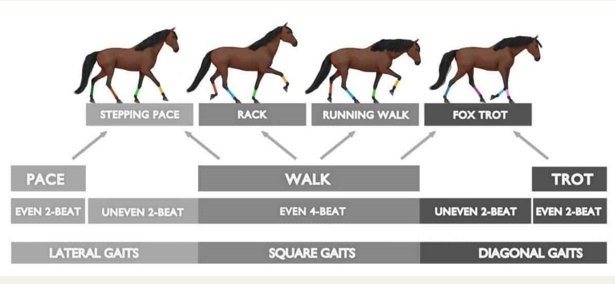
Efficient Learning of Multi-Gait Locomotion In Quadruped Robots via Central Pattern Generators

Daniel C.H. Tan, Jenny Zhang, Michael Chuah , Zhibin Li,
Albertus Hendrawan Adiwahono, Yau Wei Yun
tanchd@i2r.a-star.edu.sg, jennyzzt@i2r.as-tar.edu.sg, zhibin.li@ucl.ac.uk,
Michael_chuah@i2r.ras.a-star.edu.sg, adiwahono@i2r.a-star.edu.sg, wyyau@i2r.a-star.edu.sg

Motivation

Gaits are key components of locomotion. Biomechanical studies suggest that gait-switching at appropriate speeds reduces cost of transport. Gait planning is widely used in classical locomotion methods.



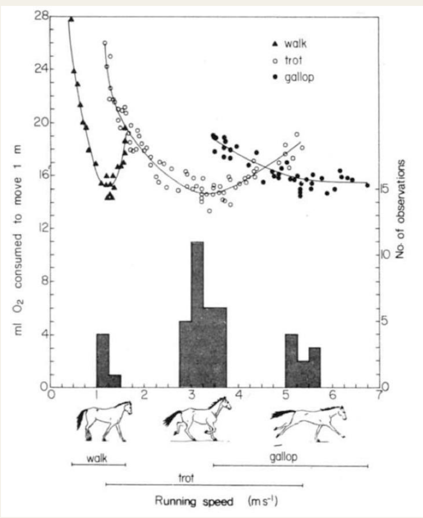


Figure 1. (above) Distinct gaits observed in the horse. (right) Gait transitions enable energy-efficient locomotion in natural quadrupeds.

Learning offers a powerful approach for designing locomotion controllers. However, integrating gait regulation into learning-based approaches is under-explored.

Our goal: develop a learning framework capable of

- Learning and executing multiple gaits
- Transitioning effectively between gaits

Key Contributions

- Formulate **principled gait representation** and parametrize **gait transition dynamics** using central pattern generators as abstract guide
- Propose **high-level motion imitation** of desired motion characteristics, leaving low-level specific motor skills free to be learned
- Demonstrate **multi-gait learning** and **gait transitions**

Control Architecture

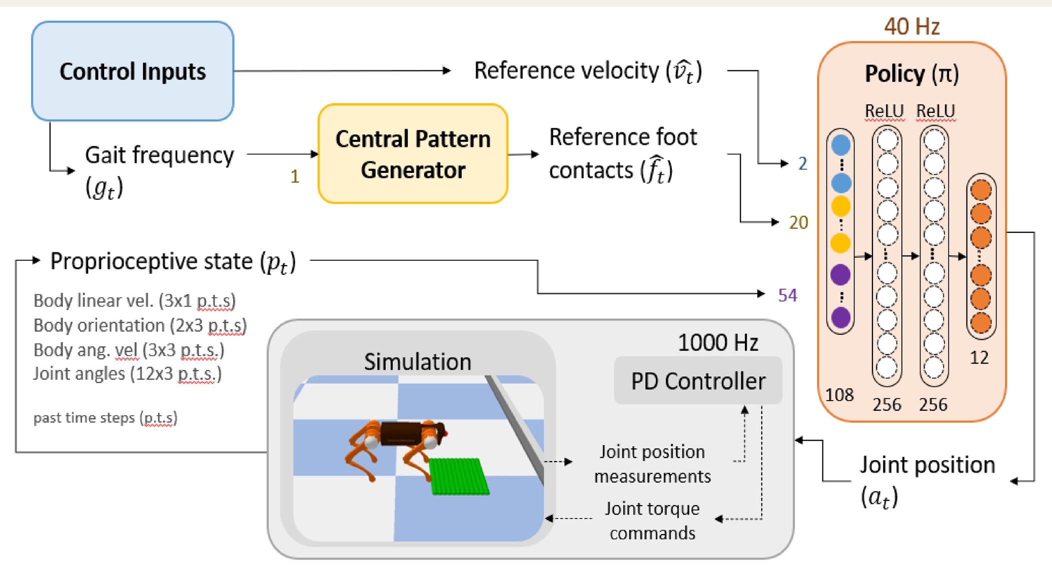


Figure 2: Our complete control architecture

Policy observes both **high-level commands** (target velocity, desired gait characteristics) as well as **low-level proprioceptive state** (various joint positions, body orientation, etc.)

Policy's actions are the target joint positions at the next time-step. Target joint positions are tracked using high-frequency PD controller in simulation.

Gait Representation

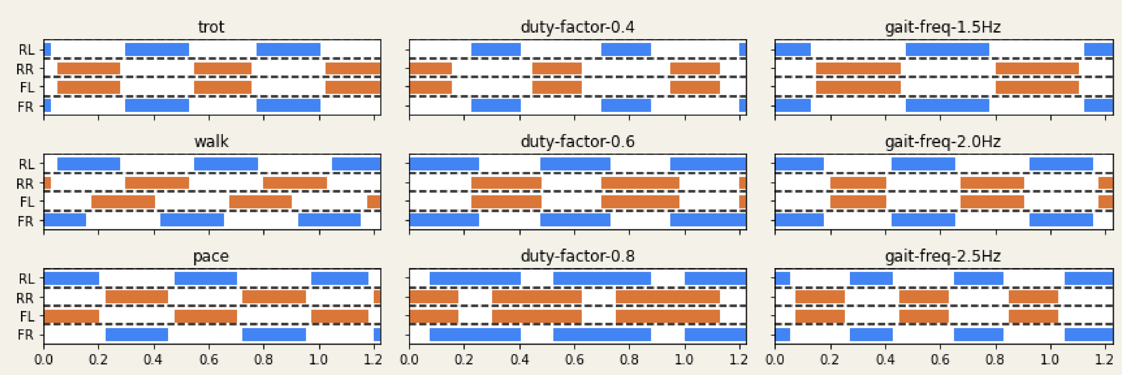


Figure 3: Our gait representation concisely captures variations across essential gait characteristics.

Gaits are parametrized by their binary **foot-ground contact state trajectory g_t.** This concisely captures three essential gait characteristics:

- Gait type
- Gait frequency
- Duty factor (stance/swing ratio)

Transition Dynamics

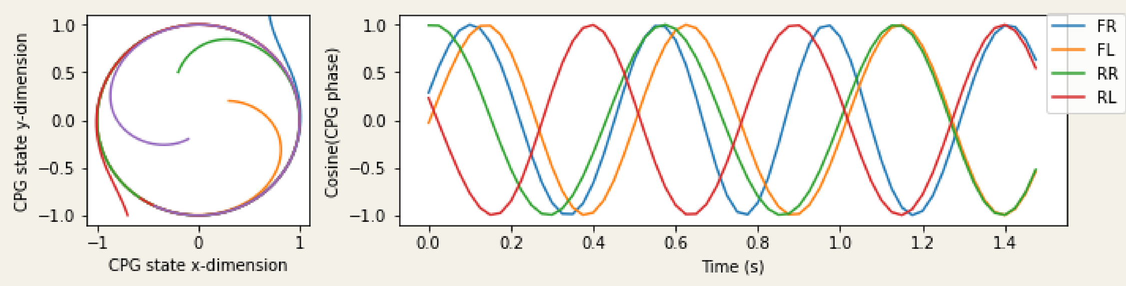


Figure 4: (a) Limit-cycle dynamics of a single central pattern generators. (b) Synchronization of 4 coupled central pattern generators

Central pattern generators (simple dynamical systems with limit-cycle behaviour) are used to generate gaits with desired characteristics.

Coupled CPGs autonomously **synchronize** to **desired phase offsets** from any initial starting condition, mirroring the relative phases of the 4 legs in locomotion gaits.

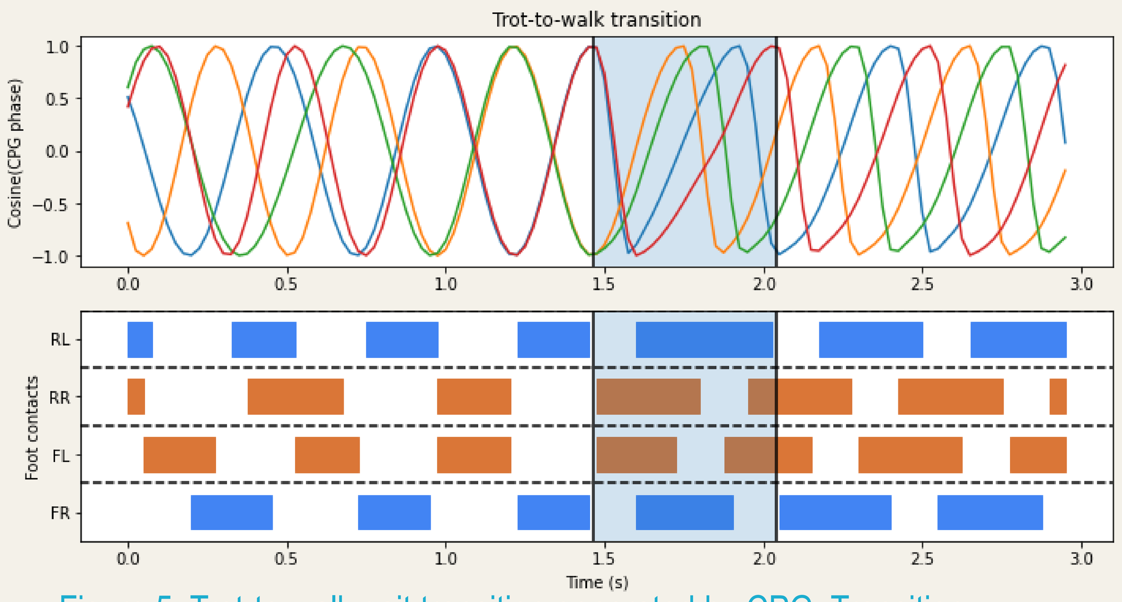


Figure 5: Trot-to-walk gait transition generated by CPG. Transition (shaded region) occurs smoothly and within a single step cycle.

When coupling coefficients are changed, phase vector **evolves smoothly** to new synchronization regime, making them suitable to parametrize gait-transition dynamics.

Training

Gait Variable	Randomization
Gait Type	Discrete(Walk, Trot)
Gait Frequency	Uniform(1.5, 2.5)
Duty Factor	Uniform(0.5, 0.75)

Policy is trained to reproduce diverse **randomized** gaits.

Policy is trained using **reinforcement learning. (PPO)** Policy is rewarded for **imitating high-level gait characteristics,** parametrized by the target foot-ground contact states. However, the reward function does not impose priors on the specific low-level joint motions, allowing more flexibility to learn motor skills autonomously. This strikes a middle ground between full low-level motion-imitation of pre-computed trajectories and vanilla reinforcement learning without imitation.

Other reward terms incentivize proper locomotion by (i) tracking the target velocity, (ii) minimizing energy, (iii) maintaining an upright posture.

Evaluation

We evaluate performance on the following gaits:

- **Walk**, a classic four-beat gait
- **Trot** and **Pace**, two-beat gaits
- **Canter**, a three-beat gait

Where not otherwise stated, default gait parameters are:

Gait Type	Gait Frequency	Duty Factor
Walk	2.0	0.75
Trot	2.0	0.5
Canter	2.0	0.66
Pace	2.0	0.5

To evaluate the closeness of fit of reference and actual foot contact trajectories, we use **Hamming similarity**:

$$s = 1 - (g_{ref} - g_{act})/T$$

Results

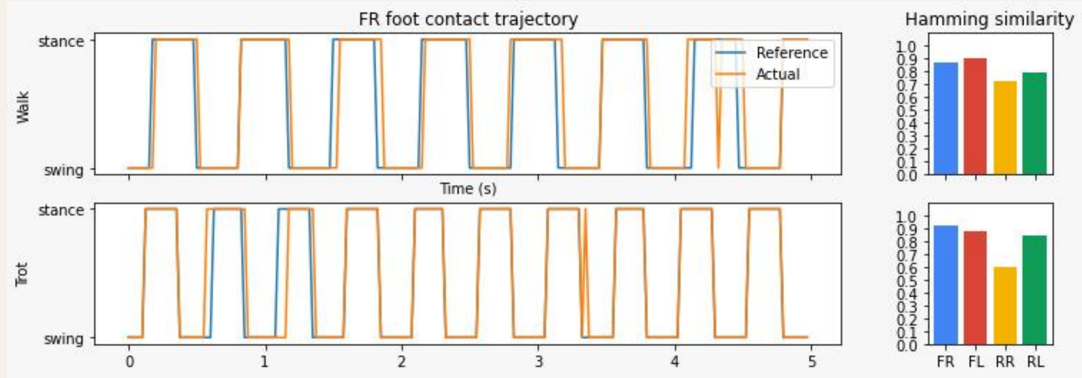


Figure 6: Reference and actual foot contact trajectories of the front-right foot for walking, trotting. Hamming similarity for all 4 feet.

Trotting

GF \ DF	0.5	0.6	0.75
1.5	0.80	0.87	0.85
2.0	0.81	0.87	0.86
2.5	0.80	0.83	0.83

Walking

GF \ DF	0.5	0.6	0.75
1.5	0.80	0.87	0.85
2.0	0.81	0.87	0.86
2.5	0.80	0.83	0.83

Hamming similarity across 18 test cases of gait frequency and duty factor, chosen within the training settings.

Multi-Gait Performance: We evaluate the model on the seen walk and trot gaits with varying gait characteristics. Across 18 test cases, Hamming similarity of s = **0.83 +/- 0.03** was attained, demonstrating effective learning within the training set.

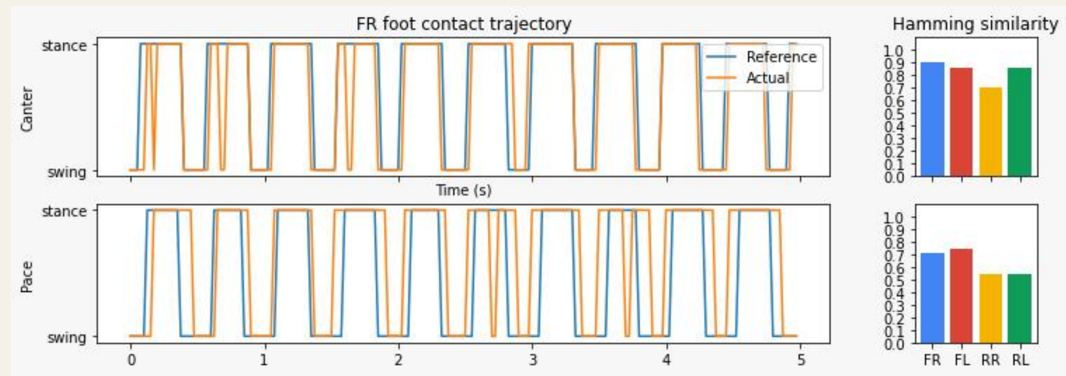


Figure 7: Reference and actual foot contact trajectories of the front-right foot for cantering, pacing. Hamming similarity for all 4 feet.

Generalization: We evaluate generalization of the model to the held-out canter and pace gaits. Both held-out gaits have a footfall order distinct from walk and trot.

The model generalized very well to cantering (s = **0.79 +/- 0.03**) and moderately well to pacing (s = **0.62 +/- 0.04**). The higher difficulty of maintaining dynamic stability in the pacing gait may explain why generalization was more limited.

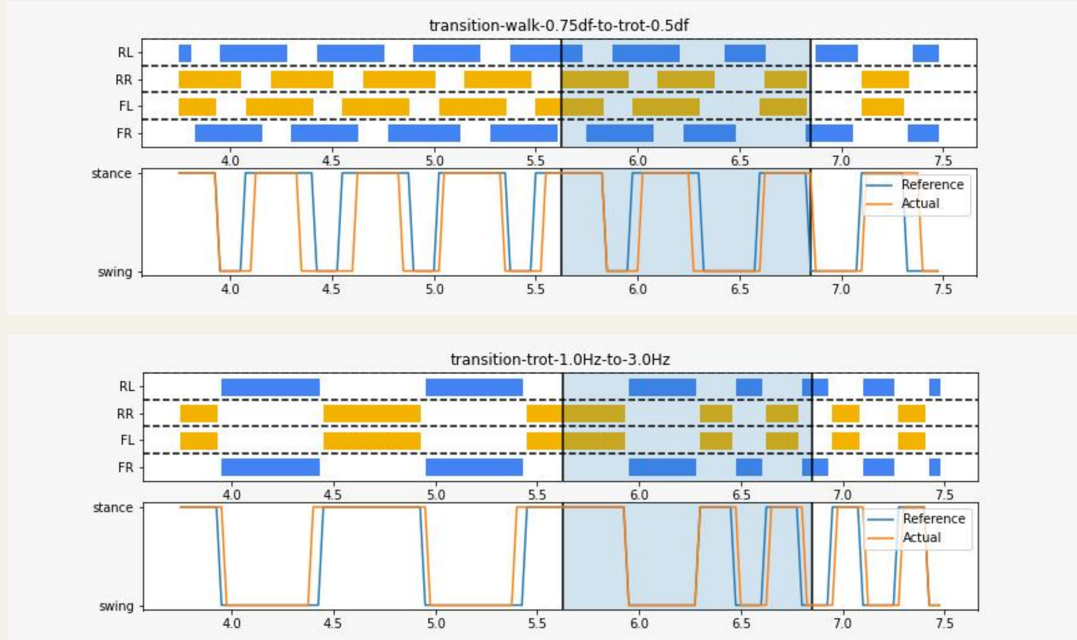


Fig 8: Reference and actual foot-ground contacts during gait transition

Gait Transitions: We demonstrate smooth transitions from walk to trot (top, **s = 0.84**) and from trotting at 1.0Hz to 3.0Hz (bottom, **s = 0.85**). Hamming similarity is measured for the transition period only (shaded).

Conclusion

We demonstrate effective multi-skill learning by combining principled task parametrizations with high-level motion imitation of motion characteristics. The careful choice of task representation simplifies the learning task and enables multi-skill generalization. Our learning framework generalizes within the set of training skills, as well as to novel skills unseen during training, and can smoothly transition between distinct skills.

In this project, the scope is limited to quadruped locomotion. Future work could explore how this framework could be extended to represent and learn generic, transferable motor skills for other domains.