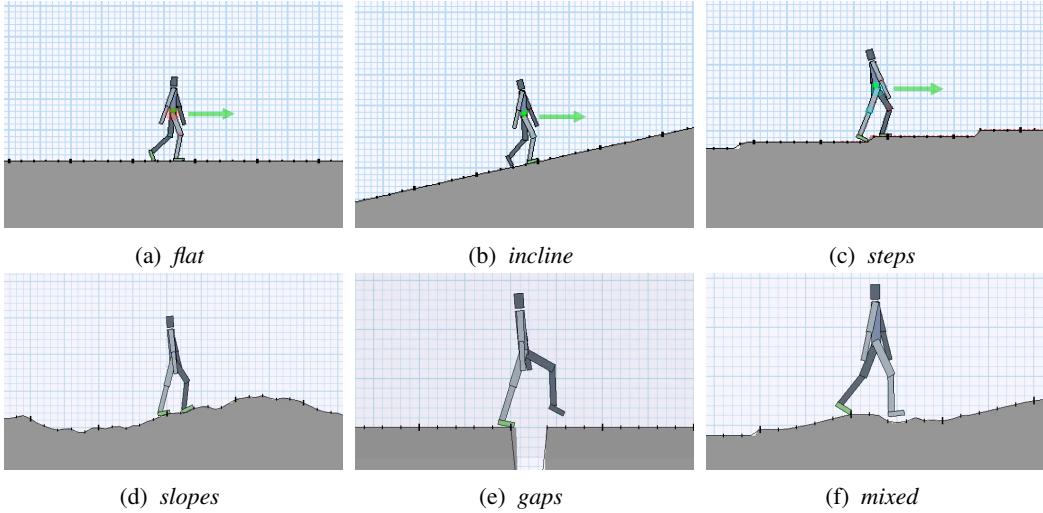
(c) *steps*

(d) *slopes*

(e) *gaps*

(f) *mixed*

Figure 7: The environments used to evaluate PLAiD.

also the complexity of flex in the system which is sometimes intended as springs are used to absorb forces. It is possible to model many of these phenomenon in a physics simulation already.

Apart from the physical phenomenon that we can and should modelled better in simulations used for RL there appear to be a number of simulation parameters that could be given values more in-line with the real world. Examples of these include: linear dampening, gravity, angular dampening, static and kinetic friction values, proper masses and densities of objects, etc. Often, the more the simulation is constructed to model the real world the more challenging solving it becomes. It would increase the community benefit to evaluate RL methods on environments that have more purpose and can be used in games an on robots.

As we further RL research we should also be pushing the simulation accuracy and task difficulty to help us converge on solutions that will work in the real world. There is a great deal of work left to be done before we can create human level intelligence on both more accurate simulation models and better learning techniques.

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