Deep Contact

Accelerating Rigid Simulation with Convolutional Networks

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University of Copenhagen

Master Thesis Defense, 2018

Outline

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Previous Work

- My first point.
- My second point.

Outline

Thesis Overview

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1. Introduction
   - Previous Work
   - Thesis Overview
2. Particles-Grid-Particles
   - Grid-Particle Method
   - Smoothed Particle Hydrodynamics
   - Bilinear Interpolation
3. Deep Learning Model
   - CNN Architecture
   - Training Configuration
4. Results and Analysis
5. Future Work

Grid-Particle Method

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Workflow

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2. The feature image will be used as input to a model(created by a convolutional neural network), then one image(the number of channels is 2) will be getting, which can be called label image.
3. For all contacts positions, interpolated values will be gener- ated based on label image. Then, the values will be used as starting iterate values for contact force solver. In our hypoth- esis, the given starting values will speed up the solver to reach convergence.

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$$A_S(\mathbf{x}) = \sum_i A(\mathbf{x}_i)W(\|\mathbf{x}_i - \mathbf{x}\|, h) \tag{3}$$

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$$W_{spiky}(\mathbf{r}, h) = \frac{15}{\pi h^6} \begin{cases} (h - \|\mathbf{r}\|)^3 & 0 \leq \|\mathbf{r}\| \leq h \\ 0 & \text{Otherwise} \end{cases} \tag{5}$$

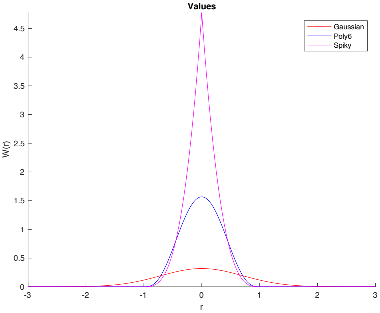

Figure: Comparation of different kernels, we set smoothing length $h = 1$ here.

Smoothed Particle Hydrodynamics
Kernels

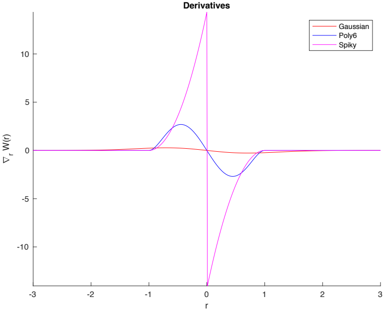

Figure: Comparation of gradient of different kernels, we set $h = 1$ here.

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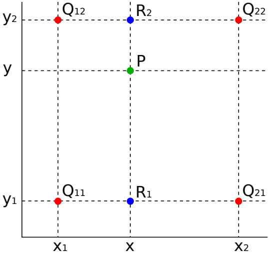

Figure: The figure shows the visualization of bilinear interpolation. The four red dots show the data points and the green dot is the point at which we want to interpolate.

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$$f(x, y) \approx \frac{y_2 - y}{y_2 - y_1} f(x, y_1) + \frac{y - y_1}{y_2 - y_1} f(x, y_2) \tag{7}$$

SPH method
Experiments

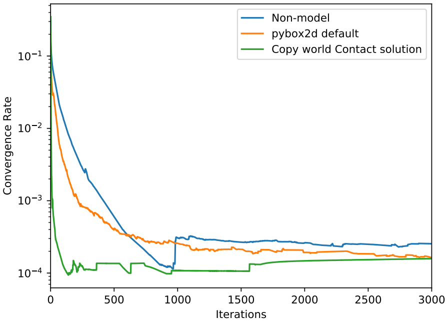
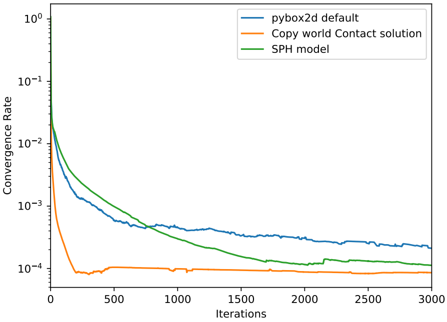


Figure: Average convergence rate for different models(not including **SPH-based model**).



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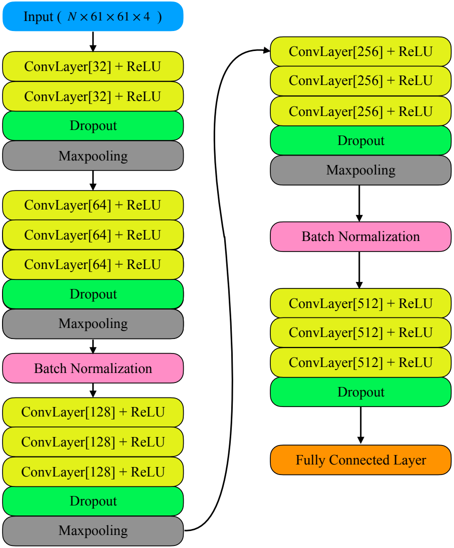
CNN Architecture



Outline

Training Hyperparameter

Hyperparameter	Setting
Activation function	ReLU
Weight initilization	He normal
Weight regularizer	L2
Convolution border mode	Same
Stride	2
Kernel size	$(3, 3)$
Dropout rate	0.1
Optimizer	SGD
Initial Learning Rate	$1 \times 5 \times 10^{-3}$
Batch Size	200
Epoch	1000
Validation Rate	0.2

Table: Hyperparameter settings.

Simulation Configuration

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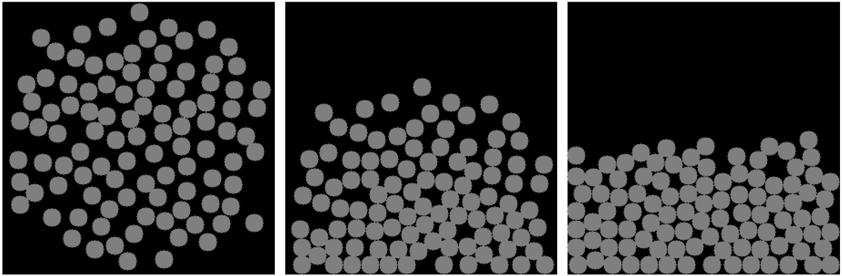
- **Simulation Setting** there will be totally 600-steps simulation. For each step, $\Delta t = 0.01s$, and the number of iteration in each step will be set as fixed, 3000.



(a) Time Step=0 (b) Time Step=200 (c) Time Step=400

Figure: Visualization for experiment simulation

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- For a given d, $h \geq \frac{\sqrt{2}}{2} d \approx 0.71d$

Results and Analysis

SPH parameters(**Poly6**)

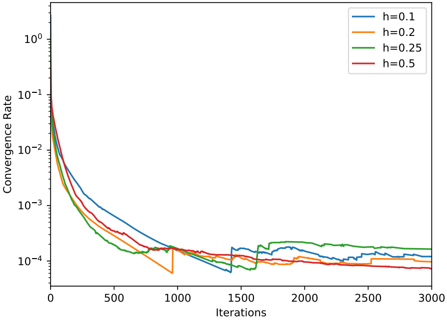
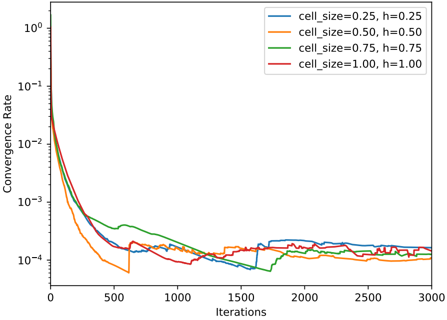


Figure: The grid size d is set 0.25. $h = 0.1, 0.2, 0.25, 0.5$ is tested respectively. This figure shows different coveragence rate based on different h value. The kernel is **Poly6**



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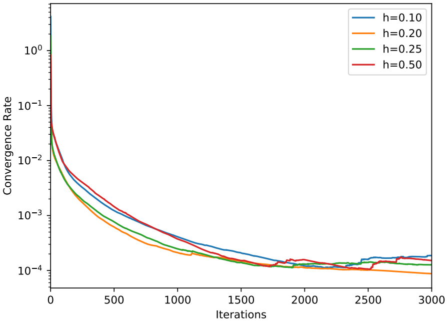
SPH parameters(**Spiky**)



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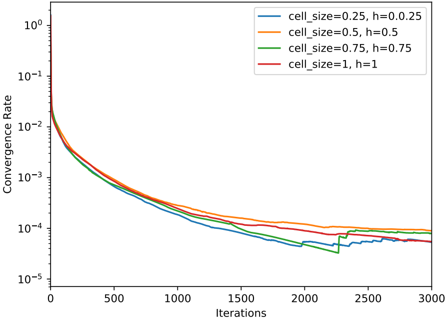

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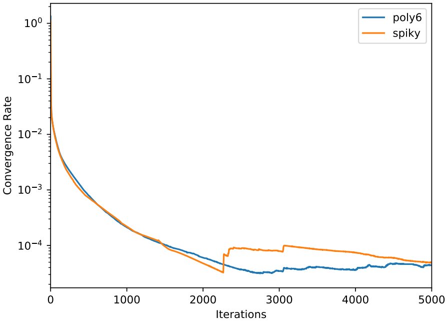

Figure: Coveragence rate for kernel **Poly6** anf **Spiky**. $h_{\text{poly6}} = d_{\text{poly6}} = 0.5$, while $h_{\text{spiky}} = d_{\text{spiky}} = 0.25$

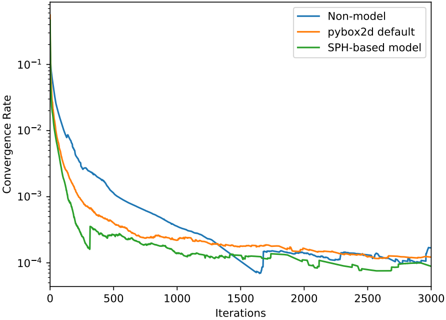

Figure: Coveragence rate for models(different initial values for $\boldsymbol{\lambda}$).

- **Input Size**, the input will be $61 \times 61 \times 4$. Since the orginal world is 30×30 and grid size is $d = 0.5$, the generated grid would be 61×61. There would 4 channels$[m, v_x, v_y, \omega]$

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- **Training Environment**, GPU(*GeForce GTX 1080 Ti, 11 Gbps GDDR5X memory*) held by Image Section, DIKU.

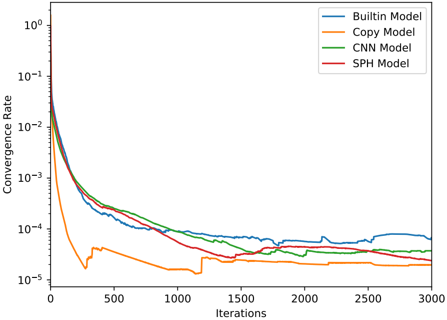

Figure: The final result. Add the final CNN solution to compare with other methods.

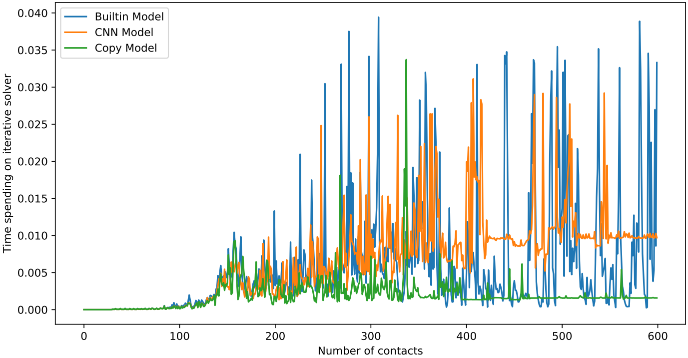

Figure: Time spent for contact solver iteration

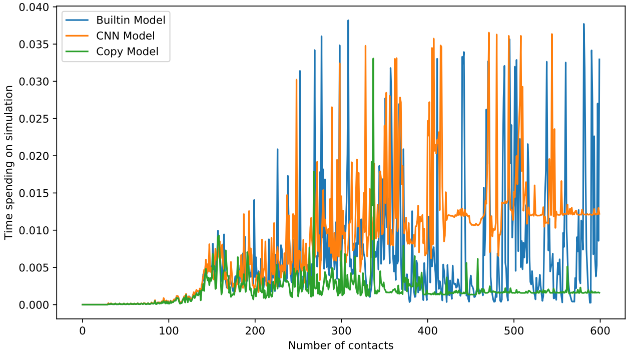

Figure: Time spend for the whole contact solution(including warm starting calculation).

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- **CNN-Model** actually makes the iterative solver converge faster. But it is not a great improvement to buit-in warm starting.
- **CNN-Model** performs very similar to **SPH-Model**, which means the CNN predicts contact image well.
- Due to the limitation of the SPH-based method, **CNN-Model** just gets a small improvement compared with **Builtin-Model**. And it cannot perform as good as **Copy-Model**.

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3. **More Shapes Experiments**

For Further Reading I

A. Author.
Handbook of Everything.
Some Press, 1990.

S. Someone.
On this and that.
Journal of This and That, 2(1):50–100, 2000.