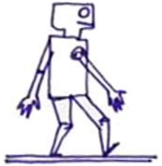
Artificial Locomotion

Should we LEARN or OPTIMIZE?

Nicolas Mansard

Gepetto
LAAS-CNRS & ANITI



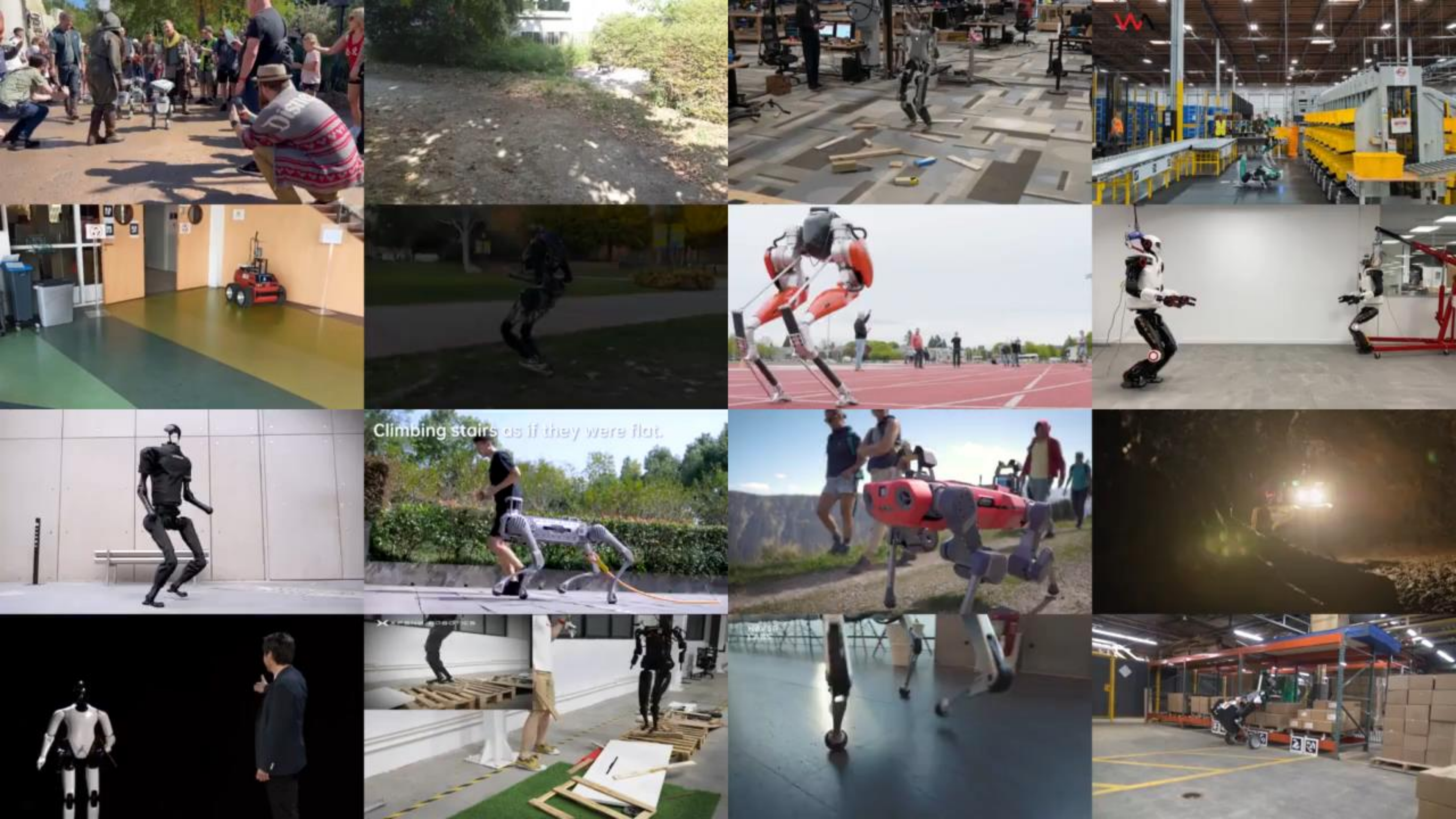
Legged Locomotion

Robots that can **go anywhere.**

Inspirations …

Marc Raibert *et coll.* MIT Leg Lab (… - 1995)

Karl Sims *et coll.* Evolved Virtual Creatures (1994)


Climbing stairs as if they were flat.

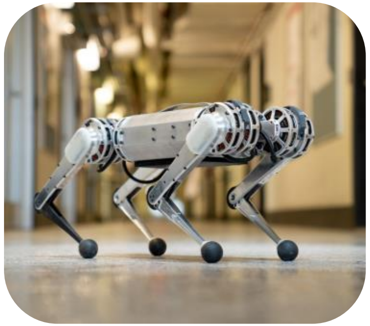
Why is legged robotics *particularly* interesting?

Task-based morphology

wheels

On flat floor

4 legs



If you have enough space

6 legs

Increased safety

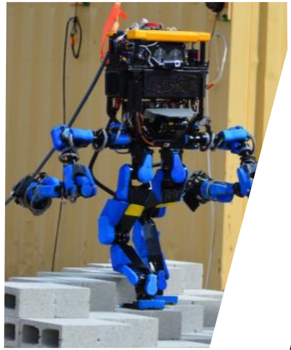
2 legs

Constrained range

X legs+arms+whhels

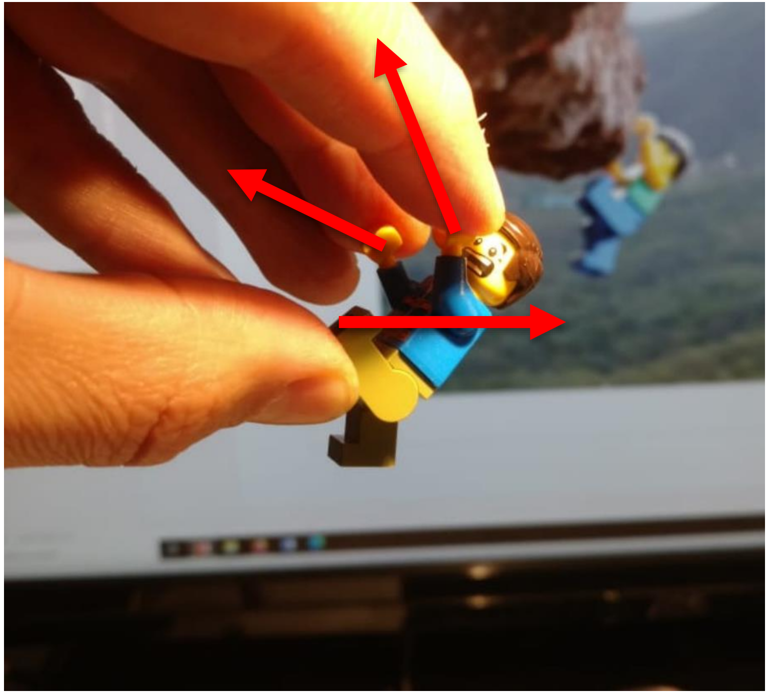
Mixed solution

???



Move in human-centric environments …

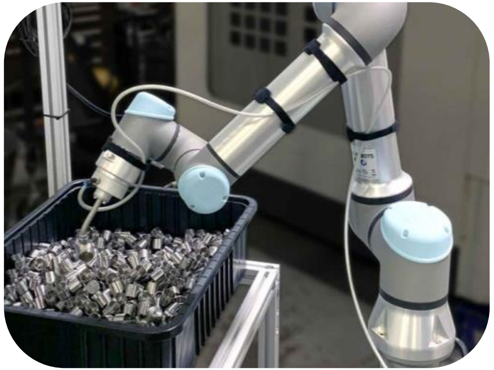
Locomotion and *manipulation* are dual problems



Manipulation

Locomotion

Apply forces on your environment …

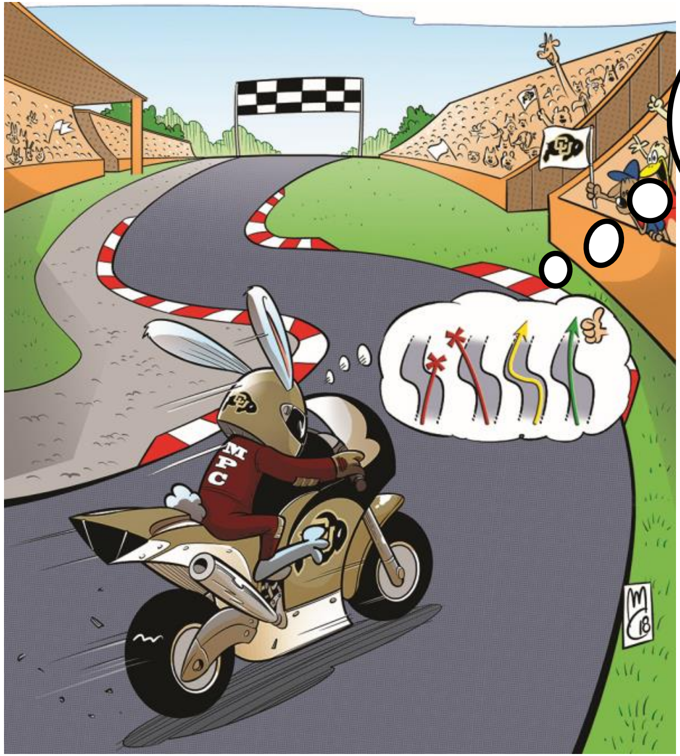


Versatile manufacturing

Flying hands

Mobile manipulators

Predictive control



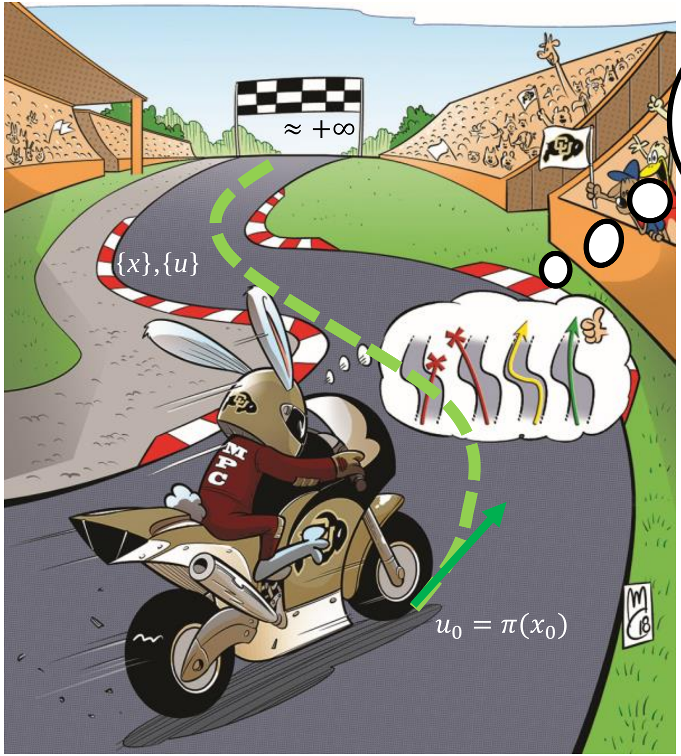
Original artwork by Michele Carminati,
commissioned by Marco M. Nicotra (U. Colorado Boulder)

Decide: future robot trajectory

By optimizing an objective function
(eg minimum energy)

Imposing:
- Known initial state
- Known evolution model (simulator)
- … and other constraints

Predictive control



Original artwork by Michele Carminati,
commissioned by Marco M. Nicotra (U. Colorado Boulder)

$$\min_{\substack{X=(Q,\dot{Q}),\\ U=\tau}} \int_0^T l(x_t, u_t)\, dt$$

so that
$$x(0) = \hat{x}$$
$$\dot{x}(t) = \underbrace{f(x(t), u(t))}_{\textit{Simulator}}, \ \forall t=0..T$$

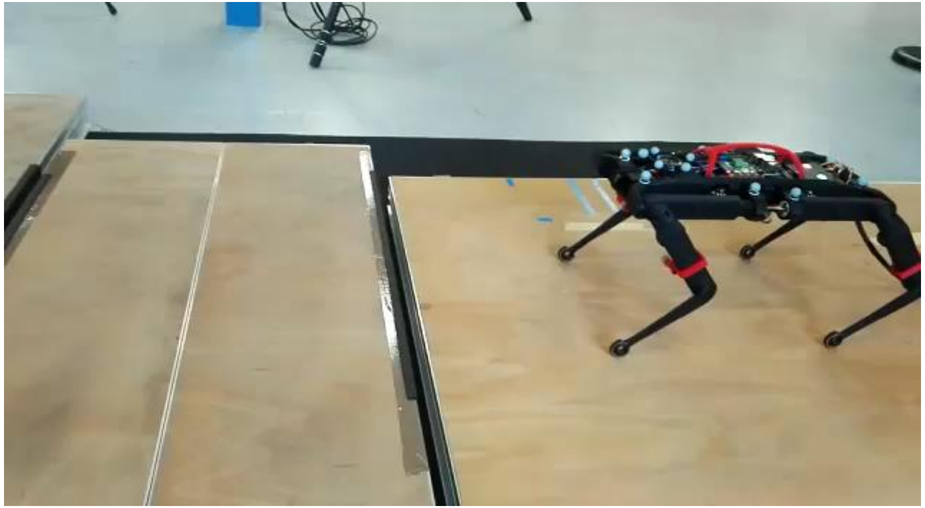
Example

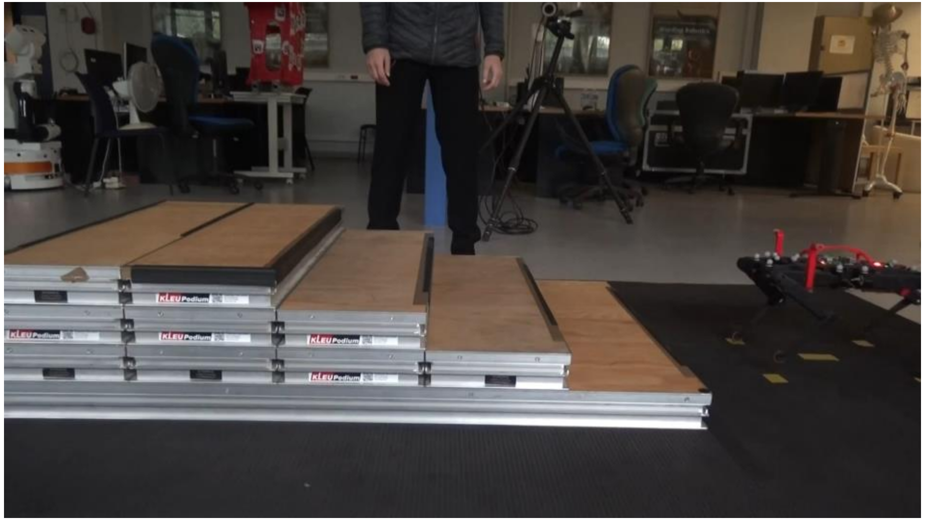
Core Components

3D Printed Actuator Shells

3D Printed Body Structure

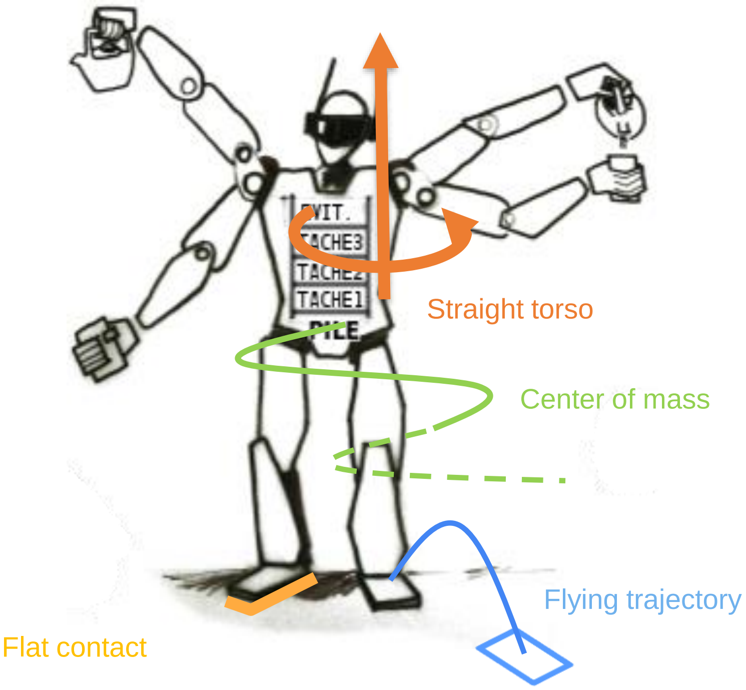
Custom Electronics

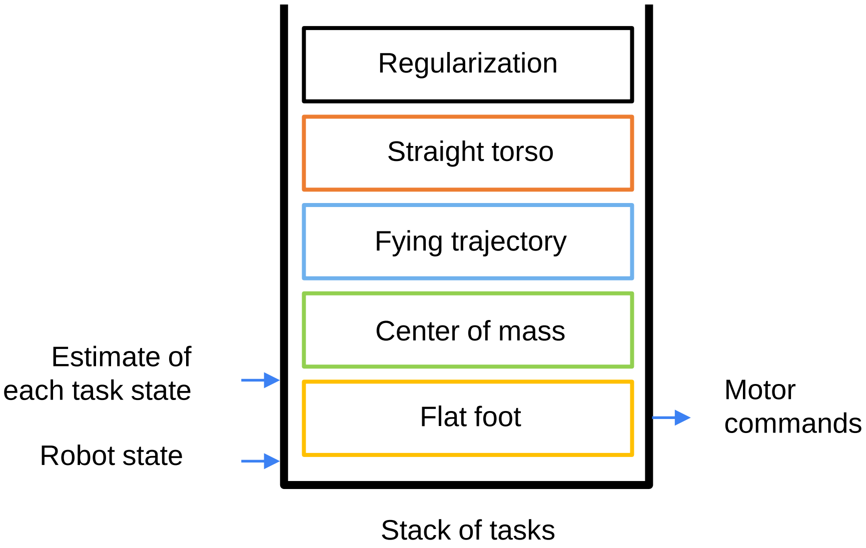


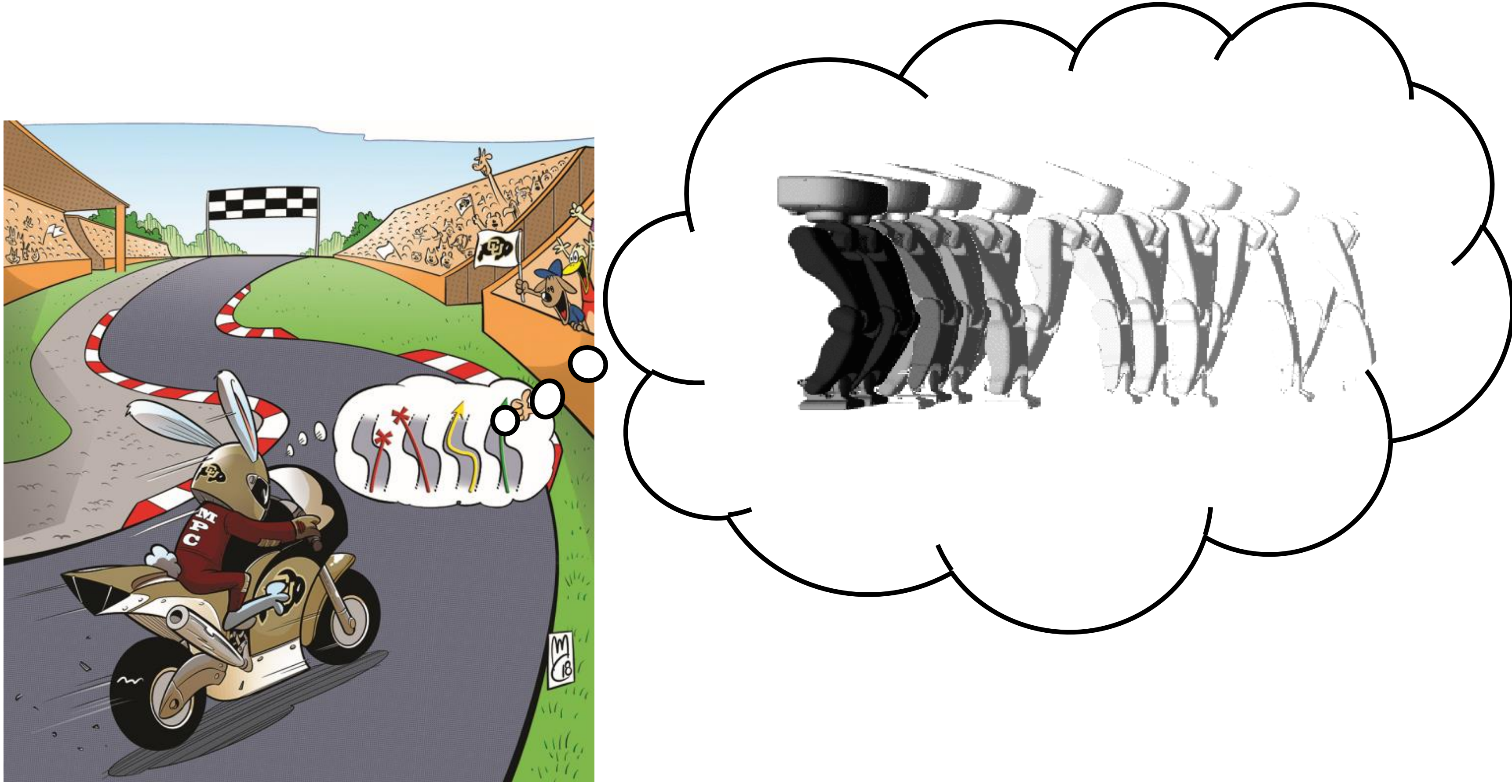


Operation control

… or *task-space* control







Original artwork by Michele Carminati,
commissioned by Marco M. Nicotra (U. Colorado Boulder)

Efficient solvers …

Carlos Mastalli
Univ. Watt @ Edinbourgh

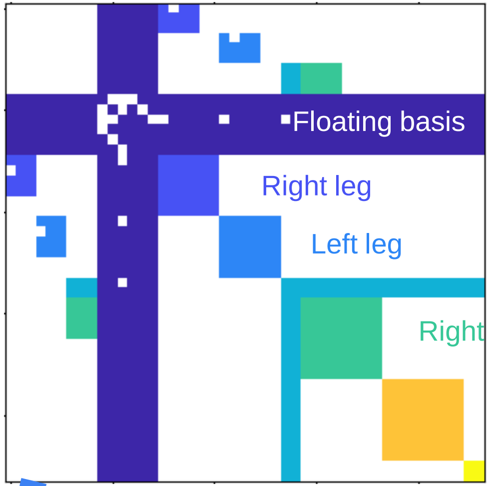
- Features expected from a good optimal control solver
  - Stable prediction: **multiple shooting**
  - Sparsity: **differential dynamic programming**
  - Strict constraints: **augmented Lagrangian**
  - Our solver incorporates all three !

- Performance on real case studies
  - 4 trot cycles for a quadruped: 8K vars, 12 iterations, **9ms / iter**
  - 2 steps for a humanoid: 12K vars, 18 iterations, **13ms / iter**

Crocoddyl
https://github.com/loco-3d/crocoddyl

Mastalli et al. (ICRA'20) – https://hal.science/hal-02294059/

… for efficient problems



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L_{ux} & & & & L_{uu} & & & F_u^T & & & \\
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 & & L_{ux} & & & & L_{uu} & & & & F_u^T \\
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-I & & & & & & & & & & \\
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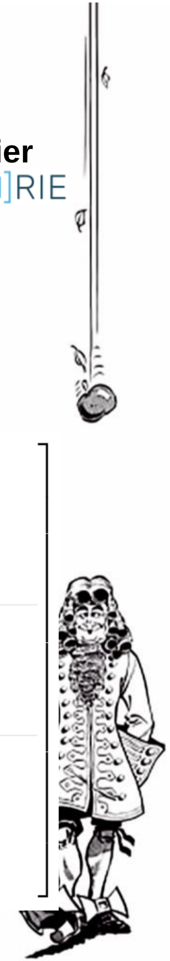
 & \ddots & \ddots & & & \ddots & & & & & \\
 & & F_x & -I & & & F_u & & & &
\end{array}\right]
$$

Justin Carpentier
Inria Paris PR[AI]RIE

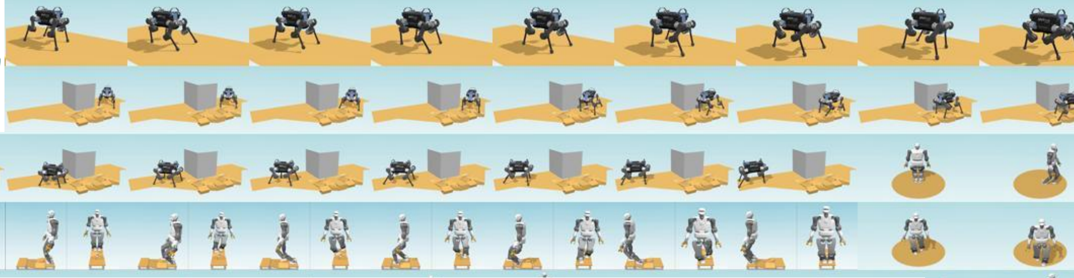


Pinocchio
https://github.com/stack-of-tasks/pinocchio

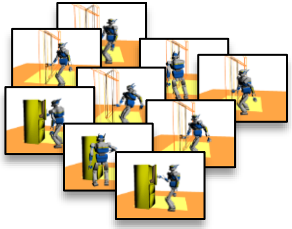
BSD
BSD-2 License

Carpentier et al. (2019) – https://hal.science/hal-01866228v2

Memory of motion



Off-line
Optimization and encoding



Off-line
Exploration by optimization
Globalization

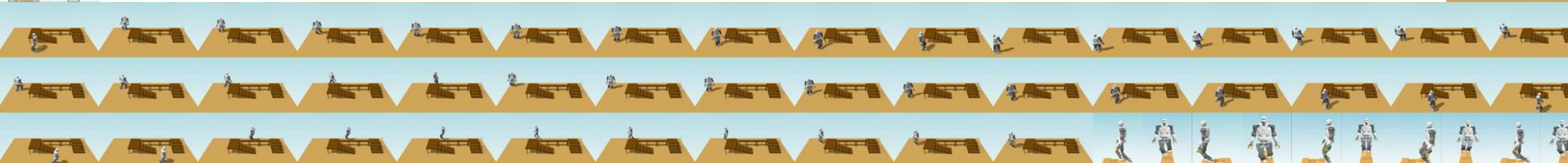
$$\min_{\substack{X=(Q,\dot{Q}),\\ U=\tau}} \int_0^T l(x_t, u_t)\,dt$$

$$\text{s.t.} \quad x(0) = \hat{x},$$

$$\dot{x}(t) = f\big(x(t), u(t)\big), \forall \text{t=0..T}$$

On-line
Whole-body predictive control
High-freq by local convergence

https://github.com/MeMory-of-MOtion/docker-loco3d

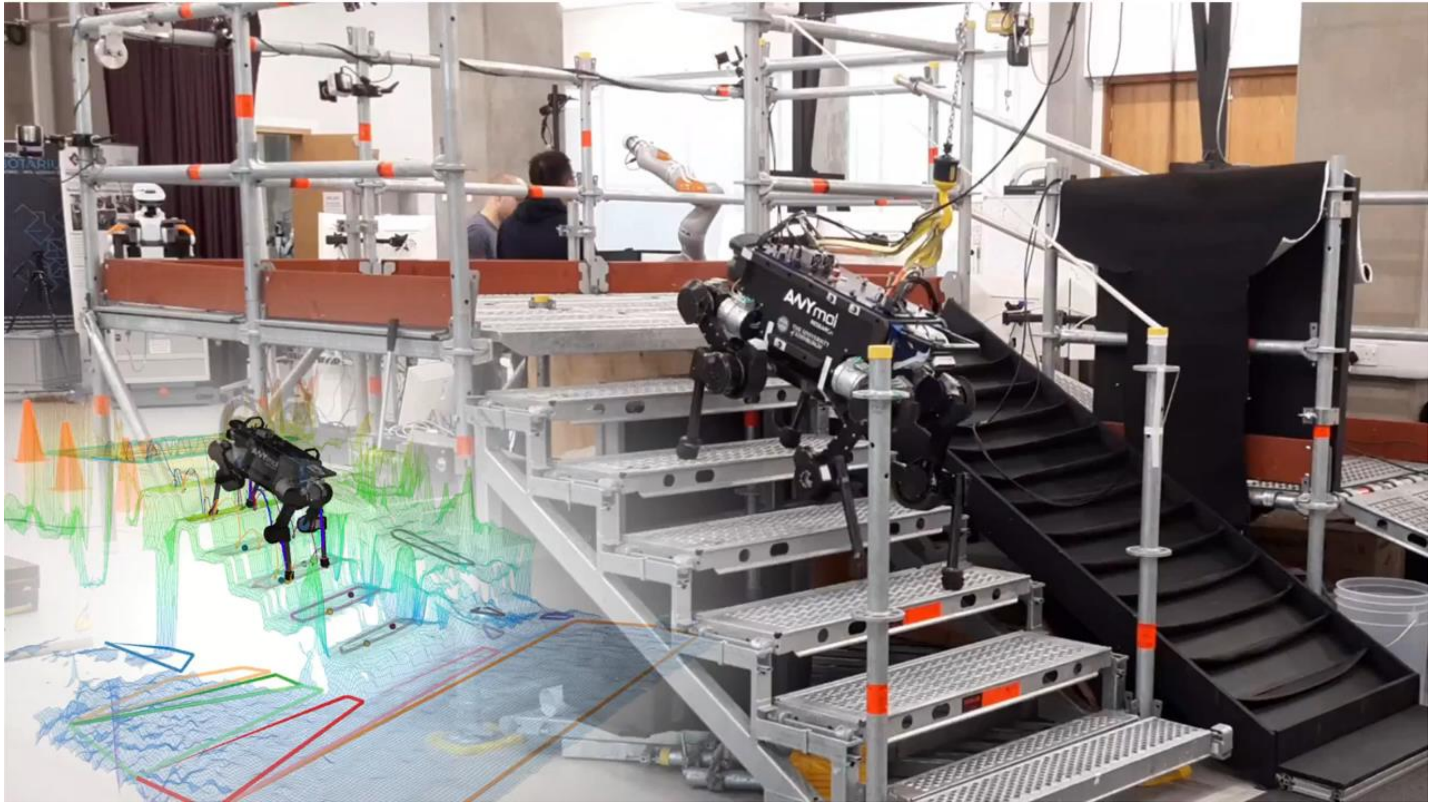


Efficient solver … for efficient problems

Ewen Dantec

Dantec et al. (RAL’22) – [https://cnrs.hal.science/hal- 03419712v2](https://cnrs.hal.science/hal-03419712v2)

Efficient solver … for efficient problems



Thomas Corberes

Steve Tonneau

Corberes et al. (subm IJRR'23) – https://arxiv.org/abs/2305.08926

Constraints with proximal augmented lagrangian

$$\min_x f(x) \;\; s.t \;\; g(x) \leq 0$$

- (Proximal) augmented Lagrangian

$$L_\mu(x, \square) = f(x) + \frac{1}{2\mu}\|g(x) + \mu\lambda\|_+^2 - \frac{\mu}{2}\|\lambda\|^2$$

- Primal update

$$\begin{bmatrix} \nabla^2 L & \nabla g \\ \nabla g^T & -\mu \end{bmatrix} \begin{bmatrix} \Delta x \\ \lambda \end{bmatrix} = -\begin{bmatrix} \nabla f + \lambda^T \nabla g \\ 0 \end{bmatrix}$$

- Dual update

$$\lambda \mathrel{+}= g/\mu$$

Jallet et al. (subm TRO 2023) – https://hal.science/hal-04332348v1

Optimal control induces sparse structure

$$
\left[\begin{array}{cccc|ccc|cccc}
L_{xx} & & & & L_{xu} & & & -I & F_x^T & & \\
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& & L_{xx} & & & & L_{xu} & & & -I & F_x^T \\
& & & L_{xx} & & & & & & & -I \\
\hline
L_{ux} & & & & L_{uu} & & & & F_u^T & & \\
& \ddots & & & & \ddots & & & & \ddots & \\
& & L_{ux} & & & & L_{uu} & & & & F_u^T \\
\hline
-I & & & & & & & & & & \\
F_x & -I & & & F_u & & & & & & \\
& \ddots & \ddots & & & \ddots & & & & & \\
& & F_x & -I & & & F_u & & & &
\end{array}\right]
$$

$$
\begin{bmatrix}
\Gamma_1 & M_1^T & 0 & 0 & \cdots & 0 \\
M_1 & \Gamma_2 & M_2^T & 0 & \cdots & 0 \\
0 & M_2 & \Gamma_3 & M_3^T & \cdots & 0 \\
0 & 0 & M_3 & \Gamma_4 & \ddots & 0 \\
\vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & 0 & 0 & \ddots & \Gamma_T
\end{bmatrix}
\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ s_4 \\ \vdots \\ s_T \end{bmatrix}
=
\begin{bmatrix} g_1 \\ g_2 \\ g_3 \\ g_4 \\ \vdots \\ g_T \end{bmatrix}
$$

Crocoddyl

Jordana+Kleff+Meduri et al (subm TRO 2023) – https://ens.hal.science/hal-04330251v1

Progress in numerical optimization

- With a augmented Lagrangian approach (with Willow@Inria)
  - Using proximal formulation to handle the conditioning
  - Following the main-stream literature
  - Implemented in a proposition of renew of Crocoddyl (Aligator package)

Jallet et al. (subm TRO 2023) – https://hal.science/hal-04332348v1

- With a SQP approach (with MiM@NYU)
  - Using the operator-splitting method (OSQP) with Ricatti linear solver
  - Following the main-stream literature
  - Implemented as an ad-on to Crocoddyl (MiM-solver package)

Jordana+Kleff+Meduri et al (subm TRO 2023) – https://ens.hal.science/hal-04330251v1

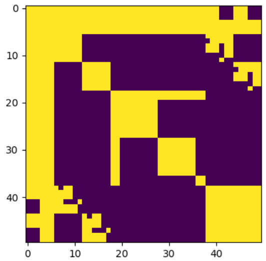
Haffemayer et al (subm ICRA) – https://hal.science/hal-XXX

Efficient dynamics with constraints

- Forward dynamics with (bilateral) constraints

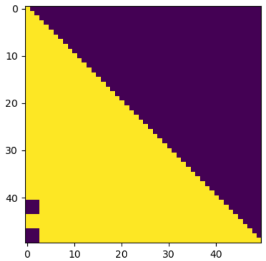
$$M\ddot{q} + b = \tau + J^T f$$
$$J\ddot{q} = \gamma_0$$

- KKT structure



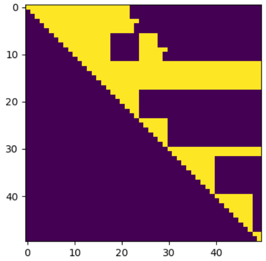
Classical Cholesky decomposition is not sparse

$$\sqrt{\begin{bmatrix} M & J^T \\ J & 0 \end{bmatrix}}$$

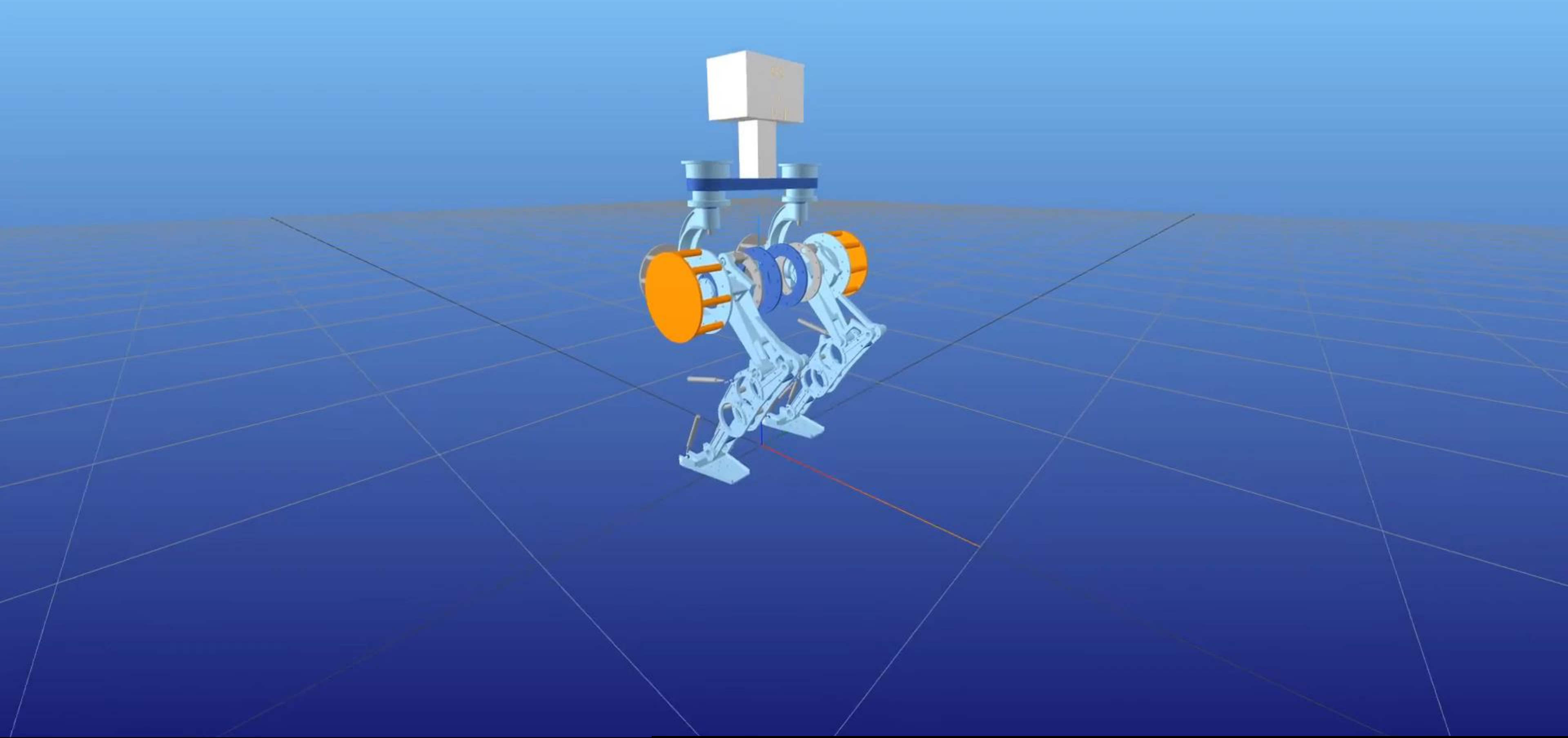


Permutting the terms and using UDUT decomposition

$$\sqrt{\begin{bmatrix} 0 & J \\ J^T & M \end{bmatrix}}$$

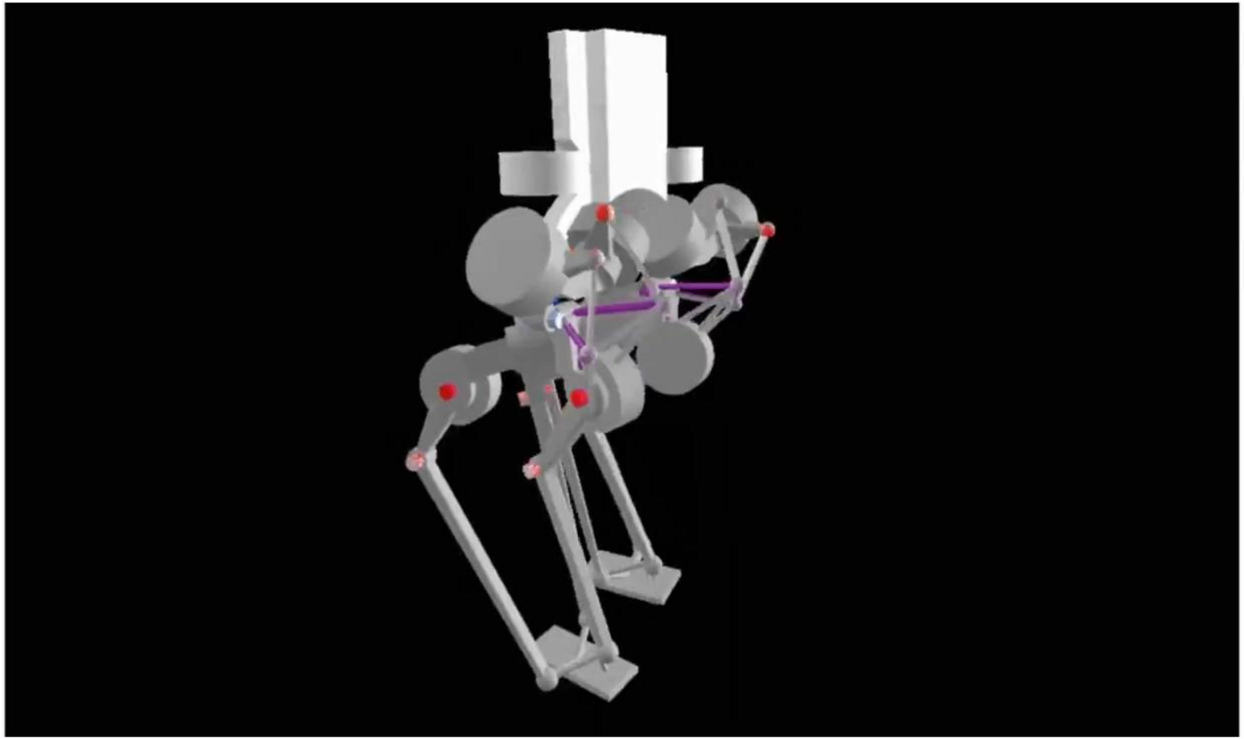


Closed Kinematic Loops as Contraints



Kinematics of the architecture

New biped architecture proposed with fully-parallel kinematics



Batto et al. (Hum'23) – https://hal.science/hal-04191553v2

$$\min_{\substack{X=(Q,\dot{Q}),\\ U=\tau}} \int_0^T l(x_t, u_t)\,dt$$

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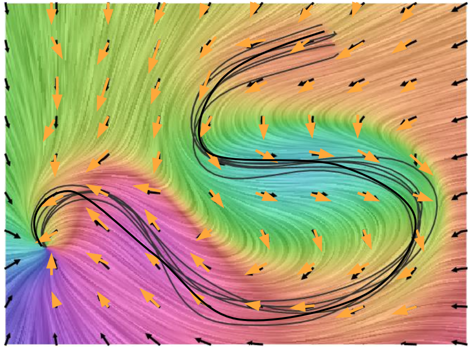


Trajectory optimization

$U: t \longrightarrow u(t)$

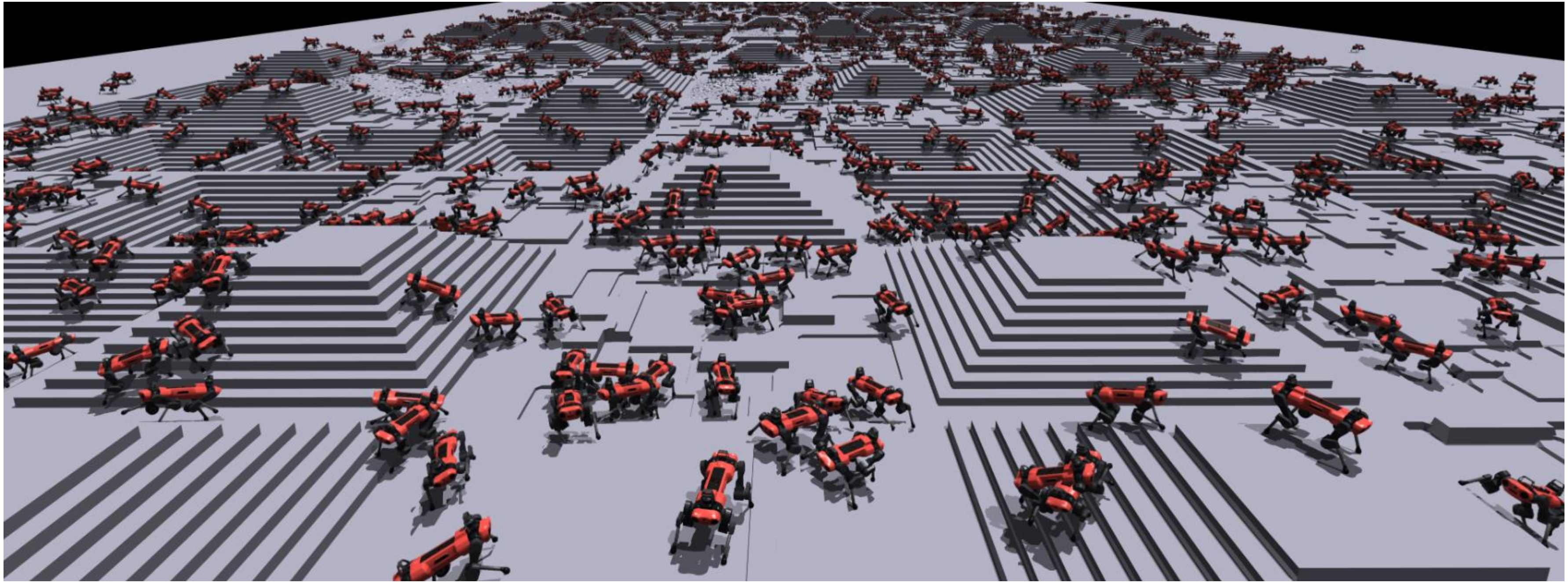
Motion planning

Policy optimization

$\Pi: x \longrightarrow u = \Pi(x)$

Reinforcement learning

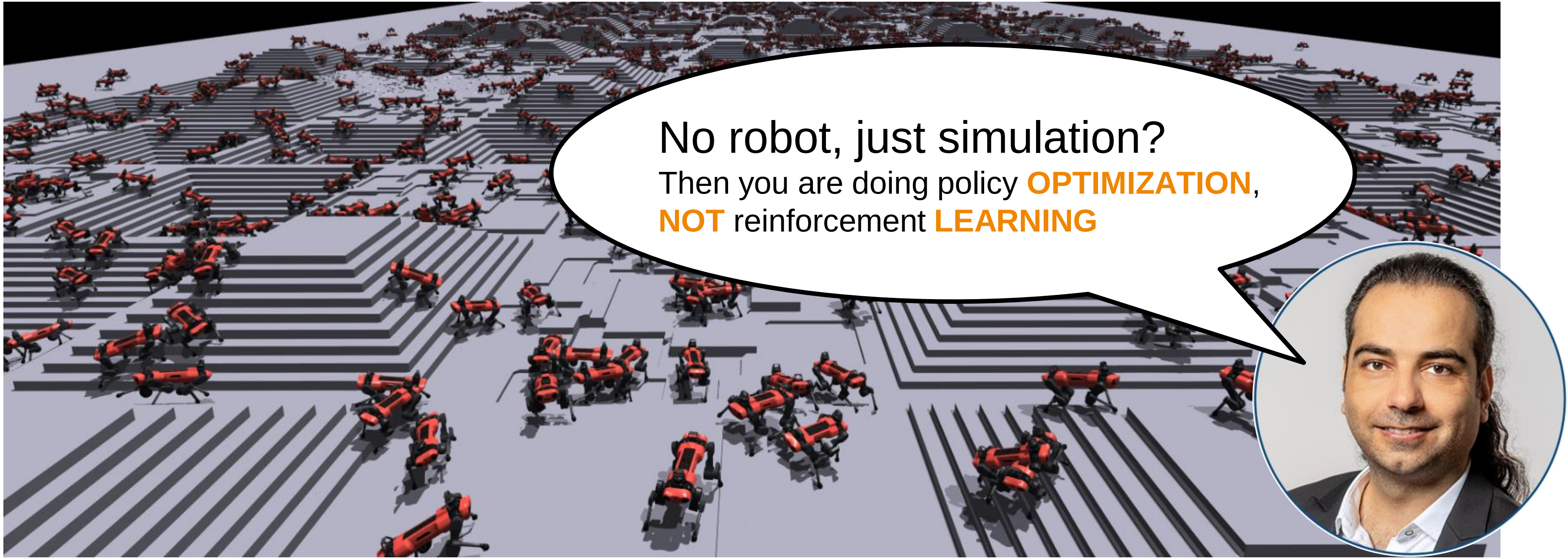
Policy optimization



Optimize the policies in physics simulators, then transfer on real robots.

Isaac Gym: High Performance GPU-Based Physics Simulation For Robot Learning, Makoviychuk et al., 2021
Learning to Walk in Minutes Using Massively Parallel Deep Reinforcement Learning, Rudin et al., CoRL 2021

Policy optimization *(aka RL from simu)*



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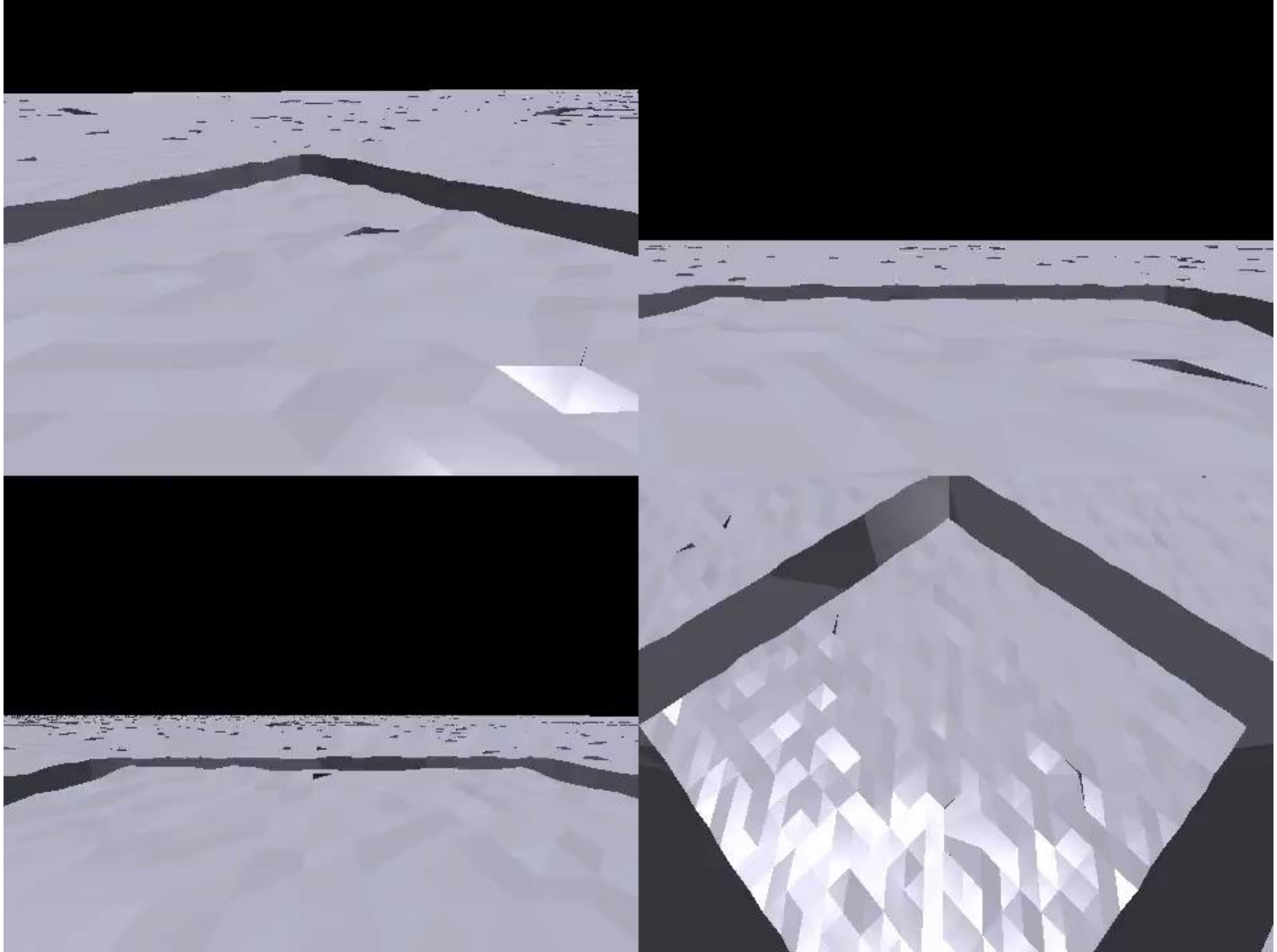
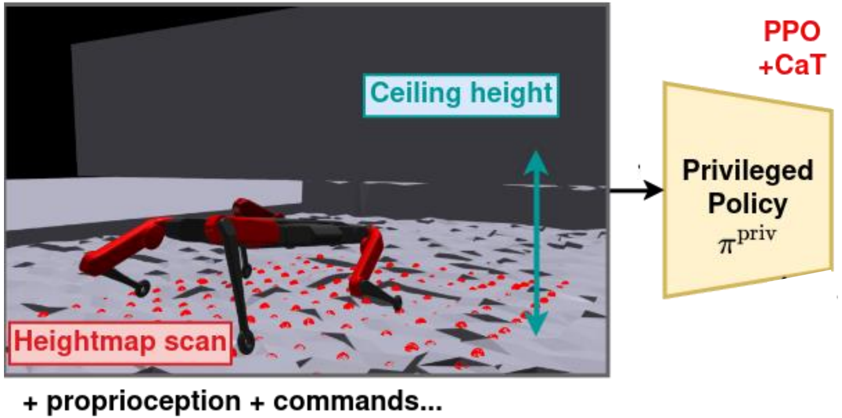


Example of shot put forbidden technique

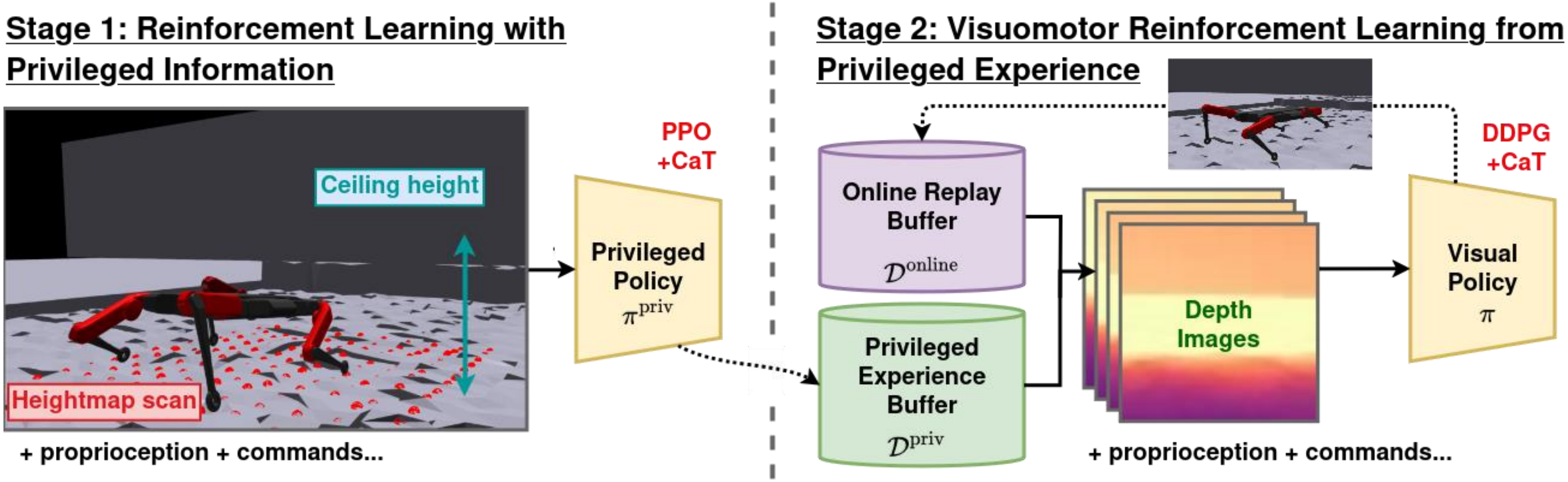
Stage 1: Reinforcement Learning with Privileged Information



Constrained RL with CaT and PPO from **privileged information** without images:

- Elevation map
- Ceiling height

Collecting data is fast

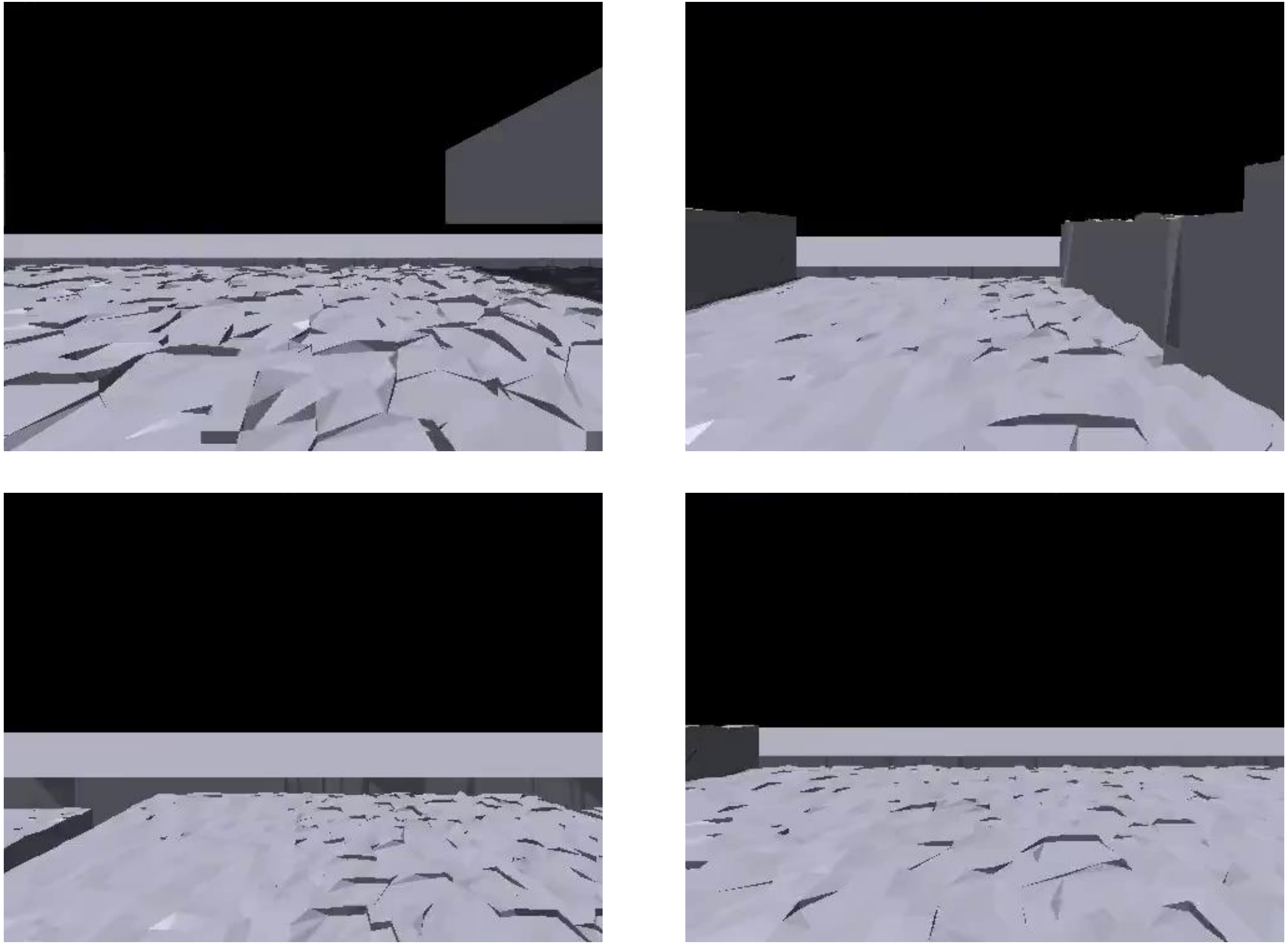


Highly sample-efficient RL + CaT

- Off-policy RL
- Privileged experience transfer
- High replay ratio, asymmetric actor-critic, layer norm critic...

Collecting data is slow

Efficient Online Reinforcement Learning with Offline Data, Ball et al., ICML23
Continuous control with deep reinforcement learning, Lillicrap et al., ICLR16



CoRL 2024

SoloParkour: Constrained Reinforcement Learning for Visual Locomotion from Privileged Experience

Elliot Chane-Sane*, Joseph Amigo*, Thomas Flayols, Ludovic Righetti, Nicolas Mansard

Gepetto
LAAS-CNRS

NYU

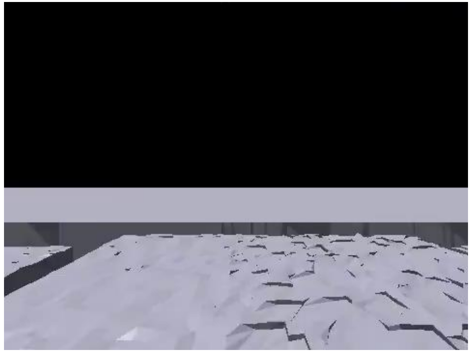
Limit

Modify the algorithm

Analyze the movements

Repeat until “it looks good”

ex: reward engineering



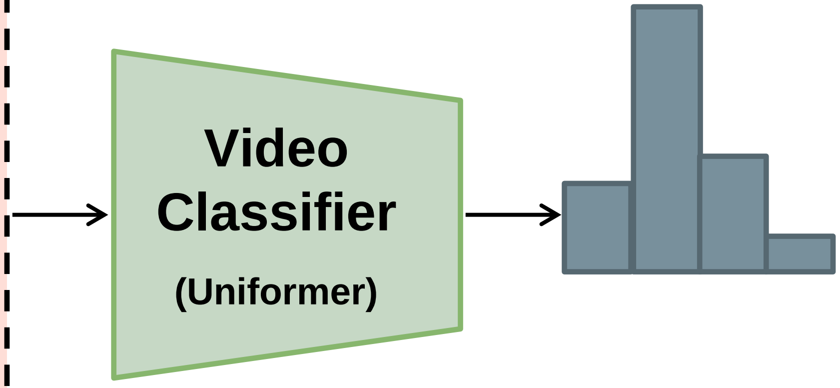
Looking good = animal-like ?

Can we directly optimize for visually successful robot motions ?

Can robots learn by watching thoushands of wild animal videos from the internet ?

Video-Based Reward Function

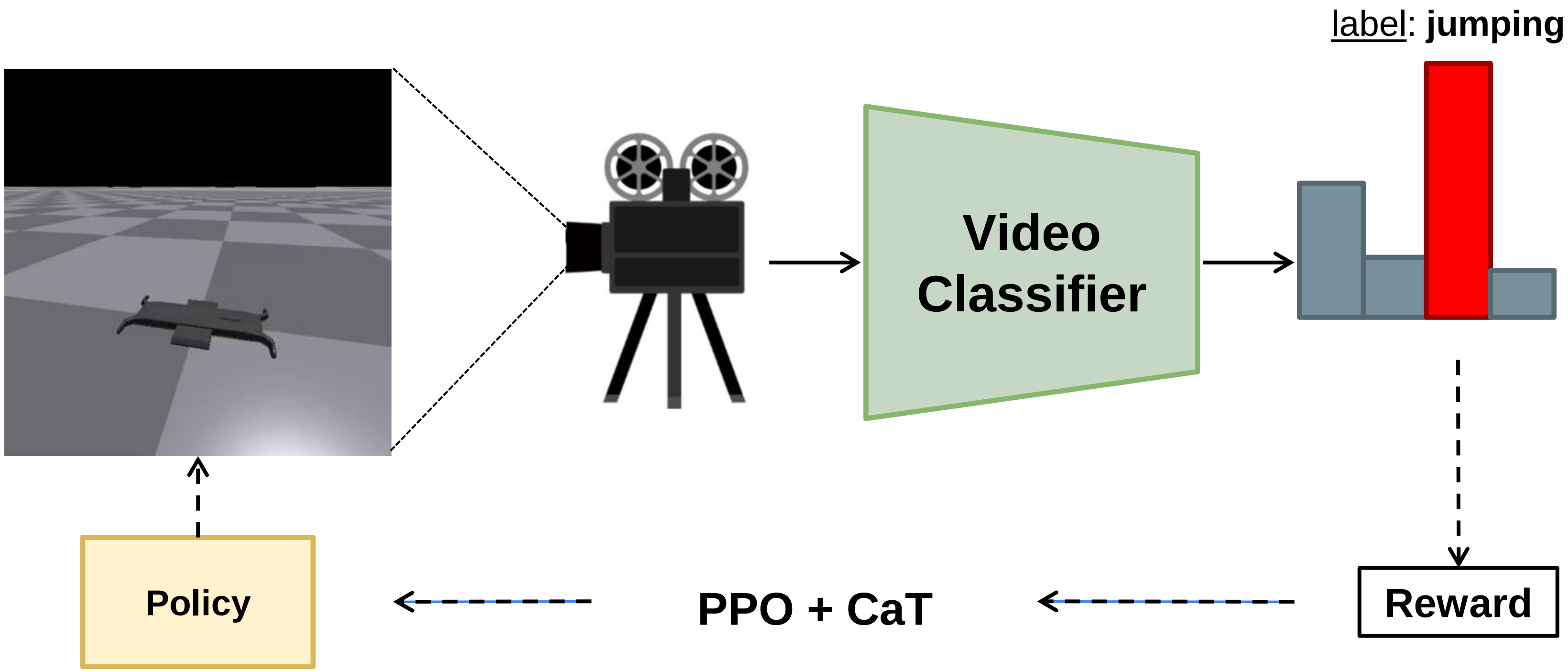
Anymal Kingdom Dataset



selected 8,791 videos for training

Animal Kingdom: A Large and Diverse Dataset for Animal Behavior Understanding, Ng et al., CVPR 2022
UniFormer: Unified Transformer for Efficient Spatiotemporal Representation Learning, Li et al., ICLR 2022

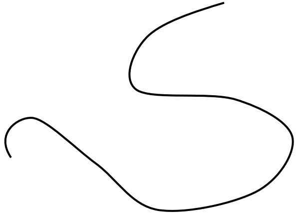
Reinforcement Learning from Wild Animal Videos



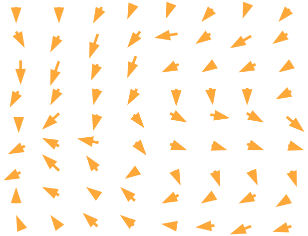
The classifier trained on animal videos transfers **zero-shot**


Walking

$$\min_{\substack{X=(Q,\dot{Q}),\\ U=\tau}} \int_0^T l(x_t, u_t)\,dt$$
$$\text{s.t.}\quad x(0) = \hat{x},$$
$$\dot{x}(t) = f\big(x(t), u(t)\big), \forall t=0..T$$

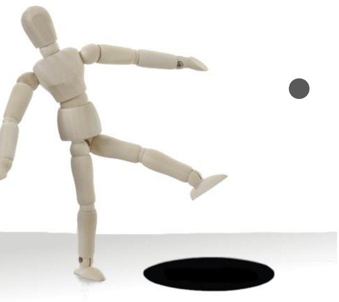


- ✓ trajectory optimization
- ✓ super-linear convergence
- ✓ real-time computation
- ✓ constraint satisfaction
- – local minima (no global policy)
- – difficulty with discontinuous dynamics
- – no inclusion of multi-modal sensing



- ✓ (global) policy optimization
- ✓ handles discontinuities
- ✓ multi-modal sensing inclusion
- – no guaranteed convergence
- – little use of model information
- – difficult transfer to robots
- – no constraint satisfaction

Messages to memorize



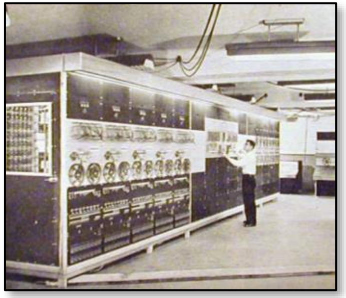
- Motion optimization is needed
  - Generalization: MPC is one-shot learning
  - Constraint satisfaction: road to IA with guarantees
  - Robotics needs a lot of numerical accuracy

- Motion learning is needed
  - Globalization comes from learning
  - No time to reinvent the wheel on-line

- There is a lot of intelligence in the hardware

Impact sociétal

Harvard computer (1950)

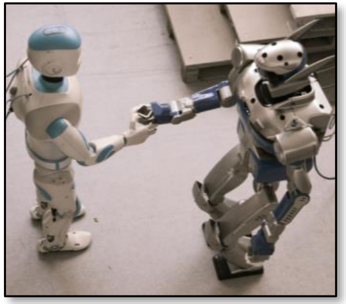


Internet

Informatique mobile

Prototypes
de laboratoire

50 ans plus tard…



Romeo (2010) et HRP-2 (2001)

?

?

Robots armés

© Getty Images

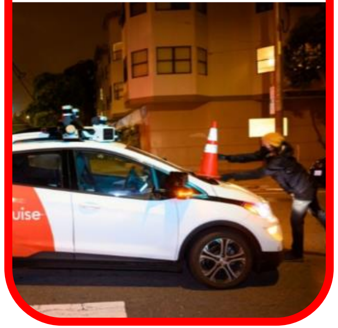
Gadget technologique

© Monsters forever

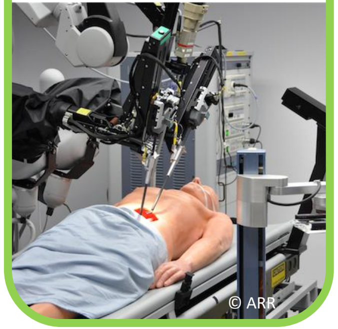
Confiscation du travail

© Franz Steiner

Voiture autonome



Robotique médicale



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Agriculture intelligente

© Naio Tech

Compétitivité

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Libération du travail

© `Getty Images