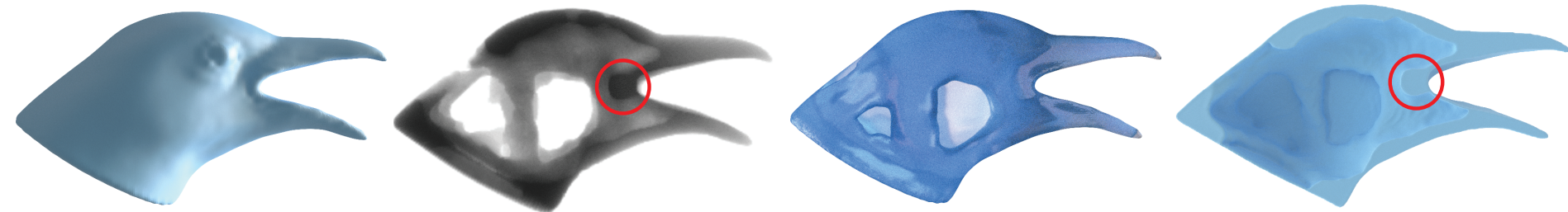


Fast and Robust Stochastic Structural Optimization



Qiaodong Cui¹ Timothy Langlois² Pradeep Sen¹ Theodore Kim³

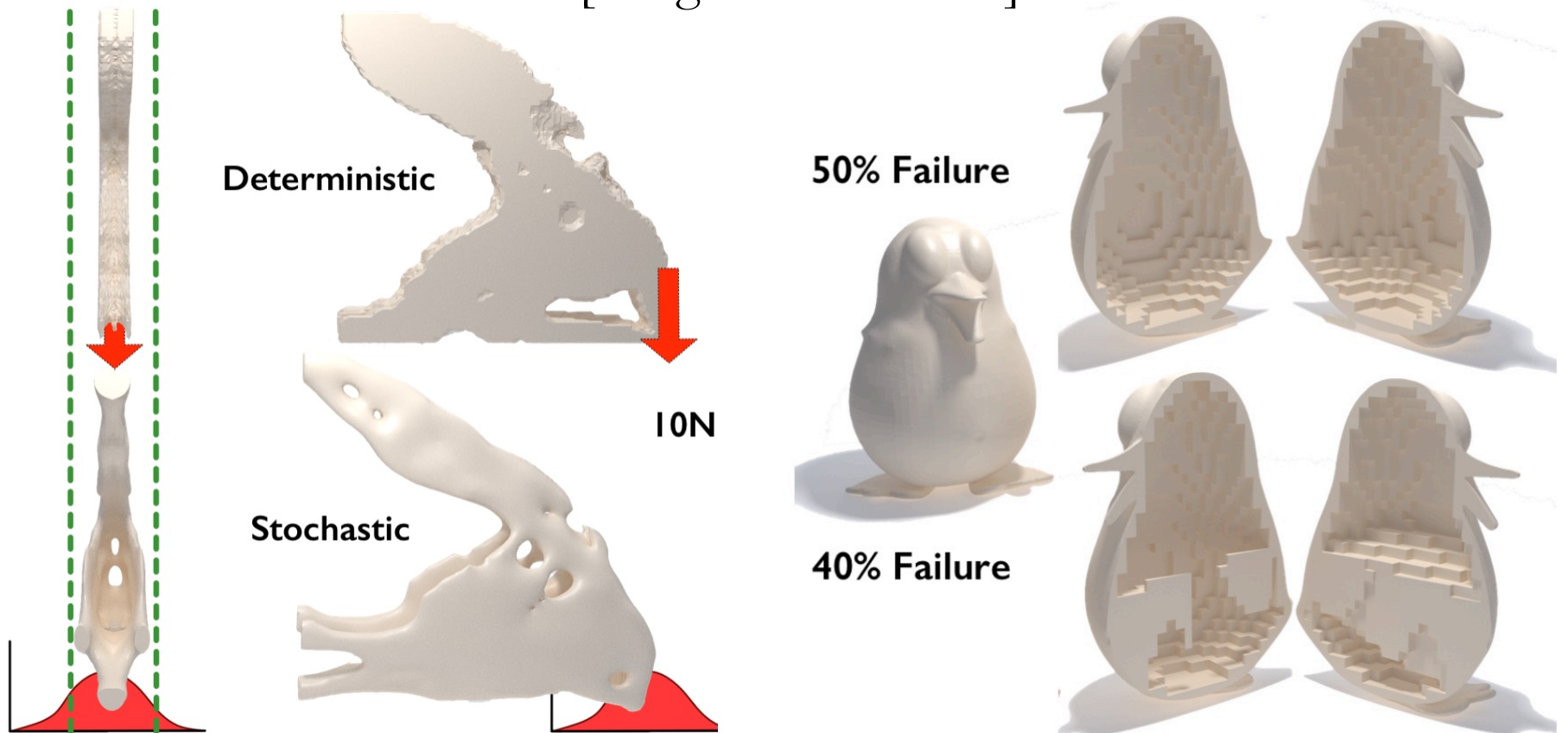
University of California, Santa Barbara¹

Adobe Research²

Yale University³

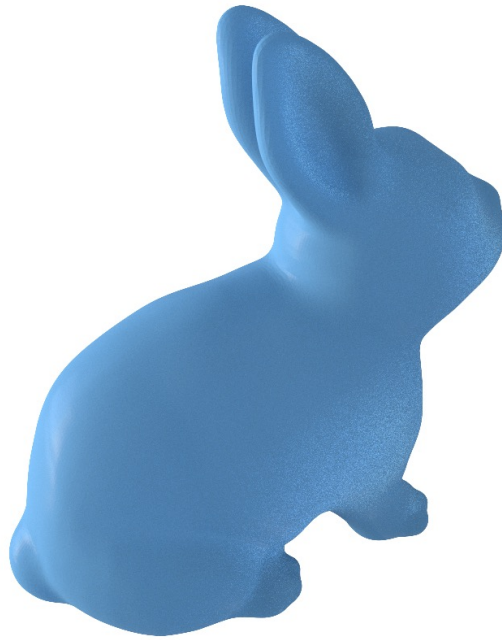
Stochastic Structural Optimization

[Langlois et al. 2016]

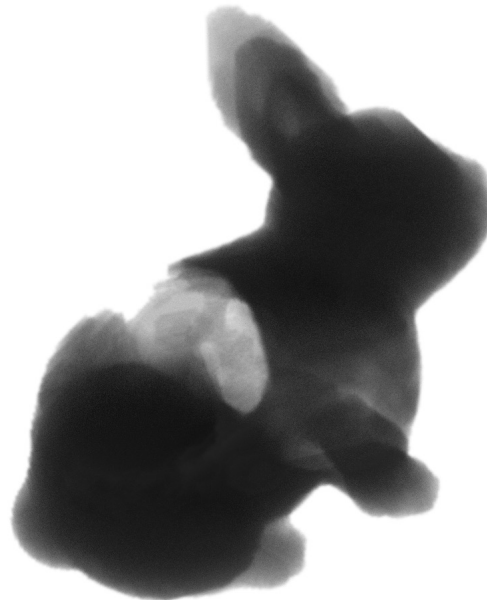


$26 \times 34 \times 28 \sim 1 \text{ hrs per iteration}$

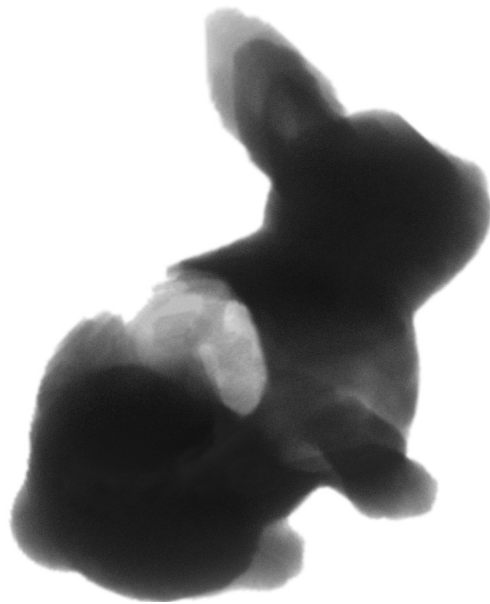
Initial
shapes:



[Langlois et al.]

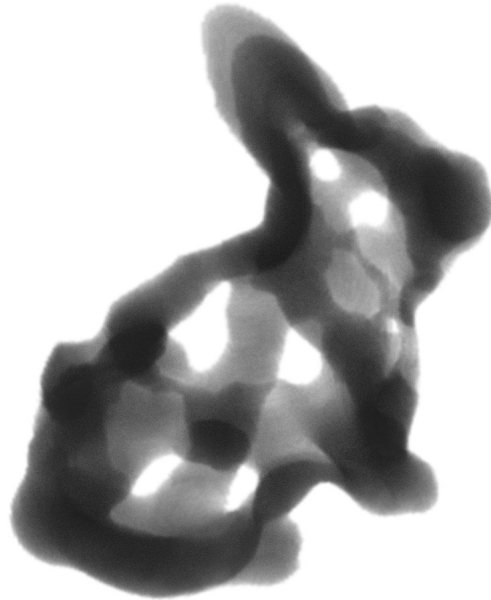


[Langlois et al.]



~ 6 hrs per iteration
97.3 g

Ours



~ 2.4 minutes per iteration
36.7 g

$28 \times 44 \times 28$

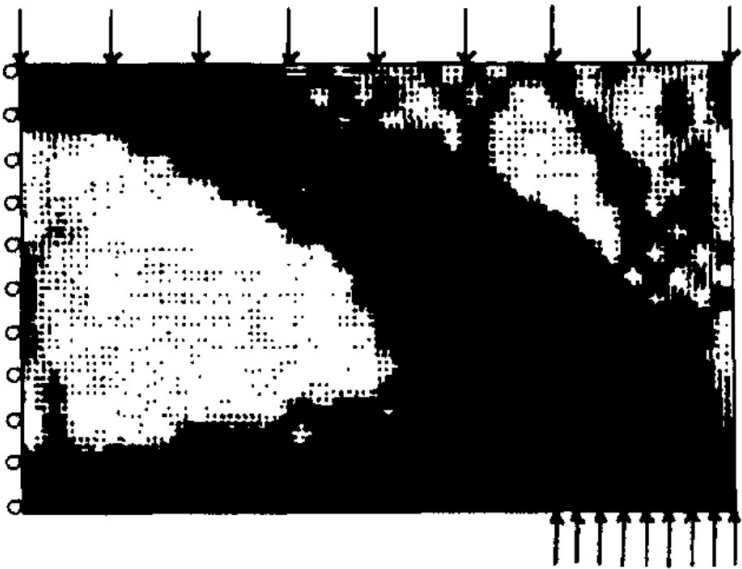
Outline

- Previous work
- Stochastic Structural Optimization
- Our methods
- Results
- Conclusions and future work

Outline

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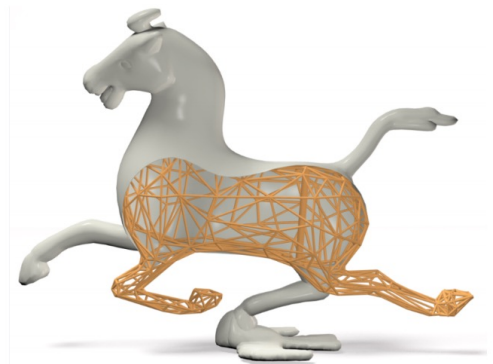
Structure Optimization



[Bendsoe et al. 1989]



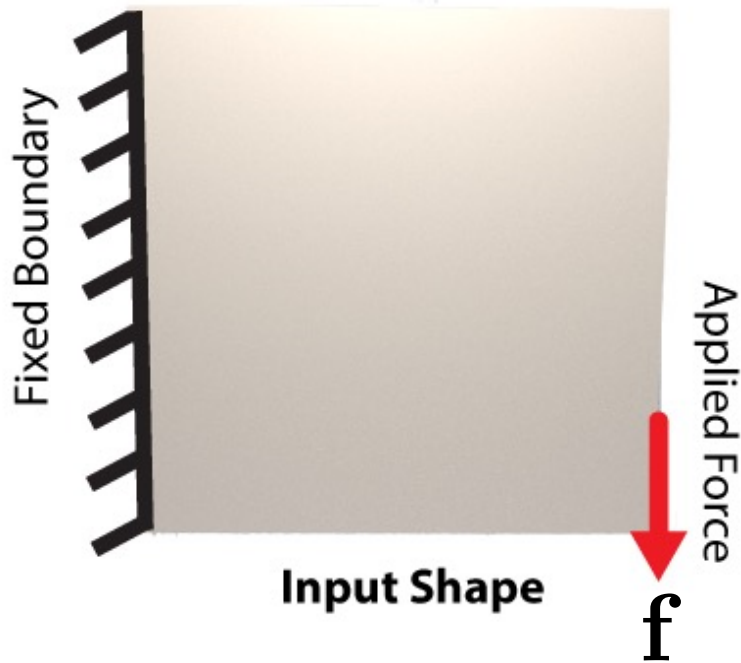
(a)



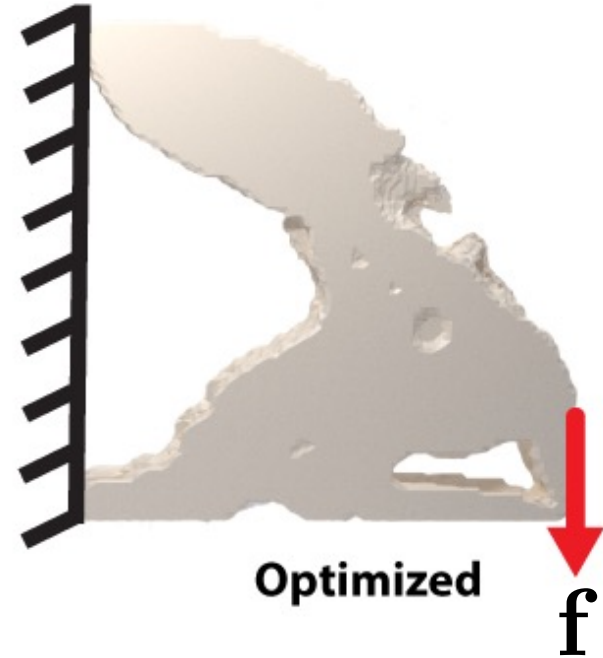
(b)

[Wang et al. 2013]

Structure Optimization



Input Shape



Optimized

$$\mathbf{u} = \mathbf{K}^{-1} \mathbf{f}$$

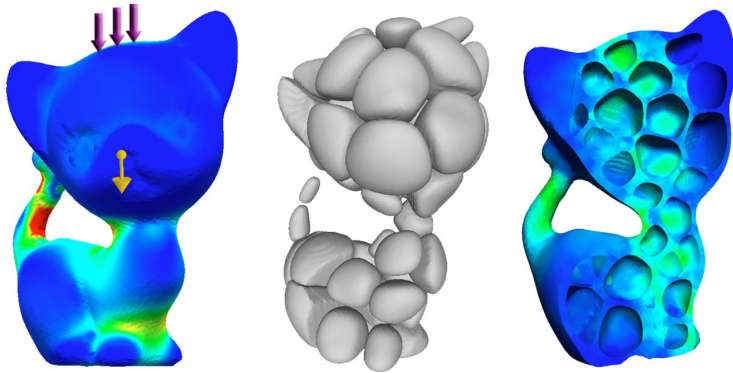
\mathbf{f} is fixed

Compliance: $\mathbf{u}^T \mathbf{K} \mathbf{u}$

Minimization: $\min_{\omega} \mathbf{u}^T \mathbf{K} \mathbf{u}$

Structure Optimization

Compliance Minimization



[Lu et al. 2014]

Weight Minimization



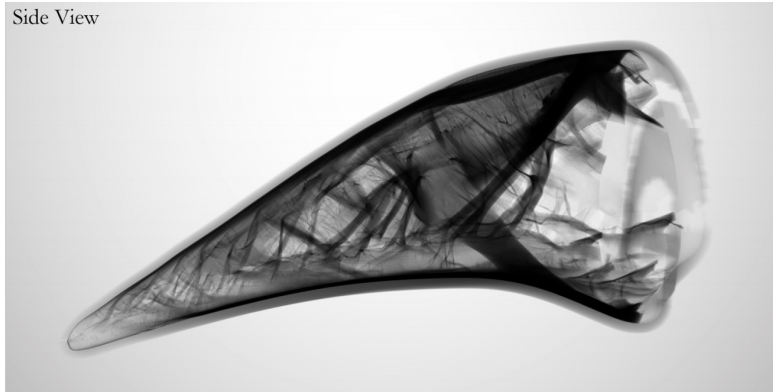
(a) Compliance minimization ($C = 27592.9$)



(b) Mass minimization ($m = 2577.8$)

[Lee et al. 2012]

Side View



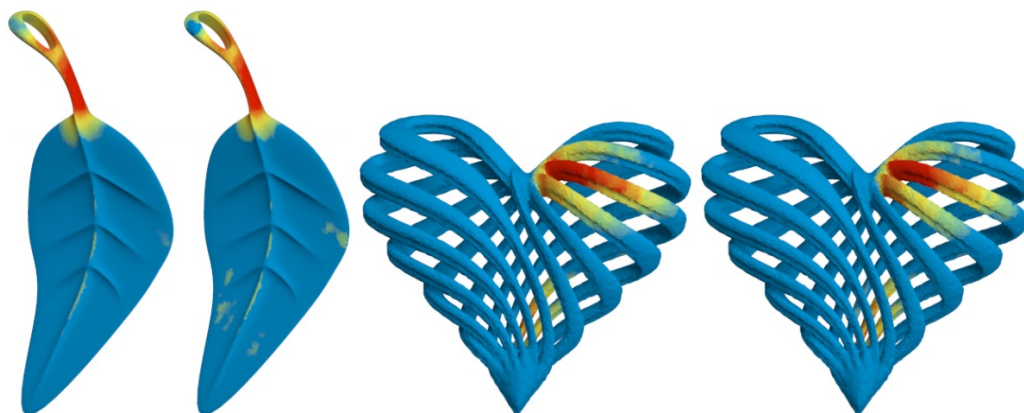
[Liu et al. 2018]



[Ulu et al. 2018]

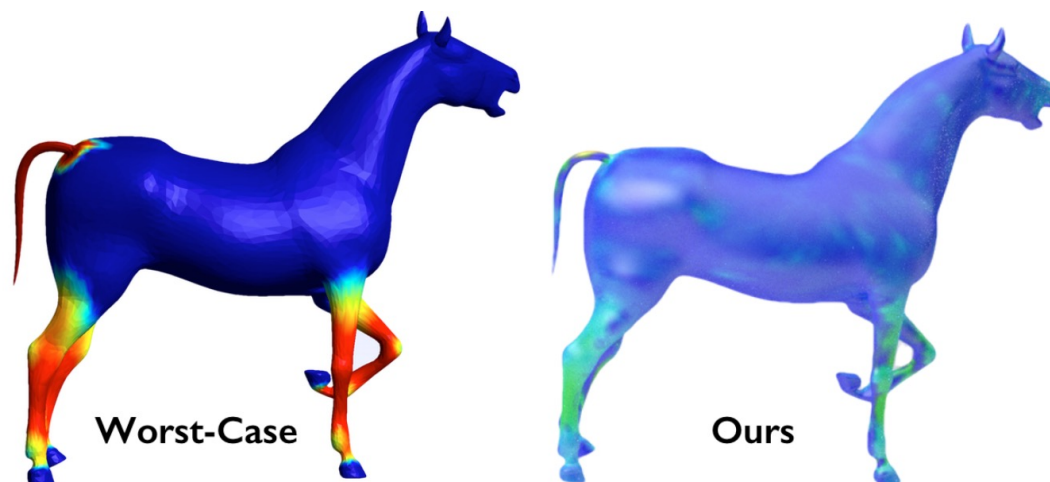
Failure Analysis

Worse Case
Structure Analysis



[Zhou et al. 2013]

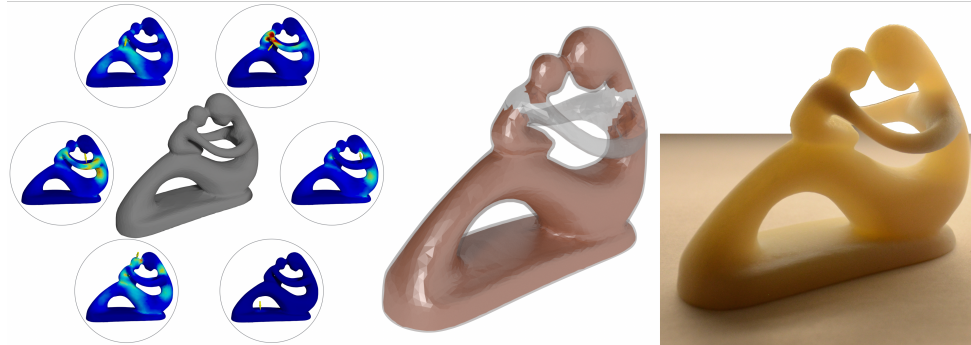
Stochastic Case
Structure Analysis



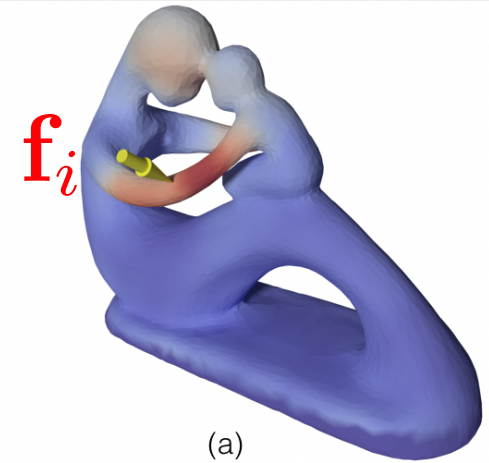
[Langlois et al. 2016]

Structure Optimization

Worse Case Structure Optimization

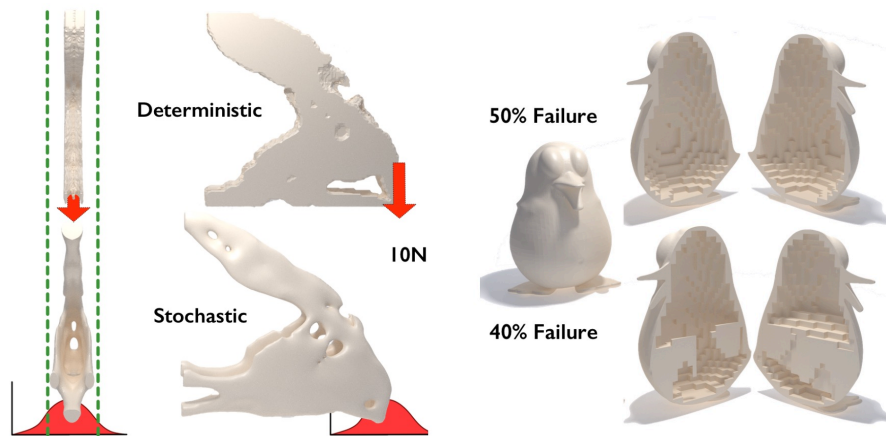


[Ulu et al. 2017]

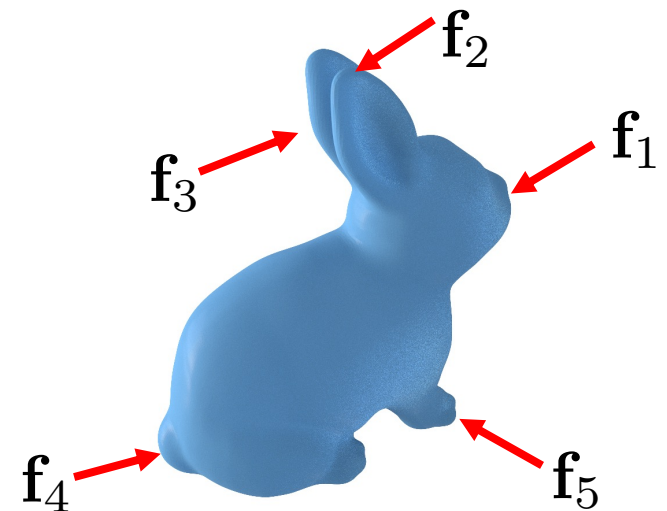


(a)

Stochastic Structure Optimization



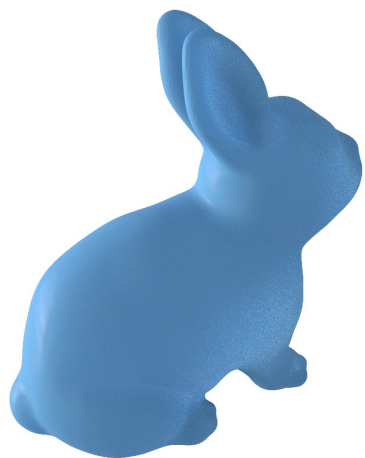
[Langlois et al. 2016]



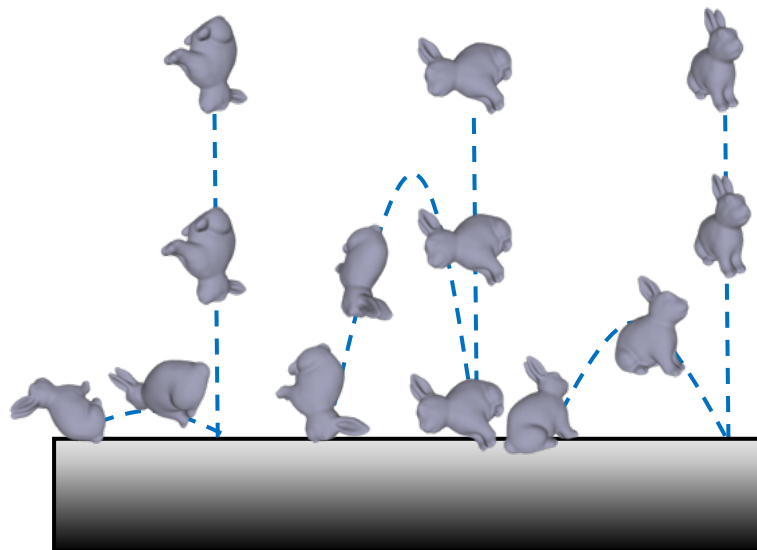
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Stochastic Structural Optimization

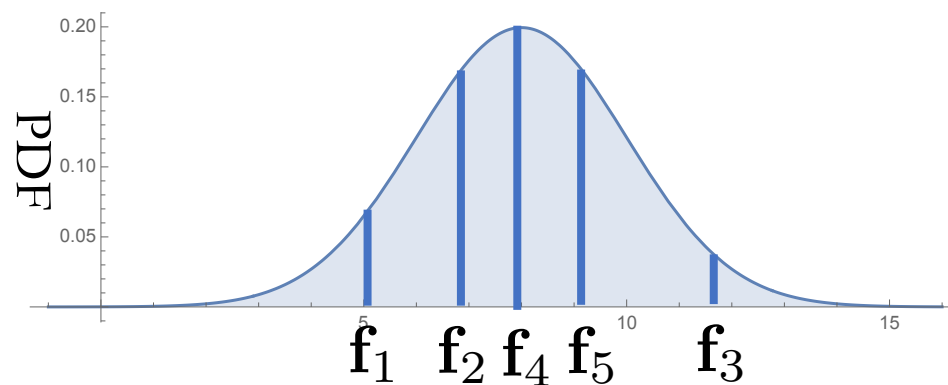
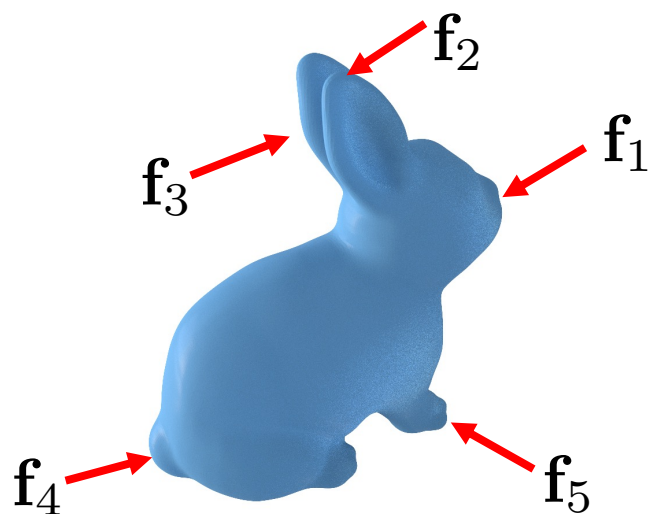


Initial Design

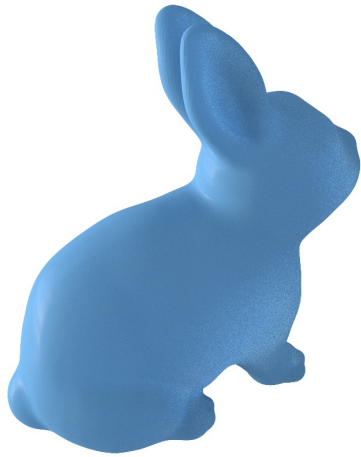


Rigid body simulation

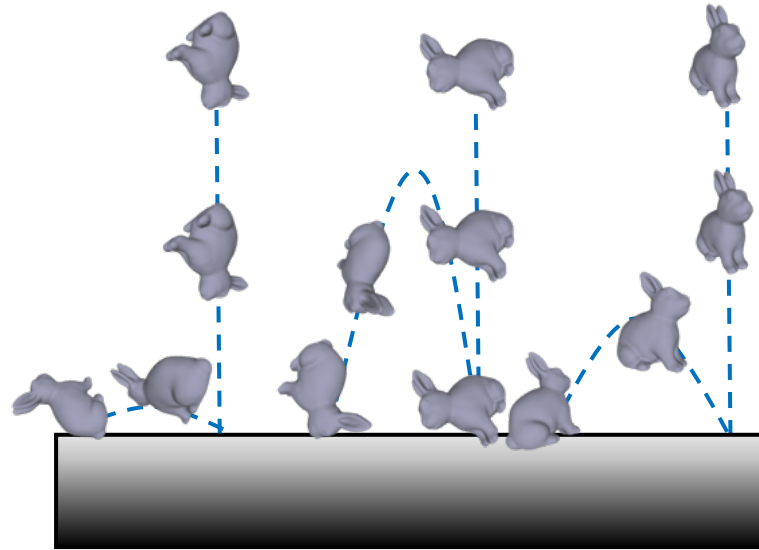
Force sample: \mathbf{f}_i



Stochastic Structural Optimization



Initial Design

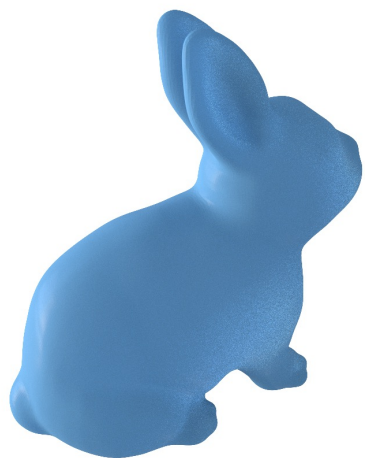


Rigid body simulation

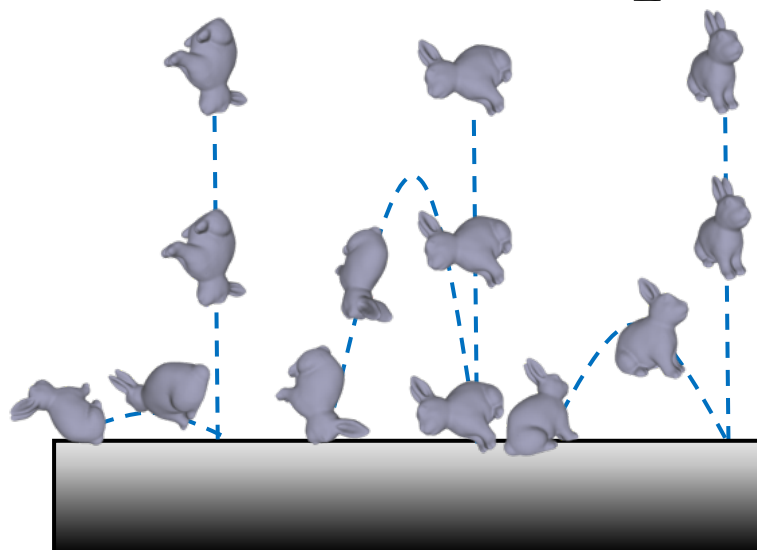
Force sample: \mathbf{f}_i

Force matrix: $\mathbf{F} = [\mathbf{f}_1 \dots \mathbf{f}_{n_s}]$

Stochastic Structural Optimization



Initial Design



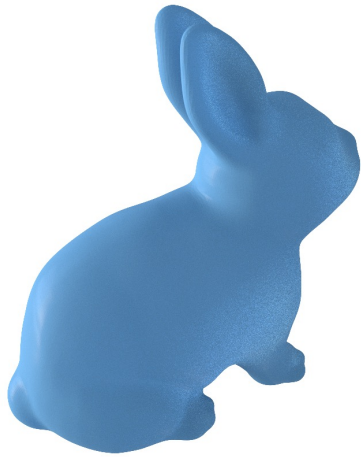
Rigid body simulation

Force sample: \mathbf{f}_i

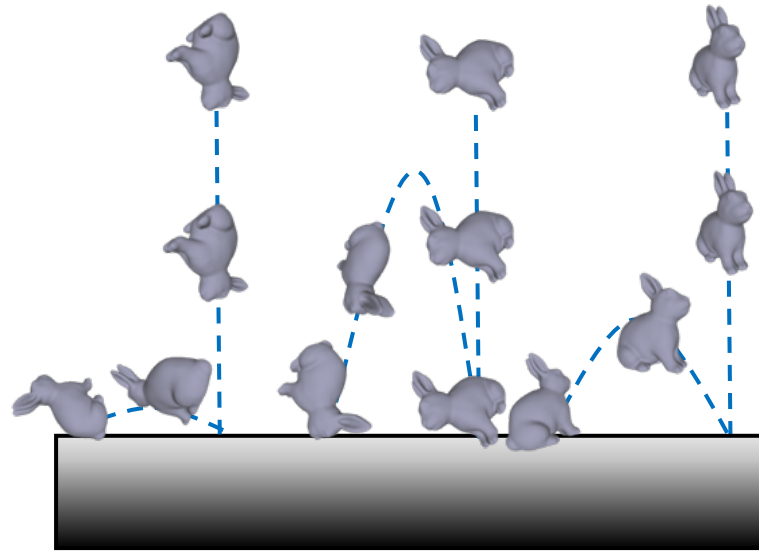
$$\begin{array}{c} \text{blue bar} \\ \alpha_i \in \mathbb{R}^r \end{array} = \begin{array}{c} \text{blue box} \\ \bar{\mathbf{F}} \in \mathbb{R}^{3n \times r} \end{array} \times \begin{array}{c} \text{blue bar} \\ \mathbf{f}_i \in \mathbb{R}^{3n} \end{array}$$

$\bar{\mathbf{F}}^T$

Stochastic Structural Optimization



Initial Design



Rigid body simulation

Force sample: \mathbf{f}_i

Force matrix: $\mathbf{F} = [\mathbf{f}_1 \dots \mathbf{f}_{n_s}]$

$$\mathbf{K} \in \mathbb{R}^{3n \times 3n}$$

PCA: $\mathbf{f}_i \approx \bar{\mathbf{F}} \boldsymbol{\alpha}_i$

$$\bar{\mathbf{F}} \in \mathbb{R}^{3n \times r}$$

FEM solver: $\boldsymbol{\sigma}^i = \mathbf{C} \mathbf{B} \mathbf{K}^{-1} \bar{\mathbf{F}} \boldsymbol{\alpha}^i$

$$\boldsymbol{\alpha}^i \in \mathbb{R}^r$$

Stochastic Structural Optimization

Maximum Von Mises Stress:

$$s^i = \frac{1}{\hat{\sigma}} \max_e (S(\boldsymbol{\sigma}_e^i)) \begin{cases} e = 1 \dots m \\ i = 1 \dots n_s \end{cases}$$

Probability of survival:

$$P(s < 1) = \int_0^1 p(s) ds.$$

Optimization Criteria:

$$\min \sum_{e=1}^m \omega_e$$

s.t. $P(s < 1) > \Theta.$

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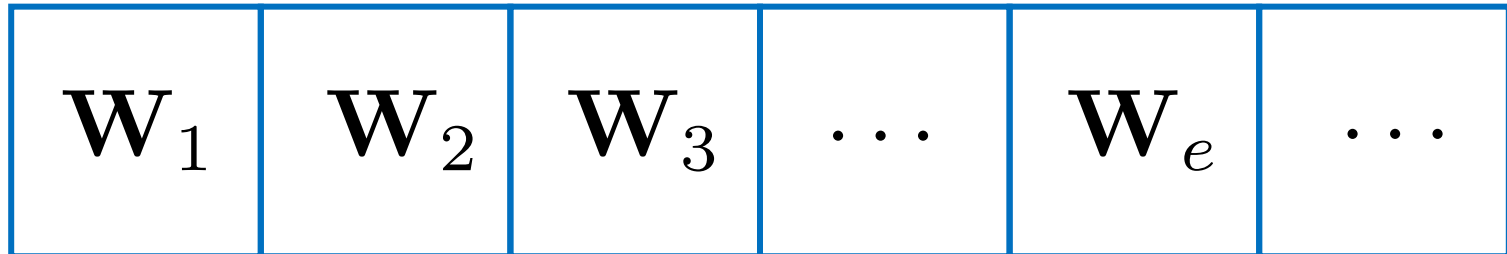
Previous Method

- Gradient based optimization: Method of Moving Asymptotes (MMA) is used.

$$\frac{\partial P(s < 1)}{\partial \boldsymbol{\omega}} = (\mathbf{K}^{-1} \mathbf{Y} \bar{\mathbf{U}}^T) : \frac{\partial \mathbf{K}}{\partial \boldsymbol{\omega}} + \boxed{(\mathbf{K}^{-1} \mathbf{Y}) : \frac{\partial \bar{\mathbf{F}}}{\partial \boldsymbol{\omega}}} + \mathbf{x} + \mathbf{t}$$

Force Basis Derivative: $\frac{\partial \bar{\mathbf{F}}}{\partial \boldsymbol{\omega}_e} = \bar{\mathbf{F}} \mathbf{W}_e$

$\mathbf{W}_e \in \mathbb{R}^{r \times r}$
 $\bar{\mathbf{F}} \in \mathbb{R}^{3n \times r}$



Previous Method

- Naïve evaluation is quadratic

Matrix production: $\bar{\mathbf{F}}\mathbf{W}_e \longrightarrow O(3n^2r^2) \approx O(n^2r^2)$

$$\mathbf{Z} = \mathbf{K}^{-1}\mathbf{Y} \in \mathbb{R}^{3n \times r}$$

Matrix contraction: $\mathbf{Z} : \bar{\mathbf{F}}\mathbf{W}_e \longrightarrow O(3n^2r) \approx O(n^2r)$

Our Linear Method

Static per element: \mathbf{Z} , $\bar{\mathbf{F}}$

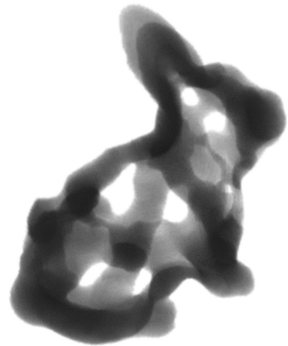
Varying per element: \mathbf{W}_e

$$\mathbf{Z} : \bar{\mathbf{F}} \mathbf{W}_e = (\bar{\mathbf{F}}^T \mathbf{Z}) : \mathbf{W}_e$$

Precompute: $(\bar{\mathbf{F}}^T \mathbf{Z}) \in \mathbb{R}^{r \times r} \longrightarrow O(3nr^2) \approx O(nr^2)$

Contraction : $(\bar{\mathbf{F}}^T \mathbf{Z}) : \mathbf{W}_e \longrightarrow O(nr)$

Our Linear Method



$28 \times 44 \times 28$

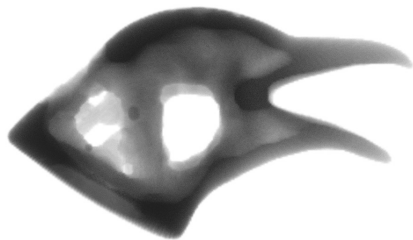
[Langlois et al. 2016]

~ 6.0 hrs per iteration

Ours

~ 2.4 minutes per iteration

150×



$32 \times 64 \times 40$

~ 11.8 hrs per iteration

~ 5.4 minutes per iteration

131×

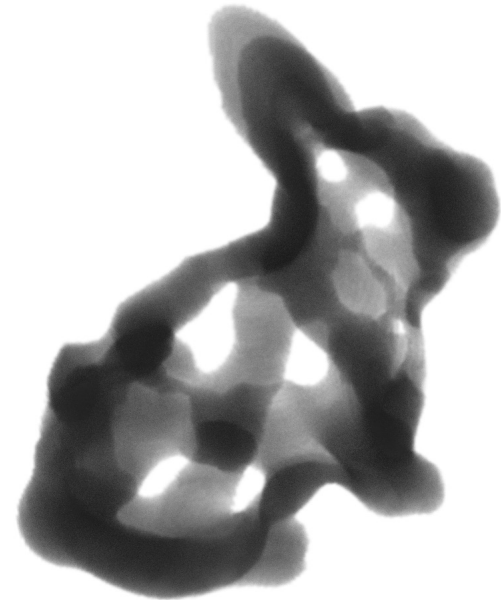
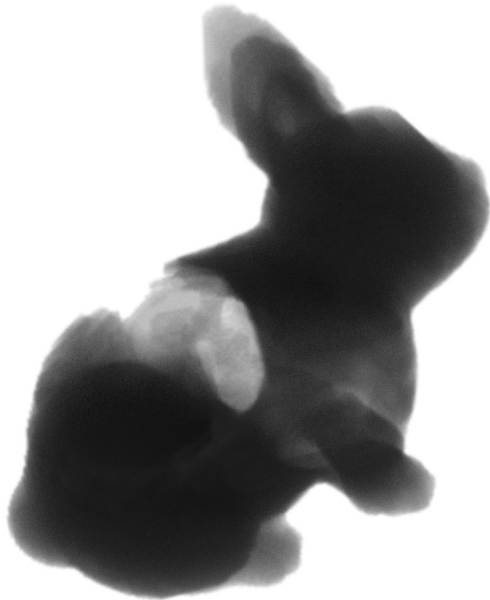
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Instabilities

[Langlois et al. 2016]

Ours



Inertia Gradients

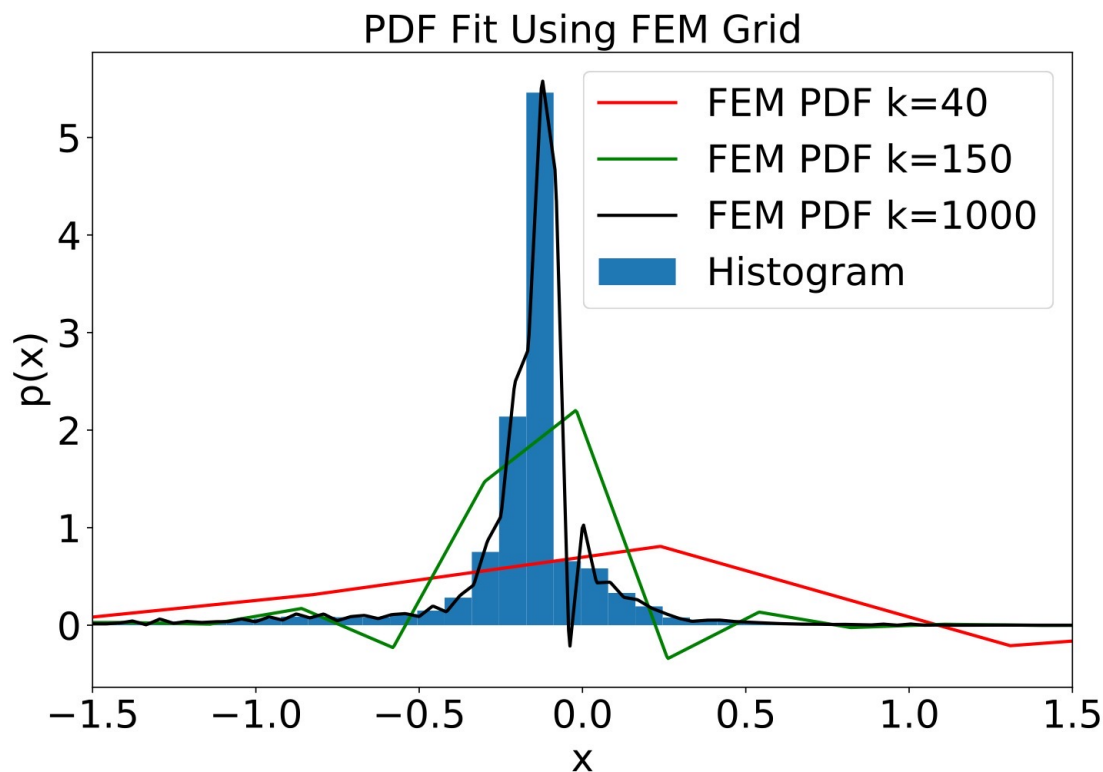
$$\frac{\partial P(s < 1)}{\partial \boldsymbol{\omega}} = (\mathbf{K}^{-1} \mathbf{Y} \bar{\mathbf{U}}^T) : \frac{\partial \mathbf{K}}{\partial \boldsymbol{\omega}} + (\mathbf{K}^{-1} \mathbf{Y}) : \frac{\partial \bar{\mathbf{F}}}{\partial \boldsymbol{\omega}} + \mathbf{x} + \mathbf{t}$$

$$\mathbf{x} = \sum_{i=1}^{n_s} \frac{\partial \boldsymbol{\alpha}^i}{\partial \boldsymbol{\omega}} \bar{\mathbf{U}}^T \mathbf{B}^T \mathbf{C}^T \mathbf{c}^i \quad \boldsymbol{\alpha}^i \in \mathbb{R}^r$$

$\frac{\partial \boldsymbol{\alpha}^i}{\partial \boldsymbol{\omega}}$ are evaluated with finite difference by computing a probability distribution function of $\boldsymbol{\alpha}^i$

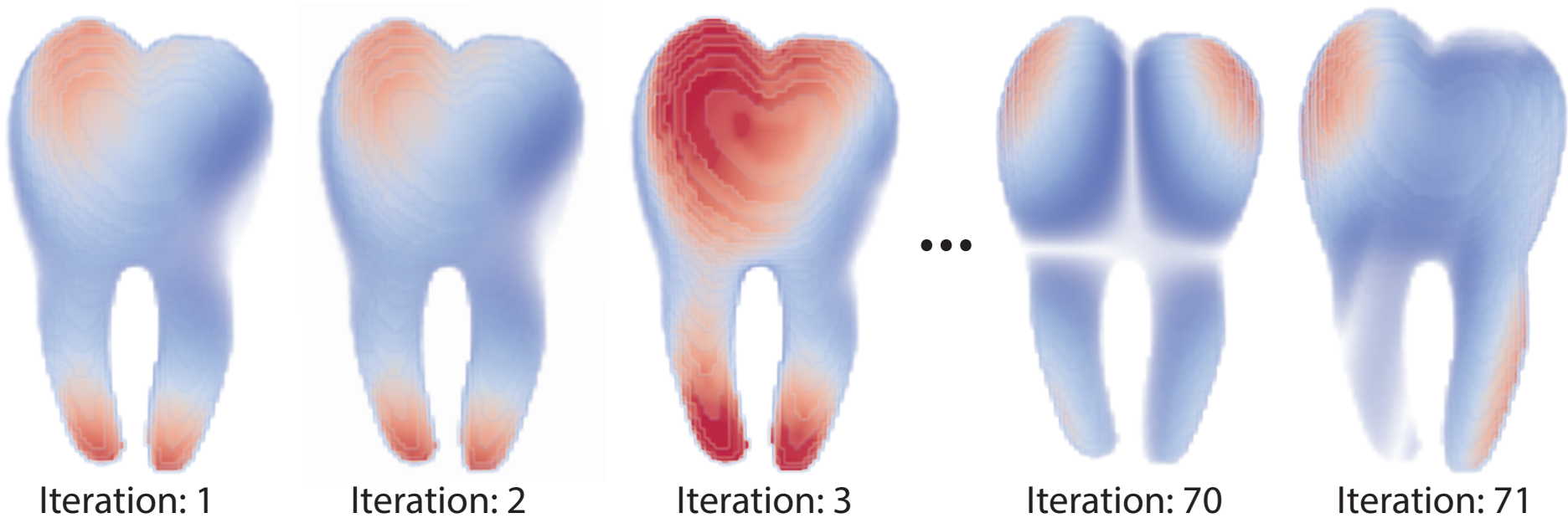
Unstable Gradients

A 1D probability distribution function $c_j(\alpha)$ is computed for each entry j , $1 \leq j \leq r$, using n_s samples.



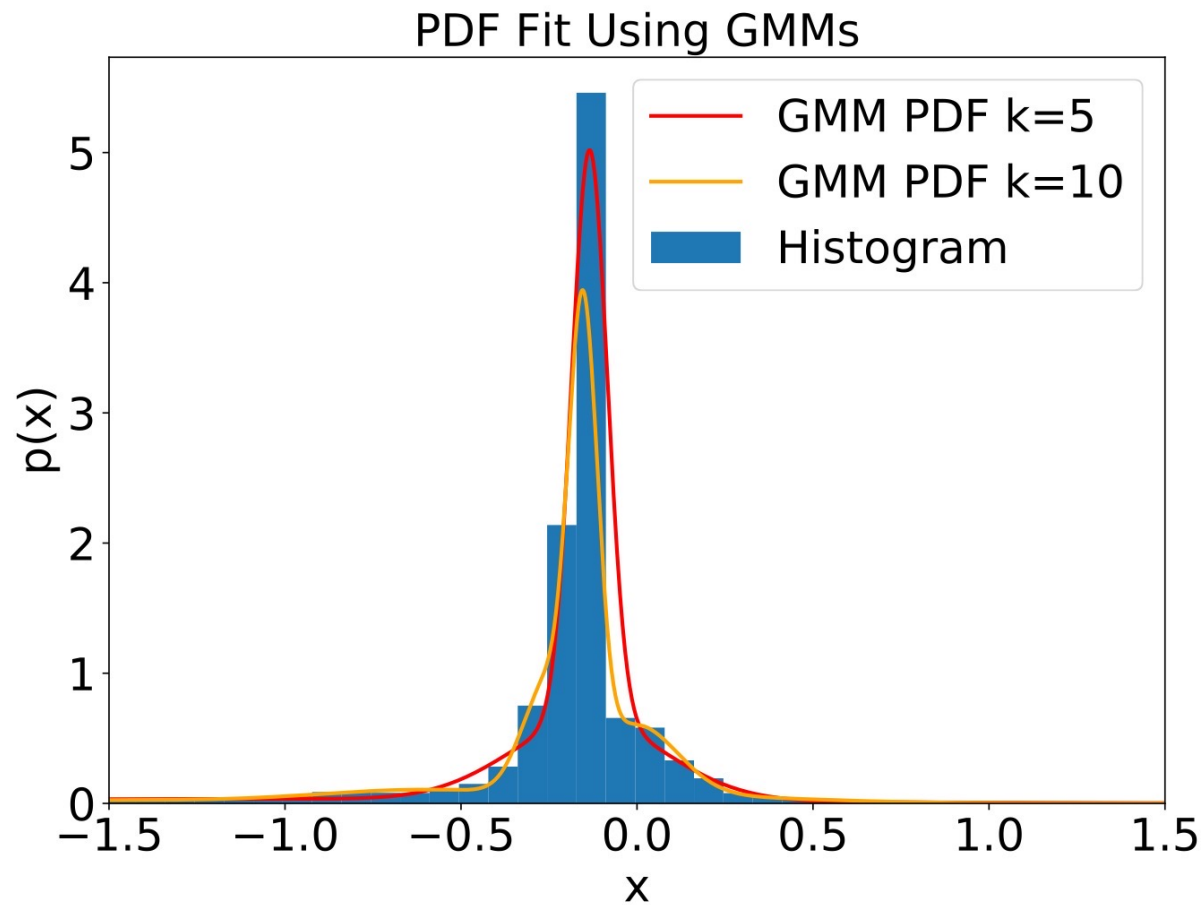
[Langlois et al. 2016]

Unstable Gradients



Stabilized Gradients

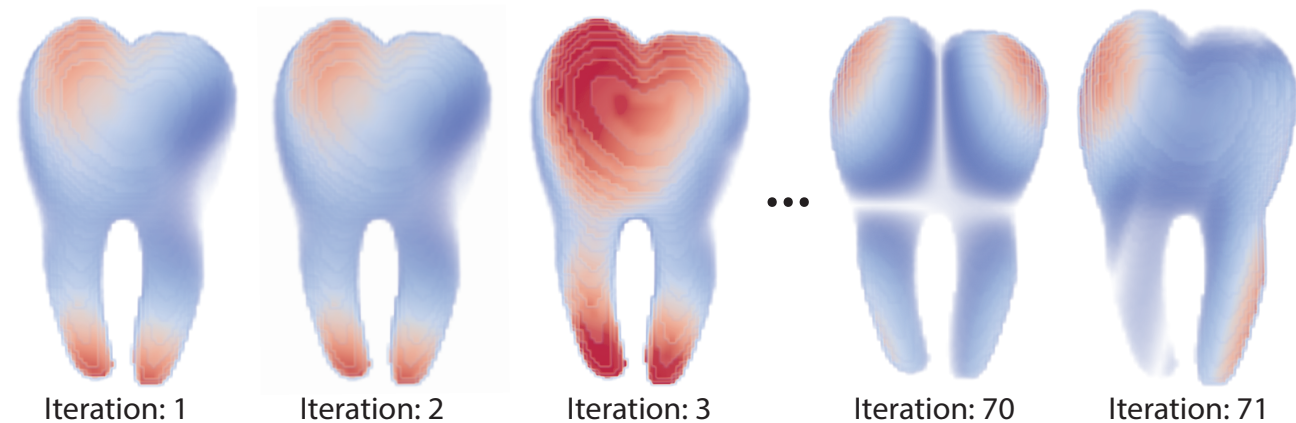
- We compute PDF with Gaussian Mixture Models



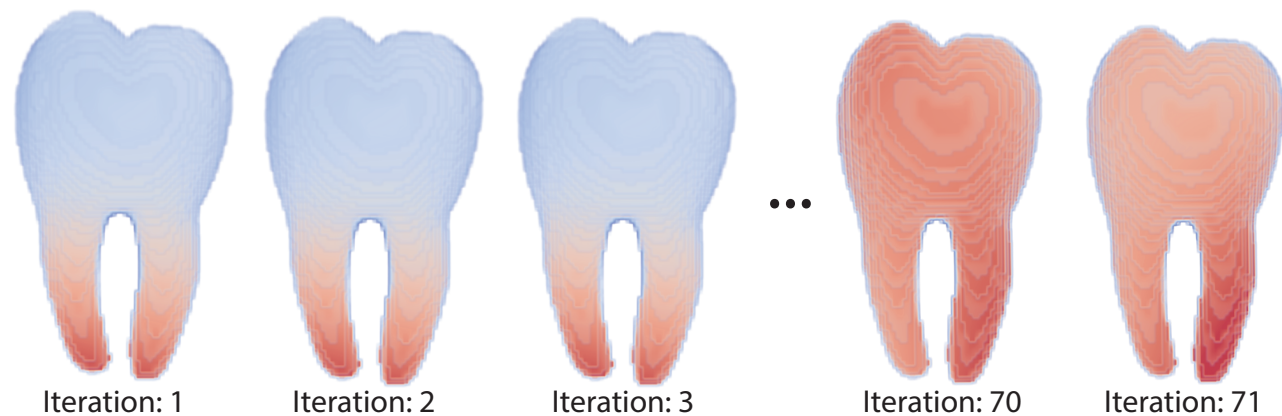
Ours

Stabilized Gradients

Optimized results



[Langlois et al. 2016]



Ours

Outline

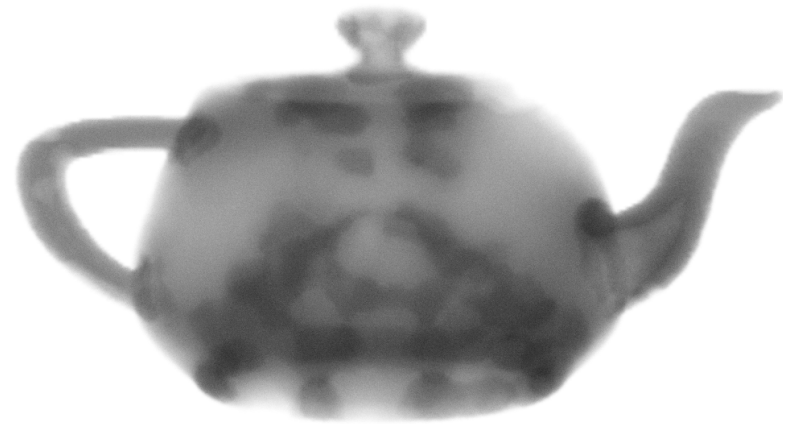
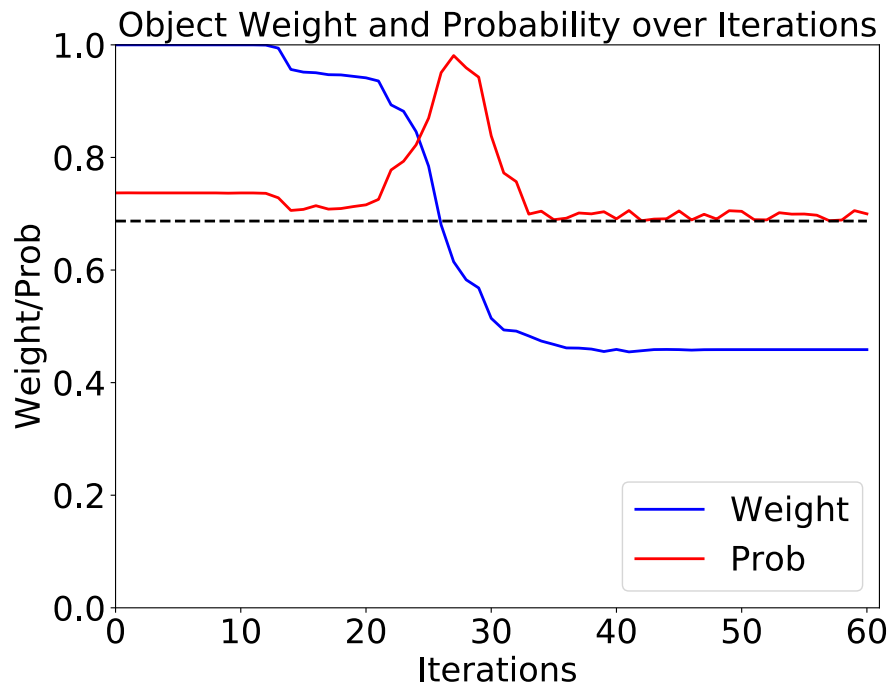
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Local Minima

The objective function: $\min f(\boldsymbol{\omega}) = \sum_{e=1}^m \omega_e$

The constraint function: $g(\boldsymbol{\omega}) = \Theta - P(s < 1) < 0$

$g(\boldsymbol{\omega})$ is extremely non-linear \longrightarrow Local minima



Iteration: 59

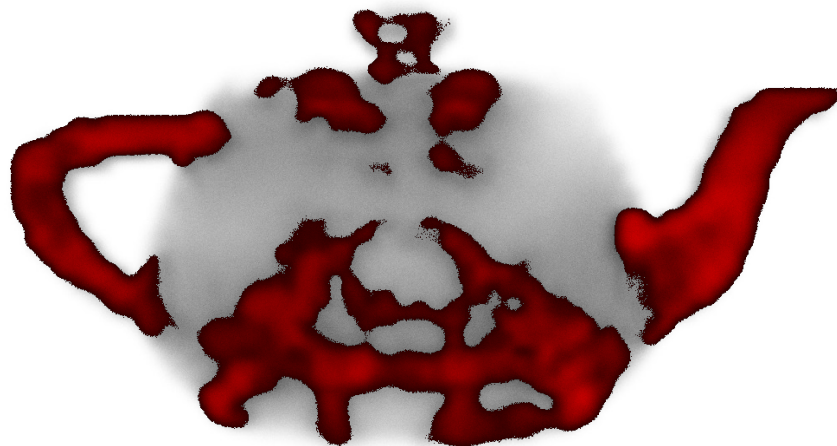
Reinforcement Structures



Intermediate results



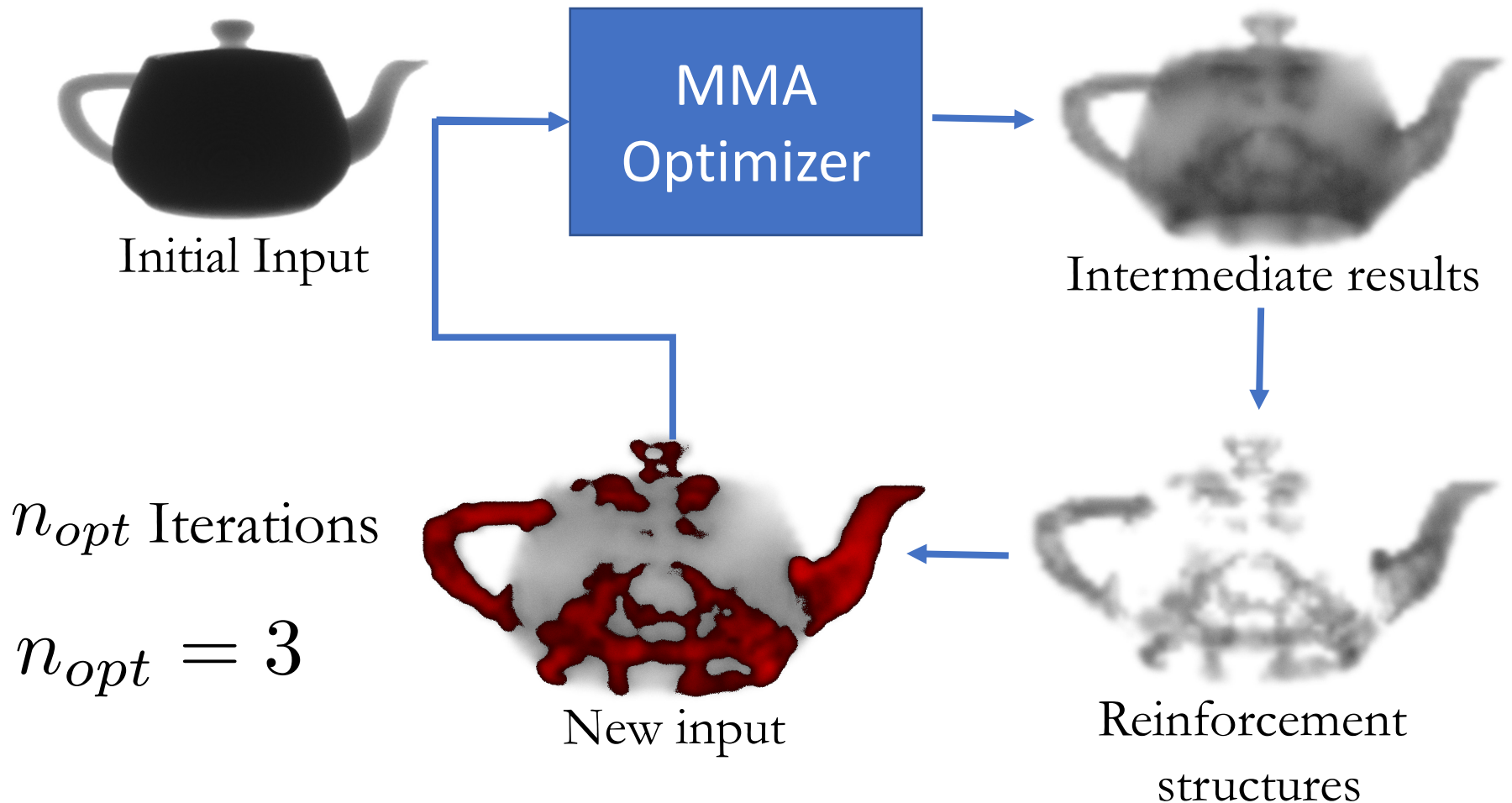
Reinforcement Structures



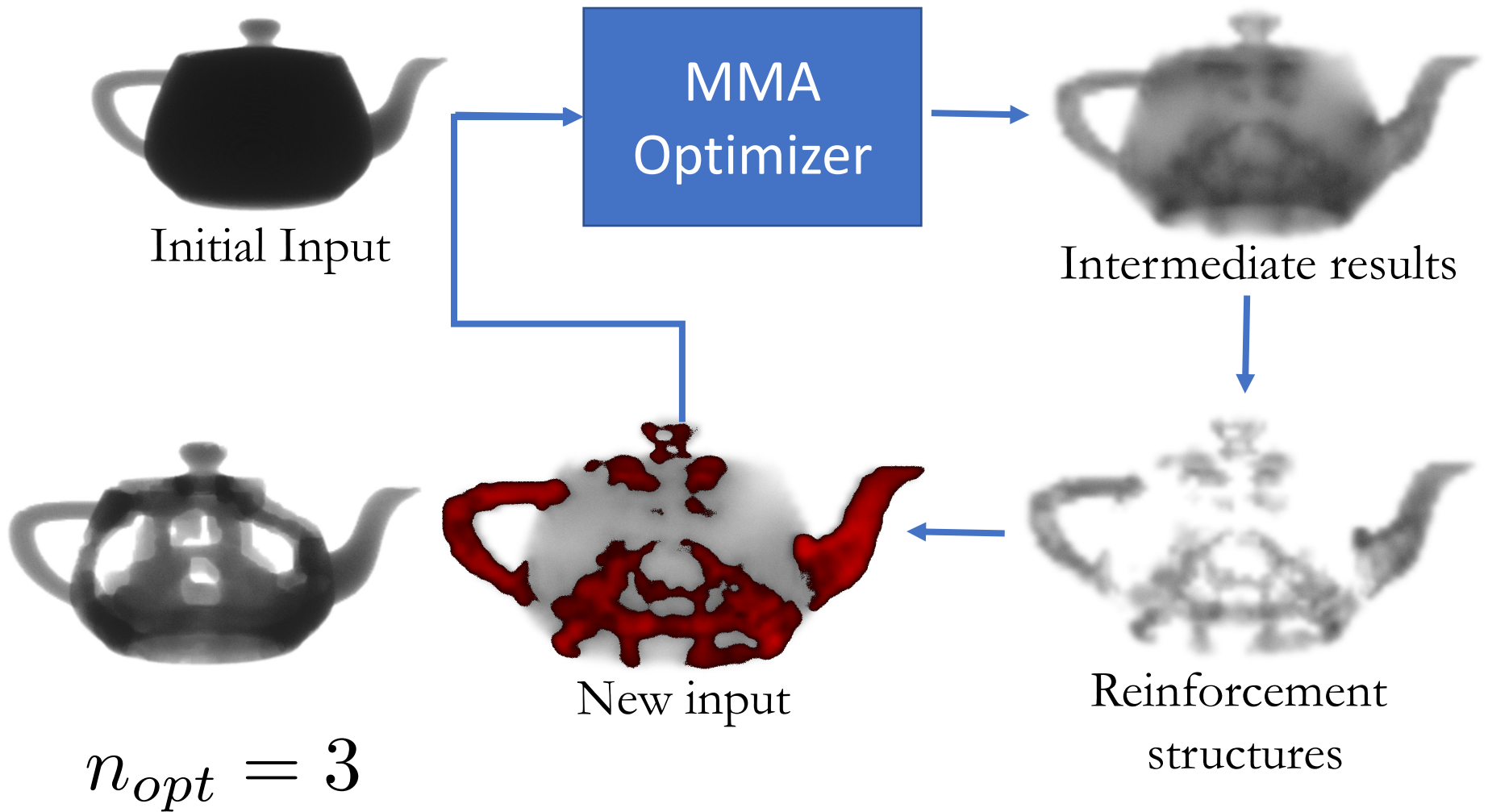
→ Constrained

Input for the the next optimization

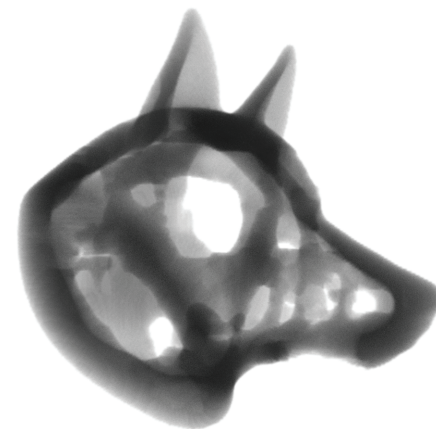
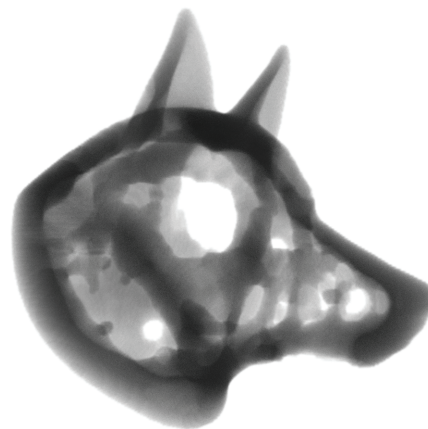
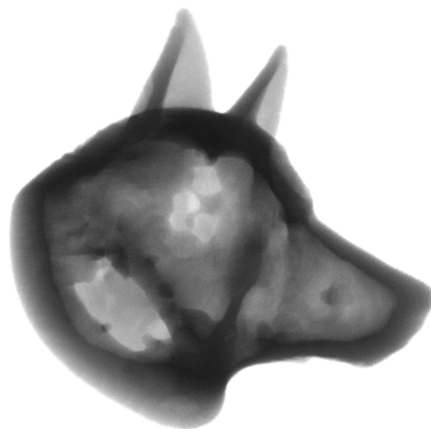
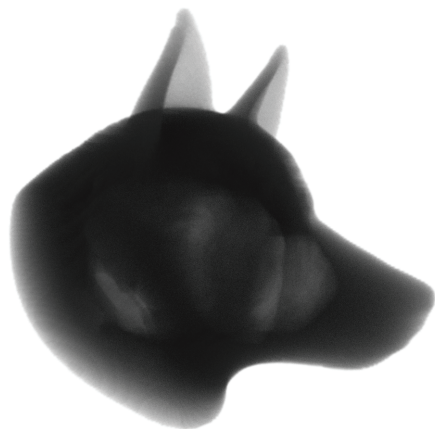
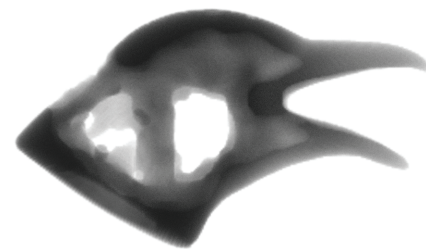
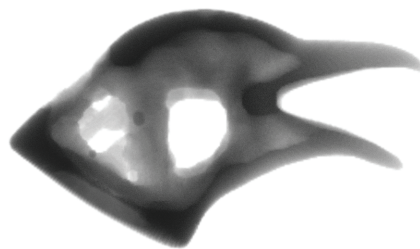
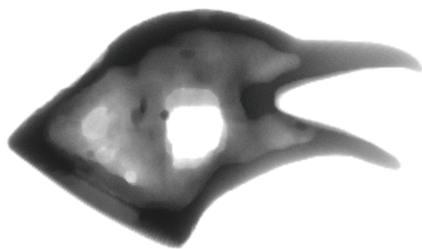
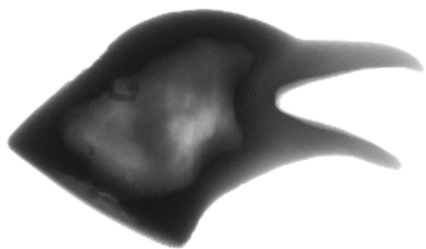
The Restart Strategy



The Restart Strategy



Parameter Choice



$n_{\text{opt}}=1$

$n_{\text{opt}}=2$

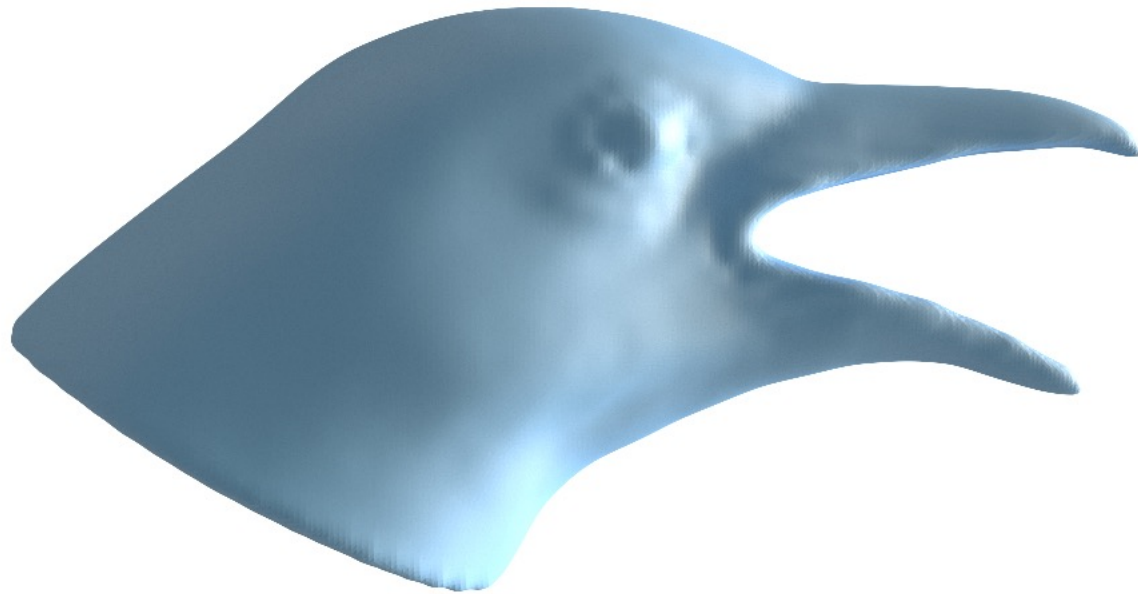
$n_{\text{opt}}=3$

$n_{\text{opt}}=4$

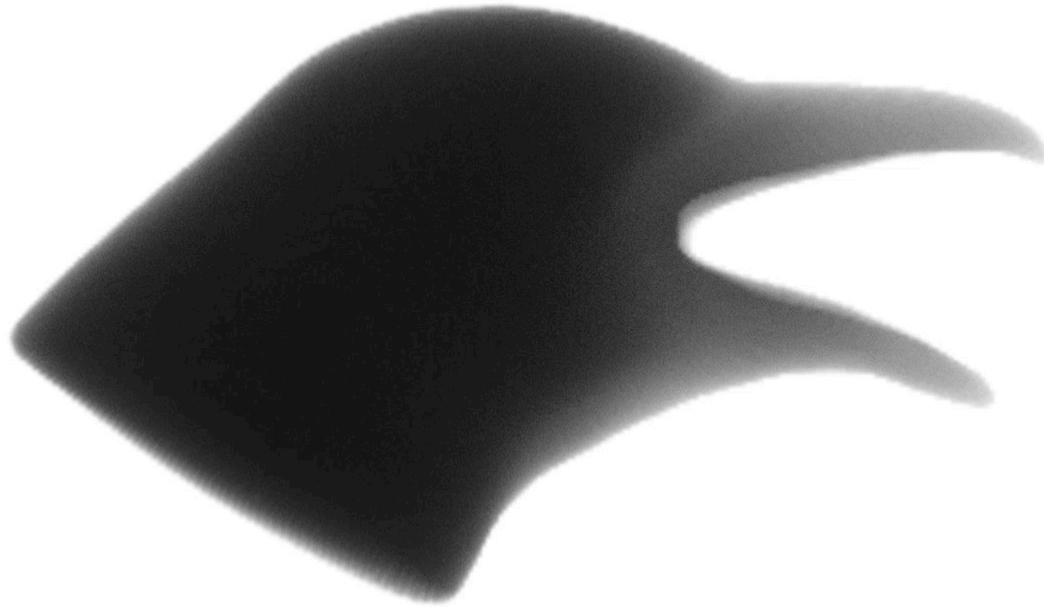
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Raven



Resolution: $32 \times 64 \times 40$



Optimization iteration: 0

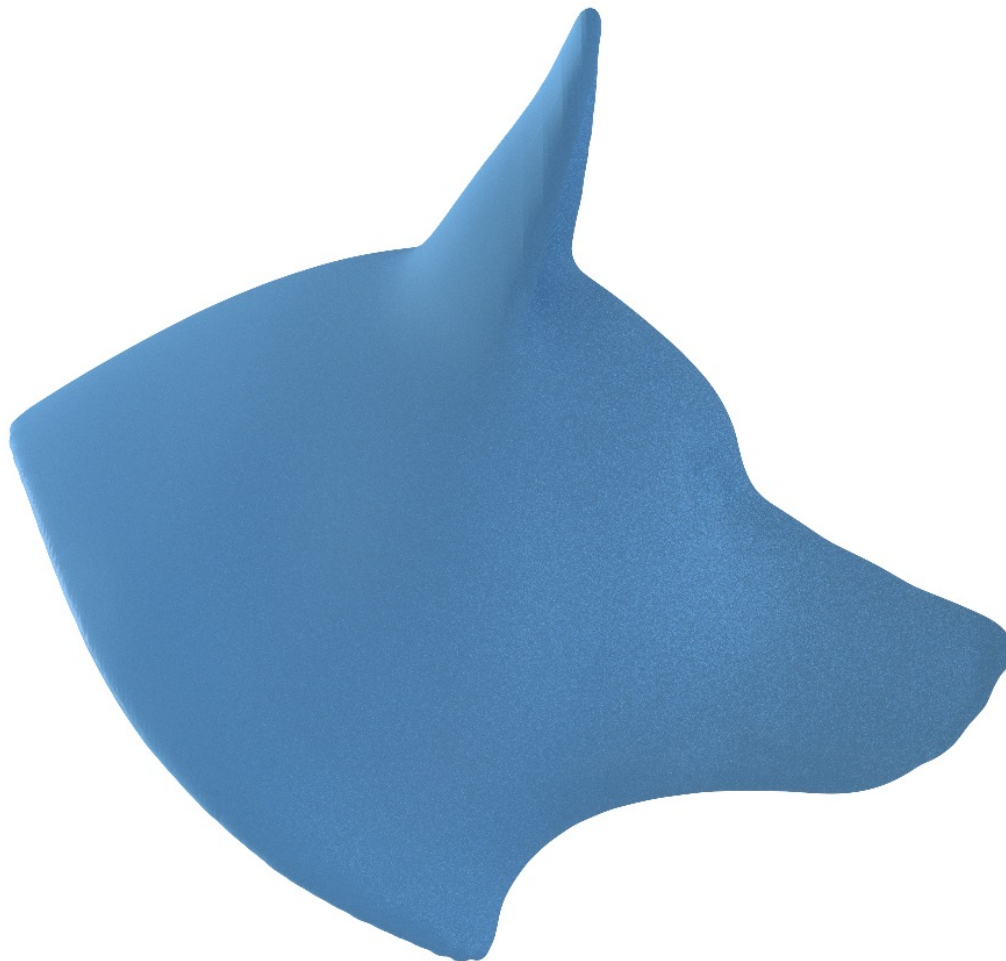
Time per iteration

Previous: 11.87 hrs

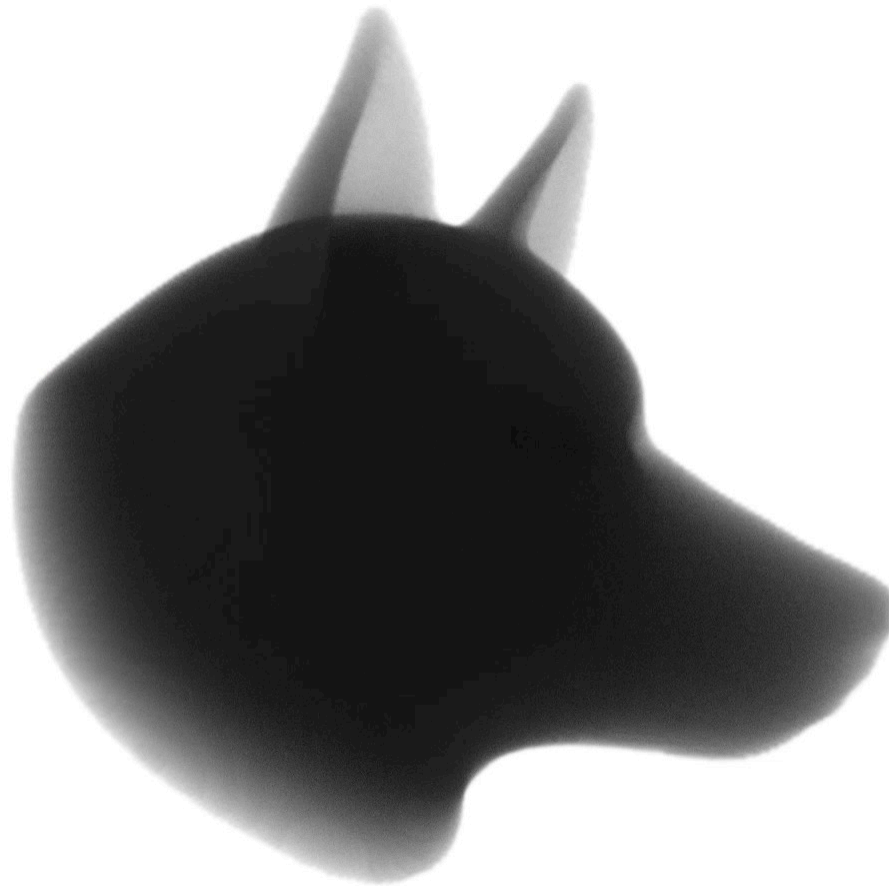
Ours: 5.46 minutes

130×

Dog



Resolution: $40 \times 64 \times 60$



Optimization iteration: 0

Time per iteration

Previous: 41.72 hrs

Ours: 7.68 minutes

326X

Armadillo



Resolution: $56 \times 64 \times 52$



Optimization iteration: 0

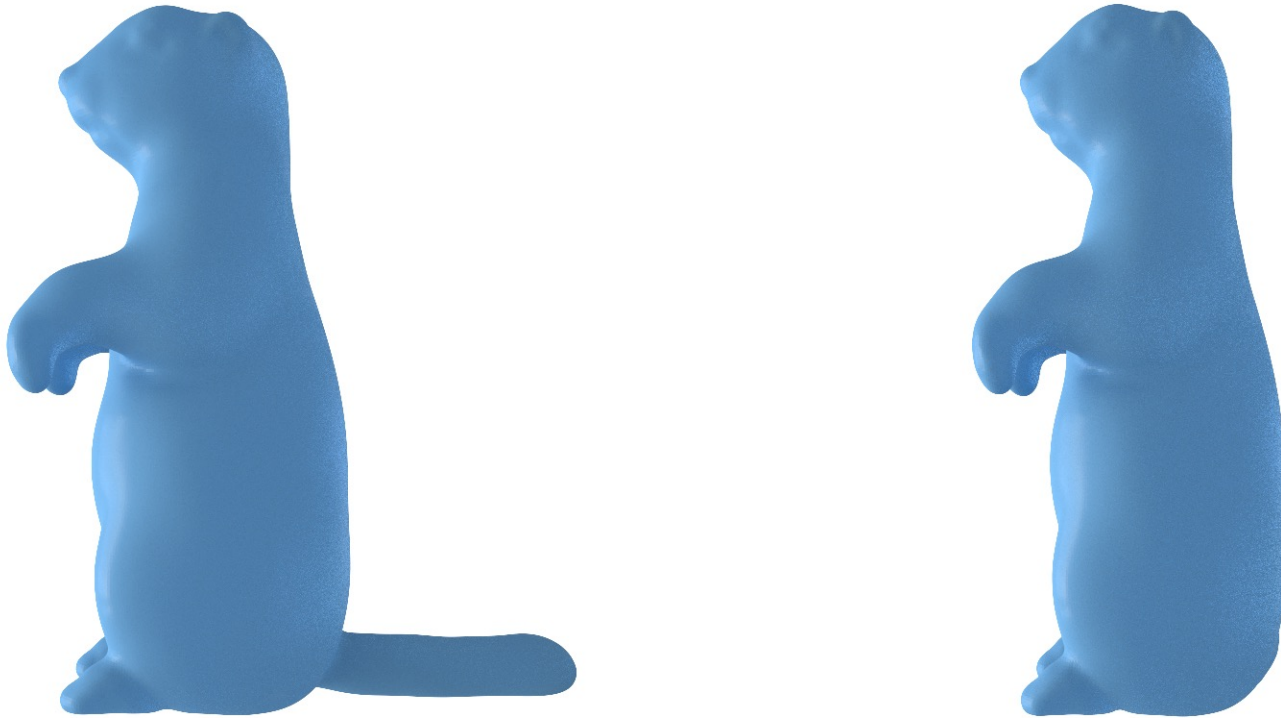
Time per iteration

Previous: 61.42 hrs

Ours: 6.6 minutes

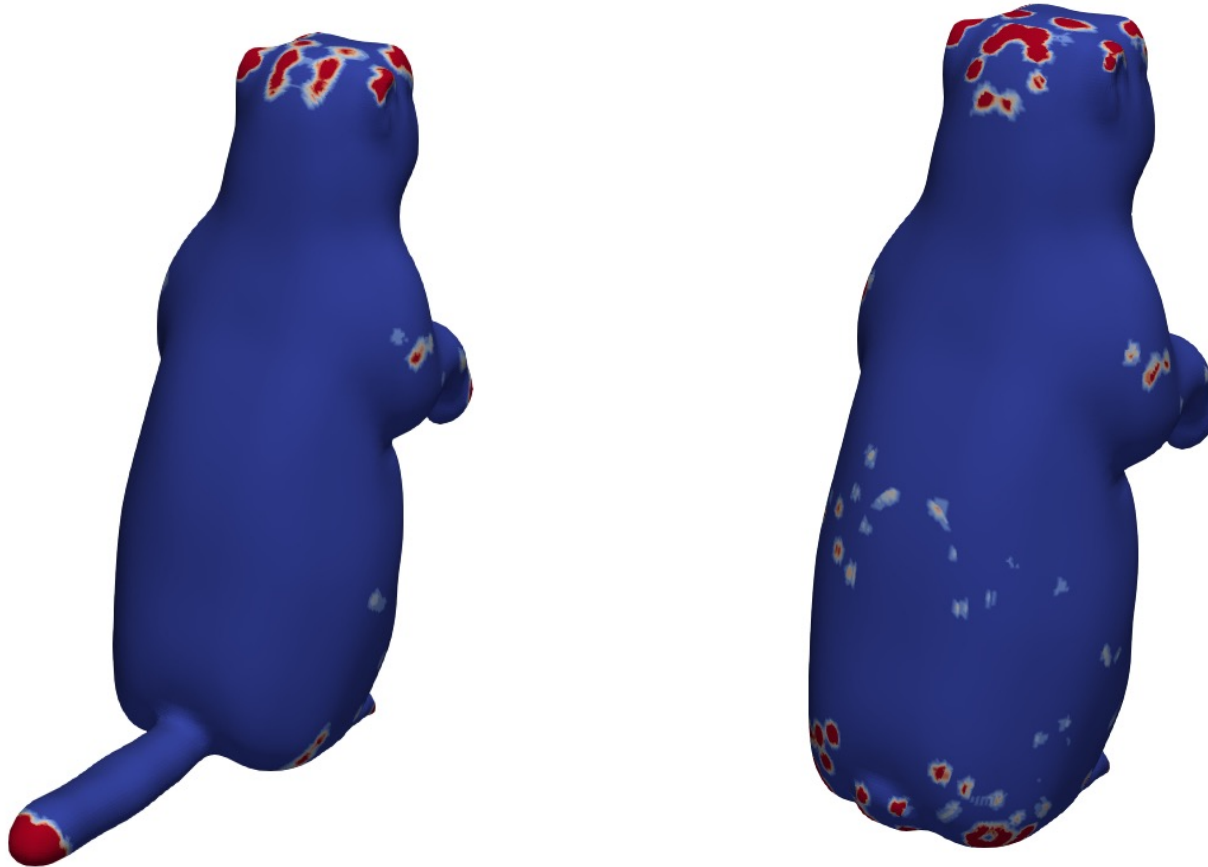
558X

Adaptative to Real World Loading



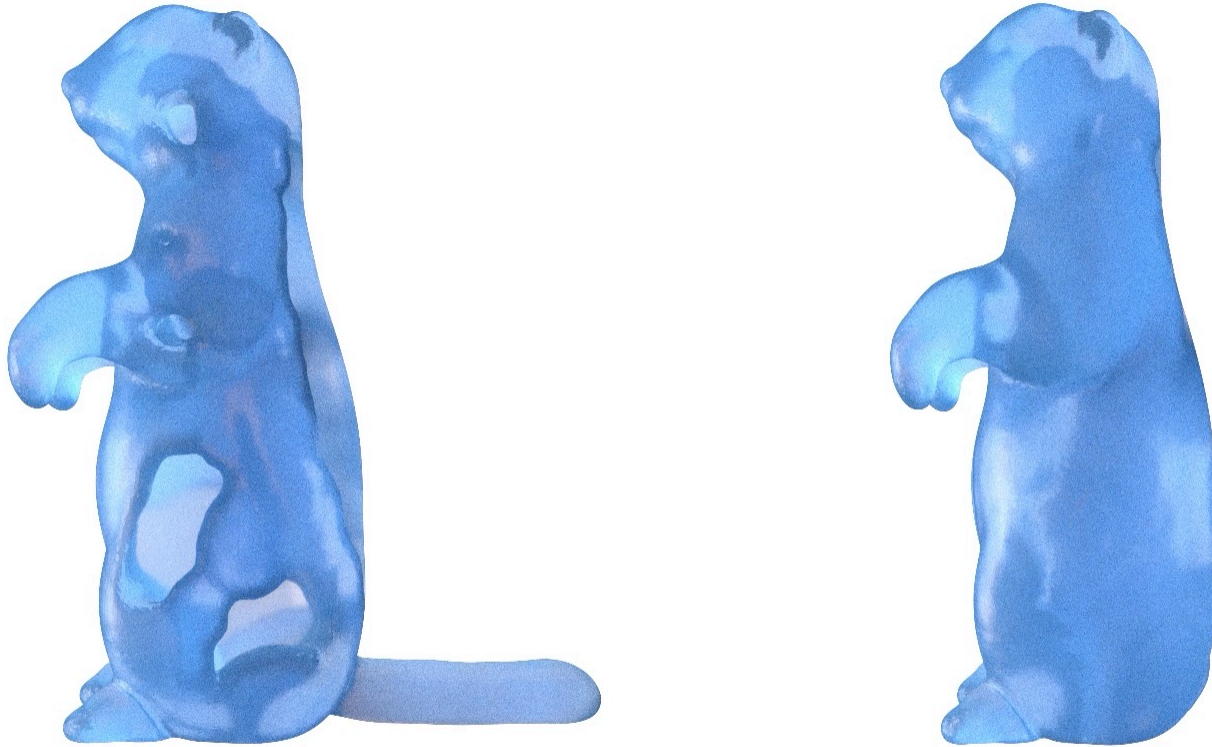
Initial Objects

Adaptative to Real World Loading



Force contact locations

Adaptative to Real World Loading



Optimized results

Adaptative to Real World Loadings



Optimized results

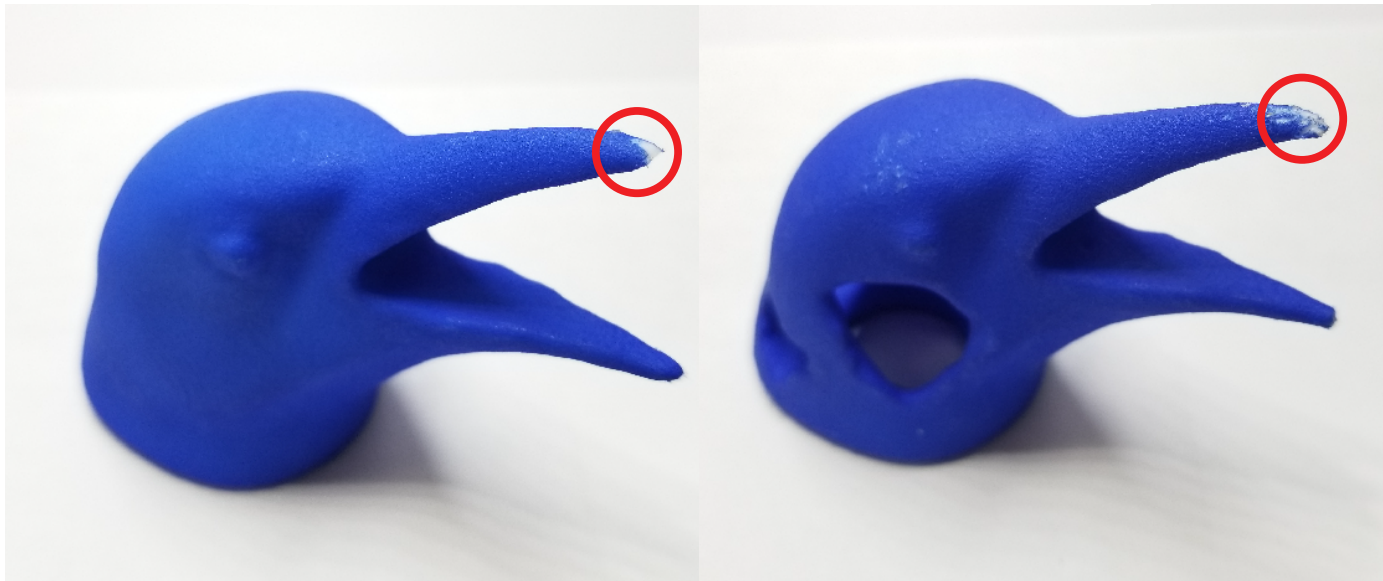
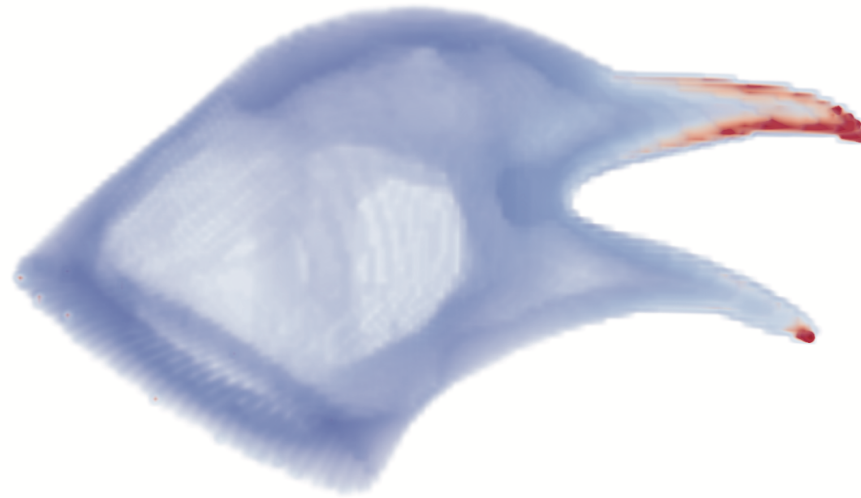
Physical Validation



Physical Validation




Physical Validation



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Contributions

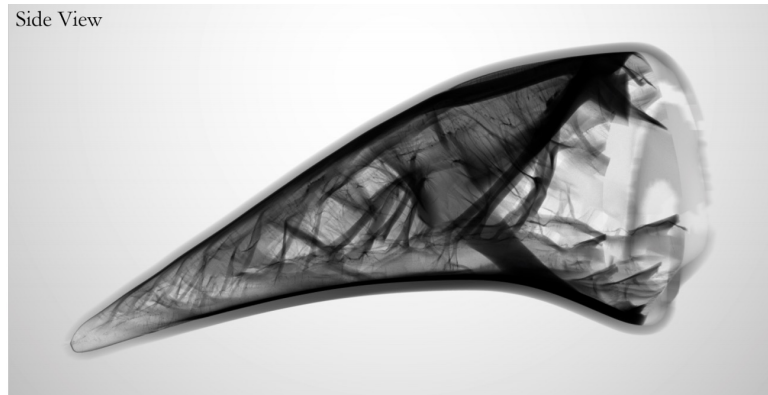
- Fast and Robust Stochastic Structural Optimization
 - Asymptotically faster $O(n^2)$  $O(n)$
 - Robust, stable probability gradients
 - A constrained restart strategy

Limitations

- Force contact locations are fixed
- Expensive gradient computation
- Requires multiple optimization passes

Future Work

- Sparse optimization
- Identify the reinforcement structures on the fly
- Incorporate shape change at contact locations



[Liu et al. 2018]

Thank You