GRiD: GPU-Accelerated Rigid Body Dynamics with Analytical Gradients

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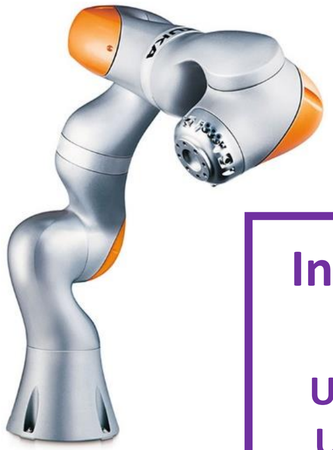

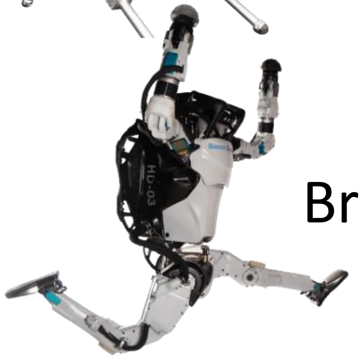

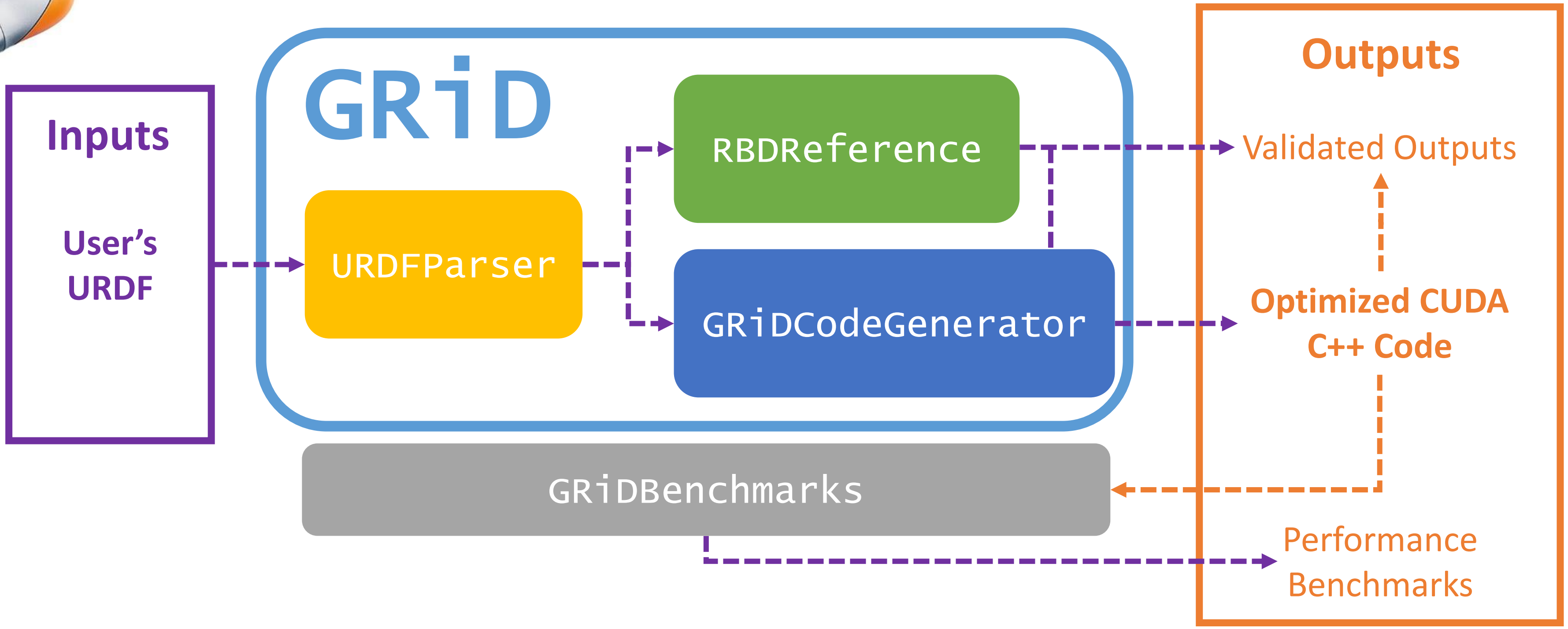

Brian Plancher[1], Sabrina M. Neuman[1], Radhika Ghosal[1], Scott Kuindersma[1,2], Vijay Janapa Reddi[1]

1: Harvard University John A. Paulson School of Engineering and Applied Sciences, 2: Boston Dynamics

GRiD: GPU-Accelerated Rigid Body Dynamics with Analytical Gradients

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GRiD makes it easy to use the GPU with robotics algorithms that use rigid body dynamics and provides up to a **7.2x speedup** and maintains **a 2.5x speedup with I/O**.

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1. Why GPU Rigid Body Dynamics?

2. GRiD's Modular Design

3. GRiD's Optimizations

4. Results

Rigid Body Dynamics Gradients are a bottleneck for planning and control (e.g., nonlinear MPC)

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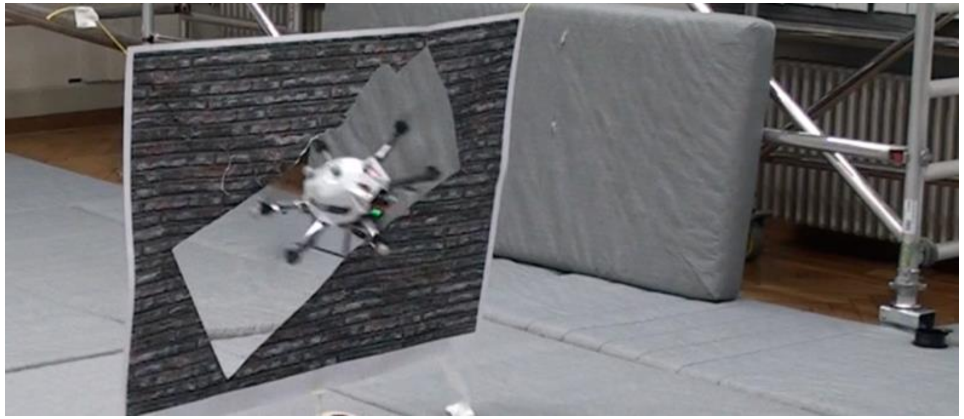

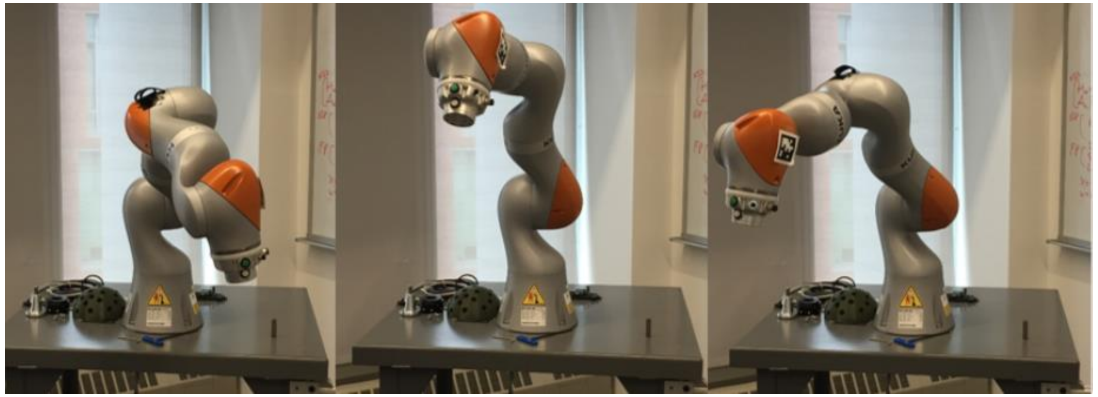

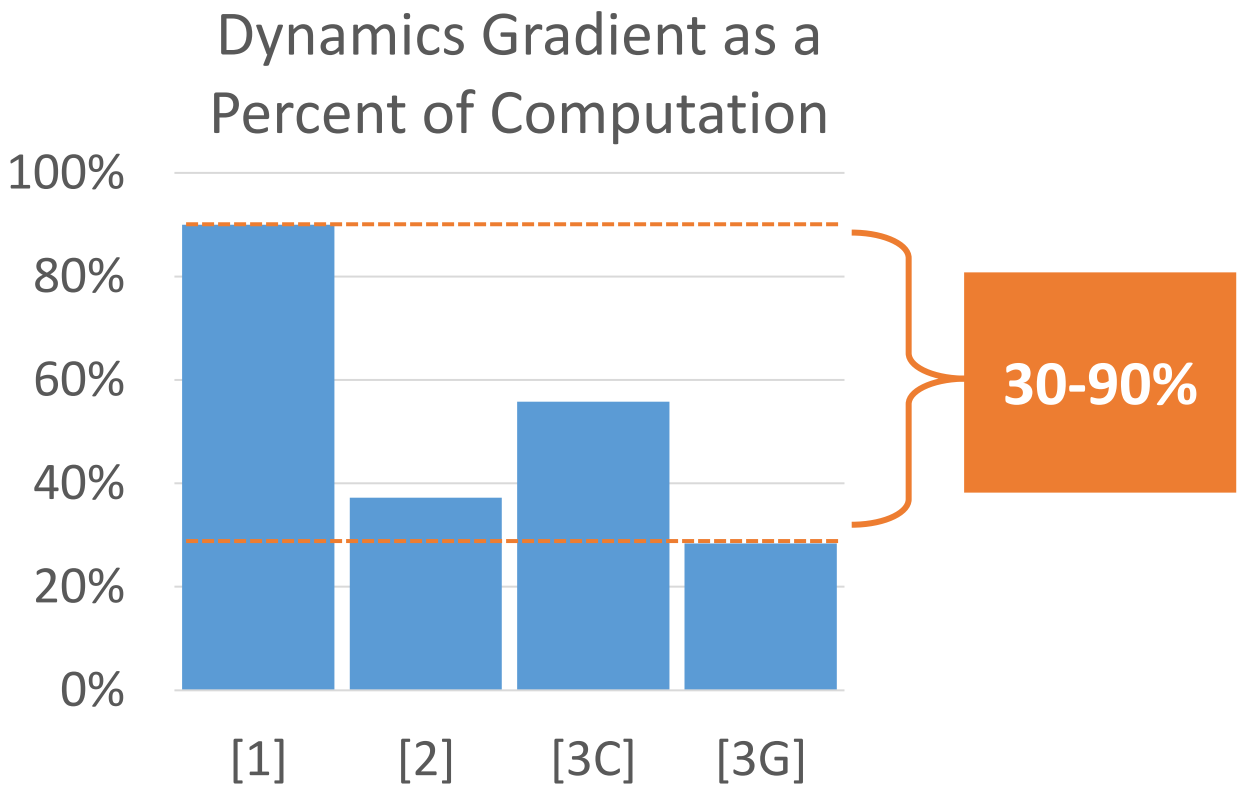

[1] J. Carpentier and N. Mansrud, "Analytical Derivatives of Rigid Body Dynamics Algorithms," RSS 2018

[2] M. Neunert, et al., "Fast nonlinear Model Predictive Control for unified trajectory optimization and tracking," ICRA 2016

[3] Best end-to-end [C]PU and [G]PU option from B. Plancher and S. Kuindersma, "A Performance Analysis of Parallel Differential Dynamic Programming," WAFR 2018

CPUs aren't getting faster

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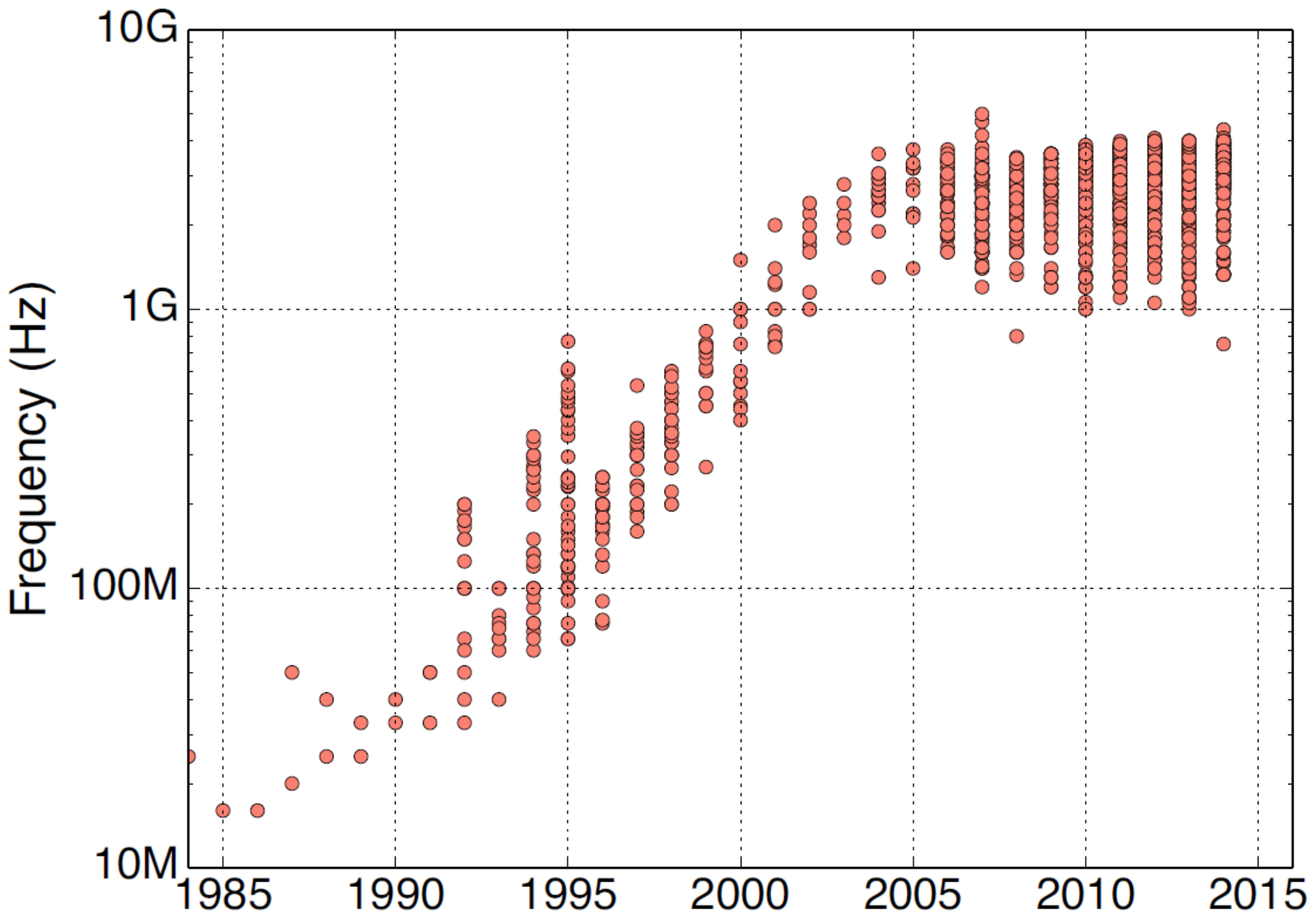

- Frequency scaling is ending (CPUs aren't getting faster)
- Massive parallelism on GPUs may be a solution for hardware acceleration

[Shao and Brooks "Synthesis Lectures on Computer Architecture" 2015]

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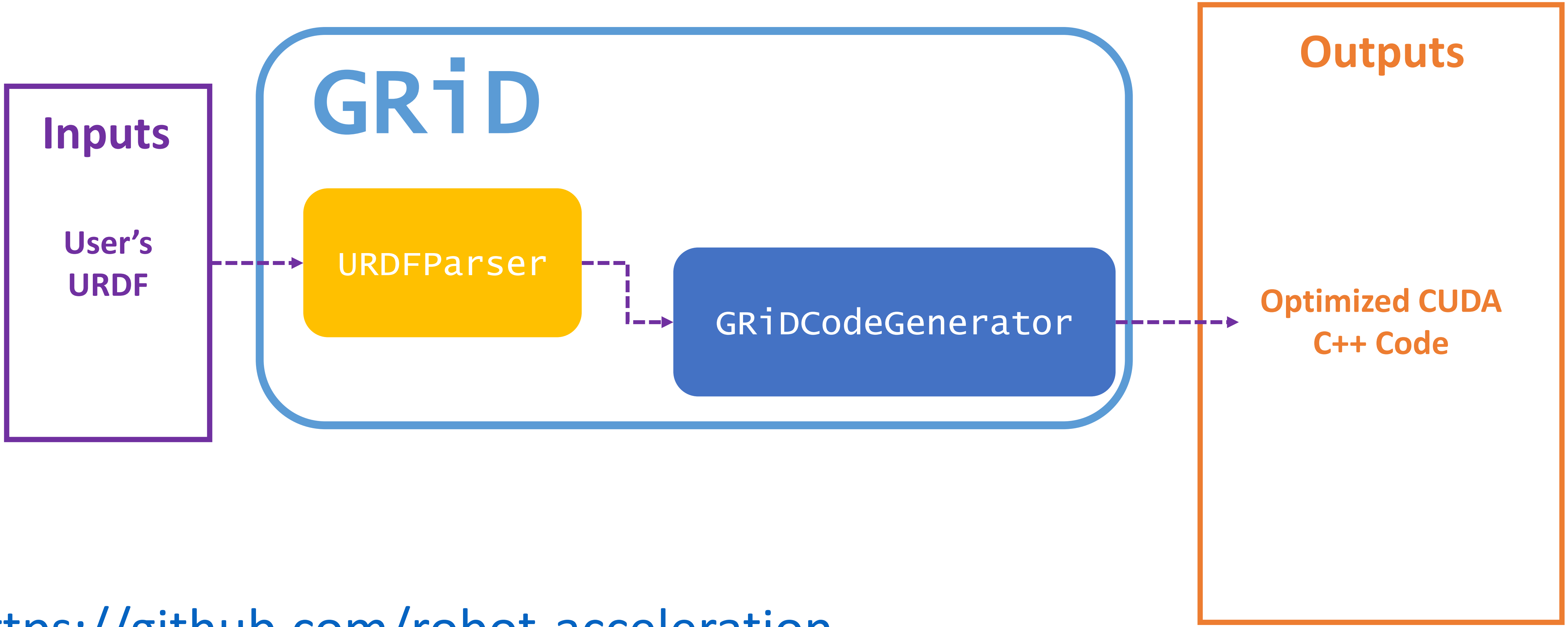

https://github.com/robot-acceleration

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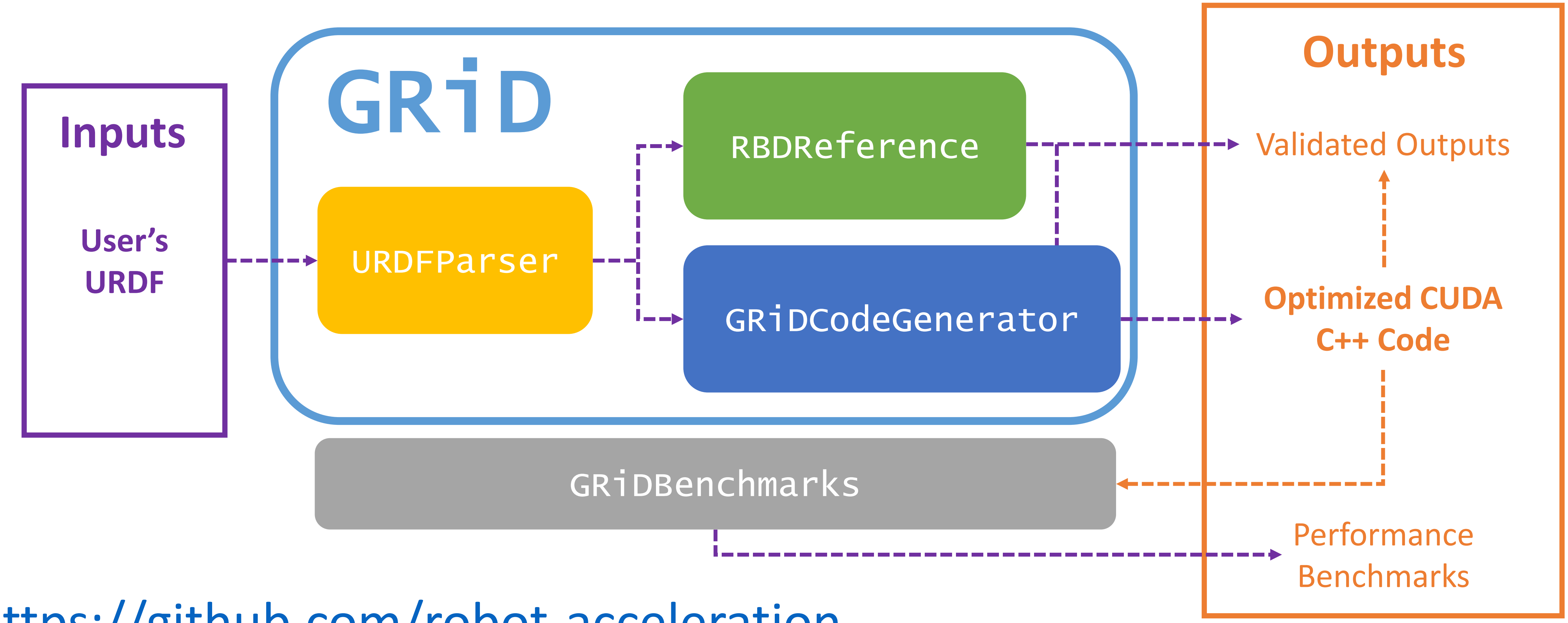

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GRiD currently supports:

- Prismatic, fixed, and revolute joints
- ID, FD, M^{-1}
- ∇ID, ∇FD with respect to $\mathbf{q}, \dot{q}, \mathbf{u}$

We are actively working to expand these features and welcome community support in this effort!

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GRiD exploits the structure of each robot to minimize memory and optimize latency

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Very serial algorithm

Algorithm 1 ∇RNEA-F$(\dot{q}, v, a, f, X, S, I) \rightarrow \partial c/\partial u$

for frame $i = 1 : N$ **do**

$$\frac{\partial v_i}{\partial u} = {}^iX_{\lambda_i}\frac{\partial v_{\lambda_i}}{\partial u} + \begin{cases} \left({}^iX_{\lambda_i}v_{\lambda_i}\right) \times S_i & u \equiv q \\ S_i & u \equiv \dot{q} \end{cases}$$

3: $$\frac{\partial a_i}{\partial u} = {}^iX_{\lambda_i}\frac{\partial a_{\lambda_i}}{\partial u} + \frac{\partial v_{\lambda_i}}{\partial u} \times S_i\dot{q}_i + \begin{cases} \left({}^iX_{\lambda_i}a_{\lambda_i}\right) \times S_i \\ v_i \times S_i \end{cases}$$

4: $$\frac{\partial f_i}{\partial u} = I_i\frac{\partial a_i}{\partial u} + \frac{\partial v_i}{\partial u} \times^* I_i v_i + v_i \times^* I_i\frac{\partial v_i}{\partial u}$$

GRiD exploits the structure of each robot to minimize memory and optimize latency

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Algorithm 2 ∇RNEA-F-GRiD$(\dot{q}, v, a, f, X, S, I) \rightarrow \partial f / \partial u$

for frame $i = 1 : n$ **in parallel do**

$\quad \alpha_i = {}^{i}X_{\lambda_i} v_{\lambda_i} \quad \beta_i = {}^{i}X_{\lambda_i} a_{\lambda_i} \quad \gamma_i = I_i v_i$

$\quad \alpha_i = \alpha_i \times S_i \quad \beta_i = \beta_i \times S_i \quad \delta_i = v_i \times S_i$

for level $l = 0 : l_{max}$ **do**

$\quad$ **for** frame $i \in l$ **in parallel do**

$$\frac{\partial v_i}{\partial u} = {}^{i}X_{\lambda_i} \frac{\partial v_{\lambda_i}}{\partial u} + \begin{cases} \alpha_i & u \equiv q \\ S_i & u \equiv \dot{q} \end{cases}$$

for frame $i = 1 : n$ **in parallel do**

$$\rho_i = \frac{\partial v_{\lambda_i}}{\partial u} \times S_i \dot{q}_i + \begin{cases} \beta_i \\ \delta_i \end{cases}$$

for level $l = 0 : l_{max}$ **do**

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for frame $i = 1 : n$ **in parallel do**

$$\frac{\partial f_i}{\partial u} = \frac{\partial v_i}{\partial u} \times^* \gamma_i \qquad \eta_i = v_i \times^* I_i$$

$$\frac{\partial f_i}{\partial u} = \frac{\partial f_i}{\partial u} + I_i \frac{\partial a_i}{\partial u} + \eta_i \frac{\partial v_i}{\partial u}$$

Refactor algorithms to expose **parallel loops of unified operations**

GRiD exploits the structure of each robot to minimize memory and optimize latency

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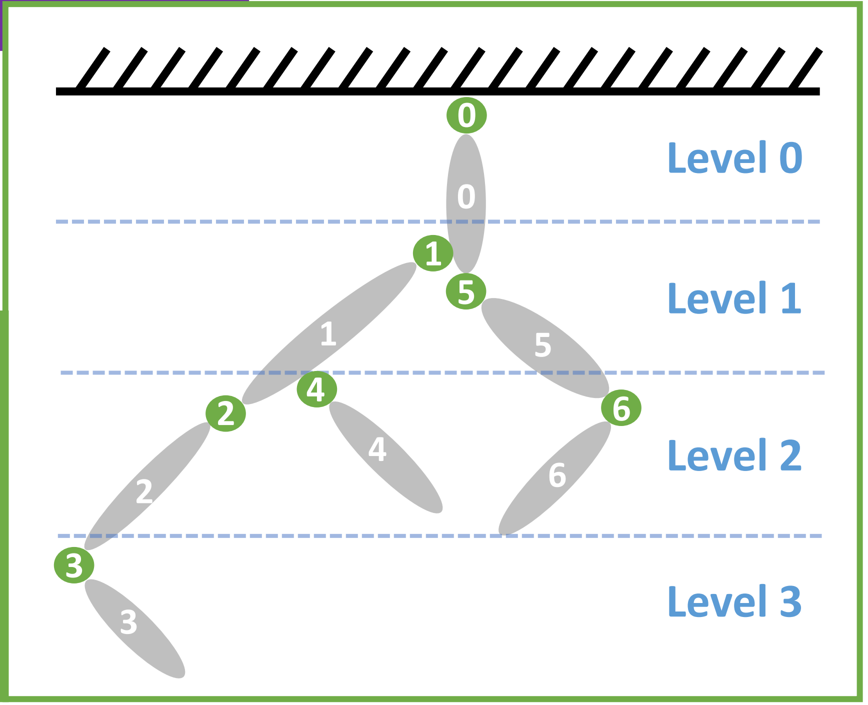
$\frac{\partial f_i}{\partial u} = \frac{\partial f_i}{\partial u} + I_i \frac{\partial a_i}{\partial u} + \eta_i \frac{\partial v_i}{\partial u}$

Refactor algorithms to expose **parallel loops of unified operations**

Compute remaining serial operations in **parallel across levels** of the rigid body tree



GRiD exploits the structure of each robot to minimize memory and optimize latency

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for level $l = 0 : l_{max}$ **do**

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for frame $i = 1 : n$ **in parallel do**

$$\rho_i = \frac{\partial v_{\lambda_i}}{\partial u} \times S_i \dot{q}_i + \begin{cases} \beta_i \\ \delta_i \end{cases}$$

for level $l = 0 : l_{max}$ **do**

$\quad$ **for** frame $i \in l$ **in parallel do**

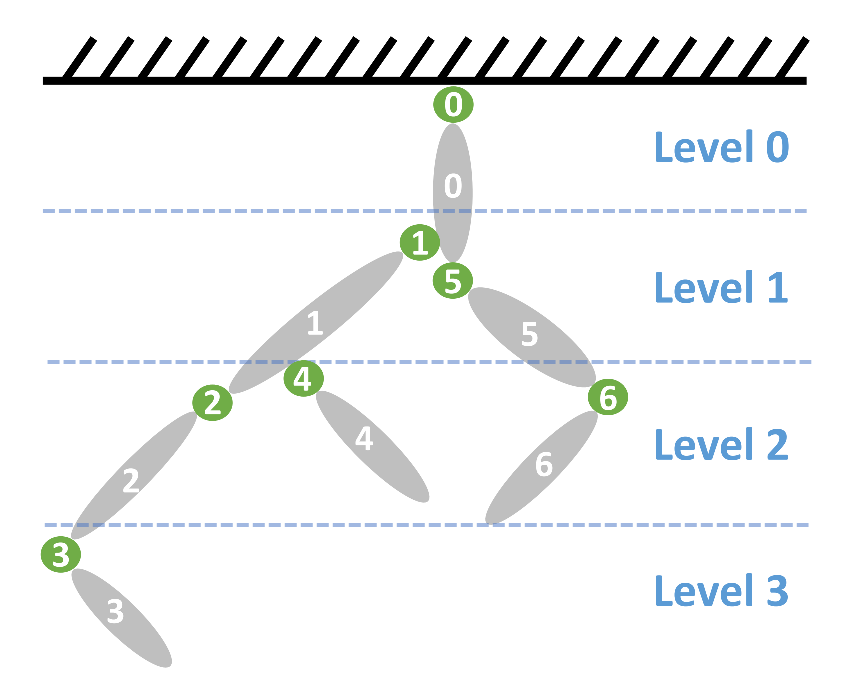
$$\frac{\partial a_i}{\partial u} = {}^iX_{\lambda_i} \frac{\partial a_{\lambda_i}}{\partial u} + \rho_i$$

for frame $i = 1 : n$ **in parallel do**

$$\frac{\partial f_i}{\partial u} = \frac{\partial v_i}{\partial u} \times^* \gamma_i \qquad \eta_i = v_i \times^* I_i$$

$$\frac{\partial f_i}{\partial u} = \frac{\partial f_i}{\partial u} + I_i \frac{\partial a_i}{\partial u} + \eta_i \frac{\partial v_i}{\partial u}$$

The **branch structure** also determines **sparsity in the columns of ∂v, ∂a, and ∂f**



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GRiD improves both computational latency and scalability

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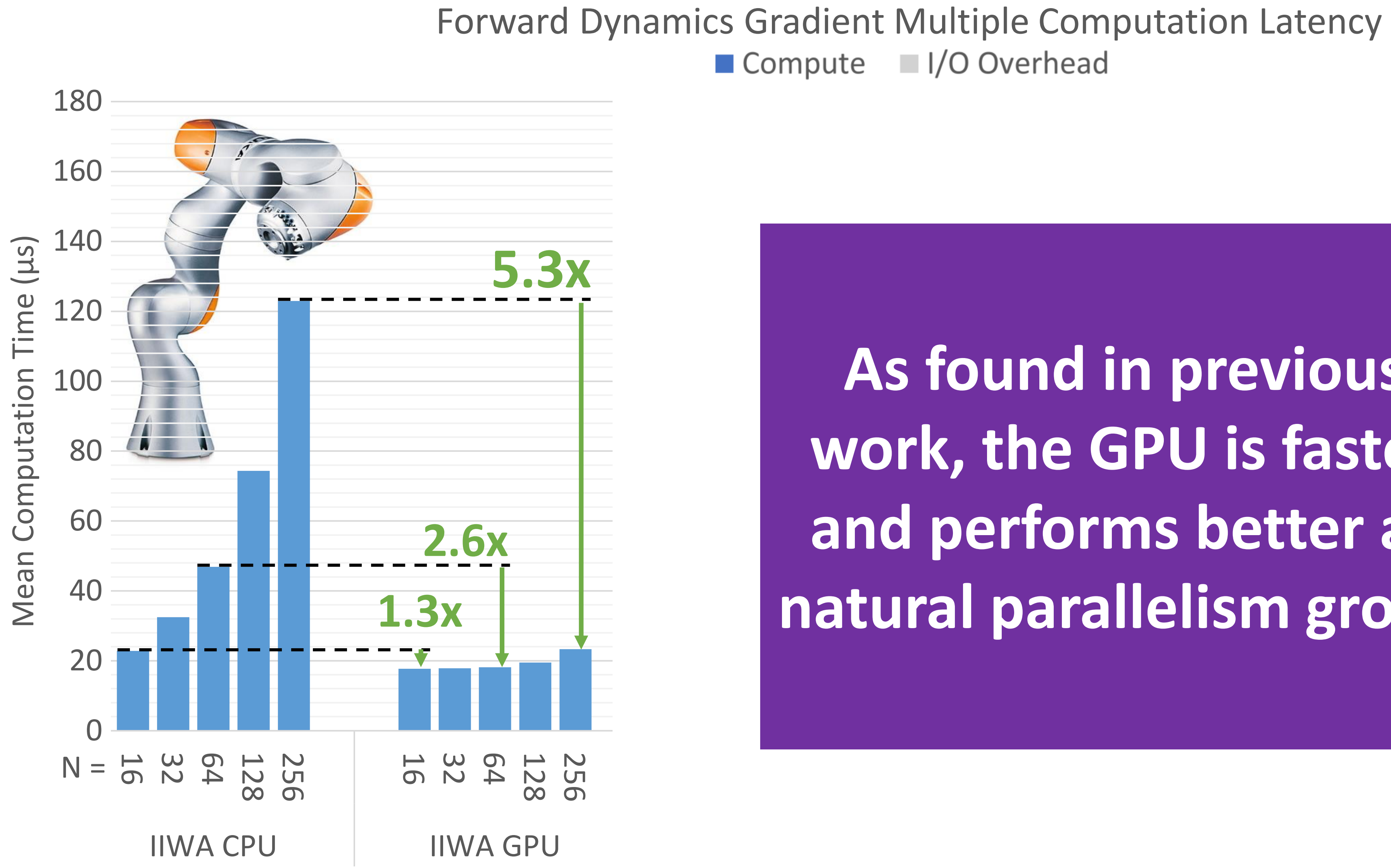

As found in previous work, the GPU is faster and performs better as natural parallelism grows

GRiD improves both computational latency and scalability

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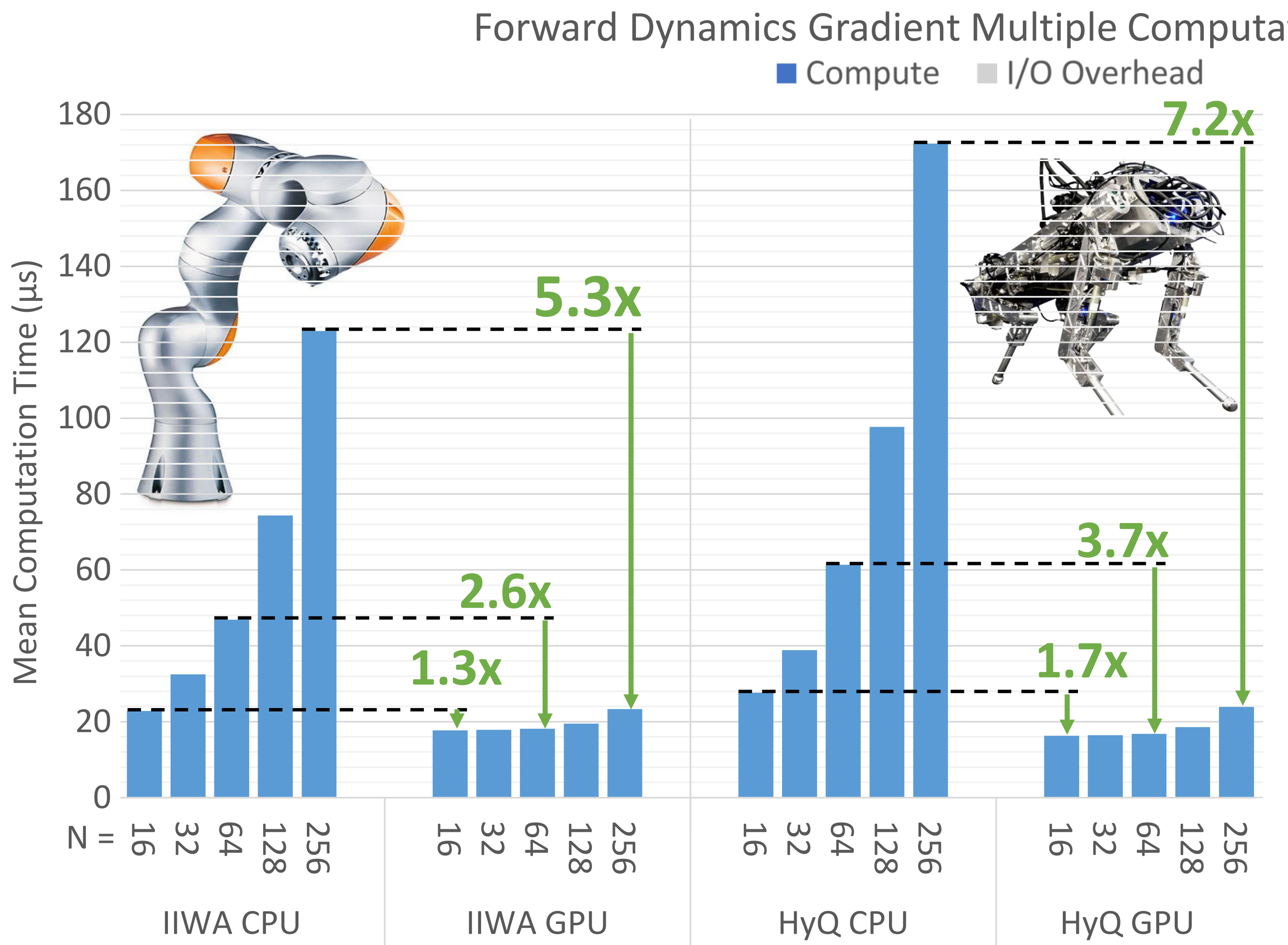

We show that the GPU does even better as robot complexity grows as well!

GRiD improves both computational latency and scalability

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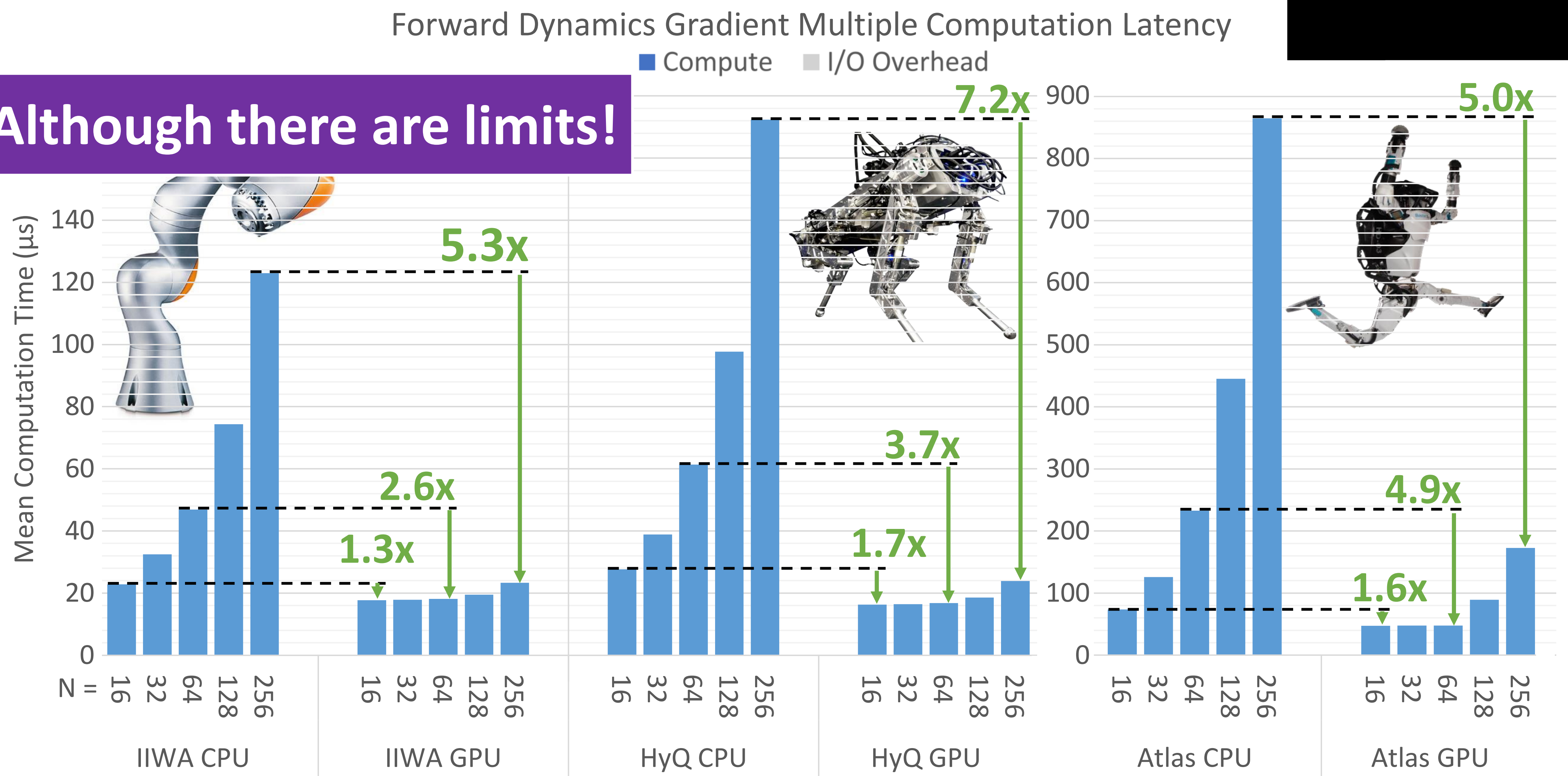
Although there are limits!



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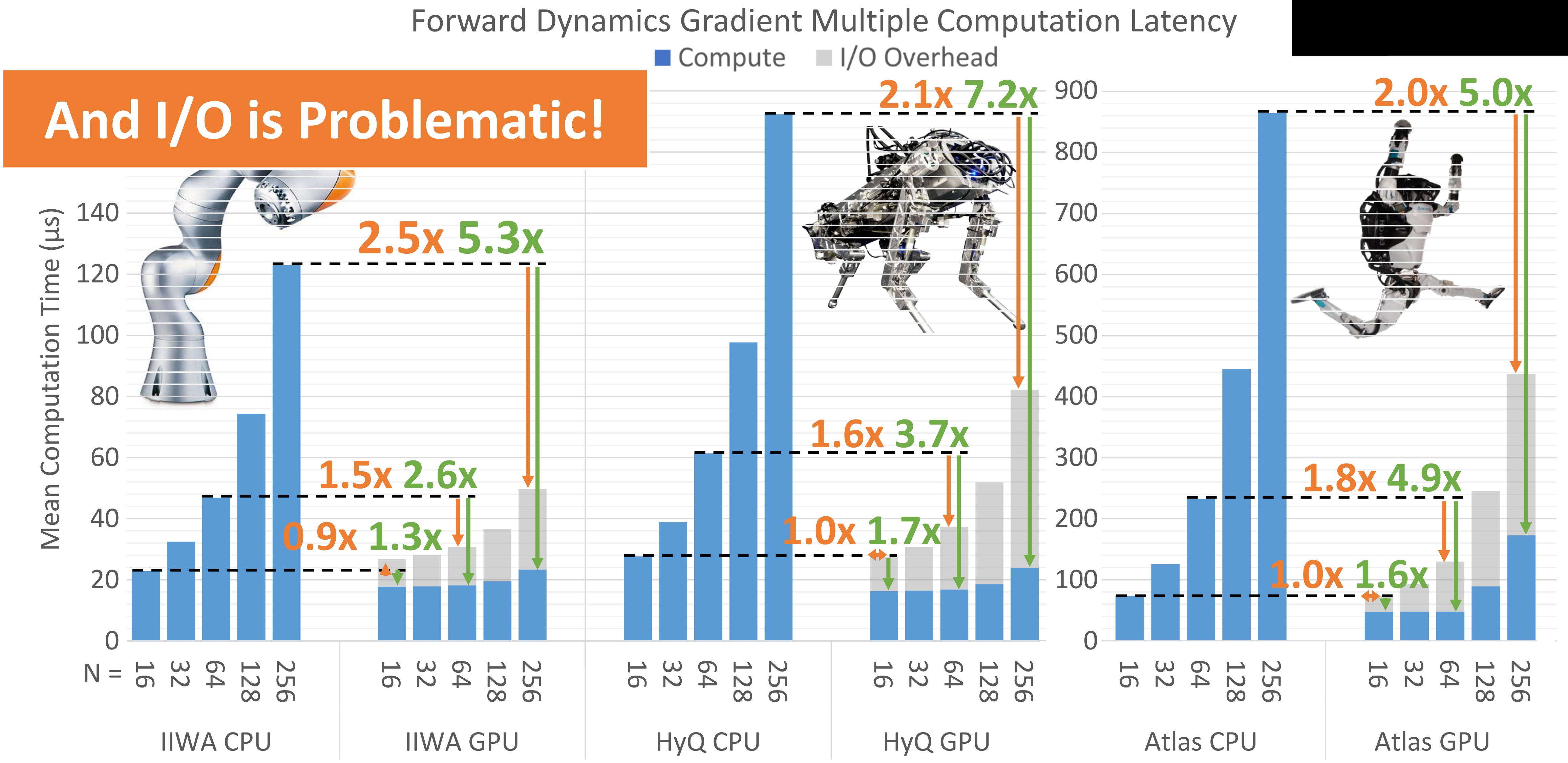

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GRiD is a **URDF to optimized CUDA C++ library** designed to provide **GPU acceleration** for rigid body dynamics algorithms and their analytical gradients. GRiD provides up to a **7.2x speedup** and maintains **a 2.5x speedup with I/O**.

GRiD makes it easy to use the GPU with robotics algorithms that use rigid body dynamics!

https://github.com/robot-acceleration

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