



Penetration-free Deformable Simulation on the GPU

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Deformable Simulation



[Li .et al 2019]



[Ruo .et al 2019]



[Smith .et al 2018]



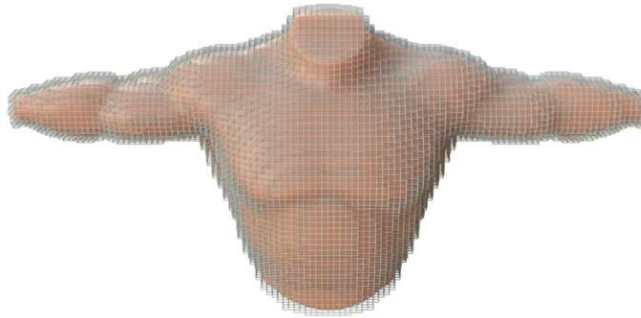
[Wang .et al 2021]

Deformable Simulation

❖ Equation of Motion:



Continuum model

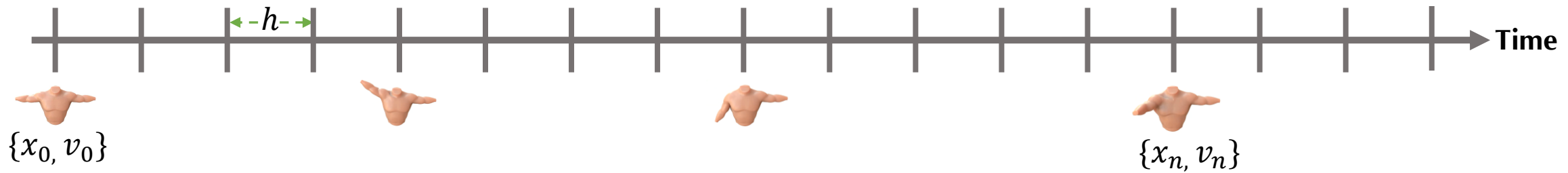


Spatial discretization



Sequence of poses

$$M \frac{d^2 x(t)}{dt^2} = f_e + f_i(x(t))$$



**Pictures and video come from [Smith .et al 2018].*

Deformable Simulation

❖ Implicit Time Integration:

$$\begin{cases} v_{n+1} = v_n + hM^{-1}(f_i(x_{n+1}) + f_e) \\ x_{n+1} = x_n + hv_{n+1} \end{cases}$$



$$\begin{cases} x_{n+1}^* = x_n + hv_n + h^2M^{-1}f_e \\ x_{n+1} = x_{n+1}^* + hM^{-1}f_i(x_{n+1}) \end{cases}$$

❖ Minimized Optimization:

$$\arg \min_x E(x) = \underbrace{\frac{1}{2} \|x - x^*\|_M^2}_{\text{inertial potential}} + \underbrace{h^2 \Psi(x)}_{\text{elastic potential}}$$

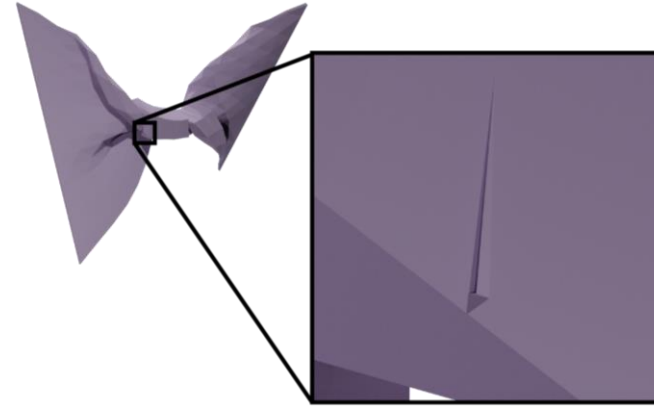
Solving a large nonlinear system is extremely slow.

- Reduced Simulation
- Position Based Dynamic (PBD)
- Projective Dynamic (PD)
- Multi-core CPUs/GPU
- Deep Learning
- ...

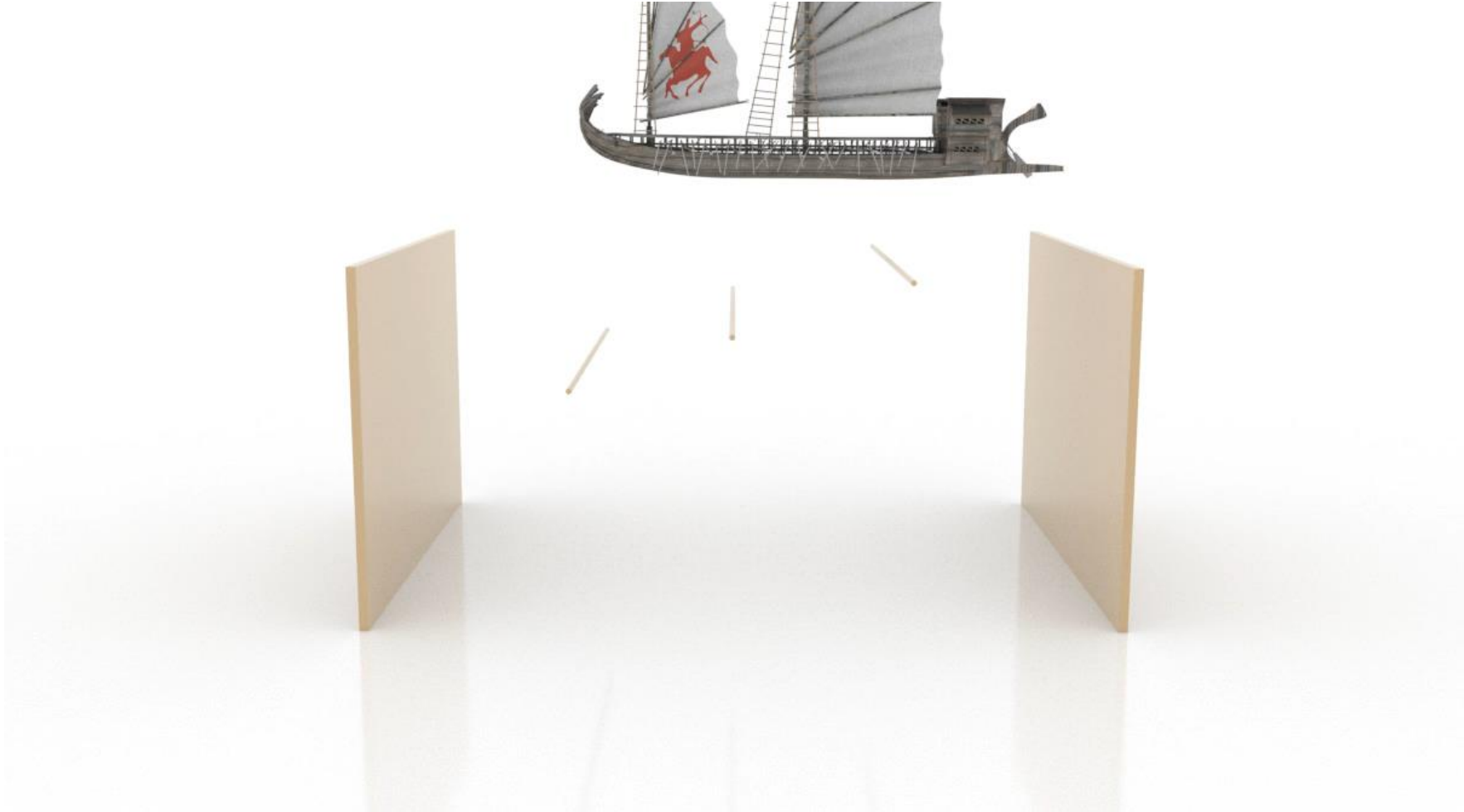
Contact

❖ Collisions introduce extra difficulties to system solver

- A lot of intersection tests (DCD or CCD)
- Resolving using penalty force/impulse
 - Artifacts and instability
 - Non-guaranteed
- Resolving using Inequality constraints
 - Convert to LCP

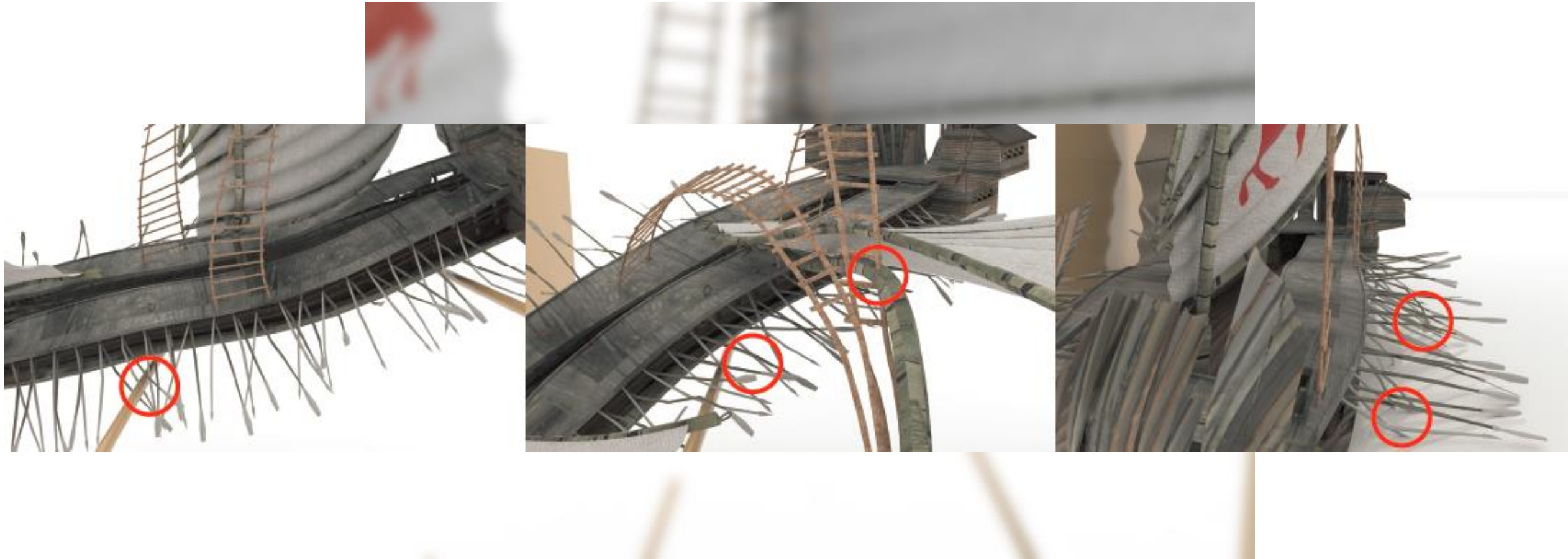


Contact



DCD + Penalty force $dt = 0.02s$

Contact



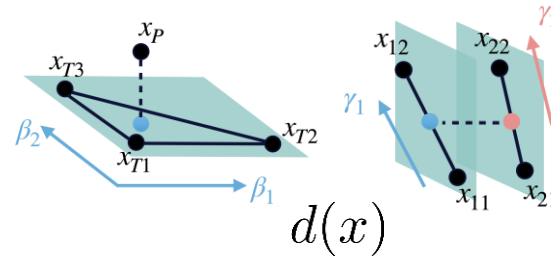
DCD + Penalty force $dt = 0.02s$

Contact

❖ Incremental Potential Contact (IPC)

$$\arg \min_x E(x) = \frac{1}{2} \|x - x^*\|_M^2 + h^2 \Psi(x) + \kappa \sum_{k \in C} b(d_k(x))$$

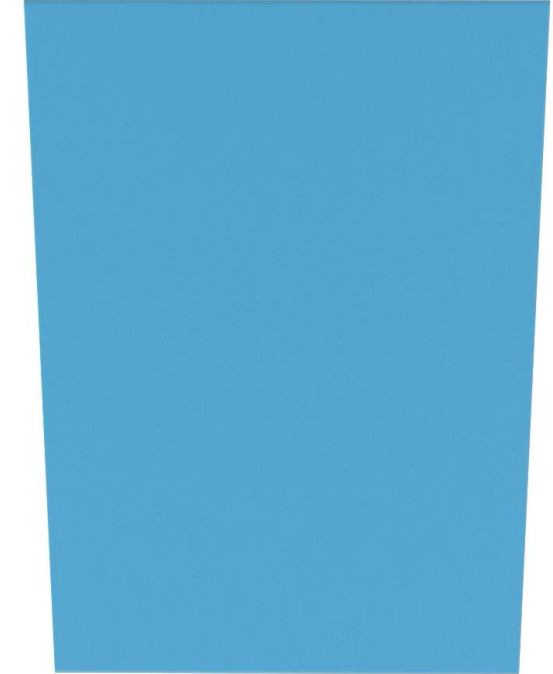
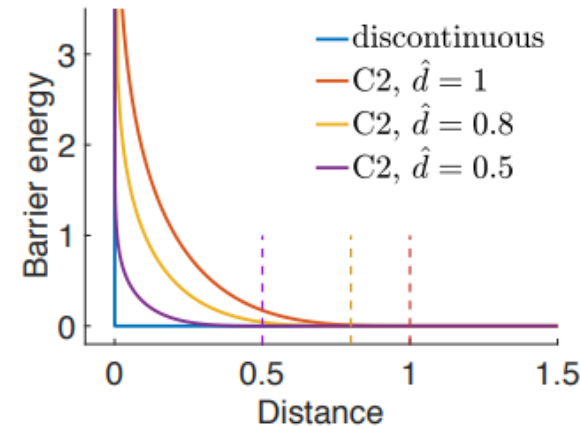
$$\text{s.t. } d(x) \geq 0$$



▪ Barrier function

$$b(d_k(x)) = \begin{cases} -(d - \hat{d})^2 \ln(\frac{d}{\hat{d}}), & 0 < d < \hat{d} \\ 0, & d \geq \hat{d} \end{cases}$$

- Unconstrained optimization problem
- Impose a large internal force
- Smooth



Projective Dynamic

❖ Projective Dynamics (PD)

- Fast simulation method

$$\arg \min_x E(x) = \frac{1}{2} \|x - x^*\|_M^2 + h^2 \sum W(x)$$

quadratic optimization



[Bouaziz .et al 2014]



Chebyshev method
[Wang .et al 2015]



Parallel Gauss-Seidel
[Fratarcangeli .et al 2015]



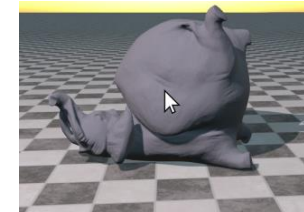
Quasi Newton Solver
[Liu .et al 2017]

$$\arg \min_{y_i} \frac{\omega_i}{2} \|A_i S_i x - B_i y_i\|_F^2, \quad \text{s.t.} \quad C_i(y_i) = 0$$

local step

$$\left(\frac{M}{h^2} + \sum_i \omega_i S_i^T A_i^T A_i S_i \right) x = \frac{M}{h^2} x^* + \sum_i \omega_i S_i^T A_i^T B_i y_i$$

global step



Reduced PD
[Brandt .et al 2018]



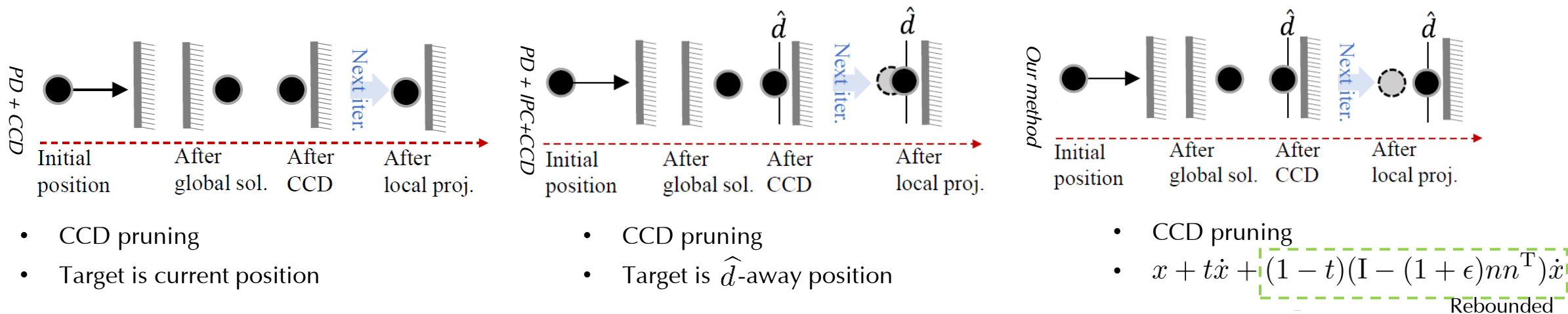
Semi-Reduced PD
[Lan .et al 2020]

- Local-global iterative solver
- Local step is parallel friendly
- Global step is a (fixed) linear system
- DCD-based collision constraint

Our Method

❖ How to offer the non-intersection in PD?

- PD + CCD, or PD + IPC+CCD?



- CCD pruning
- Target is current position

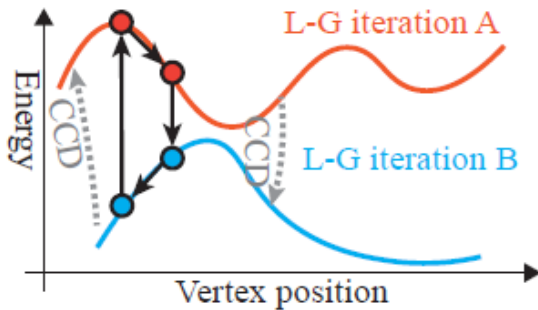
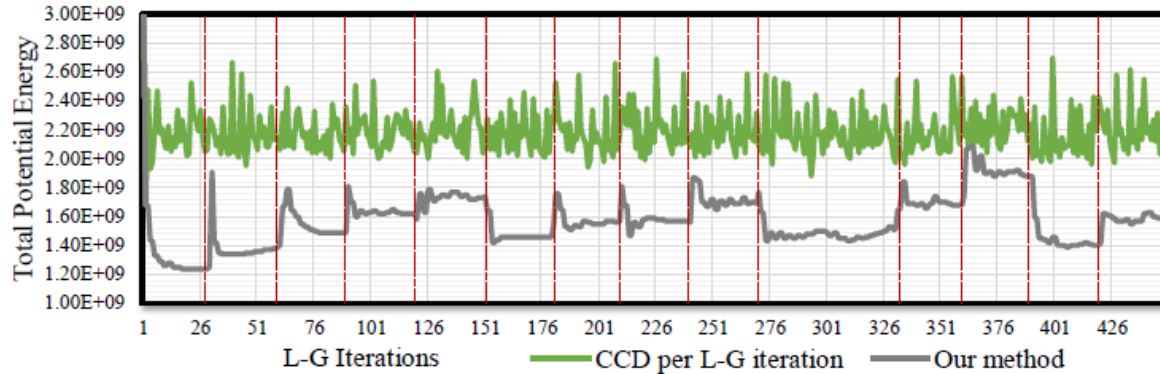
- CCD pruning
- Target is \hat{d} -away position

- CCD pruning
- $x + t\dot{x} + (1 - t)(I - (1 + \epsilon)nn^T)\dot{x}$
Rebounded

Our method

❖ Projective IPC with Tow-level Iteration Strategy

- Energy oscillating appear in single-level iteration



ALGORITHM 1: Projective IPC solver.

```

1:  $z \leftarrow x^* + h\dot{x}^* + h^2 M^{-1} f_{ext}$ ;
2:  $\tilde{x} \leftarrow x^* + h\dot{x}^* + \frac{h^2}{4} \ddot{x}^*$ ; //  $\tilde{x}$  now is a predicted position
3:  $x \leftarrow x^*, \Delta x \leftarrow \tilde{x} - x$ ; # Required many outer iterations.
4: while  $\|\Delta x\|^2 > \varepsilon_{outer}$  do
5:    $B \leftarrow \text{BarrierProjection}(x)$ ; // barrier projection (§ 4.1)
6:    $\delta E \leftarrow +\infty$ ; //  $\delta E$  is per-iteration potential change rate
7:   while  $\delta E > \varepsilon_{inner}$  do
8:      $E \leftarrow \frac{1}{2h^2} \|M^{-1}(\tilde{x} - z)\|_F^2$ ; // update momentum potential
9:      $\Psi \leftarrow \text{ElasticProjection}(\tilde{x})$ ;
10:     $\tilde{x} \leftarrow \text{GlobalSolve}$ ;
11:    update  $\delta E$ ;
12:   end
13:    $\text{CollisionCulling}(\tilde{x})$ ; // patch-based GPU culling (§ 7.2)
14:    $t_I \leftarrow \text{CCD}(x, \tilde{x})$ ; // minimum-gradient Newton method (§ 6)
15:    $\tilde{x} \leftarrow x + \frac{t_I}{h} \cdot (\tilde{x} - x)$ ; // per outer loop CCD pruning (§ 4.2)
16:    $\Delta x \leftarrow \tilde{x} - x, x \leftarrow \tilde{x}$ ; // update  $x$  and  $\Delta x$ 
17: end
18:  $\dot{x} \leftarrow \frac{x - x^*}{h}, \ddot{x} \leftarrow \frac{\dot{x} - \dot{x}^*}{h}$ ; // velocity and acceleration update

```

Aggregated Jacobi Solver

$$\underbrace{\left(\frac{M}{h^2} + \sum_i \omega_i S_i^T A_i^T A_i S_i\right)}_{D - B} x = \underbrace{\frac{M}{h^2} x^* + \sum_i \omega_i S_i^T A_i^T B_i y_i}_b$$

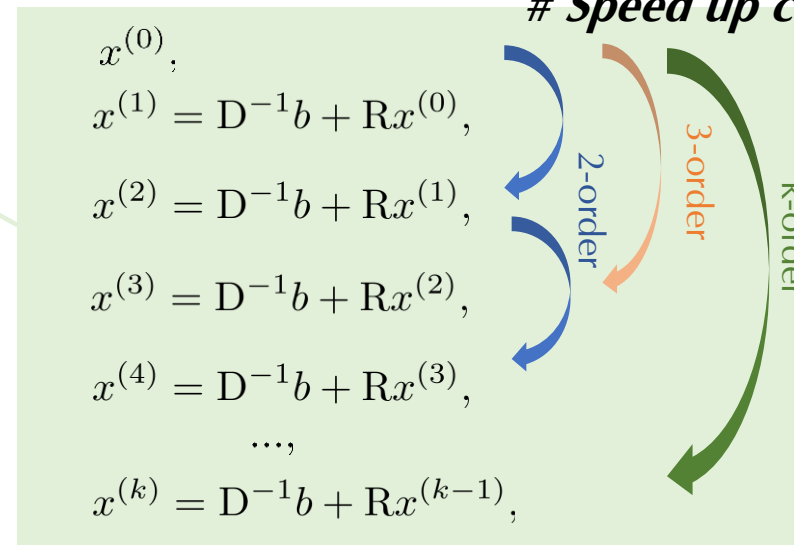
❖ Jacobi Solver

$$x^{(k)} = D^{-1}b + Rx^{(k-1)}, R = D^{-1}B$$

- Slow convergence
- Per-thread computation is too light
- Waste the overhead of GPU scheduling

Better harvests the capacity of GPUs

Speed up convergence

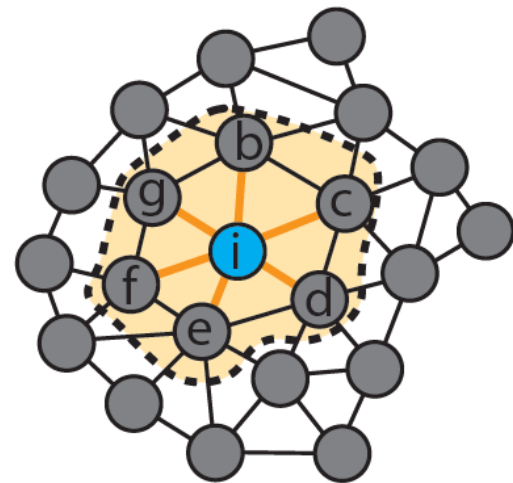


Aggregated Jacobi Solver

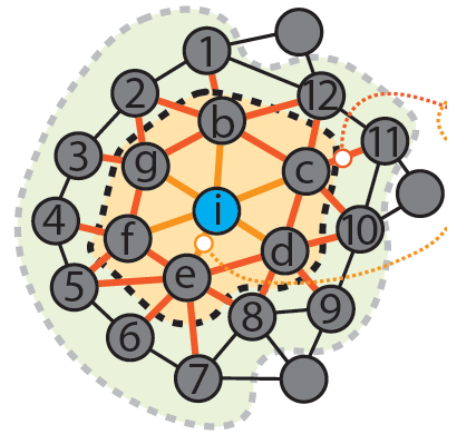
❖ A-Jacobi Solver

$$x^{(k)} = \sum_{j=0}^{l-1} R^j D^{-1} b + R^l x^{(k-1)}$$

- Compatible with Chebyshev
- Sparsity suppression
- Flexible

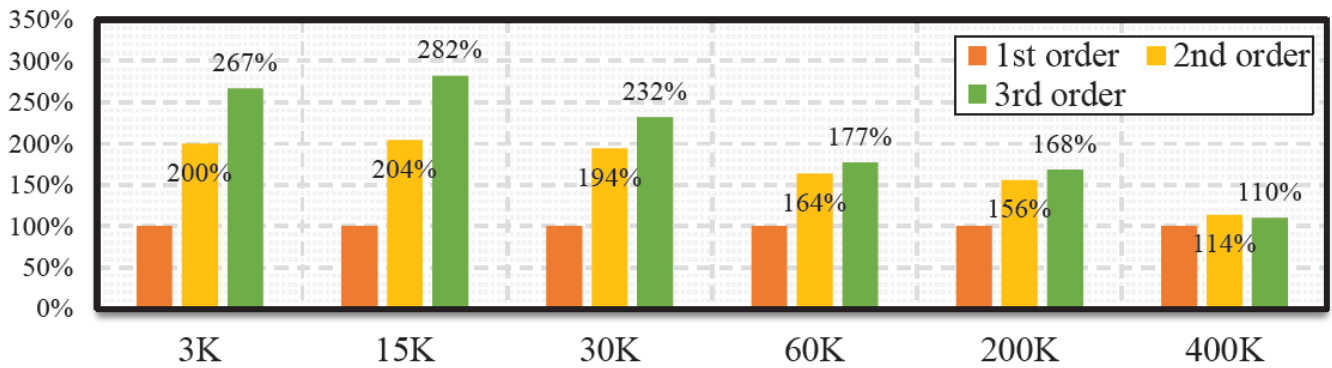


$[Rx]_i = D_{ii}^{-1} B_{ij} x_j$
 traverse 1-ring neighbors



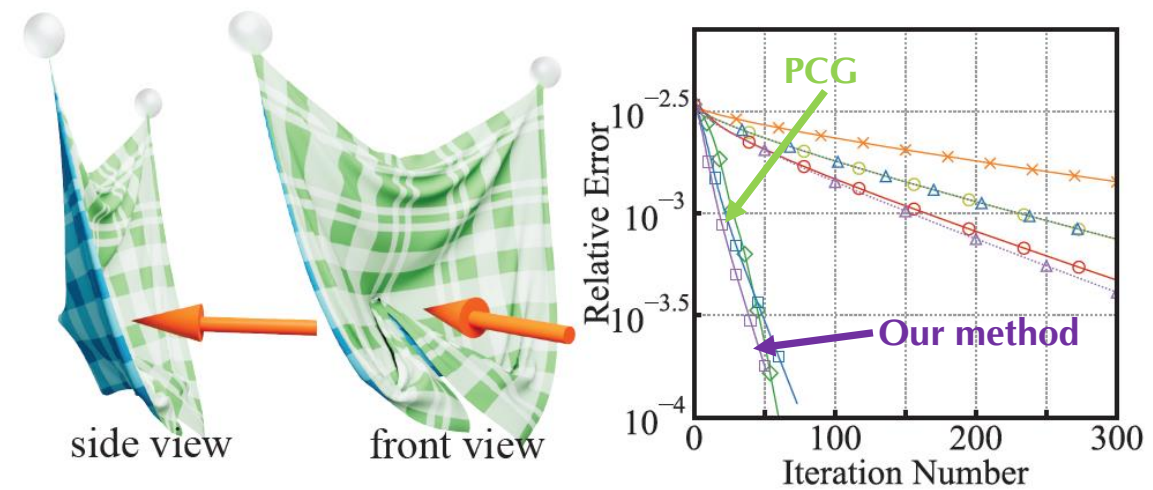
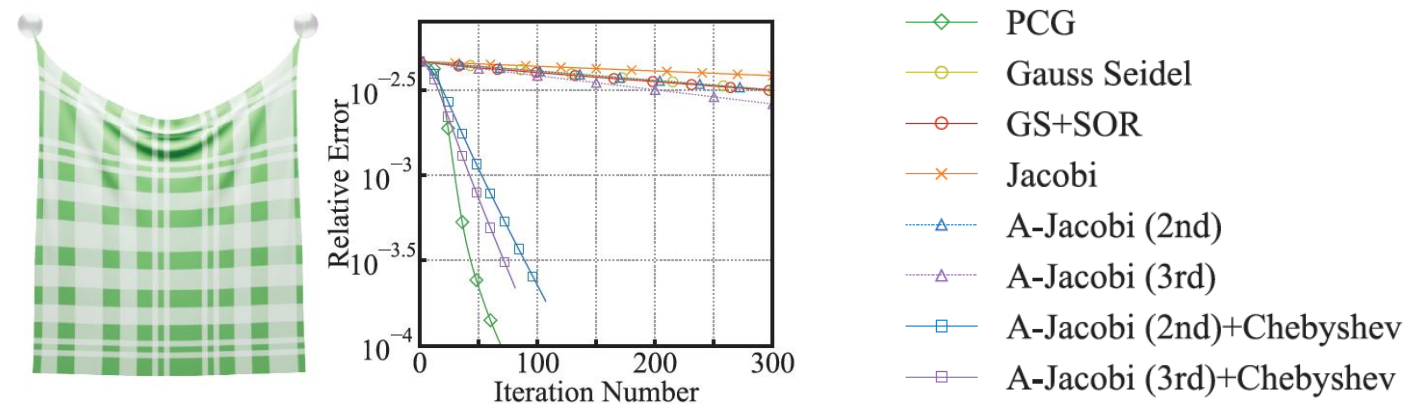
$[R^2 x]_i = D_{ii}^{-1} D_{ss}^{-1} B_{is} B_{sj} x_j$
 traverse 2-ring neighbors
 aggregated product

• A-Jacobi Performance



Aggregated Jacobi Solver

- A-Jacobi Convergence



Collision Detection

❖ Patch-based GPU Collision Culling

- Binary AABB tree
- Each leaf is a patch of geometry



Comparison to IPC: Rubber Helicopters



IPC

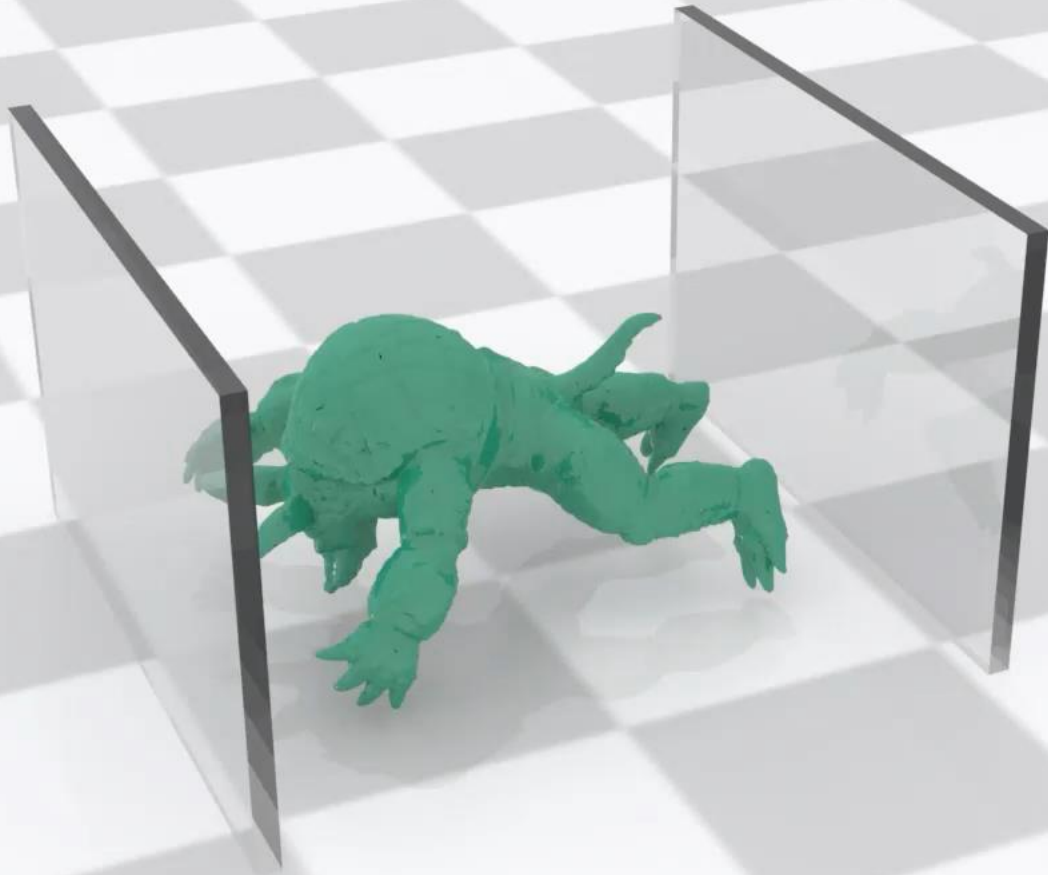


Our method **2000x Faster**

150K DOFs

11.2 – 87.1 FPS

Comparison to IPC: Flatten Armadillo



IPC

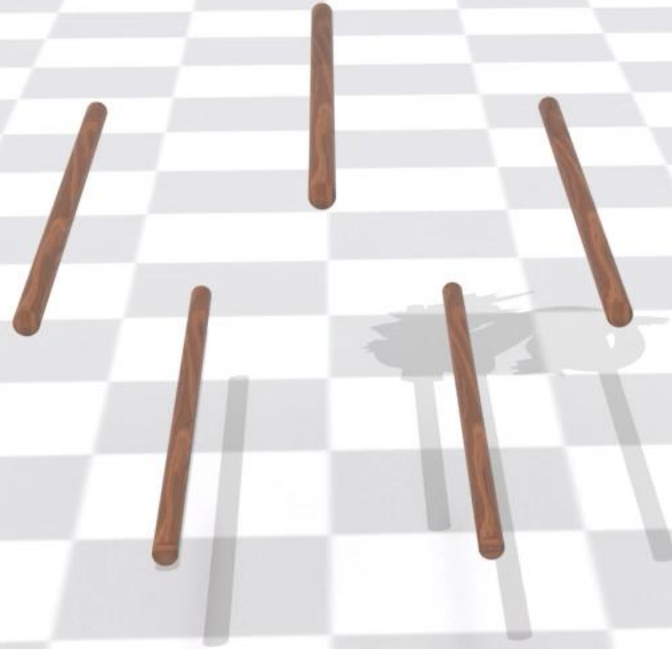


Our method **67x Faster**

10K DOFs

1.3 – 67.9 FPS

Dragon



80K DOFs

16.4 – 119.3 FPS

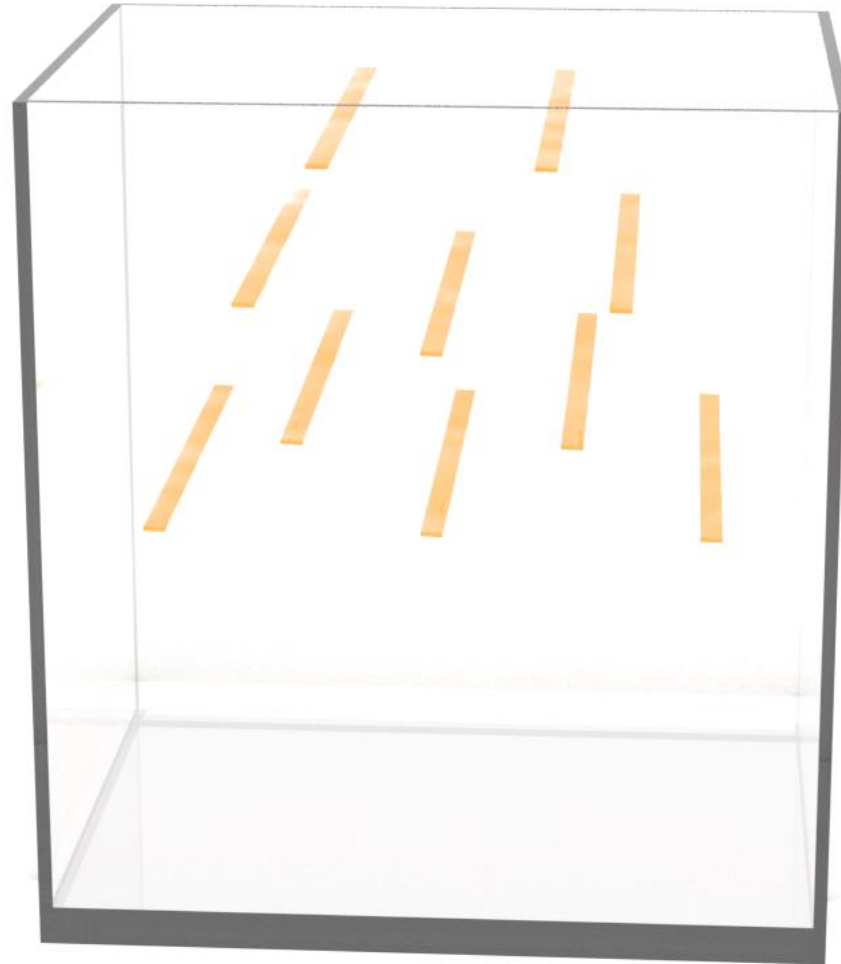
Tiered skirt



91K DOFs

12.2 – 29.1 FPS

“Animal Crossing”



218K DOFs

13.4 – 46.3 FPS

Halloween Party



249K DOFs

7.7 – 26.8 FPS