

Deep Contact

Accelerating Rigid Simulation with Convolutional Networks

J. Wu

Department of Computer Science
University of Copenhagen

Master Thesis Defense, 2018

- 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

- 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

Previous Work

- My first point.
- My second point.

- 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

Thesis Overview

- 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

In order to generate accessible data for CNN model, we transform every state into a set of grid images.

- It can make the simulation states be expressed by a set of matrixes, which can be accessible for deep neural networks.

In order to generate accessible data for CNN model, we transform every state into a set of grid images.

- It can make the simulation states be expressed by a set of matrixes, which can be accessible for deep neural networks.
-

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, ω, n_x) to a image(the number of channel is 5.), which is called feature image.

The whole workflow can be described as,

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

The whole workflow can be described as,

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

- 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

Smoothed Particle Hydrodynamics

Fundamentals

The heart of SPH is a kernel interpolation method which allows any function to be expressed in terms of its values at a set of disordered points - the particles.

Smoothed Particle Hydrodynamics

Fundamentals

The heart of SPH is a kernel interpolation method which allows any function to be expressed in terms of its values at a set of disordered points - the particles.

$$A_I(\mathbf{r}) = \int A(\mathbf{r}') W(\|\mathbf{r} - \mathbf{r}'\|, h) d\mathbf{r}' \quad (1)$$

Smoothed Particle Hydrodynamics

Fundamentals

The heart of SPH is a kernel interpolation method which allows any function to be expressed in terms of its values at a set of disordered points - the particles.

$$A_I(\mathbf{r}) = \int A(\mathbf{r}') W(\|\mathbf{r} - \mathbf{r}'\|, h) d\mathbf{r}' \quad (1)$$

where the integration is over the entire space, and W is an interpolating kernel with

Smoothed Particle Hydrodynamics

Fundamentals

The heart of SPH is a kernel interpolation method which allows any function to be expressed in terms of its values at a set of disordered points - the particles.

$$A_I(\mathbf{r}) = \int A(\mathbf{r}') W(\|\mathbf{r} - \mathbf{r}'\|, h) d\mathbf{r}' \quad (1)$$

where the integration is over the entire space, and W is an interpolating kernel with

$$\int W(\|\mathbf{r} - \mathbf{r}'\|, h) d\mathbf{r}' = 1 \quad (2)$$

For numerical work,

Smoothed Particle Hydrodynamics

Fundamentals

The heart of SPH is a kernel interpolation method which allows any function to be expressed in terms of its values at a set of disordered points - the particles.

$$A_I(\mathbf{r}) = \int A(\mathbf{r}') W(\|\mathbf{r} - \mathbf{r}'\|, h) d\mathbf{r}' \quad (1)$$

where the integration is over the entire space, and W is an interpolating kernel with

$$\int W(\|\mathbf{r} - \mathbf{r}'\|, h) d\mathbf{r}' = 1 \quad (2)$$

For numerical work,

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

Smoothed Particle Hydrodynamics

Kernels

- **Poly6**

- **Poly6**

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

- **Poly6**

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

- **Spicky**

- **Poly6**

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

- **Spicky**

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

Smoothed Particle Hydrodynamics

Kernels

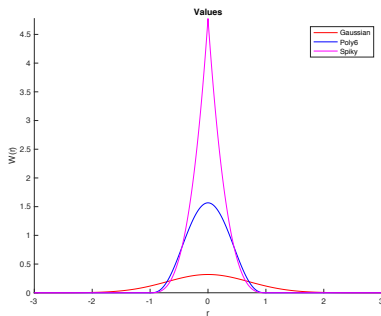


Figure: Comparison of different kernels, we set smoothing length $h = 1$ here.

Smoothed Particle Hydrodynamics

Kernels

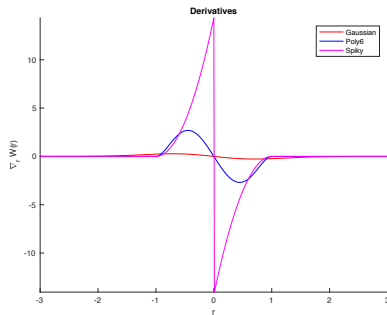


Figure: Comparison of gradient of different kernels, we set $h = 1$ here.

- 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

Bilinear Interpolation

Once getting contact grid image, we need transform the grid image to a physical state, specific contact values in each contact point. We applied bilinear interpolation in our case.

Bilinear Interpolation

Once getting contact grid image, we need transform the grid image to a physical state, specific contact values in each contact point. We applied bilinear interpolation in our case.

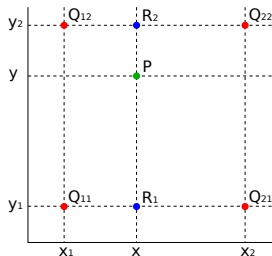


Figure: The figure shows the visualization of bilinear interpolation. The four red dots show the data points and the green dot is the point at which we want to interpolate.

- 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

- 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

① Grid-Particles Method

- ① **Grid-Particles Method**
 - SPH

① Grid-Particles Method

- **SPH** For the SPH-based method, it is still far away from perfect. It performs not much better than warm starting. The probable attempt will including trying more new kernels, using new data and algorithm for nearest neighbor searching.

① Grid-Particles Method

- **SPH** For the SPH-based method, it is still far away from perfect. It performs not much better than warm starting. The probable attempt will including trying more new kernels, using new data and algorithm for nearest neighbor searching.
- **Interpolation Method**

① Grid-Particles Method

- **SPH** For the SPH-based method, it is still far away from perfect. It performs not much better than warm starting. The probable attempt will including trying more new kernels, using new data and algorithm for nearest neighbor searching.
- **Interpolation Method** It might lose some essential information when it was interpolated back to particles. So exploring another interpolation method would be helpful to this project.

① Grid-Particles Method

- **SPH** For the SPH-based method, it is still far away from perfect. It performs not much better than warm starting. The probable attempt will including trying more new kernels, using new data and algorithm for nearest neighbor searching.
- **Interpolation Method** It might lose some essential information when it was interpolated back to particles. So exploring another interpolation method would be helpful to this project.

② Deep Learning Model,

① **Grid-Particles Method**

- **SPH** For the SPH-based method, it is still far away from perfect. It performs not much better than warm starting. The probable attempt will including trying more new kernels, using new data and algorithm for nearest neighbor searching.
- **Interpolation Method** It might lose some essential information when it was interpolated back to particles. So exploring another interpolation method would be helpful to this project.

② **Deep Learning Model**, More learning models can be explored, like Recurrent Neural Networks(RNN), Long short-term memory(LSTM).

① Grid-Particles Method

- **SPH** For the SPH-based method, it is still far away from perfect. It performs not much better than warm starting. The probable attempt will including trying more new kernels, using new data and algorithm for nearest neighbor searching.
- **Interpolation Method** It might lose some essential information when it was interpolated back to particles. So exploring another interpolation method would be helpful to this project.

② Deep Learning Model, More learning models can be explored, like Recurrent Neural Networks(RNN), Long short-term memory(LSTM).

③ More Shapes Experiments

Block Title

You can also highlight sections of your presentation in a block, with it's own title

Theorem

There are separate environments for theorems, examples, definitions and proofs.



Example

Here is an example of an example block.

Summary

- The **first main message** of your talk in one or two lines.
- The **second main message** of your talk in one or two lines.
- Perhaps a **third message**, but not more than that.
- Outlook
 - Something you haven't solved.
 - Something else you haven't solved.

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.