The Power of Gradients in Inverse Dynamics Problems

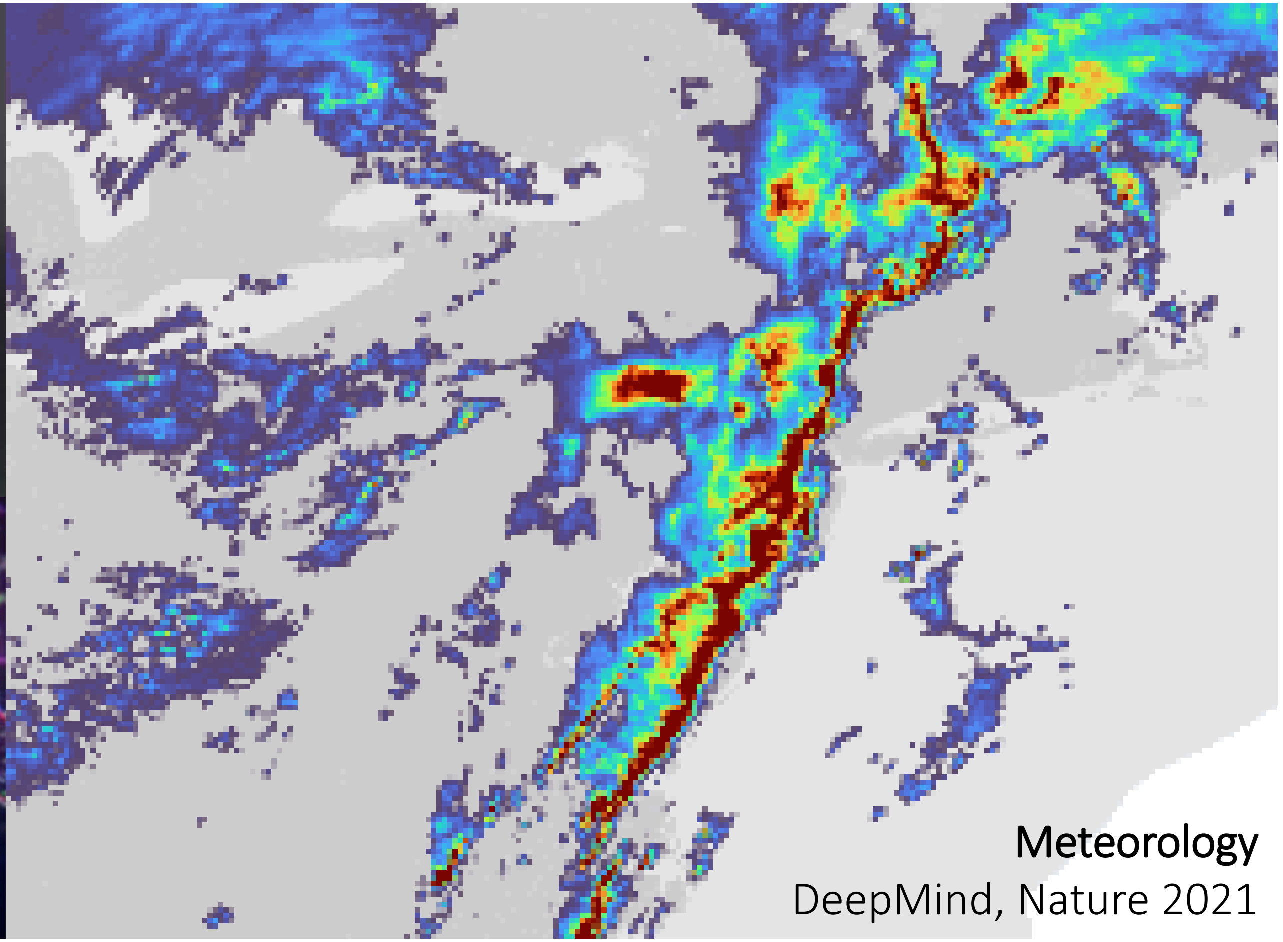
Tao Du

MIT CSAIL

What is a dynamic system?


Robotics
ETH Zurich, ANYmal


Molecular Biology
SCLS


Meteorology
DeepMind, Nature 2021

What is a dynamic system?

"A dynamical system is particle or ensemble of particles whose state varies over time and thus obeys differential equations involving time derivatives."

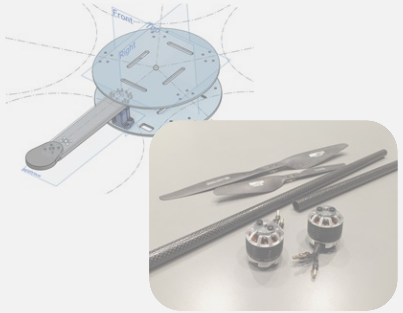
---Nature Portfolio

The forward problem in dynamic systems

$$\boldsymbol{F}_{\theta,\phi}\left(t;\boldsymbol{s},\frac{d\boldsymbol{s}}{dt},\frac{d^2\boldsymbol{s}}{dt^2},\cdots;\boldsymbol{a}\right)=\boldsymbol{0}$$

Dynamic model

The forward problem in dynamic systems

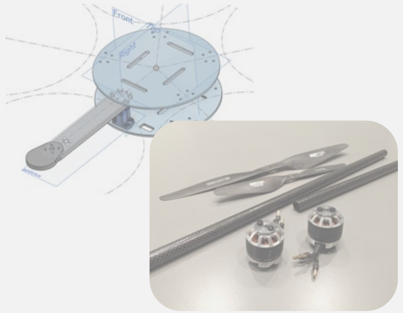


Design parameters θ

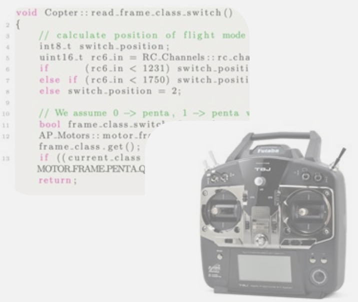
$$\boldsymbol{F}_{\theta,\phi}\left(t; \boldsymbol{s}, \frac{d\boldsymbol{s}}{dt}, \frac{d^2\boldsymbol{s}}{dt^2}, \cdots; \boldsymbol{a}\right) = \boldsymbol{0}$$

Dynamic model

The forward problem in dynamic systems



Design parameters θ

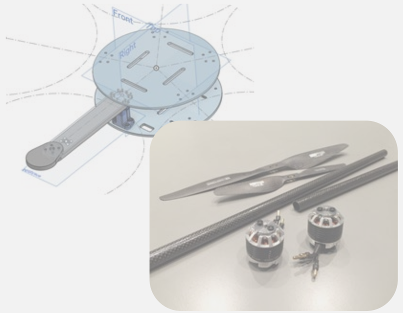


Control parameters ϕ

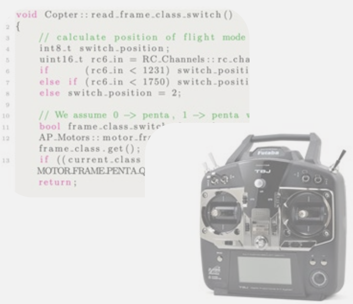
$$\boldsymbol{F}_{\theta,\phi}\left(t; \boldsymbol{s}, \frac{d\boldsymbol{s}}{dt}, \frac{d^2\boldsymbol{s}}{dt^2}, \cdots; \boldsymbol{a}\right) = \boldsymbol{0}$$

Dynamic model

The forward problem in dynamic systems



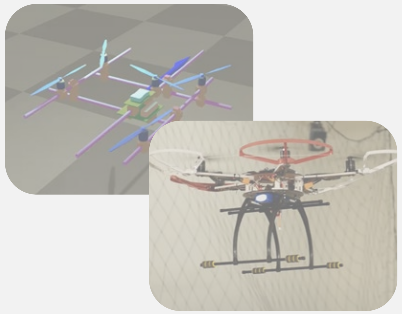
Design parameters θ



Control parameters ϕ

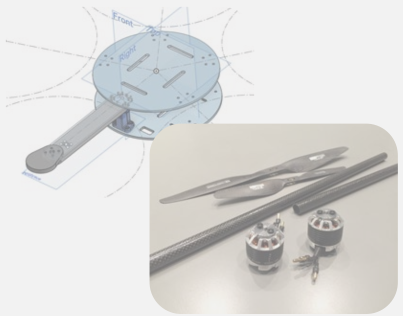
$$\boldsymbol{F}_{\theta,\phi}\left(t;\boldsymbol{s},\frac{d\boldsymbol{s}}{dt},\frac{d^2\boldsymbol{s}}{dt^2},\cdots;\boldsymbol{a}\right)=\boldsymbol{0}$$

Dynamic model

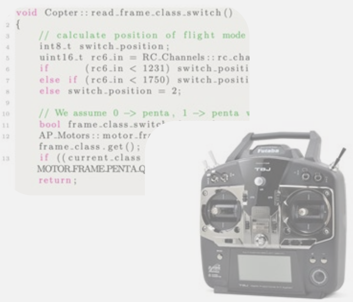


Evaluation

The inverse problem in dynamic systems



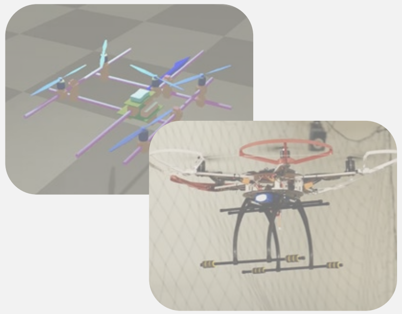
Design parameters θ



Control parameters ϕ

$$\boldsymbol{F}_{\theta,\phi}\left(t;\boldsymbol{s},\frac{d\boldsymbol{s}}{dt},\frac{d^2\boldsymbol{s}}{dt^2},\cdots;\boldsymbol{a}\right)=\boldsymbol{0}$$

Dynamic model



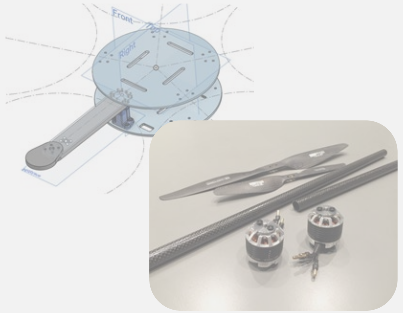
Evaluation

$$\min L(\boldsymbol{s},\boldsymbol{a})$$

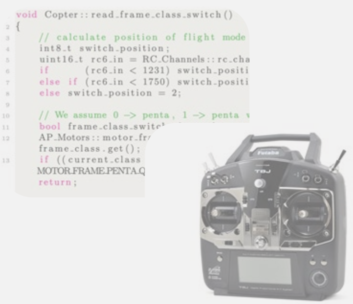
$$s.t.\ \boldsymbol{F}_{\theta,\phi}=\boldsymbol{0}$$

Optimization

The inverse problem in dynamic systems



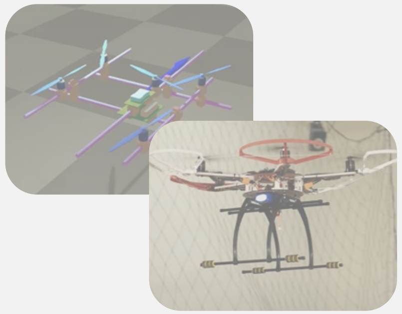
Design parameters θ



Control parameters ϕ

$$\boldsymbol{F}_{\theta,\phi}\left(t;\boldsymbol{s},\frac{d\boldsymbol{s}}{dt},\frac{d^2\boldsymbol{s}}{dt^2},\cdots;\boldsymbol{a}\right)=\boldsymbol{0}$$

Dynamic model



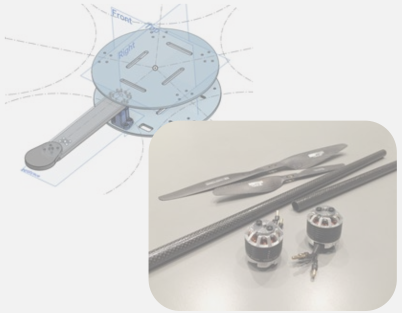
Evaluation

$$\min L(\boldsymbol{s},\boldsymbol{a})$$

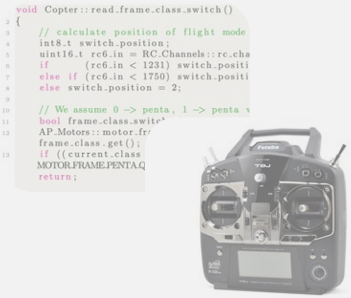
$$s.t.\ \boldsymbol{F}_{\theta,\phi}=\boldsymbol{0}$$

Optimization

Inverse dynamics is difficult to solve!



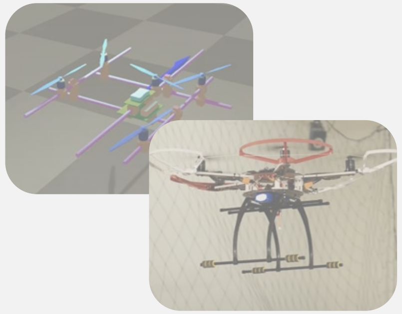
Design parameters θ



Control parameters ϕ

$$\boldsymbol{F}_{\theta,\phi}\left(t;\boldsymbol{s},\frac{d\boldsymbol{s}}{dt},\frac{d^2\boldsymbol{s}}{dt^2},\cdots;\boldsymbol{a}\right)=\boldsymbol{0}$$

Dynamic model



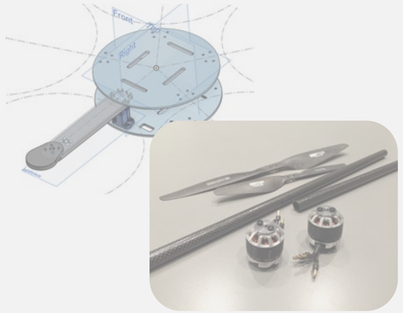
Evaluation

$$\min L(\boldsymbol{s},\boldsymbol{a})$$

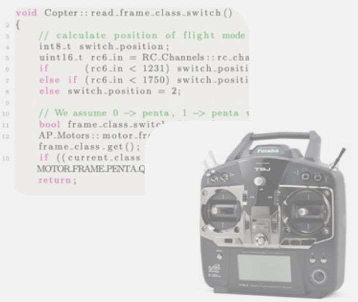
$$s.t.\ \boldsymbol{F}_{\theta,\phi}=\boldsymbol{0}$$

Optimization

Inverse dynamics is difficult to solve!



Design parameters θ



Control parameters ϕ

$$\boldsymbol{F}_{\theta,\phi}\left(t;\boldsymbol{s},\frac{d\boldsymbol{s}}{dt},\frac{d^2\boldsymbol{s}}{dt^2},\cdots;\boldsymbol{a}\right)=\boldsymbol{0}$$

Dynamic model

Sensor noise

Partial observation

...

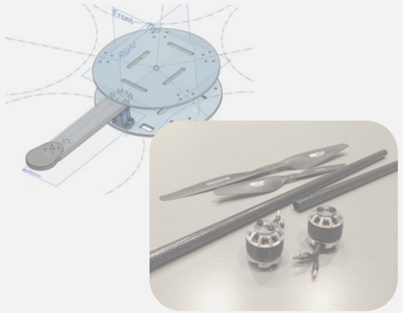
Evaluation

$$\min L(\boldsymbol{s},\boldsymbol{a})$$

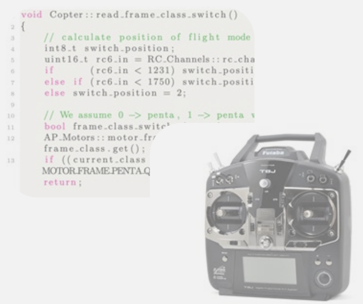
$$s.t.\ \boldsymbol{F}_{\theta,\phi}=\boldsymbol{0}$$

Optimization

Inverse dynamics is difficult to solve!



Design parameters θ



Control parameters ϕ

Nonlinearity
Expensive computation
…

Dynamic model

Sensing noise
Partial observation
…

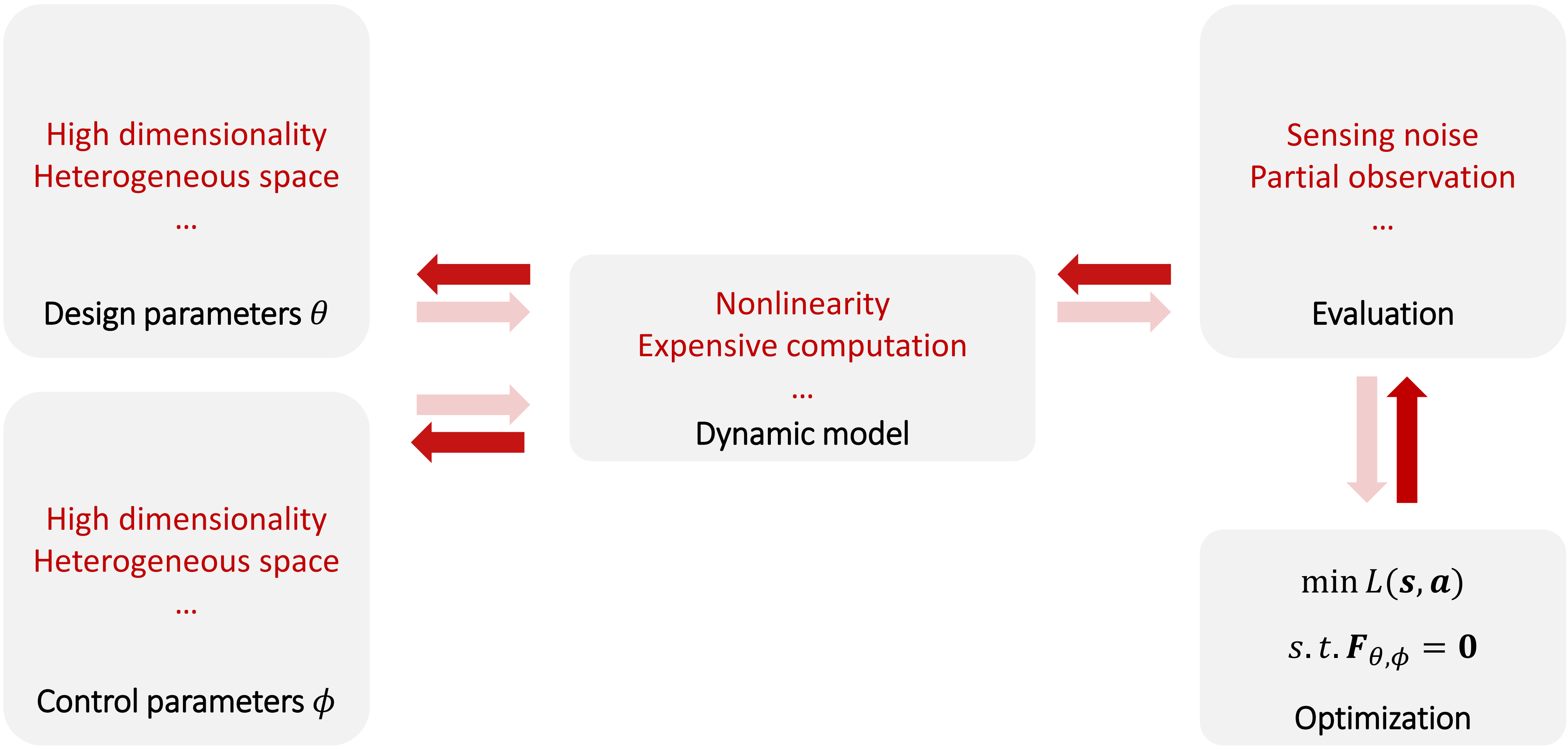
Evaluation

$$\min L(\boldsymbol{s}, \boldsymbol{a})$$

$$s.t.\ \boldsymbol{F}_{\theta,\phi} = \boldsymbol{0}$$

Optimization

Inverse dynamics is difficult to solve!



Gradients: the keyword in this talk

$$\frac{\partial \boldsymbol{F}}{\partial \theta}$$

Design parameters θ

$$\frac{\partial \boldsymbol{F}}{\partial \phi}$$

Control parameters ϕ

$$\frac{\partial \boldsymbol{s}, \boldsymbol{a}}{\partial \boldsymbol{F}}$$

Dynamic model

$$\frac{\partial L}{\partial \boldsymbol{s}, \boldsymbol{a}}$$

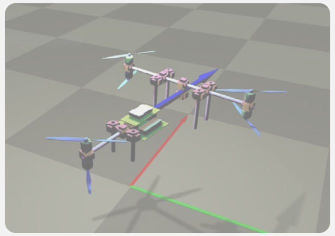
Evaluation

$$\min L(\boldsymbol{s}, \boldsymbol{a})$$

$$s.t. \boldsymbol{F}_{\theta,\phi} = \boldsymbol{0}$$

Optimization

Our endeavor



Gradients in
design and control
SIGGRAPH Asia 2016
SIGGRAPH 2021

$$\frac{\partial \boldsymbol{s},\boldsymbol{a}}{\partial \boldsymbol{F}}$$

Dynamic model

$$\frac{\partial L}{\partial \boldsymbol{s},\boldsymbol{a}}$$

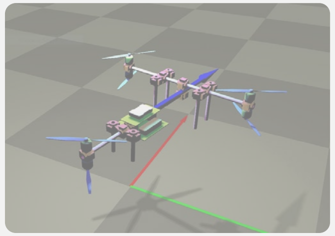
Evaluation

$$\min L(\boldsymbol{s},\boldsymbol{a})$$

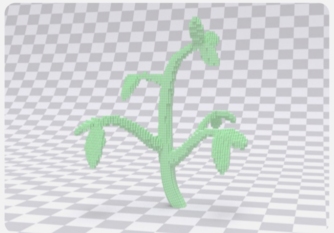
$$s.t.\ \boldsymbol{F}_{\theta,\phi} = \boldsymbol{0}$$

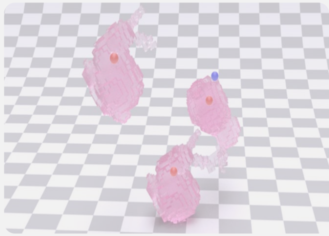
Optimization

Our endeavor



Gradients in
design and control
SIGGRAPH Asia 2016
SIGGRAPH 2021





Gradients in
dynamic models
SIGGRAPH 2022

$$\frac{\partial L}{\partial \boldsymbol{s}, \boldsymbol{a}}$$

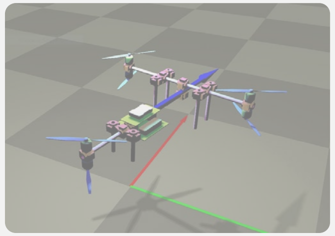
Evaluation

$$\min L(\boldsymbol{s}, \boldsymbol{a})$$

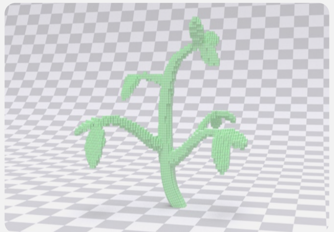
$$s.t. \boldsymbol{F}_{\theta,\phi} = \boldsymbol{0}$$

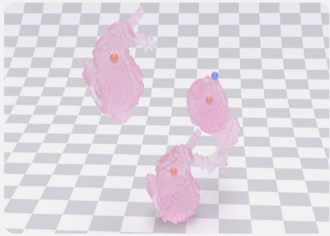
Optimization

Our endeavor

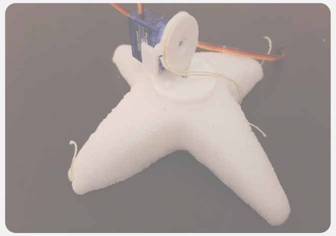


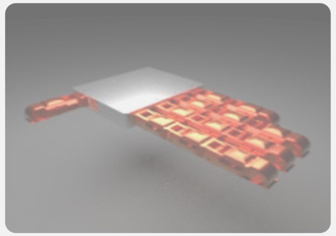
Gradients in
design and control
SIGGRAPH Asia 2016
SIGGRAPH 2021





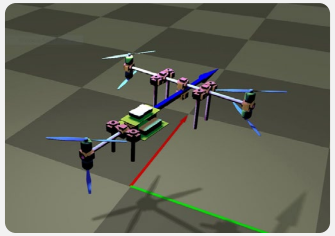
Gradients in
dynamic models
SIGGRAPH 2022



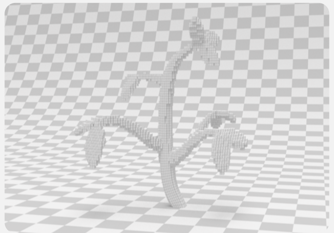


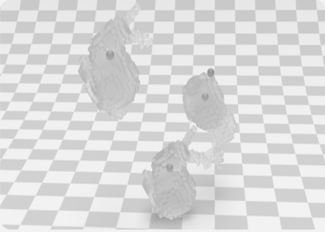
Gradients in
evaluation and
optimization
RA-L 2021
ICLR 2022

This talk will cover:

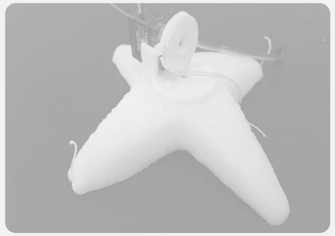


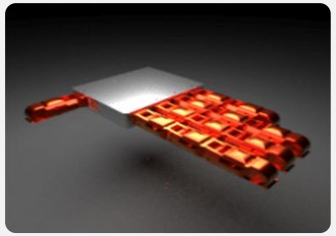
Gradients in
design and control
SIGGRAPH Asia 2016
SIGGRAPH 2021



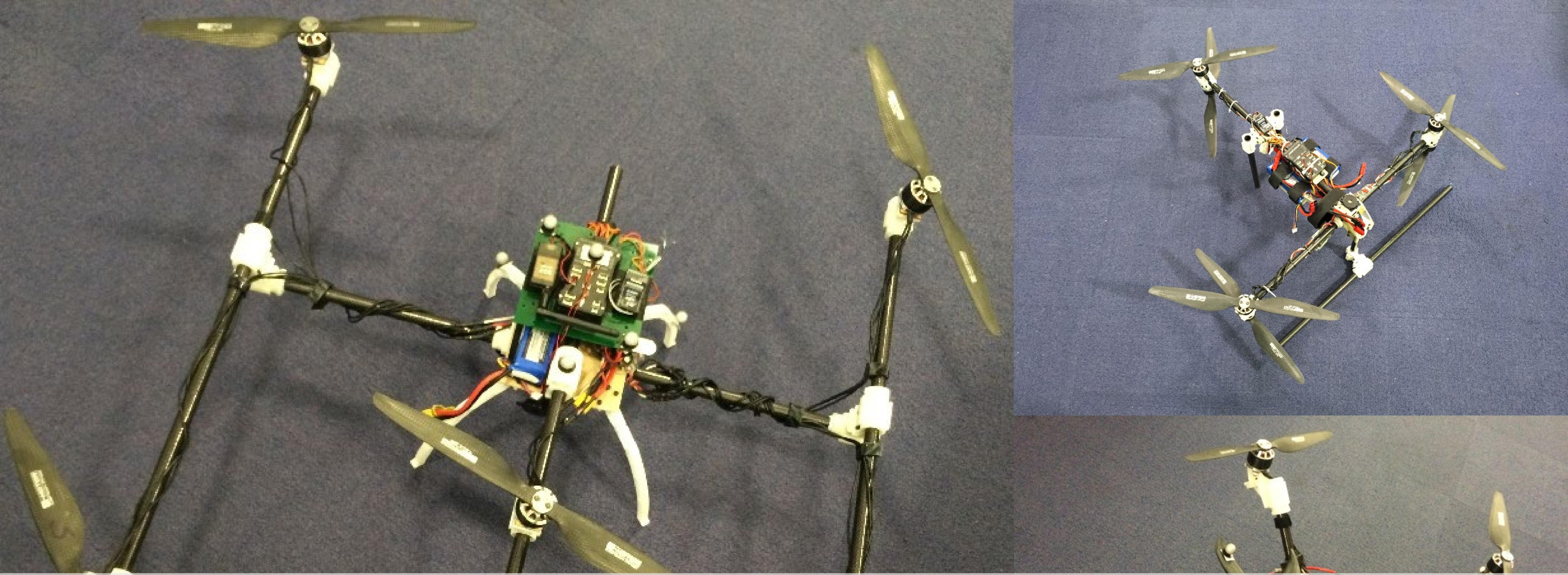


Gradients in
dynamic models
SIGGRAPH 2022





Gradients in
evaluation and
optimization
RA-L 2021
ICLR 2022



Computational Multicopter Design

Tao Du, Adriana Schulz, Bo Zhu, Bernd Bickel, Wojciech Matusik

SIGGRAPH Asia 2016

Problem statement

"Let's automate the way engineers design unmanned flying vehicles!"

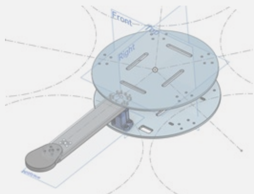
---Wojciech (my advisor), one day in the year 2015

How UAVs were designed before

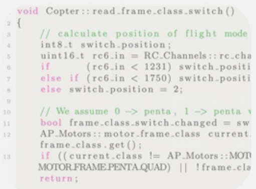
Parameters
(θ, ϕ)

How UAVs were designed before

Parameters
(θ, ϕ)

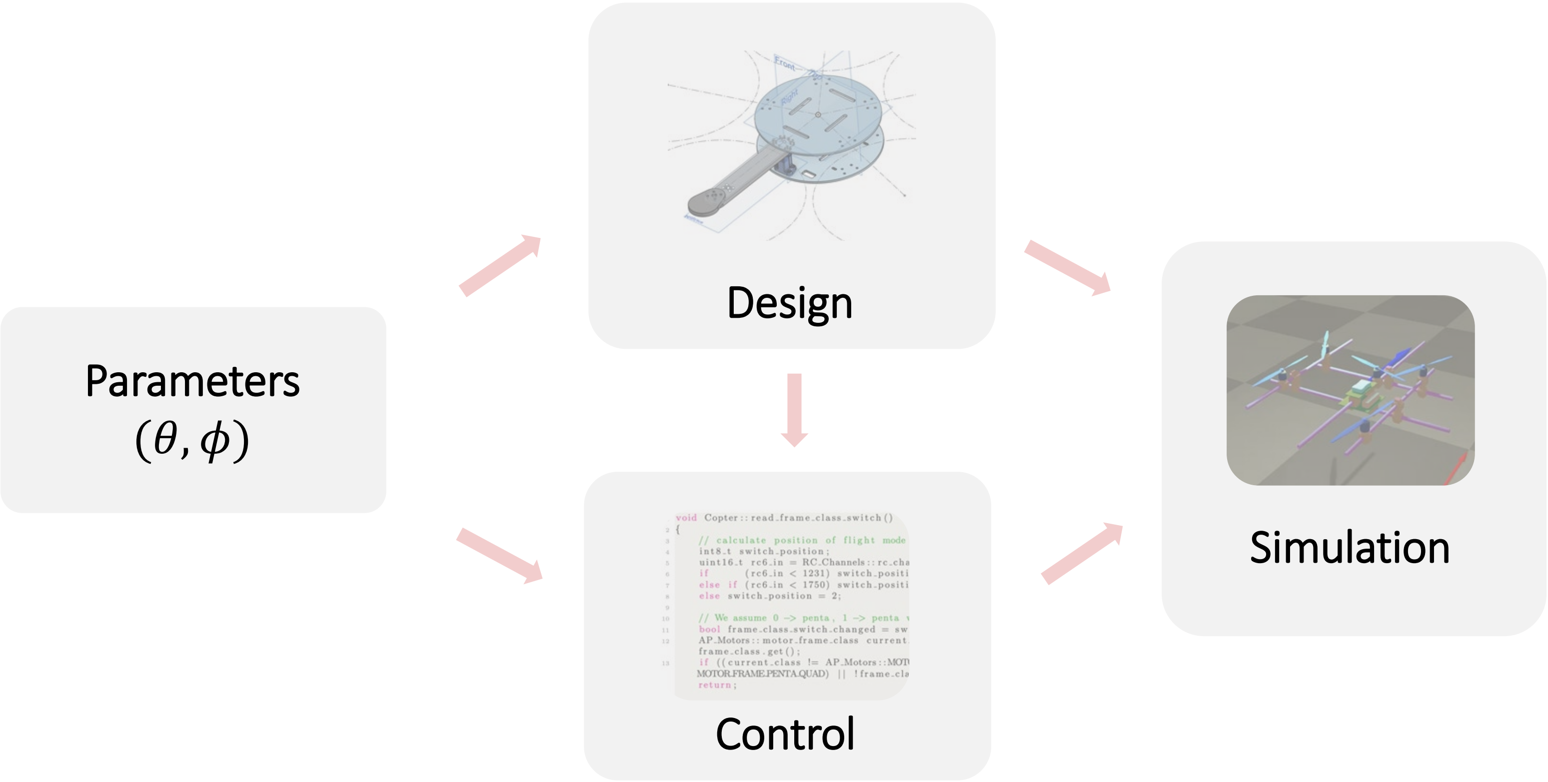


Design

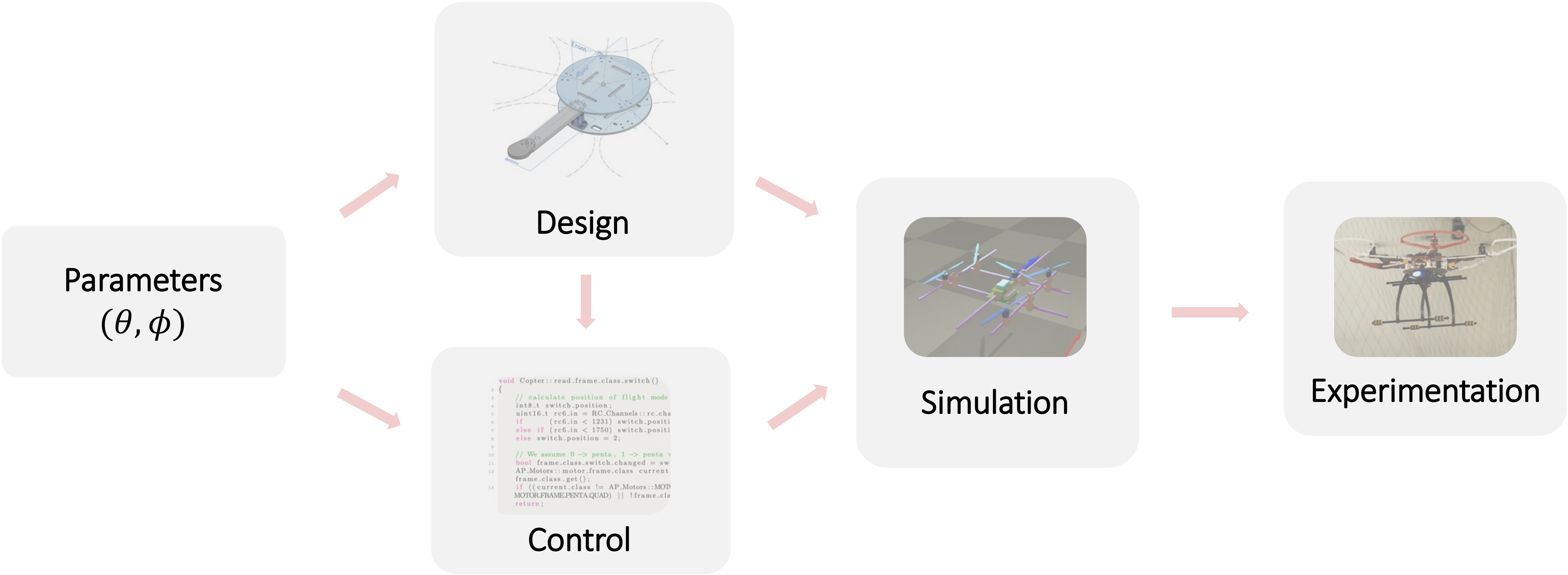


Control

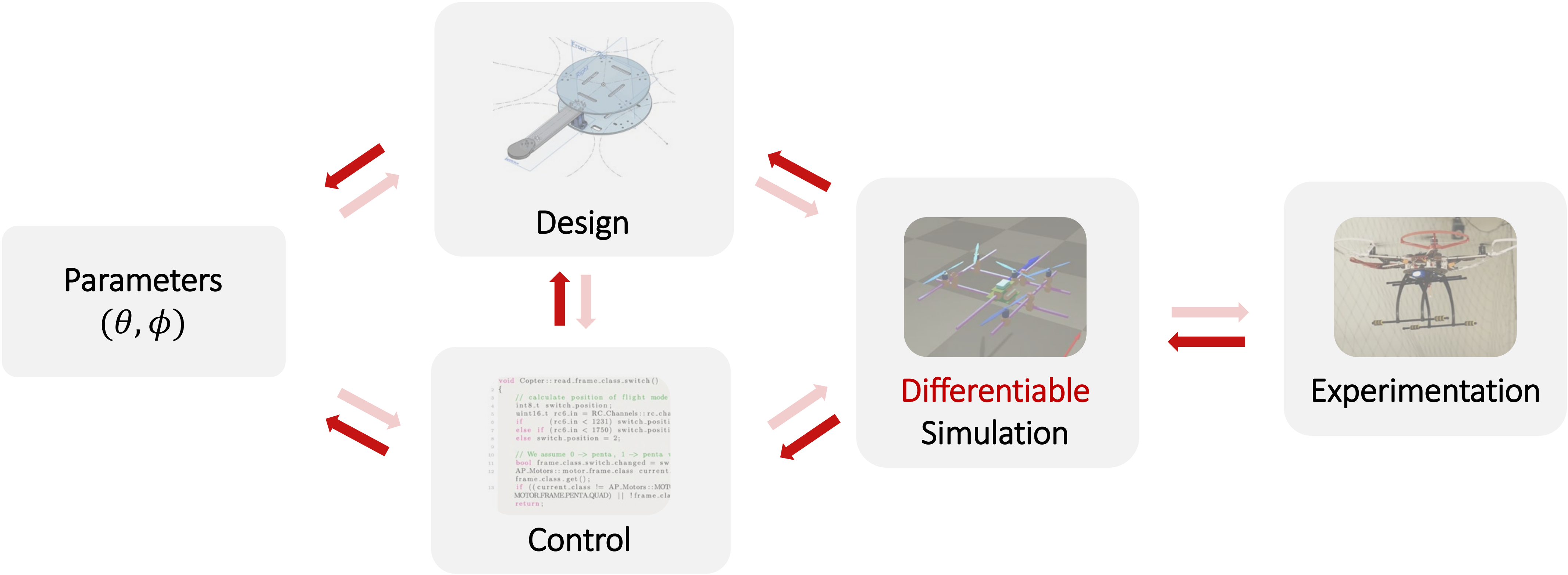
How UAVs were designed before



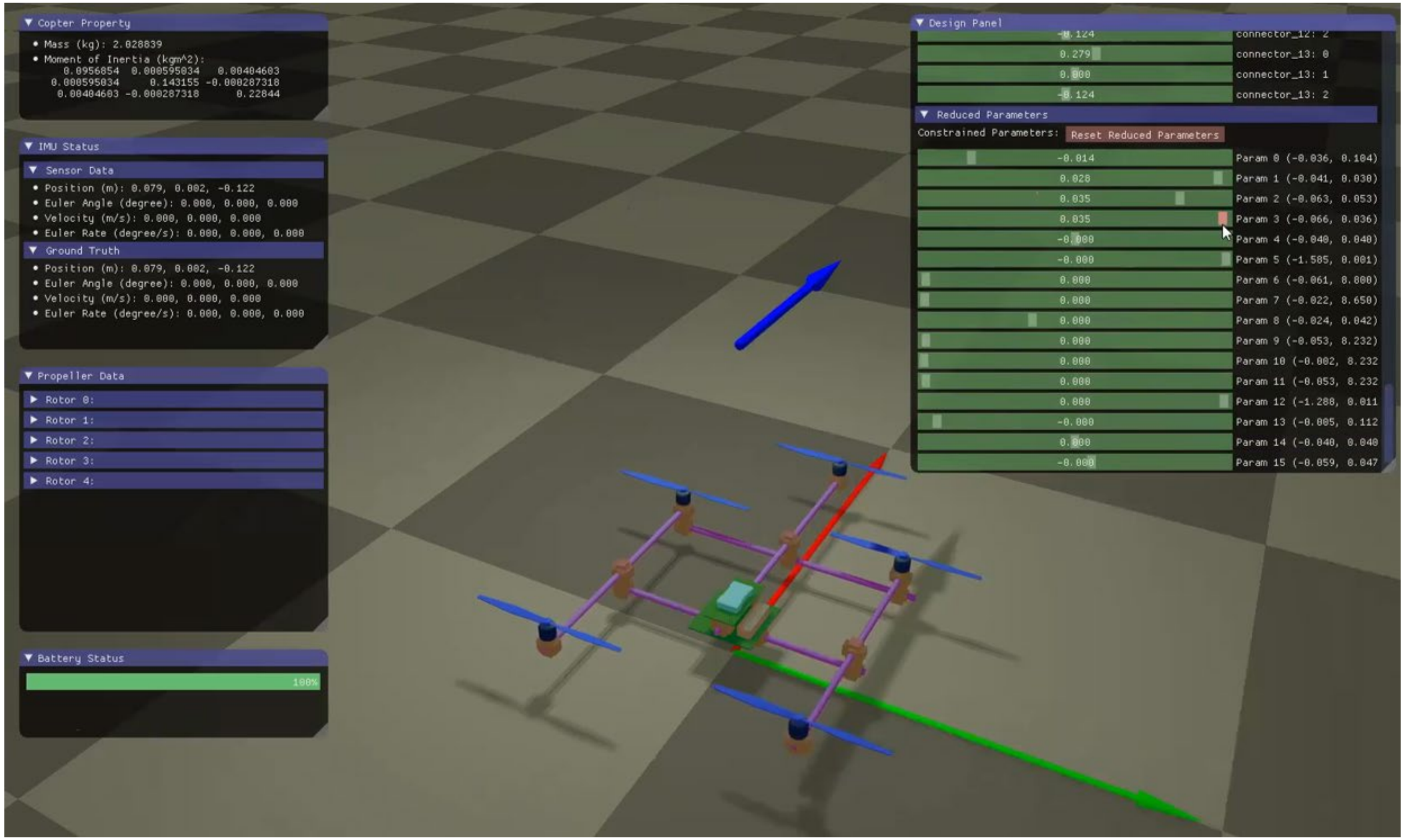
How UAVs were designed before



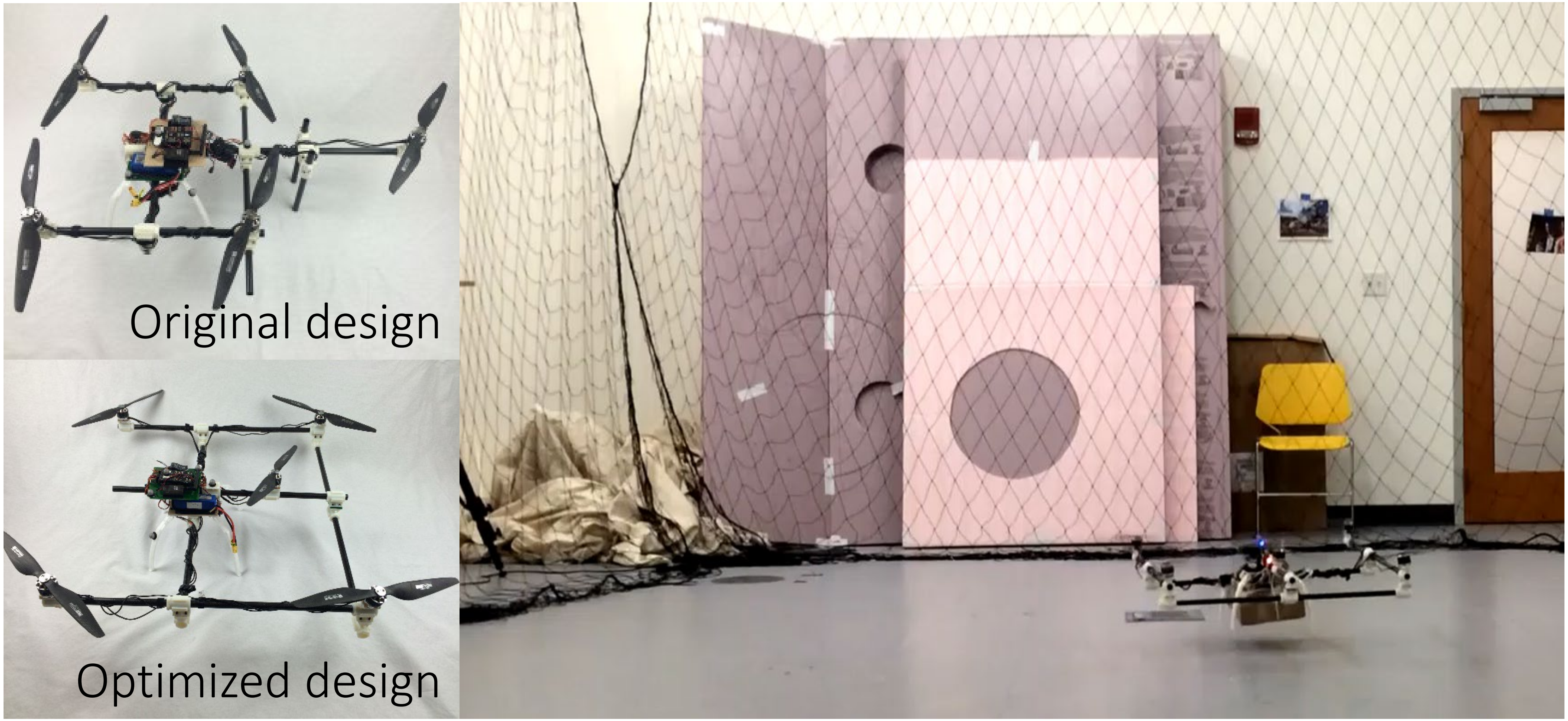
Our strategy: using gradients



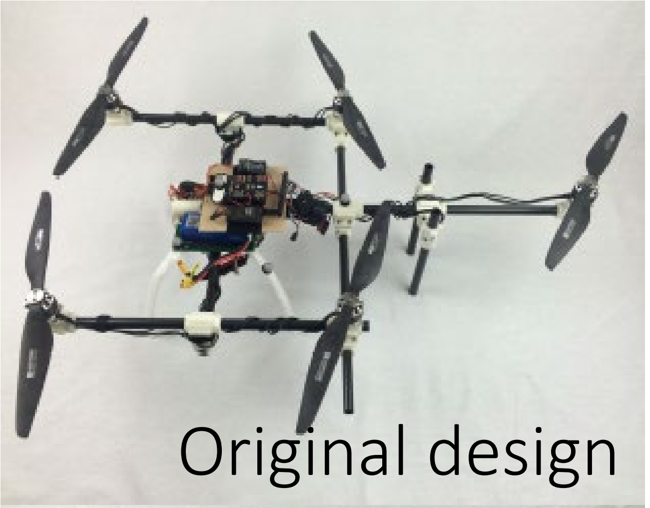
The differentiable simulator

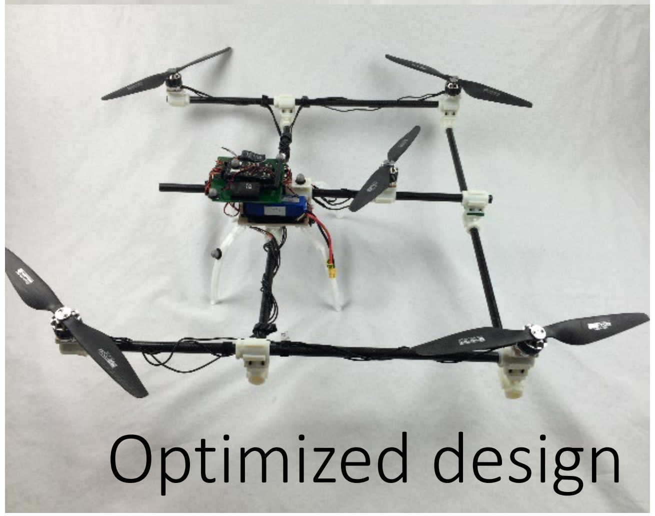


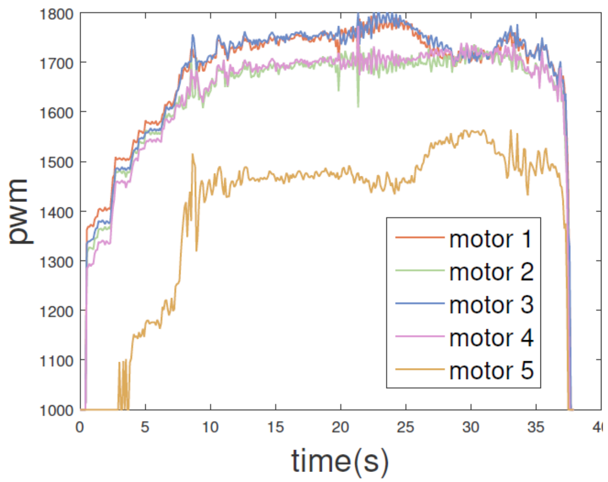
An example task: maximizing payload



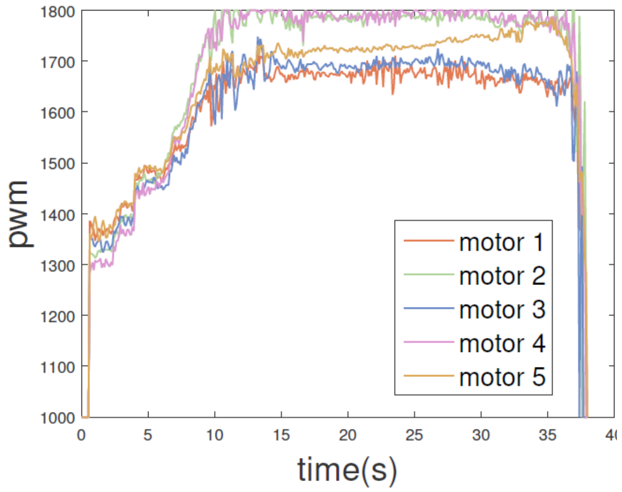
Behind-the-scene analysis





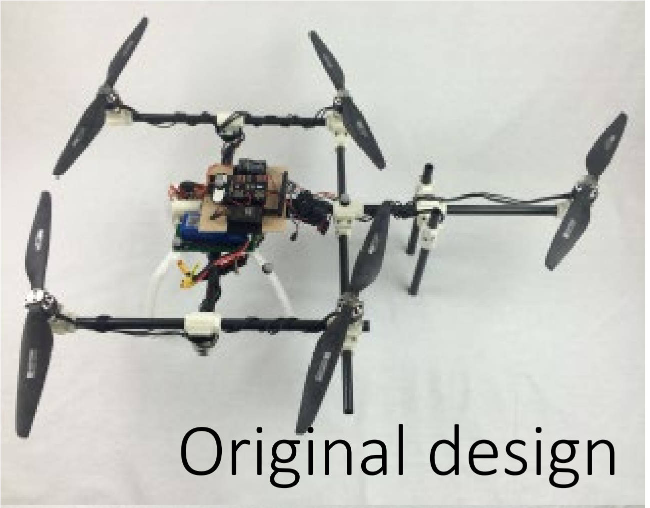


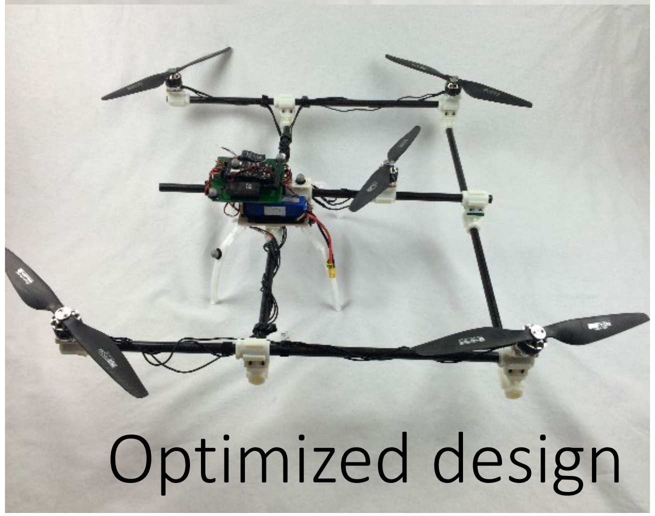
Old payload: 1047g

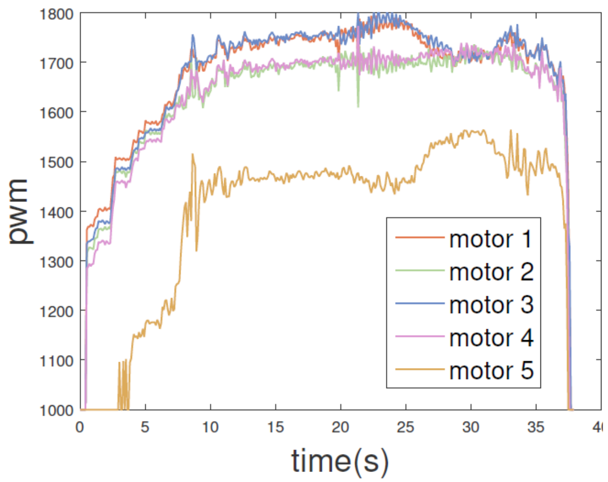


New payload: **1392g**

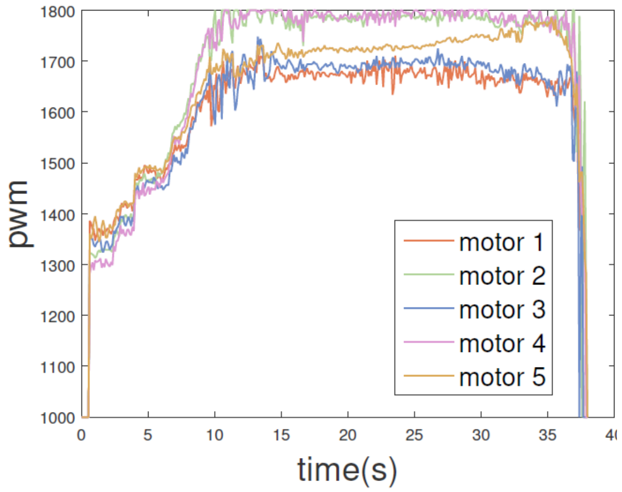
Conclusion: gradients reveal novel designs!



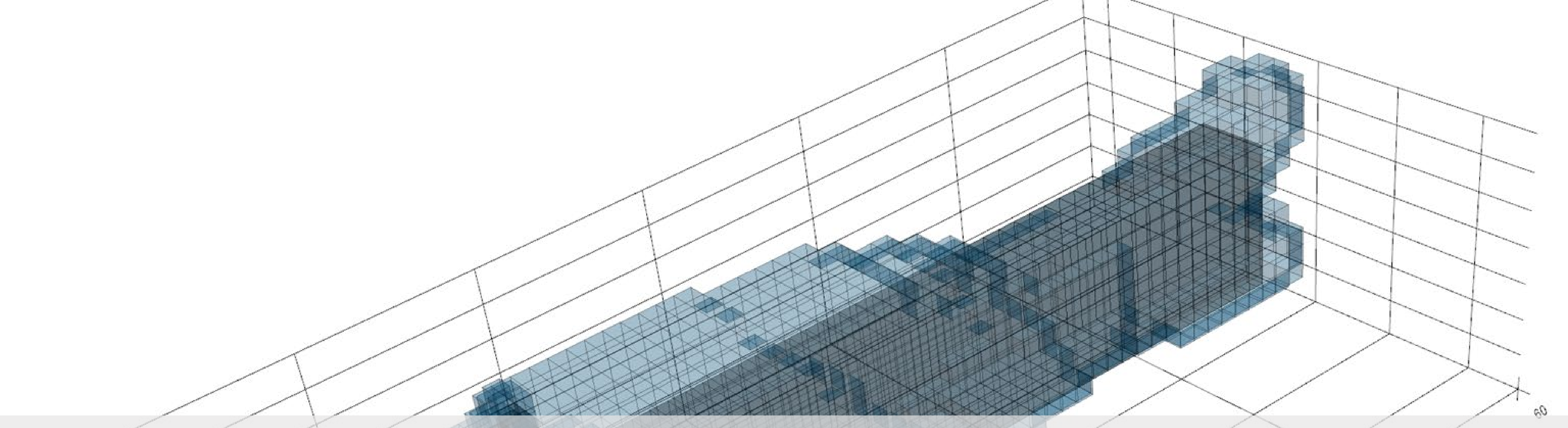




Old payload: 1047g



New payload: **1392g**



DiffAqua: A Differentiable Computational Design Pipeline for Soft Underwater Swimmers with Shape Interpolation

Pingchuan Ma, Tao Du, John Z. Zhang, Kui Wu, Andrew Spielberg, Robert K. Katzschmann, Wojciech Matusik

SIGGRAPH 2021

Problem statement

“Design robotic fish shapes that lead to extremal performance!”

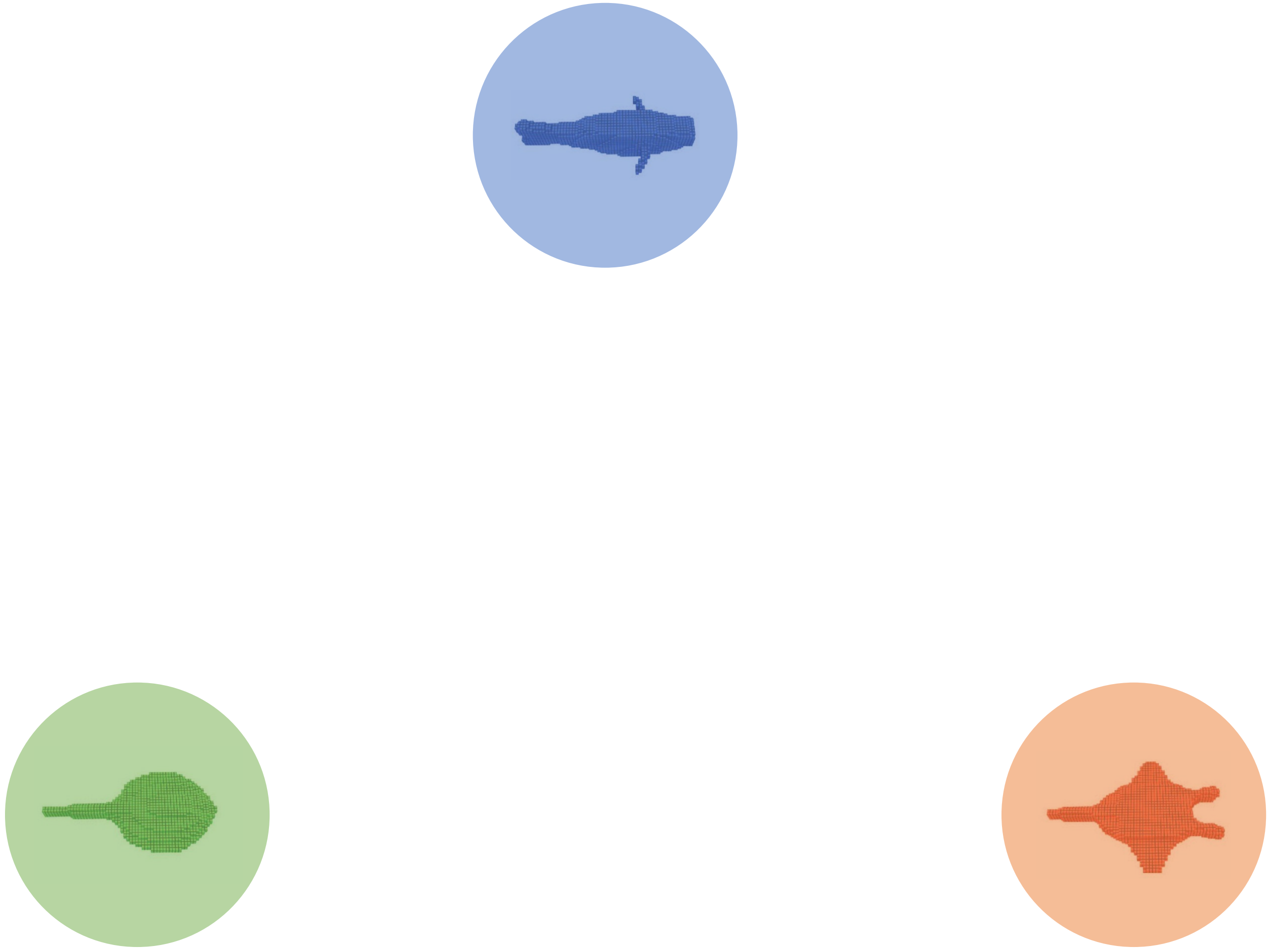
---Multiple MIT CSAIL professors and graduate students

Some unique challenges

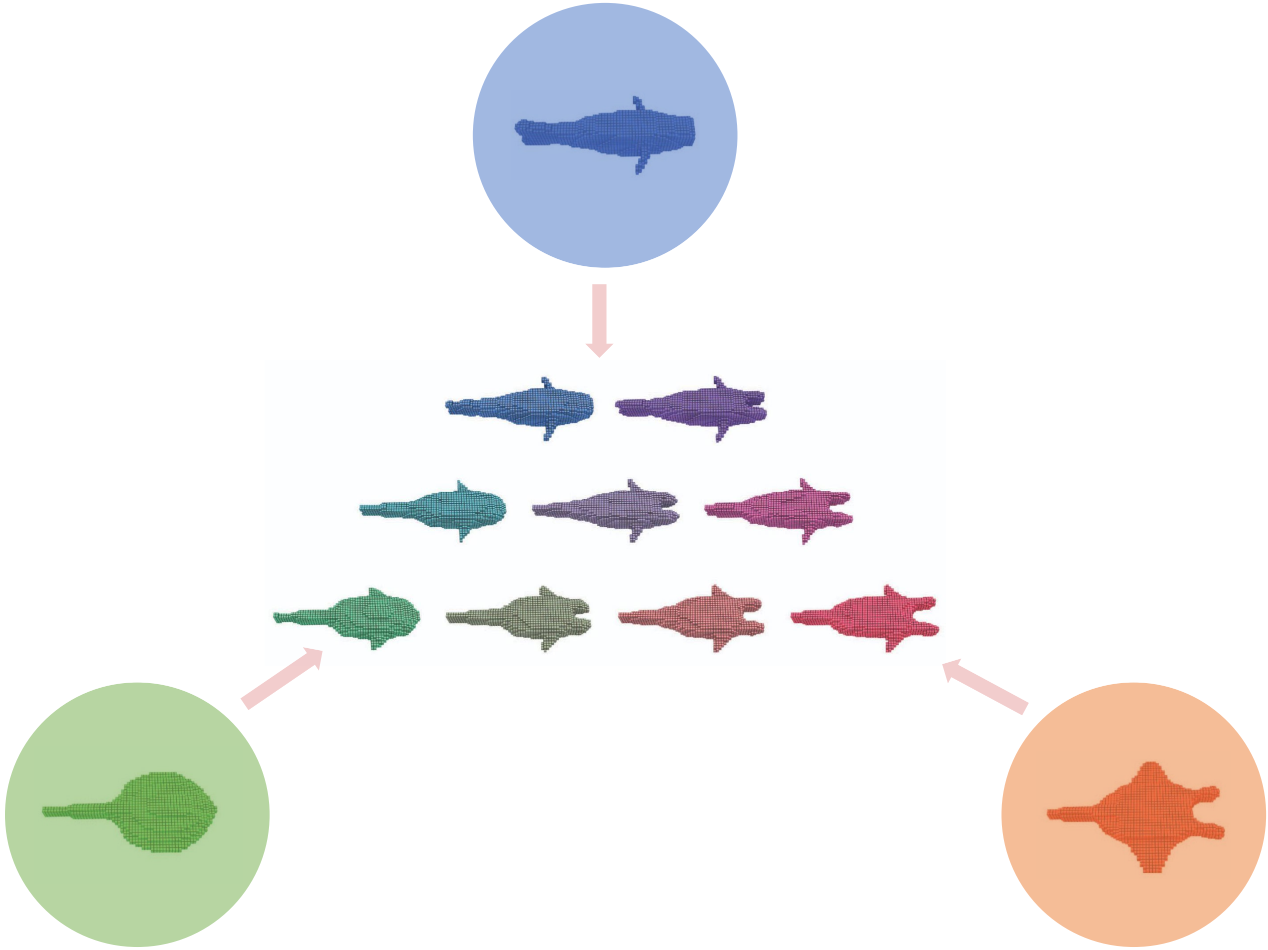
Fishes are **soft**: many degrees of freedom are needed.

Fishes are **diverse**: it’s difficult to find one compact representation for all.

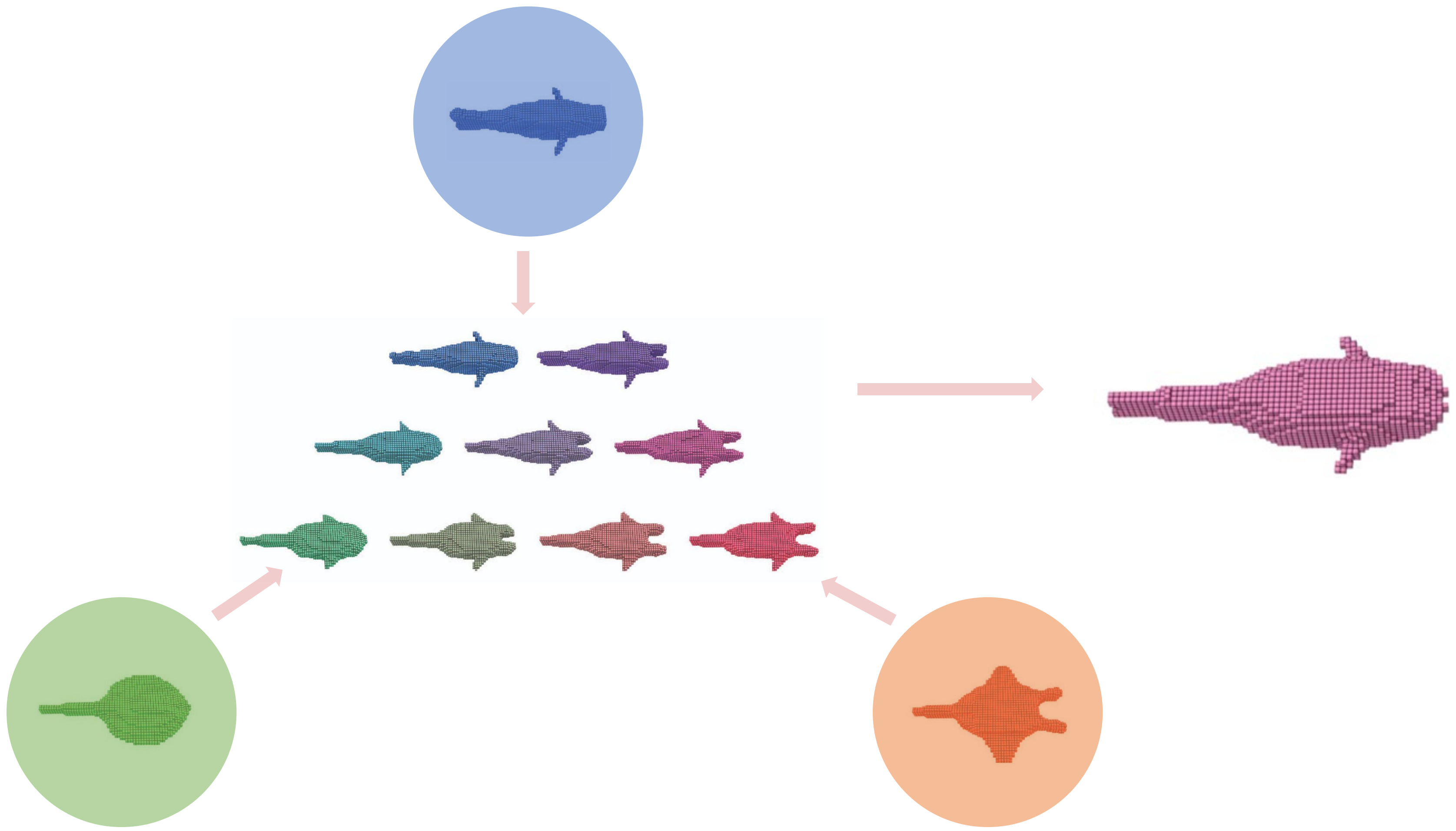
Our approach: Wasserstein gradients



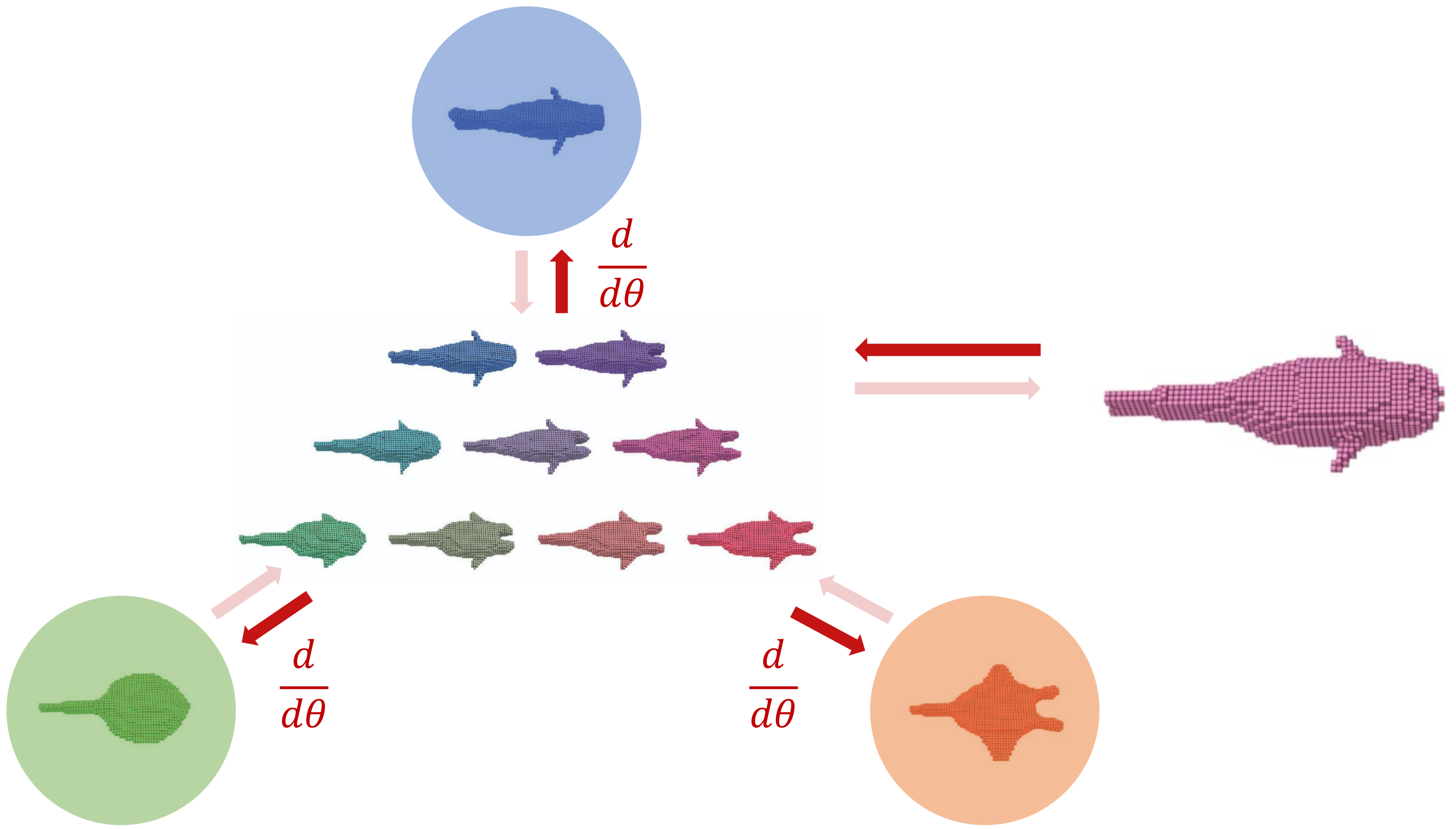
Our approach: Wasserstein gradients



Our approach: Wasserstein gradients

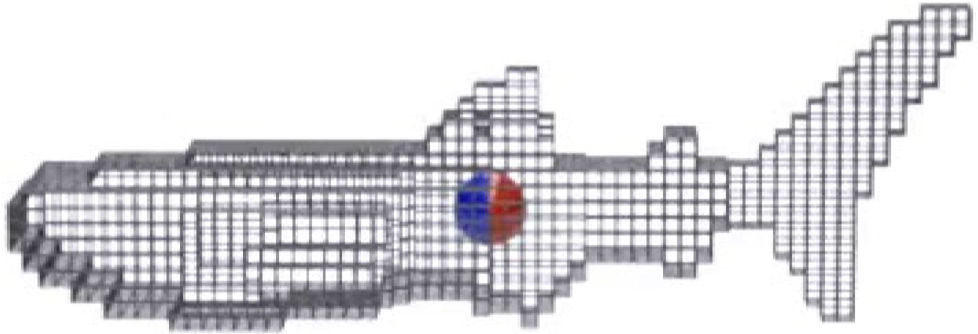


Our approach: Wasserstein gradients



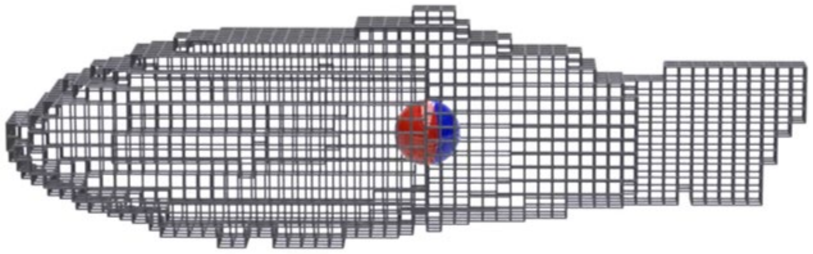
Example: flow-resistant fish

Unoptimized fish

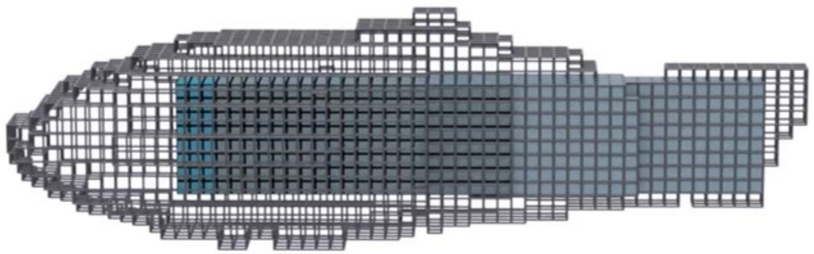


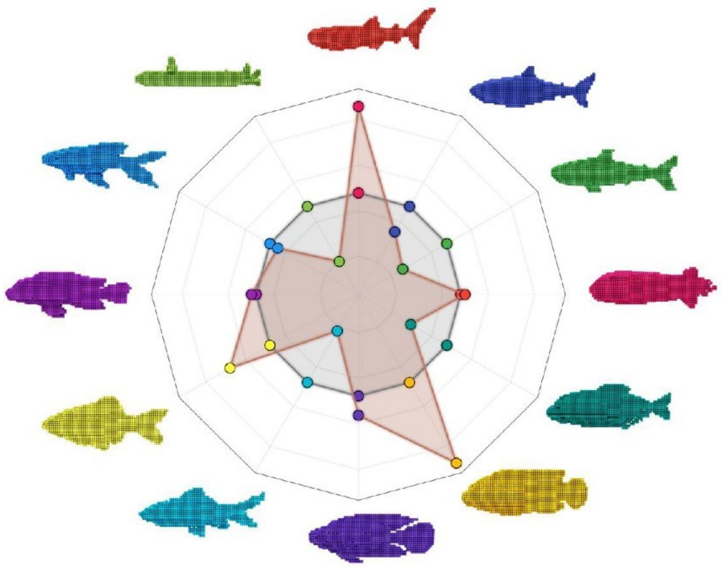
Example: flow-resistant fish

Optimized fish

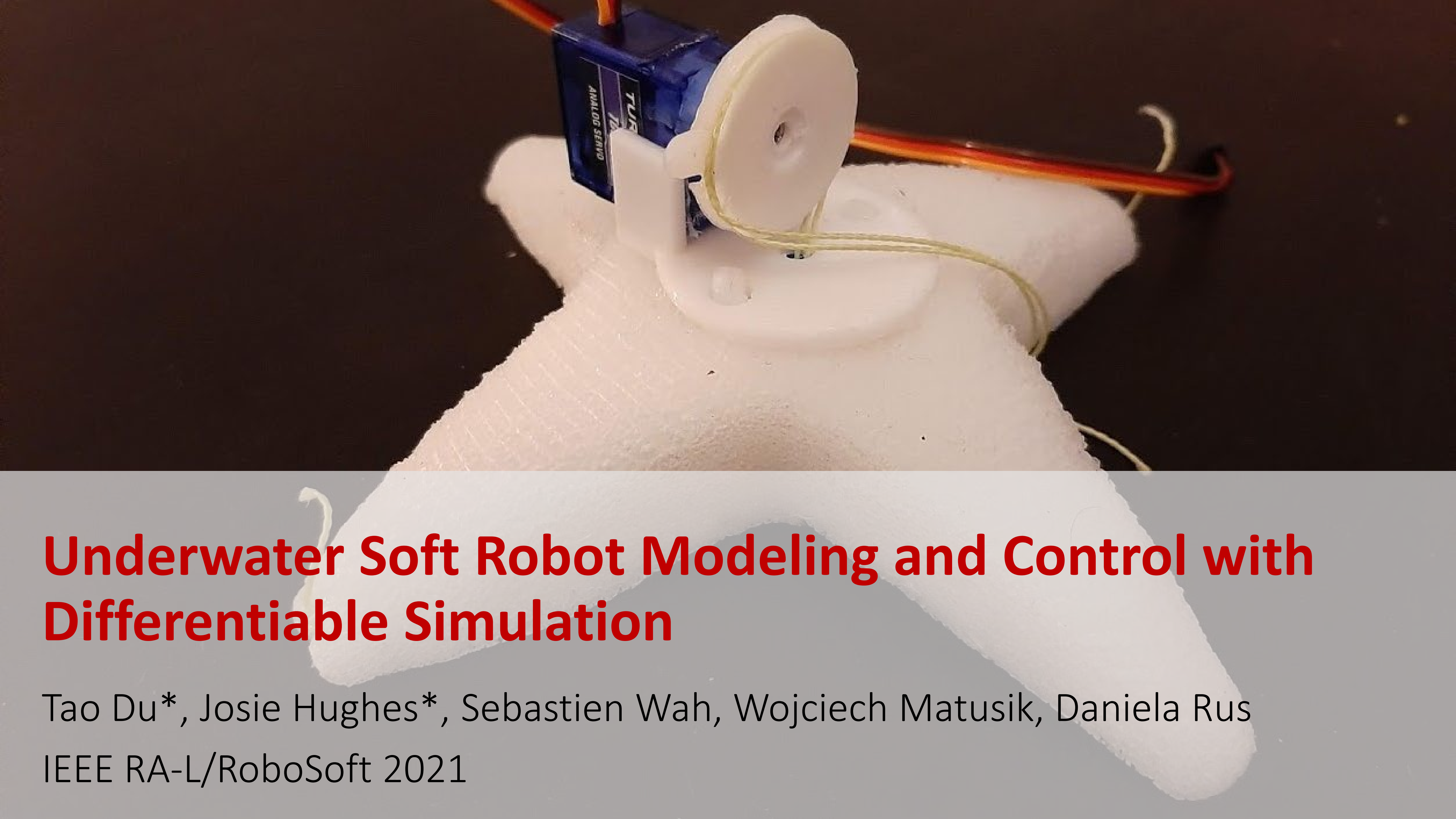


Optimized fish
(muscle activation)





Design parameters



Underwater Soft Robot Modeling and Control with Differentiable Simulation

Tao Du*, Josie Hughes*, Sebastien Wah, Wojciech Matusik, Daniela Rus

IEEE RA-L/RoboSoft 2021

RISP: Rendering-Invariant State Predictor with Differentiable Simulation and Rendering for Cross-Domain Parameter Estimation

Pingchuan Ma*, Tao Du*, Joshua B. Tenenbaum, Wojciech Matusik, Chuang Gan

ICLR 2022 (oral paper)

Problem statement

Build a digital twin of a robot from its video of motion sequences.

Problem statement

Build a digital twin of a robot from its video of motion sequences.

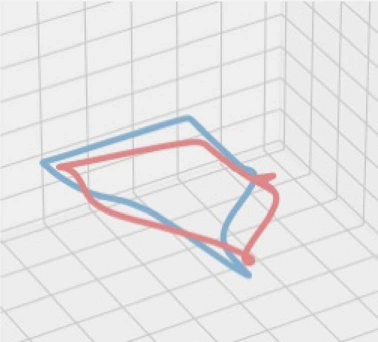
Video input

Problem statement

Build a digital twin of a robot from its video of motion sequences.

Video input

Neural network model



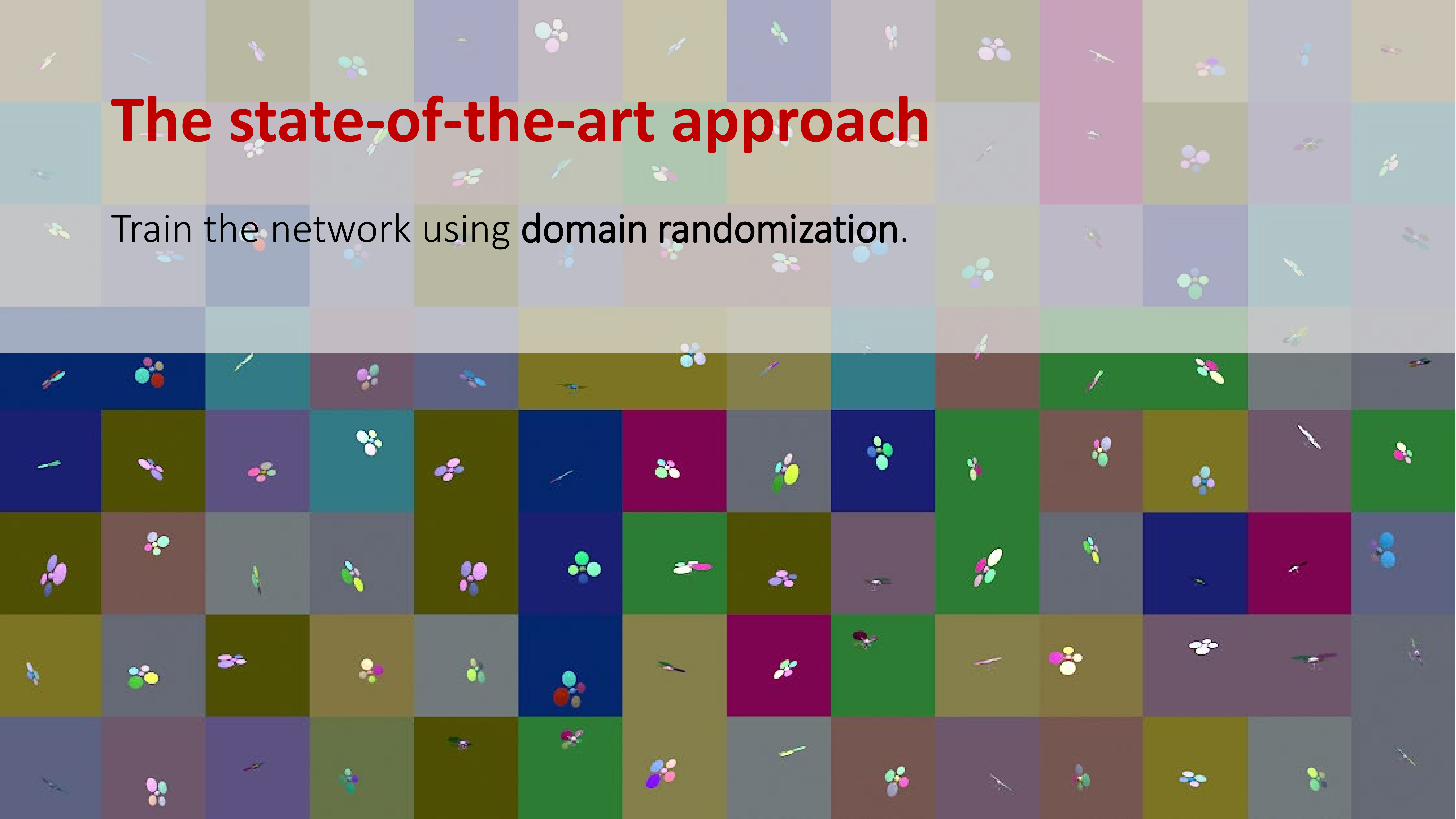
Reconstruction

states

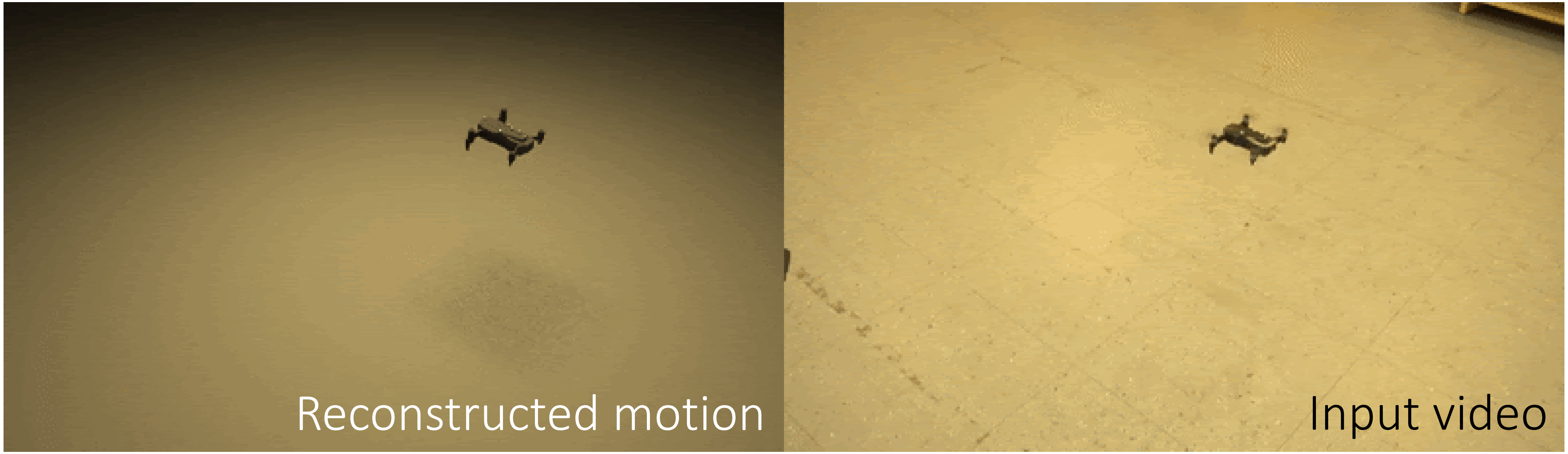
actions

The state-of-the-art approach

Train the network using **domain randomization**.



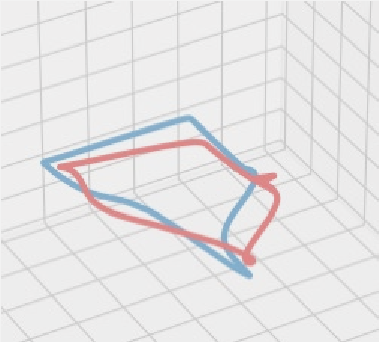
The SOTA did not work very well.



Why is the problem challenging?

Video input

Neural network model



Reconstruction

states

actions

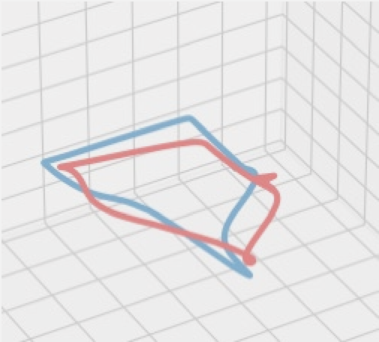
Why is the problem challenging?

Dynamic model
states
actions

Visual appearance
lighting
material
texture

Video input

Neural network model



Reconstruction
states
actions

Why is the problem challenging?

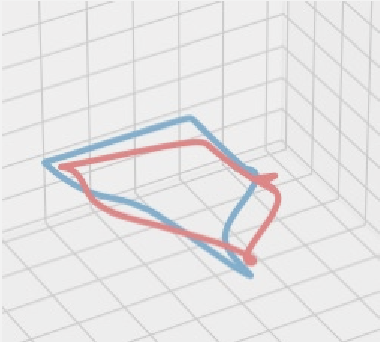
Visual appearance is difficult to reconstruct and generalize.

Dynamic model
states
actions

Visual appearance
lighting
material
texture

Video input

Neural network model



Reconstruction
states
actions

Our strategy: rendering-invariant gradients

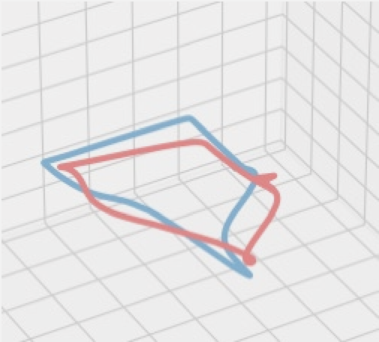
Visual appearance is difficult to reconstruct and generalize.

Dynamic model
states
actions

Visual appearance
lighting
material
texture

Video input

Neural network model



Reconstruction
states
actions

Our strategy: rendering-invariant gradients

Invariant visual appearance equals **zero** gradients!

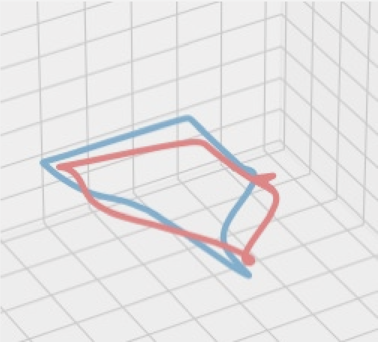
Dynamic model
states
actions

Visual appearance
lighting
material
texture

$$\frac{\partial L}{\partial} = \mathbf{0}$$

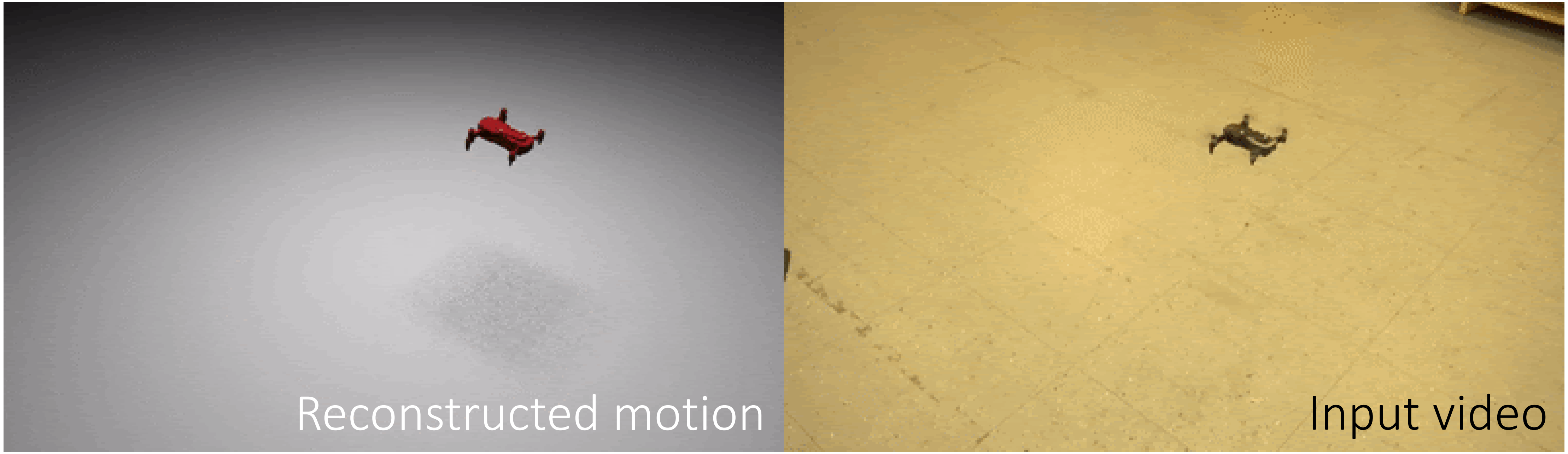
Video input

Neural network model



Reconstruction
states
actions

Our result



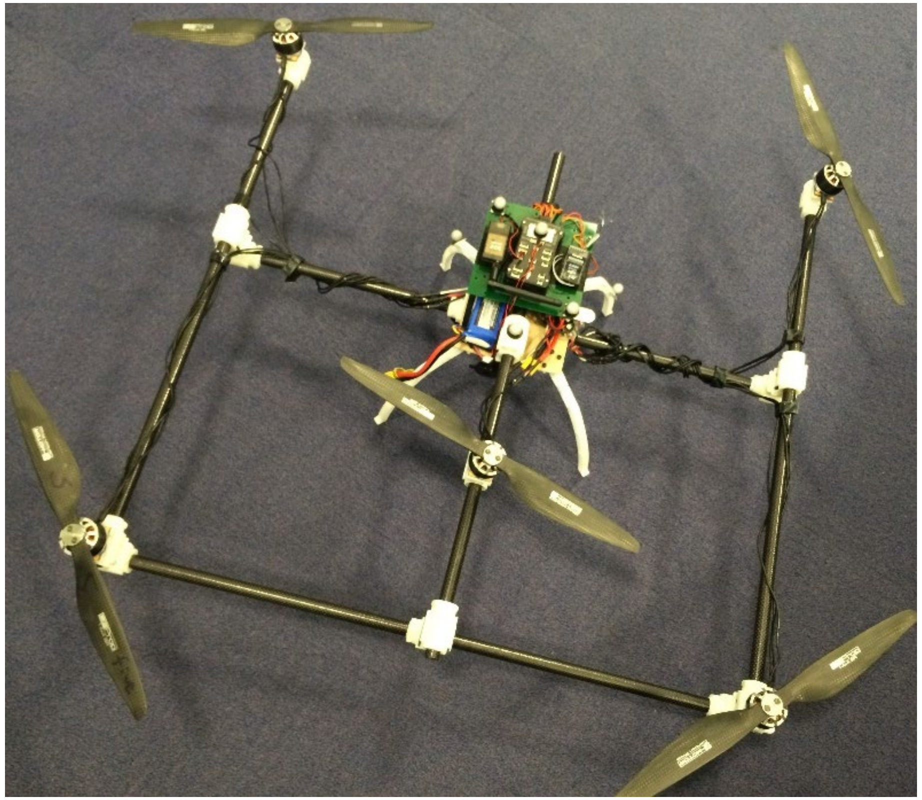
Note that the rendering configuration is intentionally made different.

Conclusions

We have shown some **creative** usages of gradients in inverse dynamics.

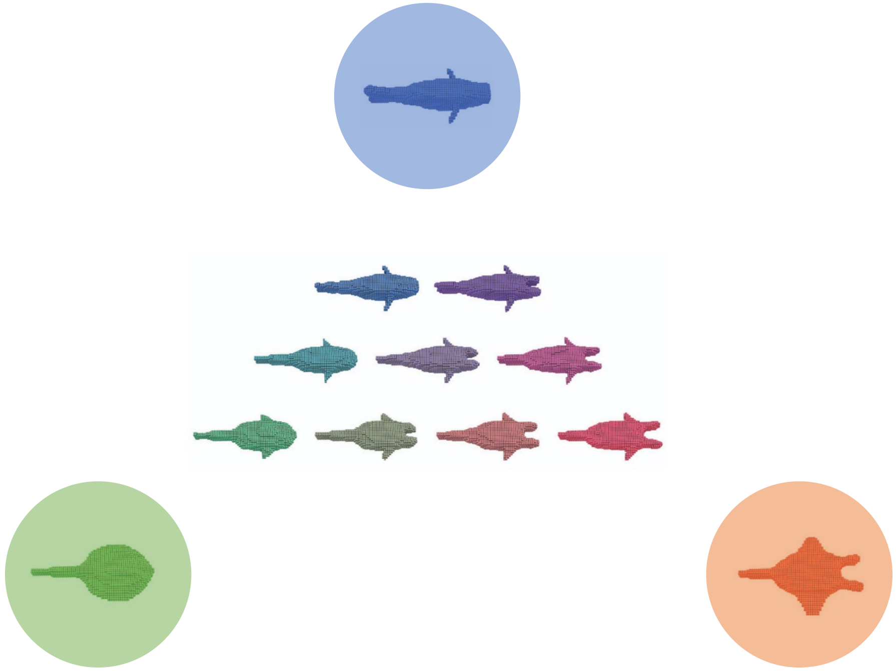
Conclusions

Performance optimization for rigid robots



Conclusions

Shape interpolation for soft robots



Conclusions

Decoupling sensing and dynamics in real-to-sim transfer.

Thank you!

Homepage: https://people.csail.mit.edu/taodu

Contact: taodu@csail.mit.edu

References

Page 2: ANYmal: https://rsl.ethz.ch/robots-media/anymal.html.

Page 2: SCLS: http://www.scls.riken.jp/en/research/01_dynamics/index.html.

Page 2: Ravuri, S., Lenc, K., Willson, M. et al. Skilful precipitation nowcasting using deep generative models of radar. Nature 597, 672–677 (2021). https://doi.org/10.1038/s41586-021-03854-z.

Page 3: Natural Portfolio. https://www.nature.com/subjects/dynamical-systems.

Page 32: video credit to Jie Xu.