POSITION-BASED SIMULATION OF ELASTIC MODELS ON THE GPU WITH ENERGY AWARE GAUSS-SEIDEL ALGORITHM

Ozan Cetinaslan

Instituto de Telecomunicações & Faculdade de Ciências, Universidade do Porto, Portugal





Physics-based visual simulations have become ubiquitous in movies, cartoons, medical applications and computer games.



Collapsed Buildings, 2012 © DigitalDomain



Sulley from Monsters Inc, $\ensuremath{\mathbb{C}}$ Disney/Pixar



Medical App. © VirtaMed



Assassin's Creed, © Ubisoft

Physics-based Simulations imitate the life-like motions!



To achieve physics-based simulations, numerical methods are employed:

- Integration Methods
 - Implicit / Explicit Euler methods
 - Verlet method
 - Second Order Integration method
 - Runge–Kutta method
 - ...
- Iteration Approaches
 - Newton's method
 - Jacobi method
 - Gauss-Seidel method



Muller, M., Heidelberger B., Hennix M., Ratcliff J., "Position Based Dynamics " VRIPhys, 2006 Journal of Visual Communication and Image Representation, 2007

Position Based Dynamics (PBD):

- Integration Methods
 - Implicit / Explicit Euler methods
 - Verlet method
 - Second Order Integration method [Bender et al. 17]
 - Runge–Kutta method
 - ...
- Iteration Methods
 - Newton's method
 - Jacobi method [Macklin et al. 14]
 - Gauss-Seidel method

The main idea is to consider the mass-spring networks as connected particles



In a very general perpective, PBD algorithm:

- First, shoots the particles with the integration method.
- After, pulls them back with the non-linear Gauss-Seidel iteration.

In a very general perpective, PBD algorithm:

- First, shoots the particles with the integration method.
- After, pulls them back with the non-linear Gauss-Seidel iteration.



That implies:

- Verlet integration predicts the position of a particle
- Gauss-Seidel loop iterates the particle till the final position is obtained
- Gauss-Seidel iteration operates based on projected constraints.



Motivation

Due to extreme dependency to **Gauss-Seidel**:

 Is it possible to improve the visual results within Gauss-Seidel on the GPU?



PBD in Literature



Faure, F.,

"Interactive Solid Animation Using Linearized Displacement Constraints" Computer Animation and Simulation Workshop, 1998



Jakobsen, T., "Advanced Character Physics" Proceedings of the Game Developers Conference, 2001



Stam J.,

"Nucleus: Towards a Unified Dynamics Solver for Computer Graphics" Proceedings of Computer-Aided Design and Computer Graphics, 2009

PBD in Literature

Wrinkle Meshes

Matthias Müller & Nuttapong Chentanez

NVIDIA

Solid Simulation with Oriented Particles

Matthias Müller

Nuttapong Chentanez NVIDIA PhysX Research

Long Range Attachments - A Method to Simulate Inextensible Clothing in Computer Games

Tae-Yong Kim, Nuttapong Chentanez and Matthias Müller-Fischer[†]

NVIDIA PhysX Research

Fast Simulation of Inextensible Hair and Fur

M. Müller T.Y. Kim N. Chentanez

Nvidia PhysX Research

Position Based Fluids

Miles Macklin * Matthias Müller †

NVIDIA

Strain Based Dynamics

Matthias Müller Nuttapong Chentanez Tae-Yong Kim Miles Macklin

NVIDIA

Position-Based Simulation of Continuous Materials

Jan Bender^a, Dan Koschier^a, Patrick Charrier^a, Daniel Weber^b

^aGraduate School CE, TU Darmstadt ^bFraunhofer IGD, Darmstadt

Direct Position-Based Solver for Stiff Rods

Crispin Deul¹, Tassilo Kugelstadt², Marcel Weiler¹ and Jan Bender²

¹Graduate School CE, TU Darmstadt ² RWTH Aachen University

General (X)PBD Algorithm

 $x^{n+1} = x^n + v^n h + h^2 w_i f_{ext}$ initialize total Lagrange multiplier $\lambda_0 = 0$, while k <Iterations do for all constraints do **GAUSS-SEIDEL PROCESS** end for k = k + 1end while update xn+1 update velocity $v^{n+1} = (x^{n+1} - x^n) / h$

Verlet Integration

$\mathbf{x}^{n+1} = \mathbf{x}^n + \mathbf{v}^n \mathbf{h} + \mathbf{h}^2 \mathbf{w}_i \mathbf{f}_{ext}$

```
initialize total Lagrange multiplier \lambda_0 = 0,
while k < Iterations do
      for all constraints do
             GAUSS-SEIDEL PROCESS
      end for
      k = k + 1
end while
update xn+1
update velocity v^{n+1} = (x^{n+1} - x^n) / h
```

Verlet Integration

 $x^{n+1} = x^n + (x^n - x^{n-1}) + h^2 w_i f_{ext}$ initialize total Lagrange multiplier $\lambda_0 = 0$, while k < Iterations do for all constraints do **GAUSS-SEIDEL PROCESS** end for k = k + 1end while update xⁿ⁺¹ update velocity $v^{n+1} = (x^{n+1} - x^n) / h$

Gauss-Seidel Process

After, the displacements of each point is calculated with a constraint function:

$$(C(x + \Delta x) = 0)$$

With the help of 1st order Taylor-expansion:

$$(C(x + \Delta x) \approx C(x) + \nabla_x C(x) \cdot \Delta x = 0)$$

Position updates are obtained as:

$$\Delta x_i = w_i \nabla_{x_i} C(x) \lambda_i \quad \text{where} \quad \lambda_i = -\frac{C(x)}{\sum_i w_i |\nabla_{x_i} C(x)|^2}$$

Gauss-Seidel Process

In the recent extension to PBD (XPBD):

XPBD: Position-Based Simulation of Compliant Constrained Dynamics

Miles Macklin Matthias Müller Nuttapong Chentanez

NVIDIA

Position updates are associated with compliance stiffness matrix in order to prevent iteration count and step-size dependency:

$$\Delta x_i = w_i \nabla_{x_i} C(x) \Delta \lambda_i$$
 where $\Delta \lambda_i = -\frac{C(x) + \tilde{\alpha} \lambda_i}{(\sum_i w_i |\nabla_{x_i} C(x)|^2) + \tilde{\alpha}}$

Gauss-Seidel Process

 $x^{n+1} = x^n + (x^n - x^{n-1}) + h^2 w_i f_{ext}$ initialize total Lagrange multiplier $\lambda_0 = 0$, while k < Iterations do for all constraints do compute $\Delta \lambda$ and Δx $\lambda_{k+1} = \lambda_k + \Delta \lambda$ $\mathbf{X}_{k+1} = \mathbf{X}_k + \Delta \mathbf{X}$ end for k = k + 1end while update xn+1



















Energy Aware Gauss-Seidel Algorithm (xⁿ)^k What about the implicit velocities? **O** (Xⁿ)^{k+3}

 $(x^n)^k$ V^k = (xⁿ)^{k+1} - (xⁿ)^k **O** (xⁿ)^{k+1}





28







Now, what do we know within the Gauss-Seidel Alg.:

- Positions
- Position changes
- Implicit velocities
- Constraint values (Potential energy values)

Now, what do we know within the Gauss-Seidel Alg.:

- Positions
- Position changes
- Implicit velocities
- Constraint values (Potential energy values)

Is it posible to create an energy balance within the Gauss-Seidel iteration?

IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS

Energy Conservation for the Simulation of Deformable Bodies

Jonathan Su, Rahul Sheth, and Ronald Fedkiw

Su et al. (2012) applied the conservation principle to a mass-spring network where:

- Velocities are based on forces.
- Hooke's law dominates the framework.
- There is an integration dependency.

However, inspired by their work, we alter the Gauss-Seidel Algorithm with the energy balance in its each iteration:

That means each iteration satisfies:



However, inspired by their work, we alter the Gauss-Seidel Algorithm with the energy balance in its each iteration:

That means each iteration satisfies:

$$\Delta KE = - \Delta PE$$

$$\frac{1}{2}m\left[\left(V^{k+1}\right)^{T}V^{k+1} - \left(V^{k}\right)^{T}V^{k}\right] = -\left[\mathcal{C}(x^{n})^{k} - \mathcal{C}(x^{n-1})\right]$$











Connectivity of the particles is a limitation for parallelism:



40

This limitation is the well-known race condition which is the attack of many threads to one particle simultaneously:



In order to avoid race condition, we have to partition the mesh structure:



This partitioning has to be done in such a way that none of the elements share any connectivity:



In order to achieve that, an intuitive Mesh Coloring Algorithm is implemented:It is a two step algorithm:

- It is a two step algorithm:
 - First, a non-adjacent array list for each member is created:



- It is a two step algorithm:
 - Second, colored groups are obtained from the non-adjacent array list:



- It is a two step algorithm:
 - Second, independent edges list is obtained from the non-adjacent array list:







Constraints

2D Meshes:

Hookean Spring:

$$C_{Hookean}(x_1, x_2) = \frac{1}{2}k(||x_2 - x_1|| - l_0)^2$$
Liu et al. 13

STVK Spring:

$$C_{StVKSp.}(x_1, x_2) = \frac{1}{2}k(||x_2 - x_1||^2 - l_0^2)^2$$
Junior et al. 18

Ani. Cont. Cloth:





Constraints

3D Meshes:

Linear Elastic Material:	$\Psi_{LinElas} = \mu \xi : \xi + rac{\Lambda}{2} tr^2(\xi)$ Sifakis & Barbic 12
STVK Elastic Material:	$\Psi_{StVKEl.} = \mu G: G + rac{\Lambda}{2} tr^2(G)$ Bender et al. 14
Neo-Hookean Elastic Material:	$\Psi_{NeoH} = rac{\mu}{2}(I_1 - log(I_3) - 3) + rac{\Lambda}{8}log^2(I_3)$ Bender et al. 14
Mooney-Rivlin Elastic Material:	$\Psi_{MooRiv} = \frac{\mu_{01}}{2} \left(\frac{I_1^2 - I_2}{I_3^{2/3}} - 6\right) + \mu_{10} \left(\frac{I_1}{I_3^{1/3}} - 3\right) + \nu_1 \left(I_3^{1/2} - 1\right)^2$ Sin et al. 13
Arruda-Boyce Elastic Material:	$\Psi_{ArrBo} = \sum_{i=1}^{n} lpha_i ({I_1}^i - 3^i)$ Smith et al. 18





Model	# of Edges	# of Faces	# of Iteration	CPU (FPS)	GPU (FPS)
Cloth	4880	3220	30	17-18	50-51
Bunny	12288	8192	15	2-3	37-38



























- In this paper, we:
 - extend the Gauss-Seidel iteration of (X)PBD algorithm with the energy balances

Summary

- In this paper, we:
 - extend the Gauss-Seidel iteration of (X)PBD algorithm with the energy balances
 - present our intuitive Mesh Coloring Alg. for parallel processing on GPU

Summary

- In this paper, we:
 - extend the Gauss-Seidel iteration of (X)PBD algorithm with the energy balances
 - present our intuitive Mesh Coloring Alg. for parallel processing on GPU
 - present the results by using many spring and constitutive material potentials

Summary

- In this paper, we:
 - extend the Gauss-Seidel iteration of (X)PBD algorithm with the energy balances
 - present our intuitive Mesh Coloring Alg. for parallel processing on GPU
 - present the results by using many spring and constitutive material potentials
 - show that our method is:
 - straightforward, stable and easy to adapt to existing frameworks.

THANK YOU!