



Master Thesis

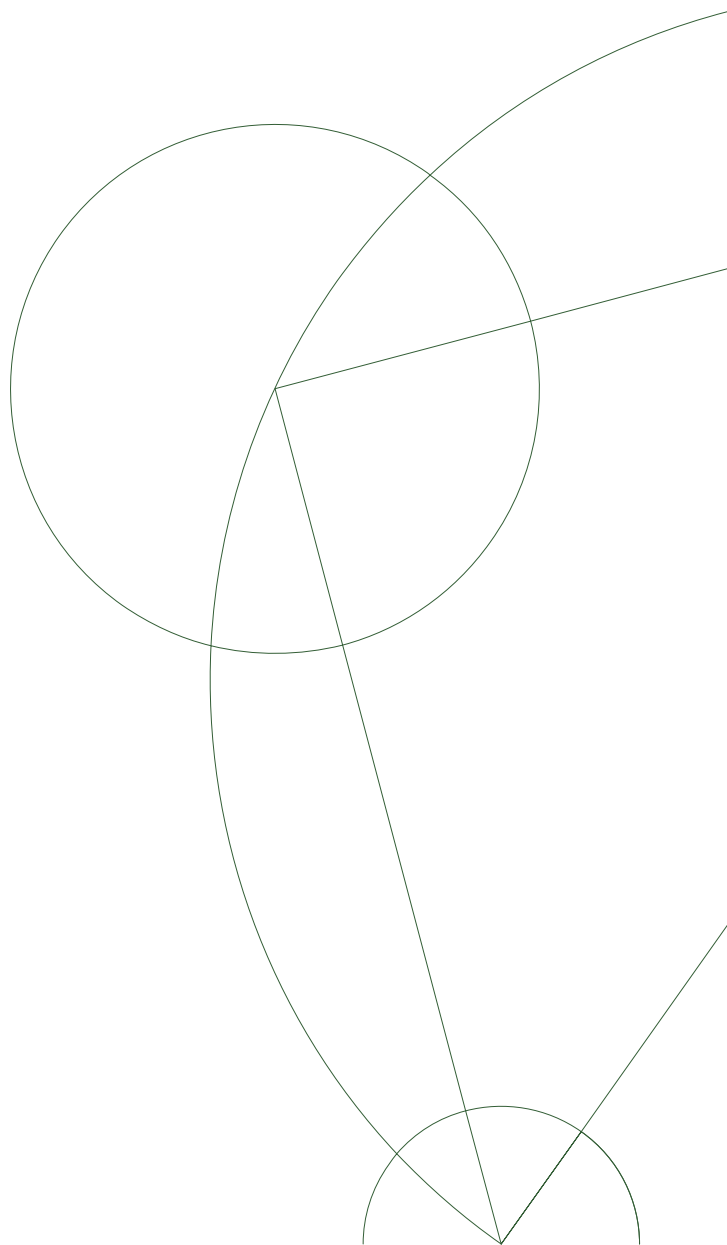
Jian Wu – xcb479@alumni.ku.dk

Deep Contact

Accelerating Rigid Simulation With Convolutional Networks

Supervisor: Kenny Erleben

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Abstract

This is a master theis from

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Chapter 1

Introduction

1.1 Motivation

1.2 Thesis Overview

Chapter 2

Rigid Body Dynamics Simulation

This chapter mainly introduces rigid body simulation to help you understand how computer simulate rigid dynamics based on traditional newton-euler equations. For more details, some contact forces solvers are described in this chapter. Afterwards, we will use one of solver to run some simulation and get the image data for the next step, grids-transfer. All the discussion about rigid simulation and contacts solver are based on 2- D view.

2.1 Rigid dynamics Simulation

2.1.1 Simulation Basics

Simulating the motion of a rigid body is almost the same as simulating the motion of a particle, so I will start with particle simulation. For particle simulation, we let function $x(t)$ describe the particle's location in world space at time t . Then we use $v(t) = \frac{d}{dt}x(t)$ to denote the velocity of the particle at time t . So, the state of a particle at a time t is the particle's position and velocity. We generalize this concept by defining a state vector $\mathbf{Y}(t)$ for a system: for a single particle,

$$\mathbf{Y}(t) = \begin{pmatrix} x_1(t) \\ v_1(t) \end{pmatrix} \quad (2.1)$$

For a system with n particles, we enlarge $\mathbf{Y}(t)$ to be

$$\mathbf{Y}(t) = \begin{pmatrix} x_1(t) \\ v_1(t) \\ \dots \\ x_n(t) \\ v_n(t) \end{pmatrix} \quad (2.2)$$

However, to simulate the motion of particles actually, we need to know one more thing – the forces. $F(t)$ is defined as the force acting on the particle. If the mass of the particle is m , then the changes of $\mathbf{Y}(t)$ will be given by

$$\frac{d}{dt}\mathbf{Y}(t) = \frac{d}{dt} \begin{pmatrix} x(t) \\ v(t) \end{pmatrix} = \begin{pmatrix} v(t) \\ F(t)/m \end{pmatrix} \quad (2.3)$$

2.1.2 Rigid Body Concepts

Unlike a particle, a rigid body occupies a volume of space and has a particular shape. Rigid bodies are more complicated, beside translating them, we can rotate them as well. To locate a rigid body, we use $x(t)$ to denote their translation and a rotation matrix $R(t)$ to describe their rotation.

2.1.3 Rigid Body Equations of Motions

Finally, we can convert all concepts we need to define the state $\mathbf{Y}(t)$ for a rigid body.

$$\mathbf{Y}(t) = \begin{pmatrix} x(t) \\ R(t) \\ P(t) \\ L(t) \end{pmatrix} \quad (2.4)$$

Like what is expressed in $\mathbf{Y}(t)$, the state of a rigid body is mainly consist by its position and orientation (describing spatial information), and its linear and angular momentum (describe velocity information). Since mass M and bodyspace inertia tensor I_{body} are constants, we can the auxiliary quantities $I(t)$, $\omega(t)$ at any given time.

$$v(t) = \frac{P(t)}{M}I(t) = R(t)I_{body}R(t)^T \quad \omega(t) = I(t)^{-1}L(t)$$

The derivative $\frac{d}{dt}\mathbf{Y}(t)$ is

$$\frac{d}{dt}\mathbf{Y}(t) = \frac{d}{dt}(x(t), R(t), P(t), L(t)) = (v(t), \omega(t) * R(t), F(t), \tau(t))$$

Data: this text

Result: how to write algorithm with L^AT_EX2e
initialization;

```
while running the simulation world do
|   read current;
|   if understand then
|   |   go to next section;
|   |   current section becomes this one;
|   else
|   |   go back to the beginning of current section;
|   end
end
```

Algorithm 1: How to write algorithms

2.2 Contact Forces Solver

2.3 Simulation Results

Chapter 3

Particle-grid-particle

3.1 SPH

3.2 Particle to grid

3.3 Grid to particle

3.4 Conclusion

Chapter 4

Deep Learning For Simulation

4.1 Convolutional Neural Networks

4.2 CNN Constructure

4.3 Traing Results

4.4 Simulation based on Trained model