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Bio-Inspired Controllers Facilitate Sim-to-Real Transfer

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1 Motivation

Locomotion strategies developed in a simulation must tackle the reality gap during real-world deployment. Inspired by the robustness displayed by the animals during locomotion, we investigated if the innate properties of CPGs (neural circuits for rhythm generation) can help reduce the reality gap. We used a representative robot model in simulation with notable differences from the actual robot. We observed that the hardware performance of the CPG-based controller (designed for an inaccurate model) was similar to the simulated performance, for low and mid-walking frequency ranges.

2 Introduction

Simulations allow for rapid exploration of locomotion strategies, making them invaluable for devising controllers for the challenging problems in locomotion. However, due to the lack of fidelity of the current simulators, transferring controllers from simulated models to the robot is nontrivial.

2.1 Sim to Real Challenges

The challenges for sim-to-real transfer arise due to the non-linear interactions with the environment, compliance of the robots, behaviour of sensors and motors, and their dysfunction. Efforts to tackle these challenges rely upon modelling the system and environment, accounting for perturbation and sim-to-real gap during training or optimization [1][2]. However, it is difficult to account for all the aspects of the sim-to-real gap. Moreover, unmodeled aspects of this gap could lead to drastic failures. Some of these issues can be palliated by understanding animals' adaptability to unexpected changes in their environment during locomotion.

2.2 Rhythm Generation in Animal Locomotion

Central Pattern Generators (CPG) are distributed networks found in the spinal cord of animals [3]. CPGs are an evolutionarily conserved trait in animals [4] [5]. They form the basis for rhythmic command generation for locomotion. Inputs from the brain and sensory feedback can modify these rhythmic commands to generate several gait patterns that allow animals to respond or adapt to their environment. CPGs offer a versatile control strategy. They can control animals with different musculoskeletal systems (e.g. c.elegans, cats, dogs, and humans) and locomotion behaviours (e.g. swimming and walking). Moreover, their stable limit cycle be-

haviour makes them resilient against perturbations [3]. In the wake of the observations on locomotion in animal, the rhythms generated by CPGs strikes one as an appropriate policy for locomotion.

3 Robotic Platform, Simulation and Control

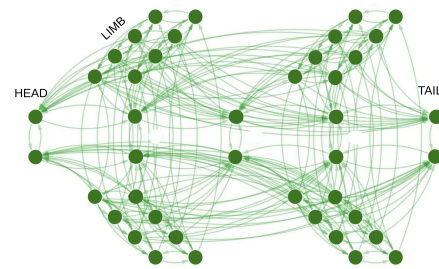


Figure 1: CPG oscillators and connectivity.

In this work, we used a bio-inspired amphibious robot, Krock-2. It has 5 DOF in the spine and 4 DOF in each limb, plus a passive joint between the hind girdle and the tail. The robot has a deformable rubber affixed between the limbs and the body, which reduces the impact from collisions with the ground. To control the robot, we employed the CPGs controller proposed by [6], with a simplified amplitude equation and double oscillator for limbs (Figure 1). An input drive, between 1 & 3, determines the frequency of oscillation (v_i) for walking.

$$\begin{aligned}\dot{\theta}_i &= 2\pi v_i + \sum_j r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij}) \\ \dot{r}_i &= a_i (R_i - r_i) \\ x_i &= r_i (1 + \cos(\theta_i))\end{aligned}\tag{1}$$

The robot was simulated using FARMS [7] and Pybullet [8]. To assess the transferability of CPGs under model discrepancy, we created a simulated model to roughly approximate the hardware platform. We used cuboidal shapes to represent the links of the robot, with weight equal to the weight of the motor it hosts. Overall the robot weighs 3.5 Kg in simulation versus 6 Kg in reality. Moreover, the passive joint between the hind girdle and tail was modeled as a fixed joint.

4 Experimental Results

To gauge the transferability of the CPG-based controller, we compared the forward speed of the simulated and the real robot. The control parameters were set manually without utilising any learning or sim-to-real techniques. Subsequently, the controller was transferred to the real robot

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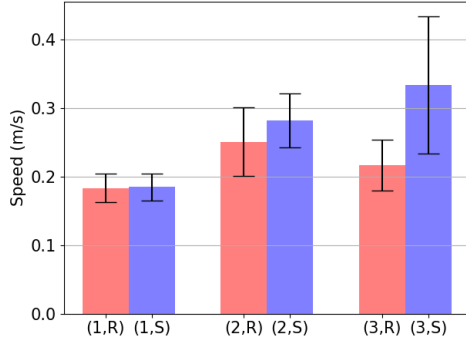


Figure 2: Comparison of forward speed on flat terrain. Tuple $(d, S/R)$ denotes the drive for the Real(R) robot or Simulated(S) robot.

without parameter adaptation. Three different drive levels were evaluated, with six random initial conditions for simulation and three for the robot. Each robot experiment was conducted twice. The top right of figure 3 summarizes the forward speed achieved for different initial conditions.

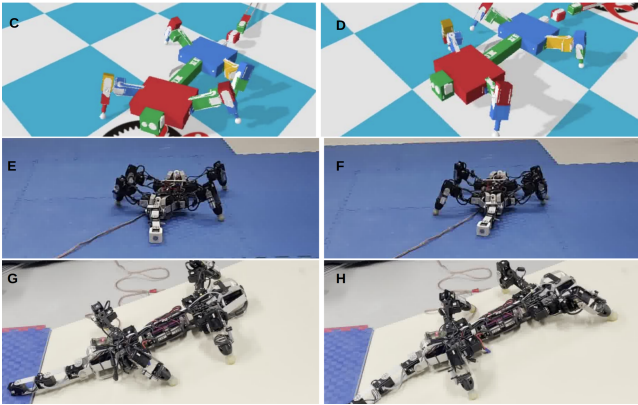


Figure 3: Top: Simulated walking gait¹ (drive = 2). Middle: Krock-2 performing the simulated walking gait². Bottom: Krock-2 walking on an incline of 15° with the same gait³.

At low drives (low frequency) the robot matched the forward speed of the simulated model. At higher drives, the gap increased. Furthermore, we tested the same controller on an inclined plane (without any modification). At 15° inclination, in simulation, we observe climbing and some turning⁴. On hardware, we observed climbing without significant turning³. At 20° inclination, the robot was unable to climb up due to slippage⁵ during hardware experiment, and we observe the same in simulation⁶.

5 Discussion & Conclusion

Presently, learning-based techniques are progressively being employed to tackle complex environments and tasks.

¹<https://tube.switch.ch/videos/XG2Sjw0HmV>

²<https://tube.switch.ch/videos/kNw2KNy0t5>

³<https://tube.switch.ch/videos/urFJJ7y2GWr>

⁴<https://tube.switch.ch/videos/eydmLgEVjE>

⁵<https://tube.switch.ch/videos/bSpNp92Tii>

⁶<https://tube.switch.ch/videos/SjtWX7Xm2q>

These techniques are known to suffer from a large sim-to-real gap. Whereas, in our work, we observed that CPG-based controllers, on the Krock-2 robot, had similar performance in simulation and in reality. The controller was able to withstand changes in the environment (flat and inclined ground) and inaccuracies in the robot model. This similarity, in part, can be attributed to the stability of the robot and the smoothness of control commands. To further delineate, future studies need to explore these properties on unstable robots and compare the performance for commands composed of complex waveforms.

We speculate that the craggy nature of the learning techniques’ output causes large sim-to-real gap. To overcome this, the properties of smoothness of the CPG-based commands, at low-level of control, may be leveraged for the sim-to-real transfer of learning-based techniques. Additionally, CPGs combined with sensory feedback have emergent properties that facilitate coordinated movements, which in turn could further facilitate the sim-to-real transfer. The transfer capability of CPG-based controllers with sensory feedback needs to be investigated.

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