Legged Robots Practical: Project 2

14.11.2023

Plan

Single Leg

- **W1:** Introduction
- **W2:** Derivation of double pendulum's kinematics and dynamics
- **W3:** Jacobian (Cartesian PD + Force Control)
- **W4:** Inverse Kinematics (compare with force control)
- **W5:** Single-leg hopping

Biped

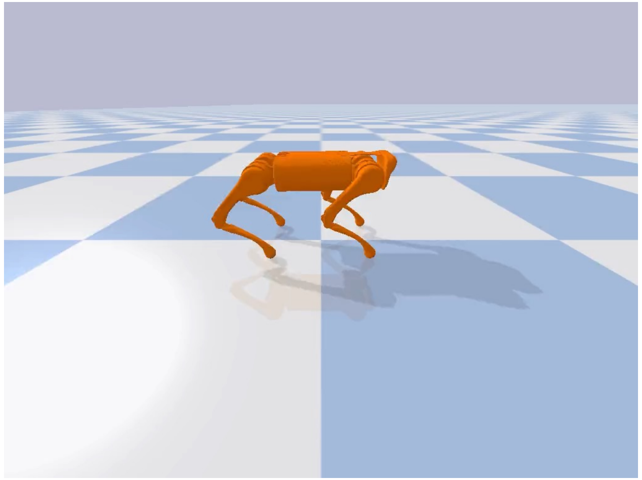
- **W6-8:** Biped Walking with Divergent Component of Motion (BD Atlas) **[Mini-Report]**

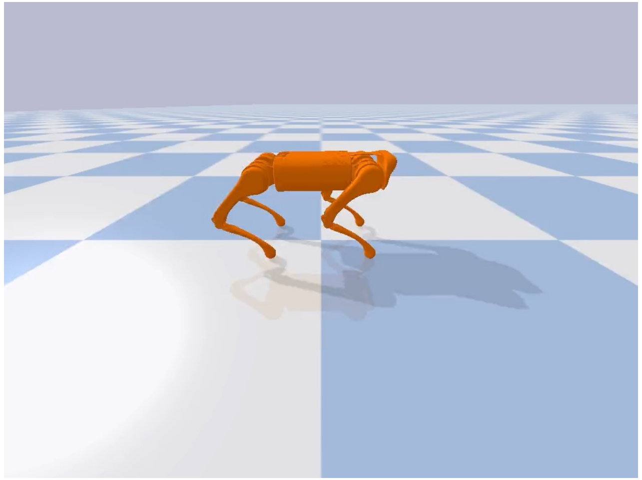
Quadruped

- **W9-10:** Quadruped CPG Trot
- **W11-14:** Quadruped Locomotion Project (CPGs, Deep RL) **[Report - Quadruped] [COMPETITION 19.12.2023]**

Part 1: Central Pattern Generators

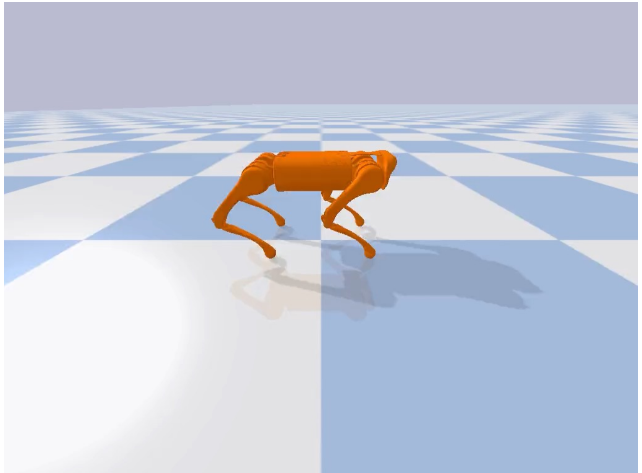
Trot

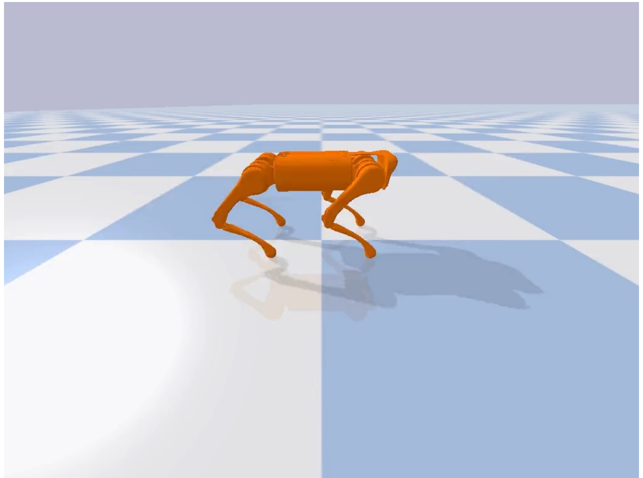




Bound

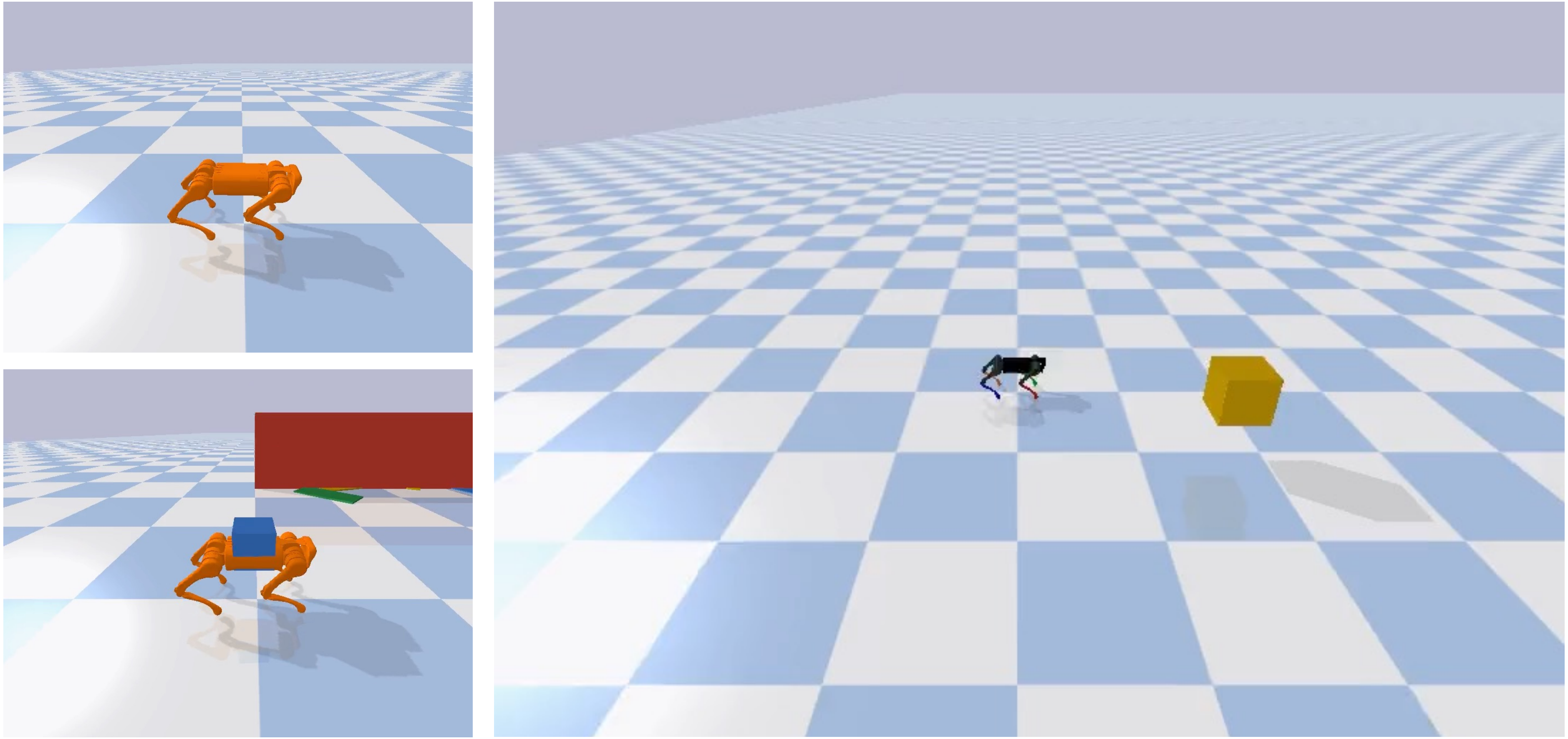
Pace



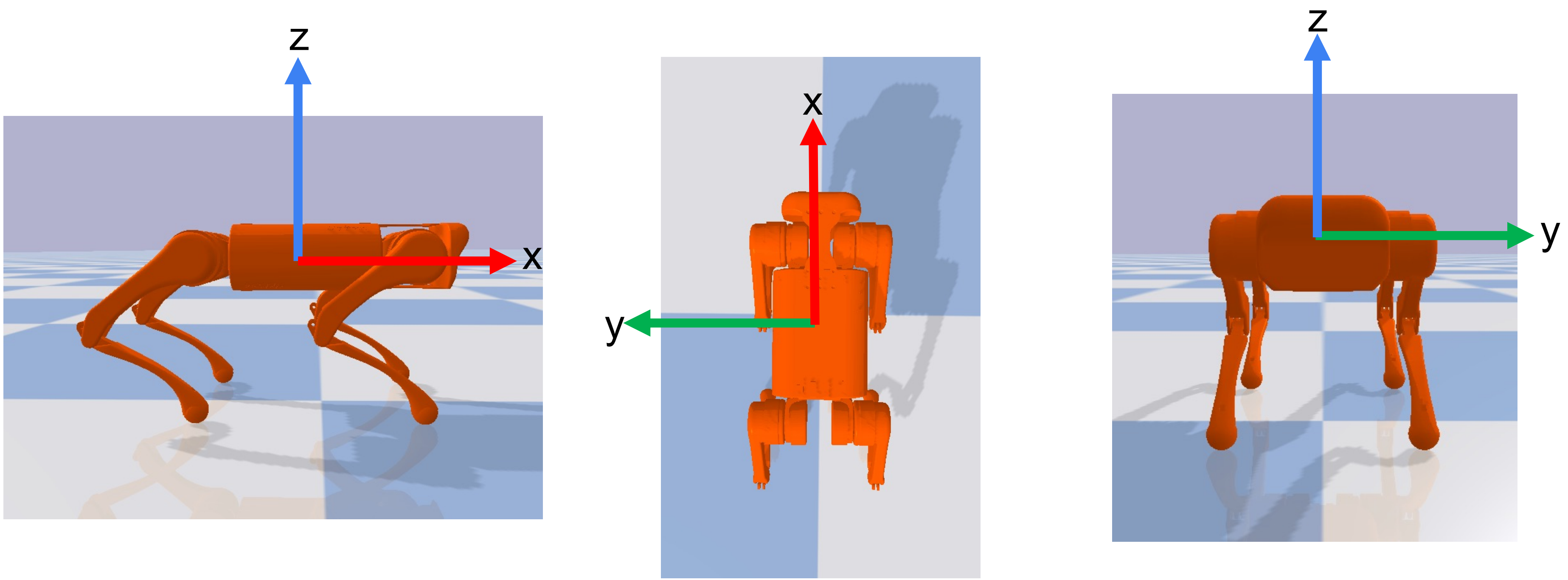


Walk

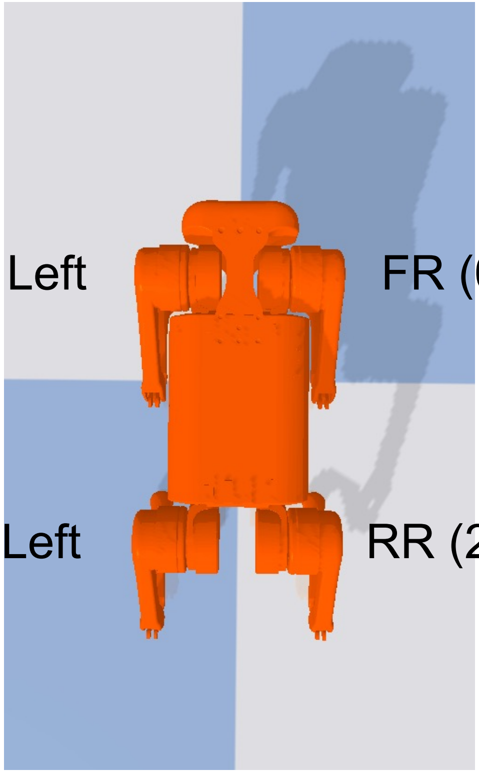
Part 2: Deep Reinforcement Learning



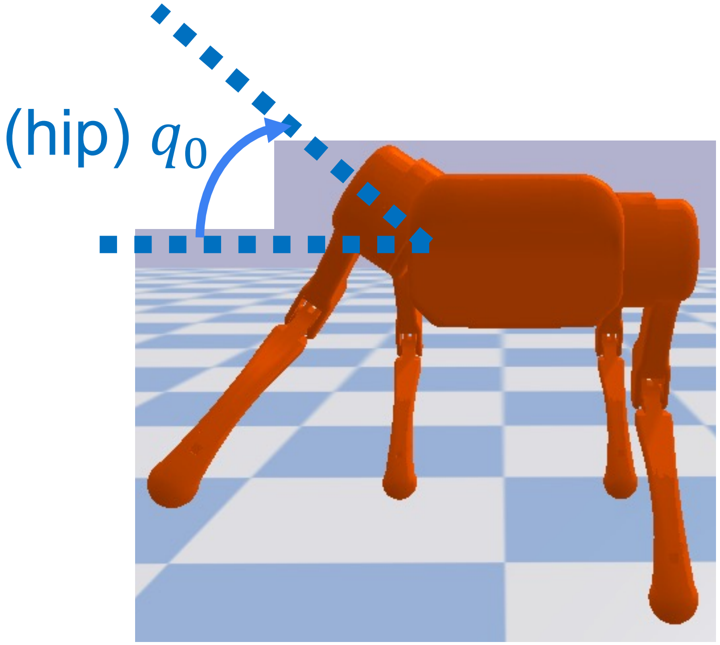
Quadruped Model Reference Frame

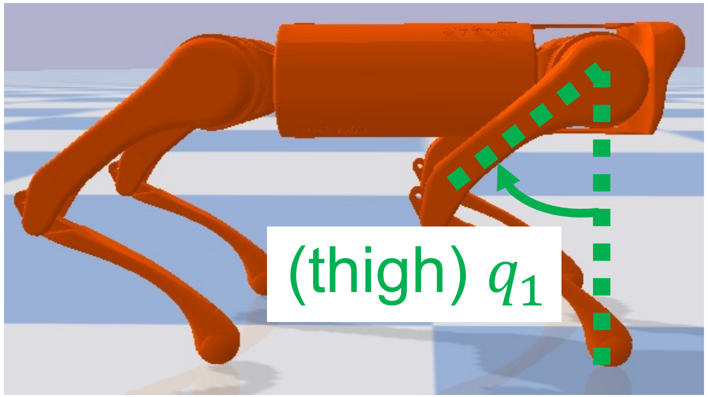


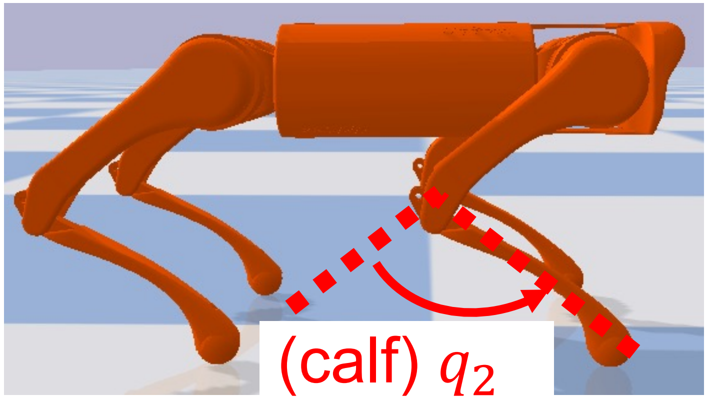
Quadruped Model Leg References



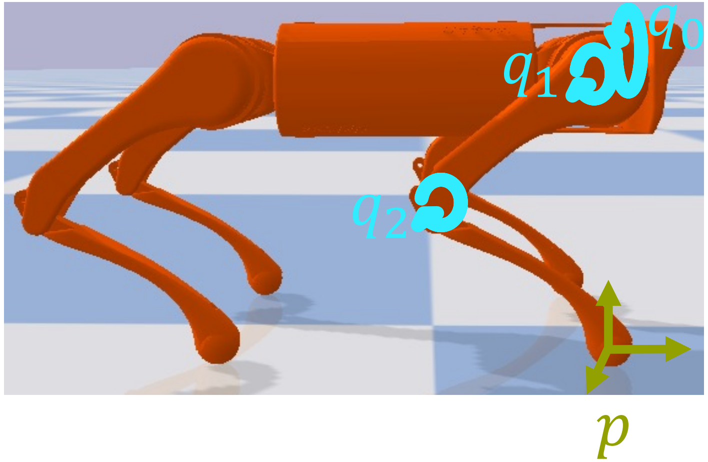
Quadruped Model Joint References







Joint angles ←→ Cartesian space (in leg frame)



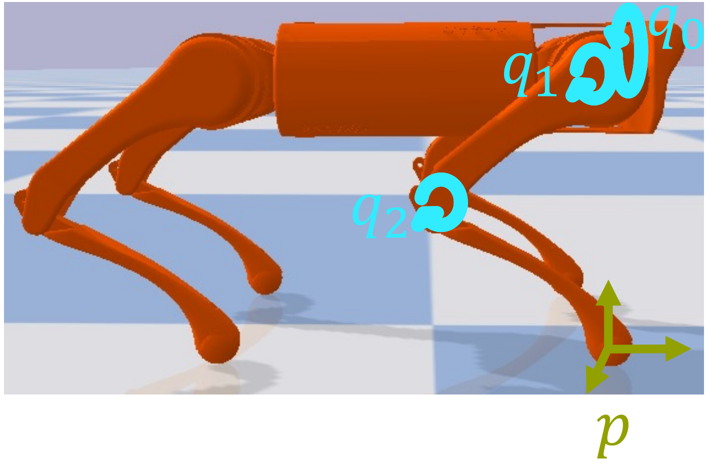
$p = f(q)$ Forward kinematics

$q = f^{-1}(p)$ Inverse kinematics

$\dot{p} = v = J(q)\dot{q}$ Foot linear velocity

$\tau = J^T(q)F$ Map desired end effector force to torques

Joint angles ←→ Cartesian space (leg frame control)



$$p = f(q)$$ Forward kinematics

$$q = f^{-1}(p)$$ Inverse kinematics

$$\dot{p} = v = J(q)\dot{q}$$ Foot linear velocity

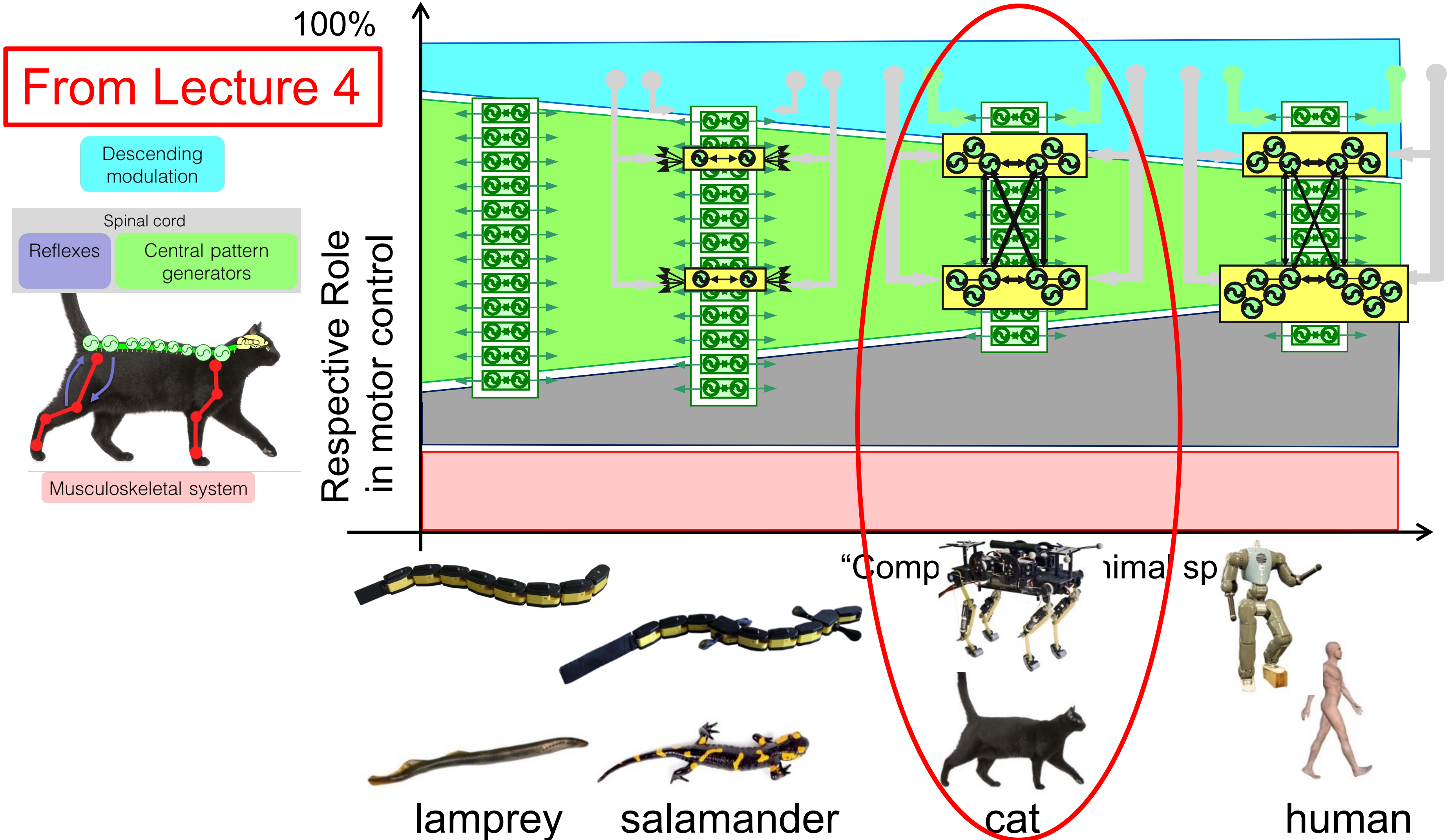
$$\tau = J^T(q)F$$ Map desired end effector force to torques

$$\tau_{joint} = K_{p,joint}(q_d - q) + K_{d,joint}(\dot{q}_d - \dot{q})$$ Joint PD

$$\tau_{Cartesian} = J^T(q)\left[K_{p,Cartesian}(p_d - p) + K_{d,Cartesian}(v_d - v)\right]$$ Cartesian PD

$$\tau_{final} = \tau_{joint} + \tau_{Cartesian}$$ Contributions from both joint PD and Cartesian PD

Central Pattern Generators: Review


From Lecture 4
100%
Descending modulation
Spinal cord
Reflexes
Central pattern generators
Musculoskeletal system
Respective Role in motor control
lamprey
salamander
cat
human

Modeling the CPG with coupled oscillators (Quadruped)

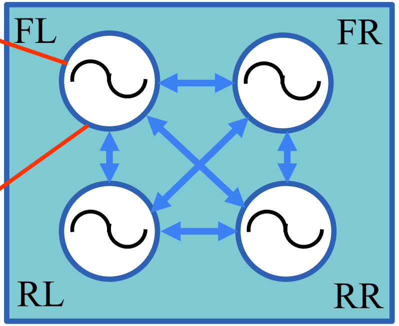
Amplitude: $$\dot{r}_i = \alpha(\mu - r_i^2)r_i$$

Phase: $$\dot{\theta}_i = \omega_i + \sum_{j=0}^{3} r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij})$$

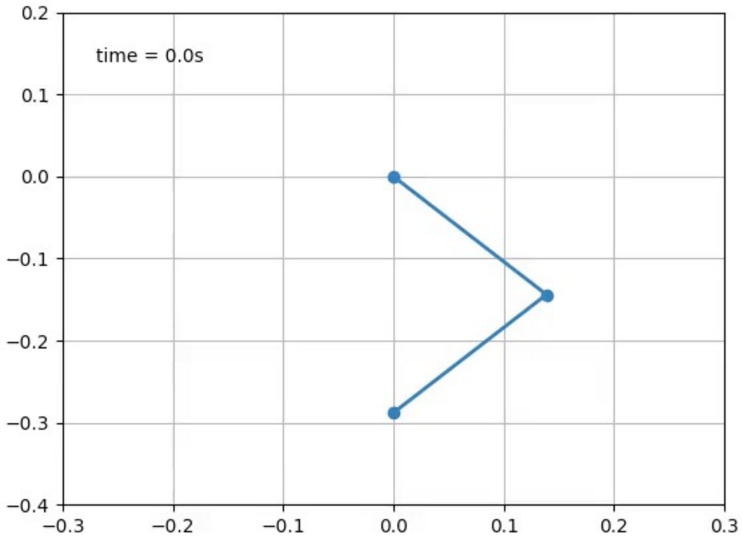
Output:

$$x_{\text{foot}} = -d_{step} r_i \cos(\theta_i)$$

$$z_{\text{foot}} = \begin{cases} -h + g_c \sin(\theta_i) & \text{if } \sin(\theta_i) > 0 \\ -h + g_p \sin(\theta_i) & \text{otherwise} \end{cases}$$



Mapping CPG States to Foot Positions with Inverse Kinematics



$$\dot{r}_i = \alpha(\mu - r_i^2) r_i$$

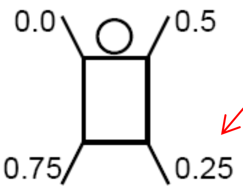
$$\dot{\theta}_i = \omega_i$$

$$x_{\text{foot}} = -d_{step} r_i \cos(\theta_i)$$

$$z_{\text{foot}} = \begin{cases} -h + g_c \sin(\theta_i) & \text{if } \sin(\theta_i) > 0 \\ -h + g_p \sin(\theta_i) & \text{otherwise} \end{cases}$$

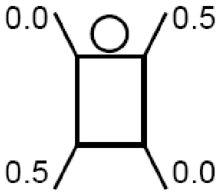
Gait Terminology

- *Stride duration* = the duration of a complete cycle (the period)
- *Swing phase* of a limb (period during which the limb is off the ground)
- *Stance phase* (period during which the limb touches the ground)
- *Duty factor* = Stance duration / Stride duration



Time of contact with ground within a whole cycle

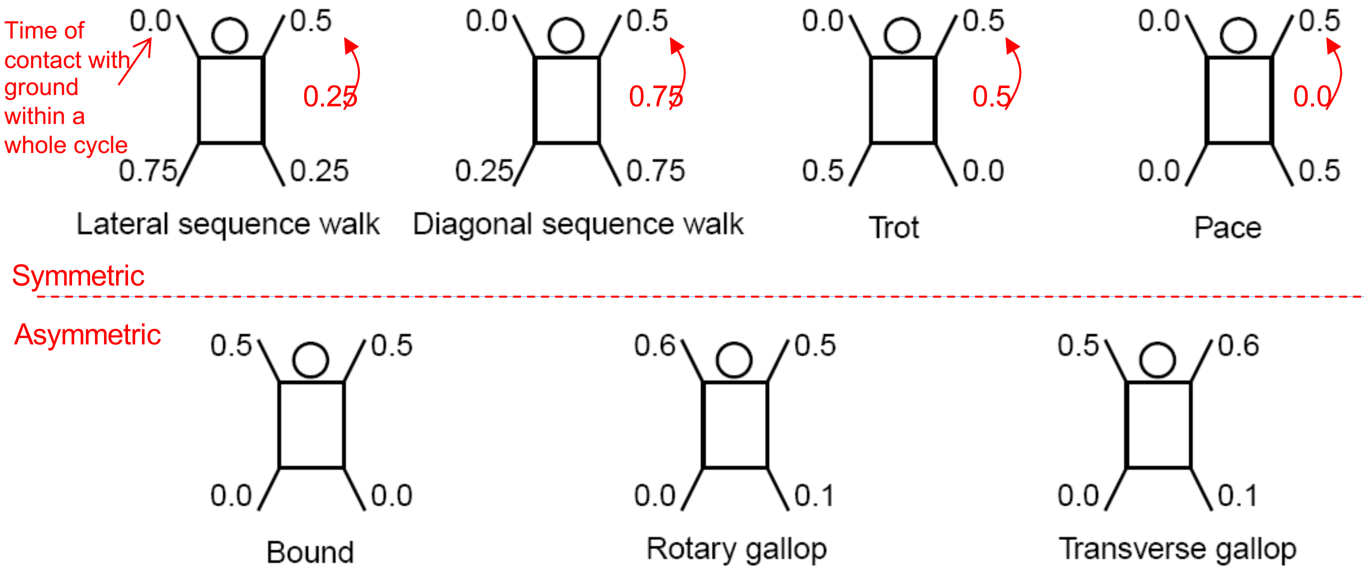
Lateral sequence walk



Trot

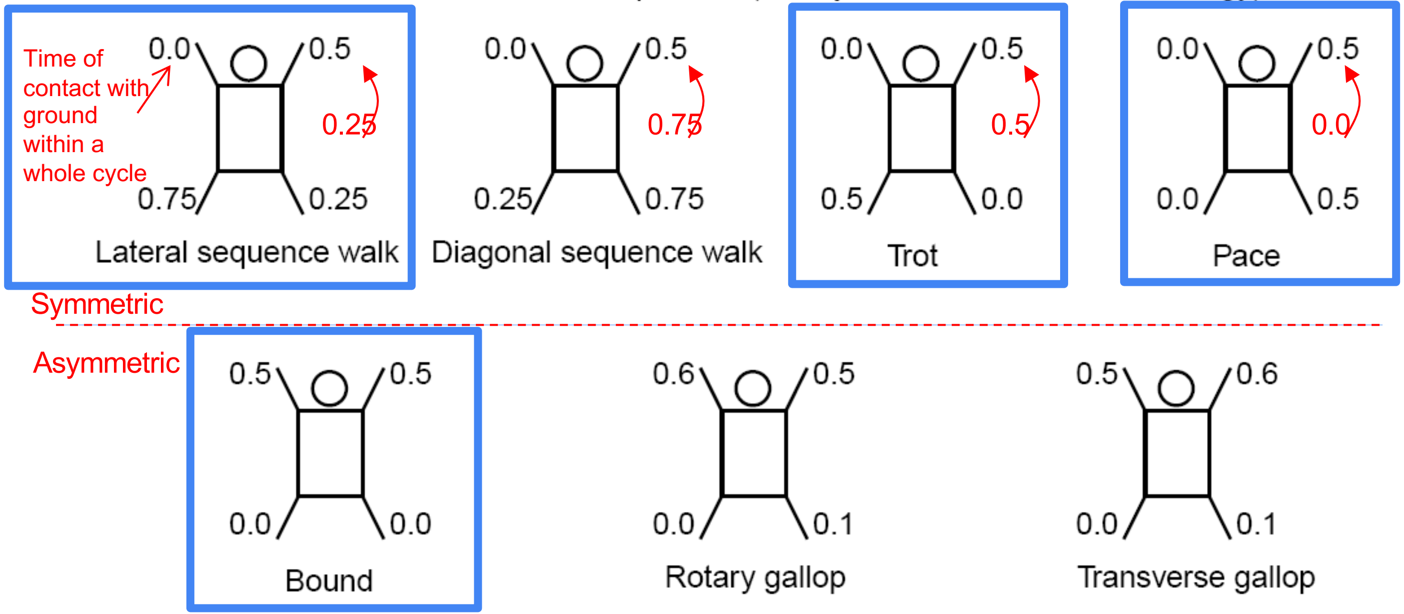
Most common quadruped gaits

Classification in terms of the footfall sequences (mainly used in mathematical biology)



Most common quadruped gaits

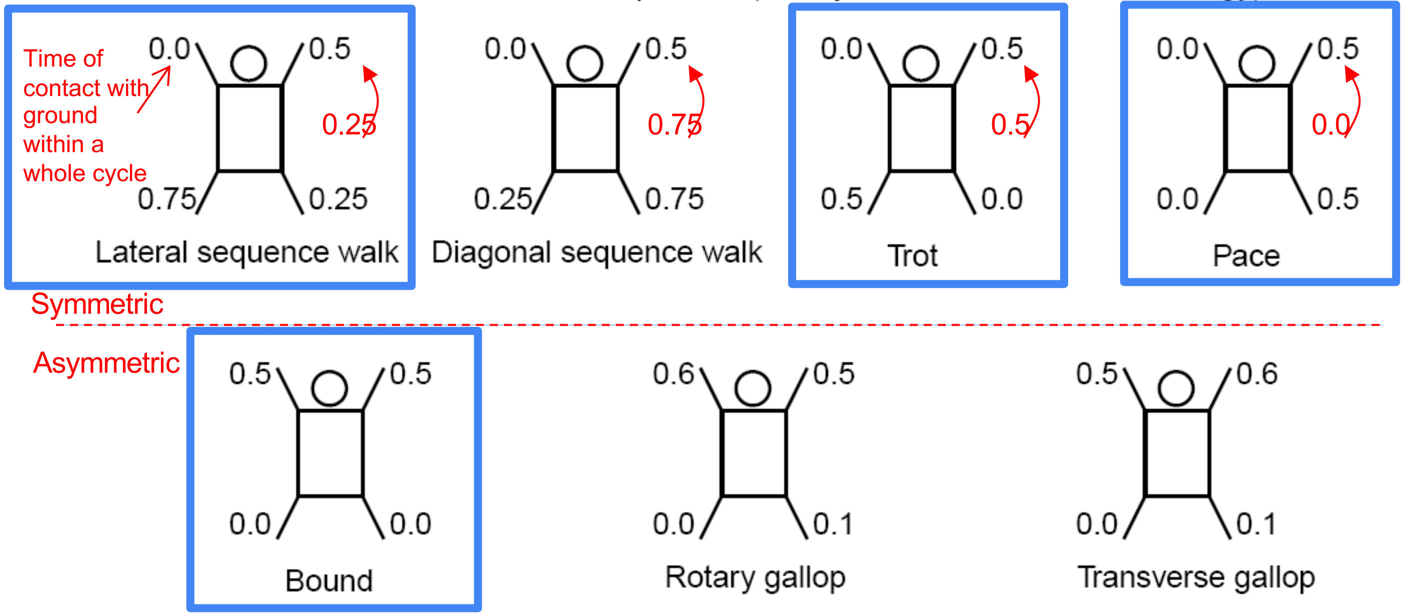
Classification in terms of the footfall sequences (mainly used in mathematical biology)



This project

Most common quadruped gaits

Classification in terms of the footfall sequences (mainly used in mathematical biology)



This project

$$\dot{r}_i = \alpha(\mu - r_i^2)r_i$$

$$\dot{\theta}_i = \omega_i + \sum_{j=0}^{3} r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij})$$

What should $\boldsymbol{\phi}$ be for each gait?

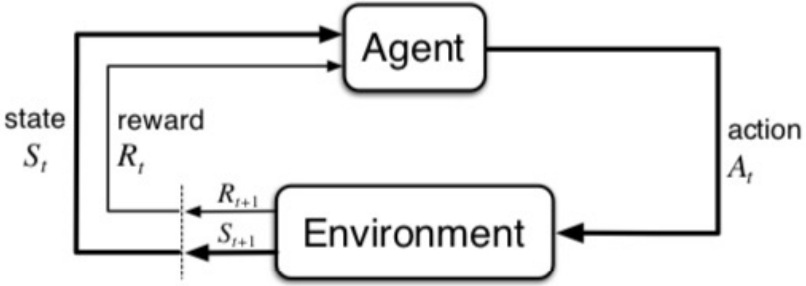
Deep Reinforcement Learning: Review

From Lecture 7

Reinforcement Learning

An MDP is defined by:

- Set of states S
- Set of actions A
- Transition function $P(s' \mid s, a)$
- Reward function $R(s, a, s')$
- Start state s_0
- Discount factor γ
- Horizon H



- Return over a trajectory $\tau = (s_0, a_0, s_1, a_1, \ldots)$

$$R(\tau) = \sum_{t=0}^{\infty} \gamma^t r_t$$

- Policy $\pi(a_t|s_t)$ maps from states s_t to actions a_t (Goal: find policy maximizing above return)
- Value function: $V^\pi(s) = \mathbb{E}_{\tau\sim\pi}[R(\tau)|s_0 = s]$
- Action-value function: $Q^\pi(s,a) = \mathbb{E}_{\tau\sim\pi}[R(\tau)|s_0 = s, a_0 = a]$
- Advantage function: $A^\pi(s,a) = Q^\pi(s,a) - V^\pi(s)$

R. Sutton and A. Barto. Introduction to Reinforcement Learning. MIT Press 1998
Deep RL Bootcamp. Berkeley CA, August 2017

From Lecture 7

Many Existing Tools for Reinforcement Learning

- RL algorithm implementations
  - stable-baselines3 https://github.com/DLR-RM/stable-baselines3 PPO, SAC
  - ray[rllib] https://github.com/ray-project/ray
  - spinningup https://github.com/openai/spinningup
  - tianshou https://github.com/thu-ml/tianshou/
  - … many others!
- Physics simulators
  - pybullet https://github.com/bulletphysics/bullet3
  - MuJoCo https://mujoco.org
  - RaiSim https://raisim.com
  - Isaac-Gym https://developer.nvidia.com/isaac-gym
  - … and others!

From Lecture 7

RL Considerations

Algorithm

- On/off policy
- Hyperparameters
- Network architecture
- Random seeds/trials

…implementation dependent!

MDP Design Decisions

- Observation space
- Action space
- Reward function

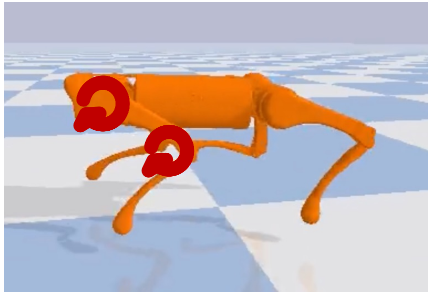
Environment Parameters

- Simulator dynamics
- Control gains – joint/Cartesian
- Control/environment time step
- Noise, latency

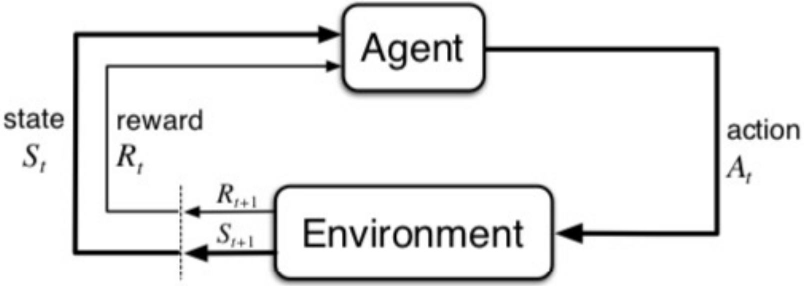
P. Henderson et al. *Deep Reinforcement Learning that Matters*. arXiv:1709.06560, 2017

From Lecture 7

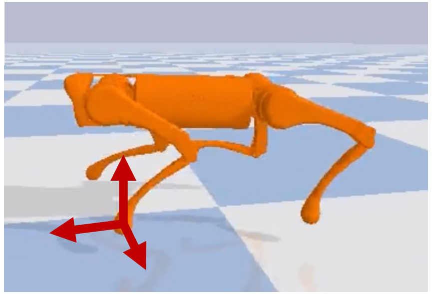
State/Action/Reward Space: A1



s_t ? i.e.
- -body (z, r, p, y)
- -body velocities
- -joint states



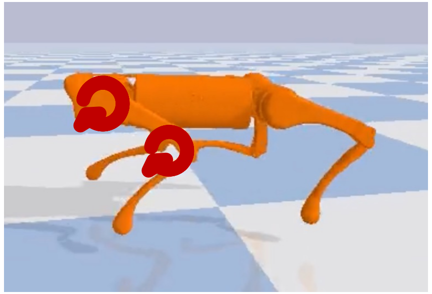
a_t ?
- -motor positions/torques
- -Cartesian PD
- -CPG state modulations



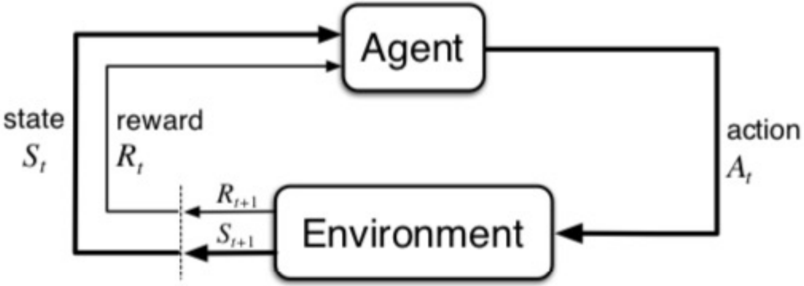
r_t ? i.e.
- -body linear velocity
- -energy penalty

From Lecture 7

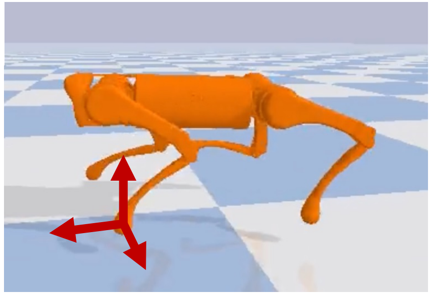
State/Action/Reward Space: A1



s_t ? i.e.
- body (z, r, p, y)
- body velocities
- joint states



a_t ?
- motor positions/torques
- Cartesian PD
- CPG state modulations



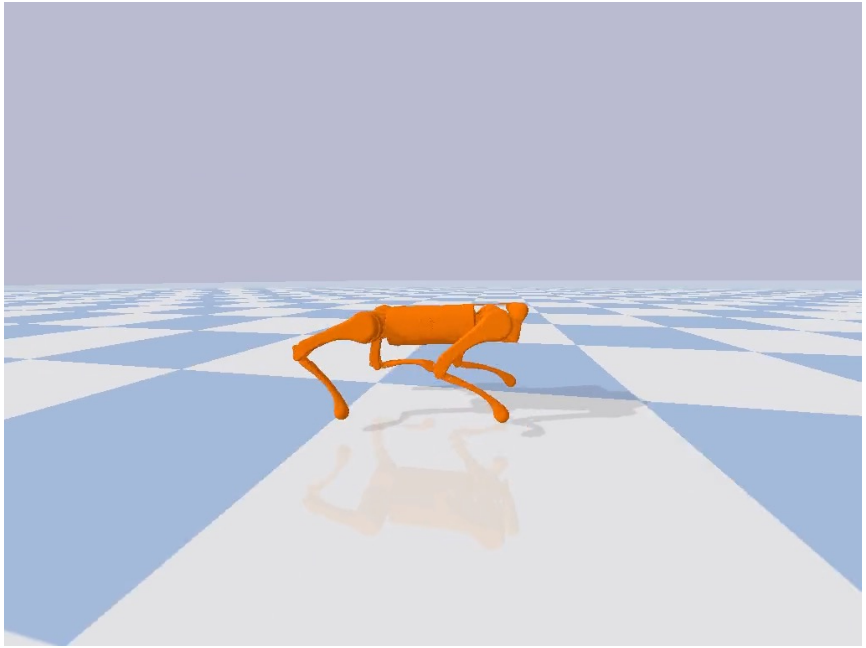
r_t ? i.e.
- body linear velocity
- energy penalty

This project: construct the MDP

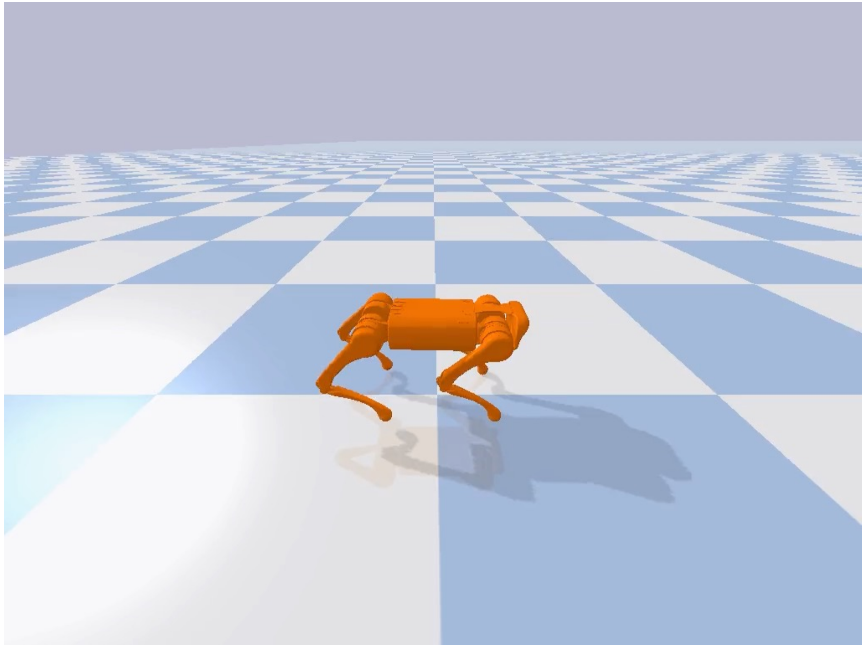
From Lecture 7

Joint Position Control vs. Cartesian PD Control (PPO/SAC)

Action Space: $a_t = q_{1 \ldots N}$

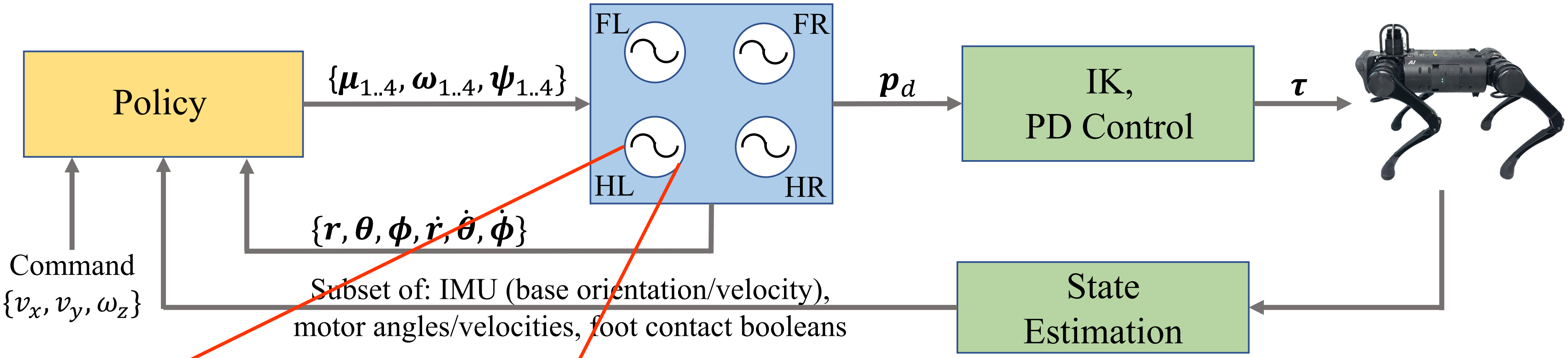


Action Space: $a_t = [x_{ee_i}, y_{ee_i}, z_{ee_i}]$



CPG-RL: Learning Central Pattern Generators for Quadruped Locomotion

From Lecture 7



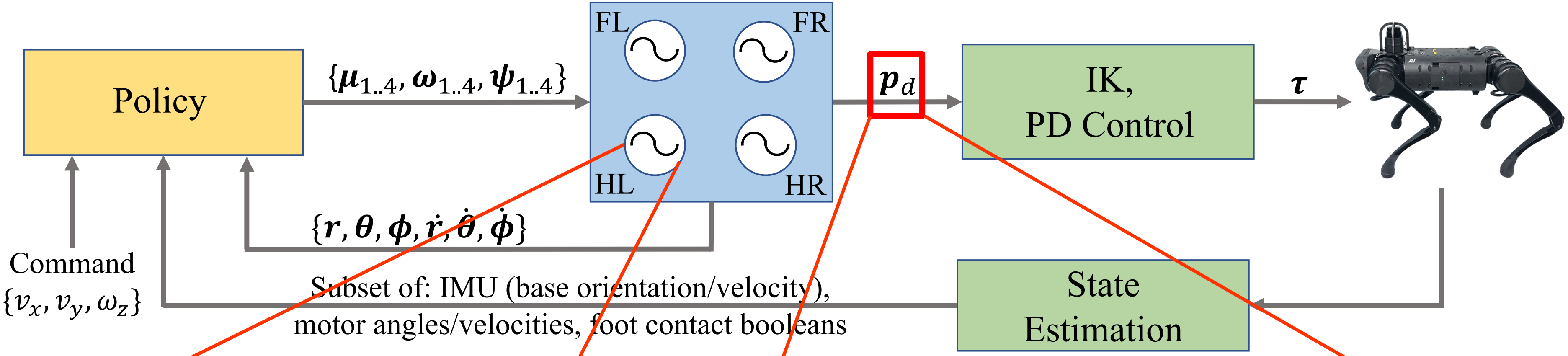
$$\dot{r}_i = \alpha(\mu - r_i^2)r_i$$

$$\dot{\theta}_i = \omega_i + \sum_{j=0}^{3} r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij})$$

G. Bellegarda, A. Ijspeert. "CPG-RL: Learning Central Pattern Generators for Quadruped Locomotion," RA-L 2022

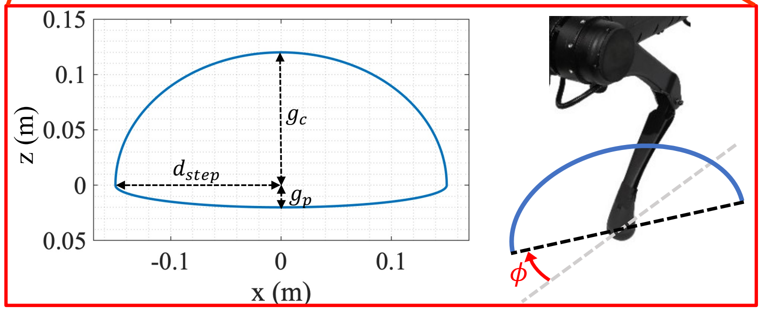
CPG-RL: Learning Central Pattern Generators for Quadruped Locomotion

From Lecture 7



$$\dot{r}_i = \alpha(\mu - r_i^2)r_i$$

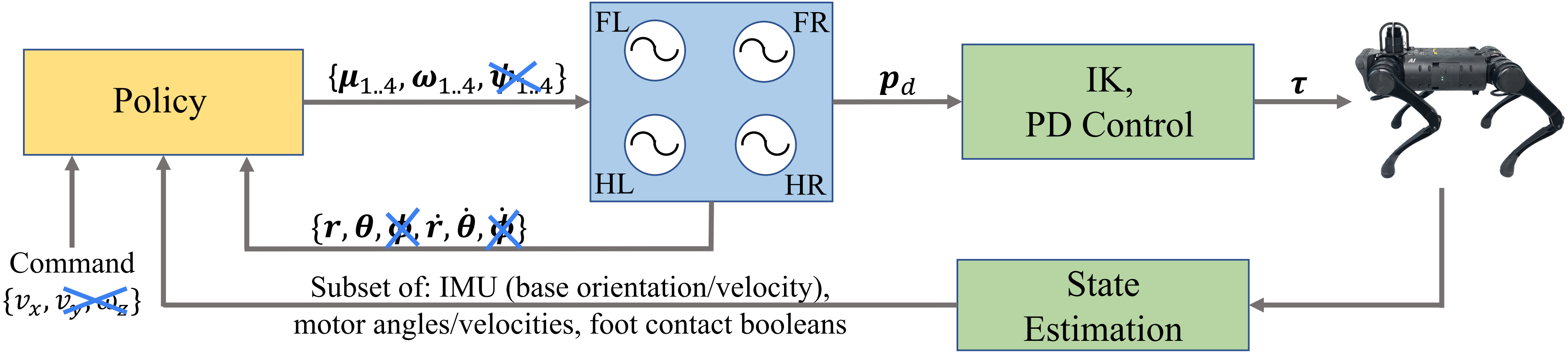
$$\dot{\theta}_i = \omega_i + \sum_{j=0}^{3} r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij})$$



G. **Bellegarda**, A. Ijspeert. "CPG-RL: Learning Central Pattern Generators for Quadruped Locomotion," RA-L 2022

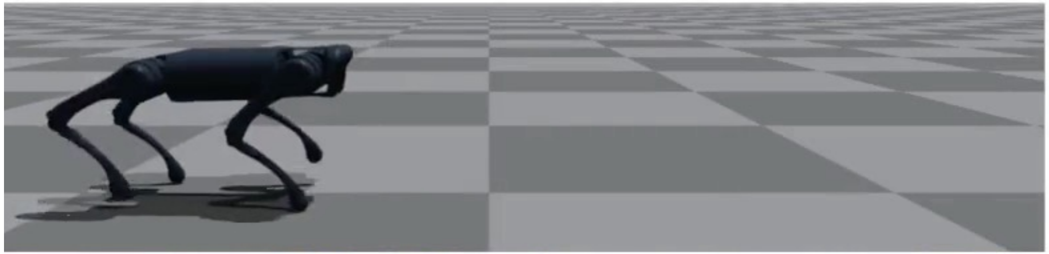
CPG-RL: Learning Central Pattern Generators for Quadruped Locomotion

From Lecture 7



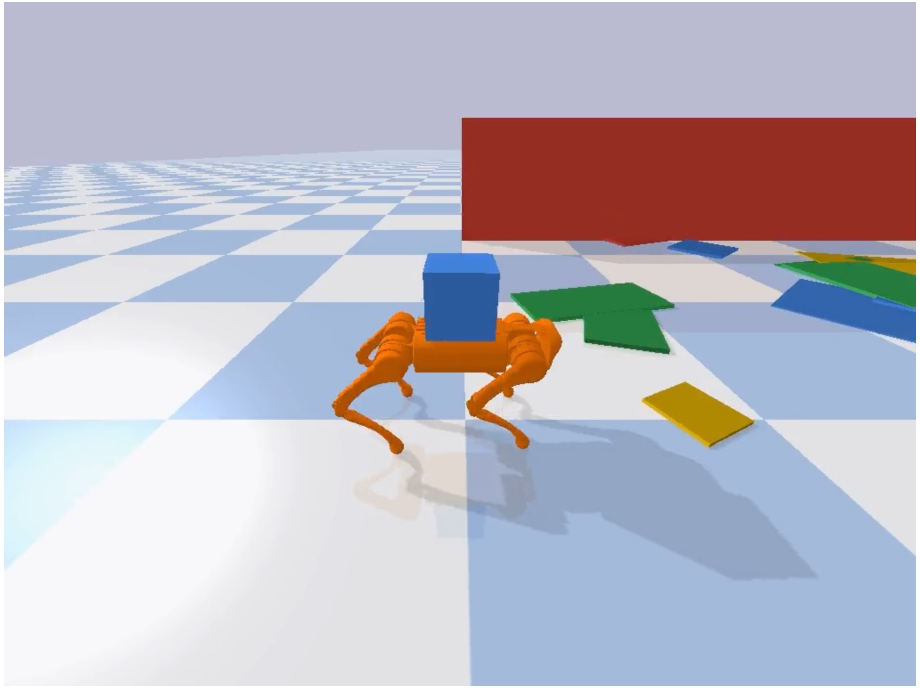
$$\dot{r}_i = \alpha(\boxed{\mu} - r_i^2)r_i$$

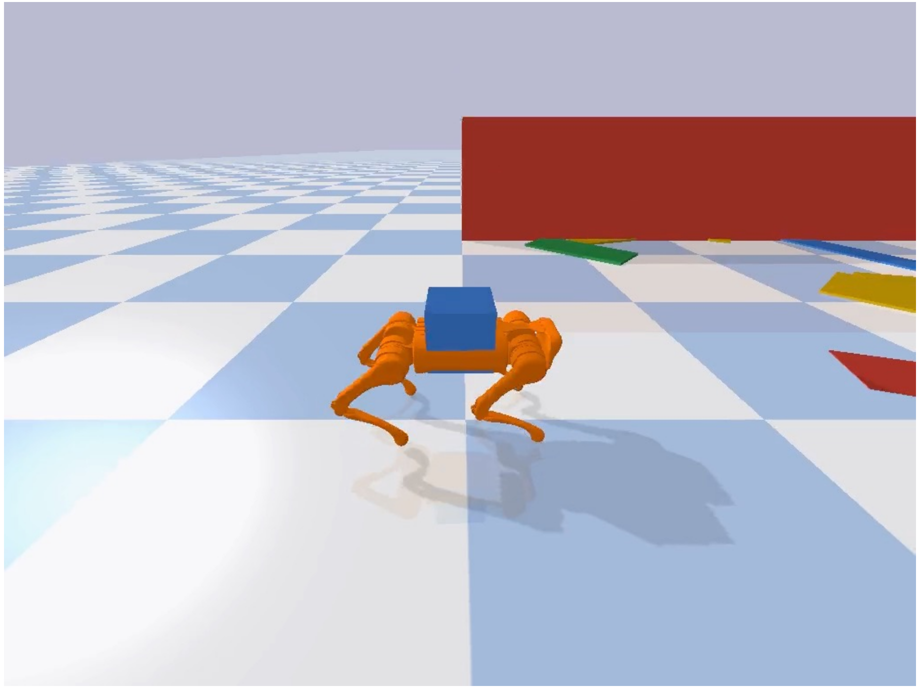
$$\dot{\theta}_i = \boxed{\omega_i} + \cancel{\sum_{j=0}^{3} r_j w_{ij} \sin(\theta_j - \theta_i - \phi_{ij})}$$



G. Bellegarda, A. Ijspeert. "CPG-RL: Learning Central Pattern Generators for Quadruped Locomotion," RA-L 2022

How robust is your approach? To be determined at the 19.12.2023 competition

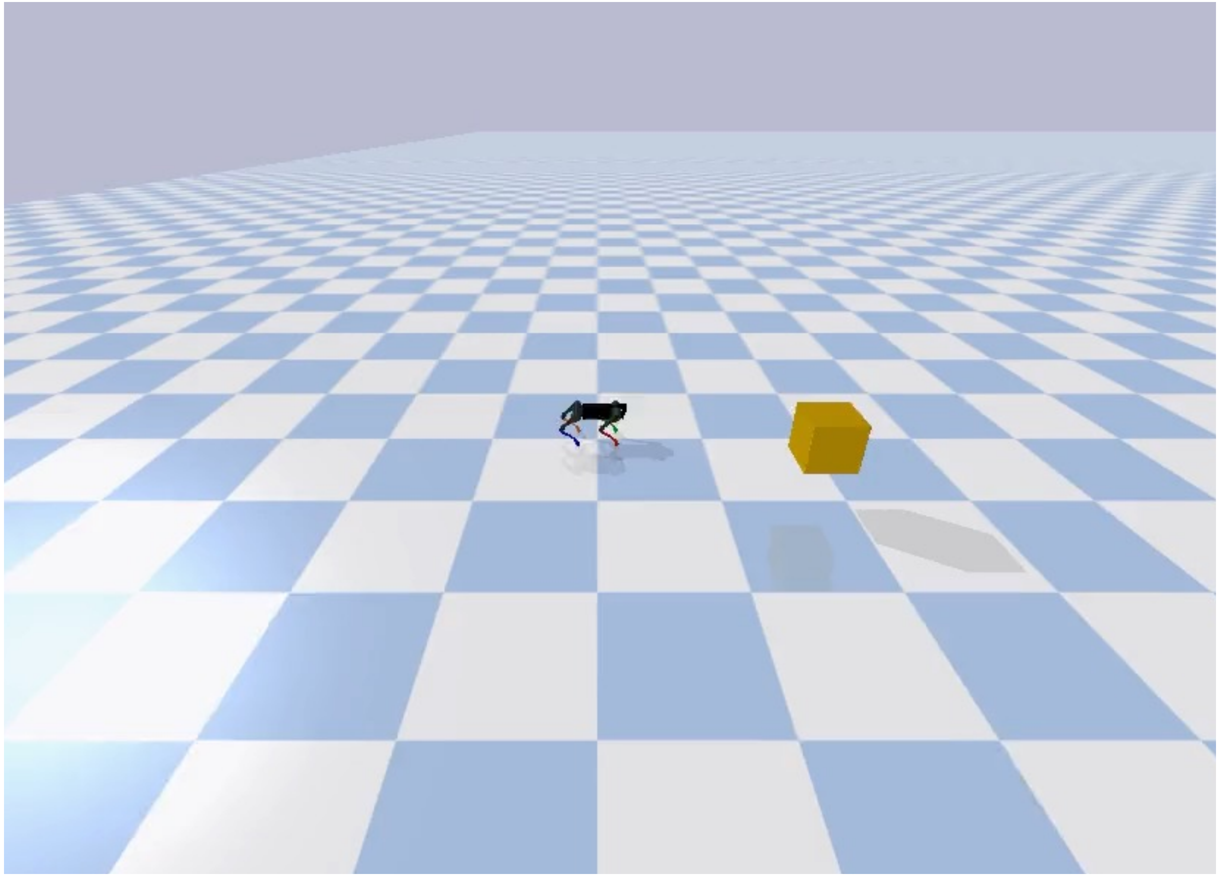




Goal oriented locomotion: what should be in the observation space and reward function?

Use function:
get_distance_and_angle_to_goal()

Sensory information in quadruped.py:
-GetBaseOrientation()
-GetBaseLinearVelocity()
…



Tips

- Monitor episode length and reward mean during training
- Training should complete within 1 million timesteps for reasonable observation space, action space, and reward function choices (with no noise in the environment)
- No training on test environment (used for competition)
- Start training early!