The Power of Gradients in Inverse Dynamics Problems

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What is a dynamic system?
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

\[ F_{\theta, \phi} \left( t; s, \frac{ds}{dt}, \frac{d^2s}{dt^2}, \cdots; a \right) = 0 \]

Dynamic model
The forward problem in dynamic systems

Design parameters $\theta$

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

Dynamic model
The forward problem in dynamic systems

Design parameters $\theta$

Control parameters $\phi$

$$F_{\theta,\phi} \left( t; s, \frac{ds}{dt}, \frac{d^2s}{dt^2}, \cdots; \alpha \right) = 0$$

Dynamic model
The forward problem in dynamic systems

Design parameters $\theta$

Control parameters $\phi$

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

Dynamic model

Evaluation
The inverse problem in dynamic systems

Design parameters $\theta$

Control parameters $\phi$

Dynamic model

$$F_{\theta,\phi}(t; s, \frac{ds}{dt}, \frac{d^2s}{dt^2}, \ldots; a) = 0$$

Evaluation

Optimization

$$\min L(s, a)$$

s.t. $F_{\theta,\phi} = 0$
The inverse problem in dynamic systems

Design parameters $\theta$

Control parameters $\phi$

Evaluation

Dynamic model

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

Optimization

$$\min L(s, a)$$

$$s.t. F_{\theta,\phi} = 0$$
Inverse dynamics is difficult to solve!

Design parameters $\theta$

Control parameters $\phi$

Dynamic model

$$F_{\theta,\phi}(t; s, \frac{ds}{dt}, \frac{d^2s}{dt^2}, \cdots; a) = 0$$

Evaluation

Optimization

$$\min L(s, a)$$

$$s.t. F_{\theta,\phi} = 0$$
Inverse dynamics is difficult to solve!

Design parameters $\theta$

Control parameters $\phi$

Dynamic model

$$F_{\theta, \phi} \left( t; s, \frac{ds}{dt}, \frac{d^2s}{dt^2}, \ldots ; a \right) = 0$$

Evaluation

Sensor noise
Partial observation

$$\min \ L(s, a) \quad s. \ t. \ F_{\theta, \phi} = 0$$

Optimization
Inverse dynamics is difficult to solve!

Design parameters $\theta$

Control parameters $\phi$

Nonlinearity
Expensive computation
Dynamic model

Evaluation

Sensing noise
Partial observation

$\min L(s,a)$
$s.t. F_{\theta,\phi} = 0$

Optimization
Inverse dynamics is difficult to solve!

\[
min \ L(s, a)
\]
\[
s.t. F_{\theta, \phi} = 0
\]

Evaluation

Sensing noise
Partial observation
...

Dynamic model

Nonlinearity
Expensive computation
...

High dimensionality
Heterogeneous space
...

Design parameters \( \theta \)

High dimensionality
Heterogeneous space
...

Control parameters \( \phi \)
Gradients: the keyword in this talk

\[ \frac{\partial F}{\partial \theta} \]
Design parameters $\theta$

\[ \frac{\partial F}{\partial \phi} \]
Control parameters $\phi$

\[ \frac{\partial s, \alpha}{\partial F} \]
Dynamic model

\[ \frac{\partial L}{\partial s, \alpha} \]
Evaluation

\[ \min L(s, \alpha) \]
\[ s.t. F_{\theta,\phi} = 0 \]
Optimization
Our endeavor

Gradients in design and control
SIGGRAPH Asia 2016
SIGGRAPH 2021

Dynamic model

\[
\frac{\partial s, \alpha}{\partial F}
\]

Evaluation

\[
\frac{\partial L}{\partial s, \alpha}
\]

min \( L(s, \alpha) \)

s.t. \( F_{\theta, \phi} = 0 \)

Optimization
Our endeavor

Gradients in design and control
SIGGRAPH Asia 2016
SIGGRAPH 2021

Gradients in dynamic models
SIGGRAPH 2022

\[
\begin{align*}
\min L(s, a) \\
\text{s.t. } F_{\theta, \phi} = 0
\end{align*}
\]

Optimization

Evaluation

\[
\frac{\partial L}{\partial s, a}
\]
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

$(\theta, \phi)$
How UAVs were designed before

Parameters $(\theta, \phi)$

Control
How UAVs were designed before

Parameters ($\theta, \phi$)

Design

Control

Simulation
How UAVs were designed before

Parameters $(\theta, \phi)$

Design

Control

Simulation

Experimentation
Our strategy: using gradients

Parameters $(\theta, \phi)$ → Design

Control

Differentiable Simulation

Experimentation
The differentiable simulator
An example task: maximizing payload
Behind-the-scene analysis

Original design

Optimized design

Old payload: 1047g

New payload: 1392g
Conclusion: gradients reveal novel designs!

Original design

Optimized design

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 $\rightarrow$ Neural network model $\rightarrow$ 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.
Our strategy: rendering-invariant gradients

**Invariant** visual appearance equals **zero** gradients!

- Dynamic model: states, actions
- Visual appearance: lighting, material, texture
- Video input
- Neural network model
- Reconstruction: states, actions

\[ \frac{\partial L}{\partial} = 0 \]
Our result

Reconstructed motion

Input video

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!

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References


Page 32: video credit to Jie Xu.