

# Deep Contact

## Accelerating Rigid Simulation with Convolutional Networks

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  - Thesis Overview
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  - Grid-Particle Method
  - Smoothed Particle Hydrodynamics
  - Bilinear Interpolation
- 3 Deep Learning Model
  - CNN Architecture
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- 4 Results and Analysis
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# Previous Work

- My first point.
- My second point.

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# Thesis Overview

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# Grid-Particle Method

## Workflow

The whole workflow can be described as,

- ① Based on Smoothed Particle Hydrodynamics (SPH), map current state( $m, v_x, v_y, \omega, n_x$ ) to a image(the number of channel is 5.), which is called feature image.

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- 3 For all contacts positions, interpolated values will be generated based on label image. Then, the values will be used as starting iterate values for contact force solver. In our hypothesis, the given starting values will speed up the solver to reach convergence.

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

# Smoothed Particle Hydrodynamics

## Kernels

- **Poly6**

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$$W_{poly6}(\mathbf{r}, h) = \frac{315}{64\pi h^9} \begin{cases} (h^2 - \|\mathbf{r}\|^2)^3 & 0 \leq \|\mathbf{r}\| \leq h \\ 0 & \text{Otherwise} \end{cases} \quad (4)$$

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

# Smoothed Particle Hydrodynamics

## Kernels

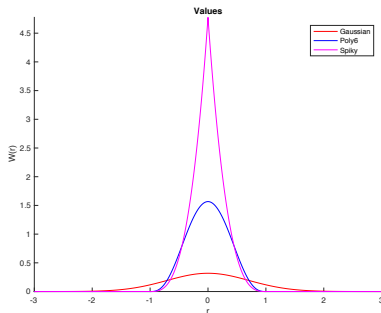
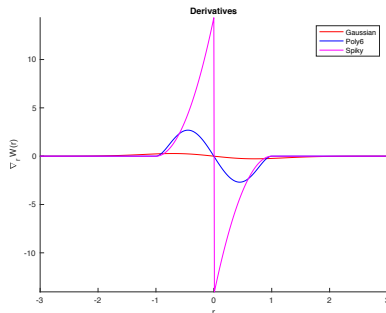


Figure: Comparison of different kernels, we set smoothing length  $h = 1$  here.

# Smoothed Particle Hydrodynamics

## Kernels



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





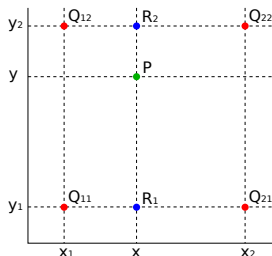
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**Figure:** The figure shows the visualization of bilinear interpolation. The four red dots show the data points and the green dot is the point at which we want to interpolate.

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# SPH method

## Experiments

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- **World Setting**

- **World Setting** the world box size is  $30 \times 30$ , and there are 50 – 100 circle rigid bodies( $r = 1$ , all circle rigid bodies in the same size.) inside the box. Initially, the rigid circles will be located following gaussian distribution<sup>2</sup>. Then, all rigid circles will fall down by gravity.

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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.

# Results and Analysis

## SPH parameters

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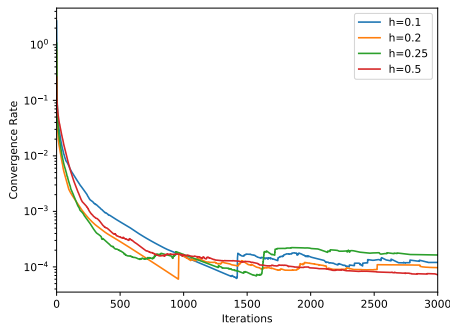
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- the smooth length  $h$  should be less than the minimum distance between two contact points  $d$ ,  $h \leq d$
- For a given  $d$ ,  $h \geq \frac{\sqrt{2}}{2}d \approx 0.71d$

# 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 coverage rate based on different  $h$  value. The kernel is **Poly6**

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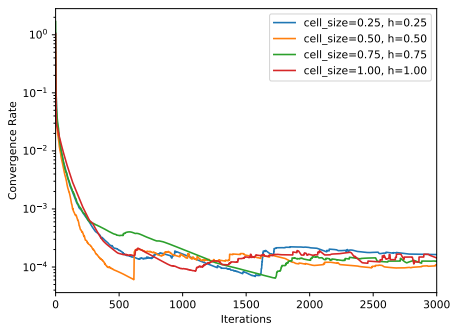
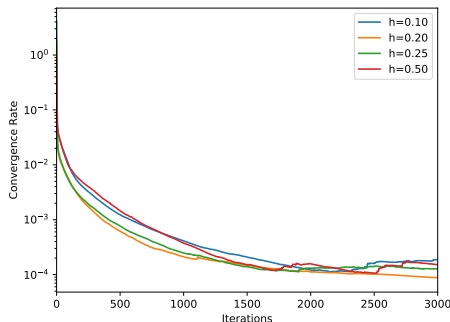


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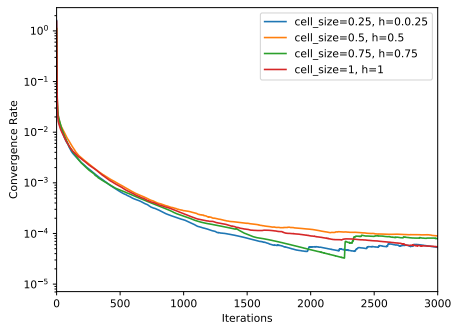
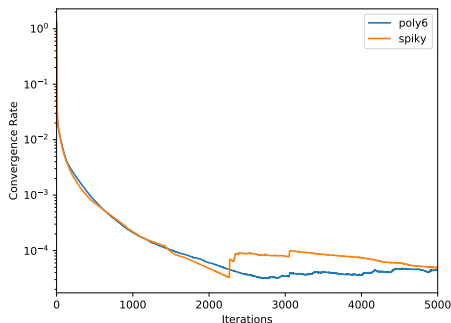


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# Results and Analysis

## SPH parameters



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

# Results and Analysis

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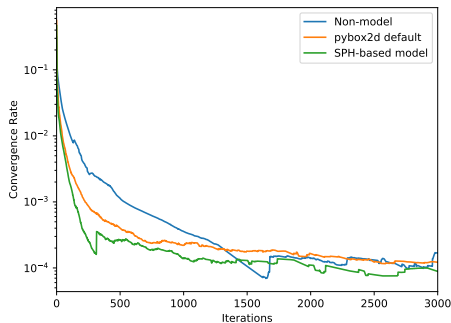
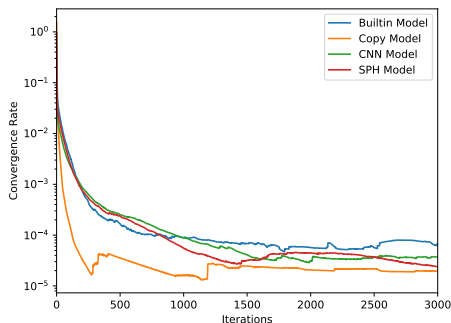


Figure: Coverage rate for models(different initial values for  $\lambda$ ).

# Results and Analysis

## Simulation on CNN



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

# Results and Analysis

## Simulation on CNN

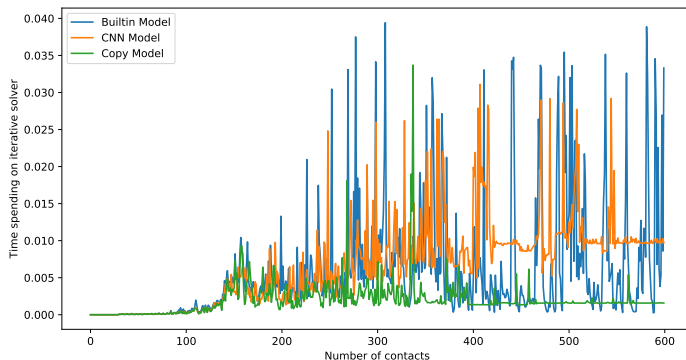
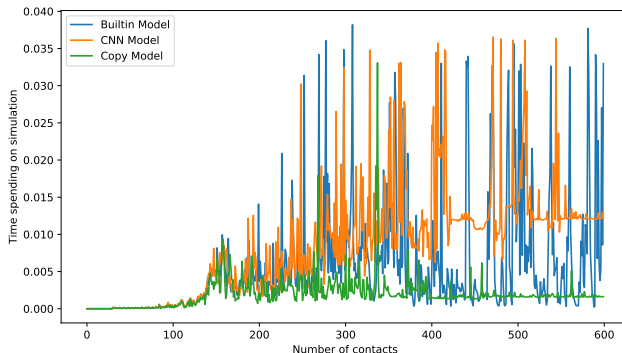


Figure: Time spent for contact solver iteration

# Results and Analysis

## Simulation on CNN



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

# Results and Analysis

## Conclusion

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- **CNN-Model** actually makes the iterative solver converge faster. But it is not a great improvement to built-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

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