物理仿真

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Ruan, Liangwang, et al. "Solid-fluid interaction with surfacetension-dominant contact." *ACM Transactions on Graphics* (TOG) 40.4 (2021): 1-12.



Zhu, Bo, et al. "A new grid structure for domain extension." *ACM Transactions on Graphics* (*TOG*) 32.4 (2013): 1-12.



Wang, Huamin. "GPU-based simulation of cloth wrinkles at submillimeter levels." ACM Transactions on Graphics (TOG) 40.4 (2021): 1-14.

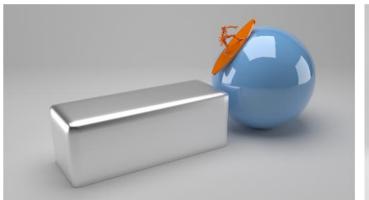


Stomakhin, Alexey, et al. "A material point method for snow simulation." *ACM Transactions on Graphics (TOG)* 32.4 (2013): 1-10.



Zhu, Bo, et al. "Codimensional surface tension flow on simplicial complexes." *ACM Transactions on Graphics (TOG)* 33.4 (2014): 1-11.







Sun, Yuchen, et al. "A material point method for nonlinearly magnetized materials." *ACM Transactions on Graphics* (TOG) 40.6 (2021): 1-13.

物理仿真

- 质点系统
 - 弹簧质点
- 软体仿真
 - 对象:
 - 一维: 绳索
 - 二维: 薄壳物体、衣服
 - 三维: 体软体
 - 现象:
 - 弹性形变与非弹性形变
 - 撕裂、破碎、爆炸
- 刚体仿真

- •流体仿真
 - •理想流体:水、空气
 - 粘性流体、非牛顿流体
 - 拟流体以及相关现象
 - •沙、雪、烟
- 其他
 - 声音
 - 锈蚀、老化、燃烧
 - 电磁
- 多物理场耦合

Kinematic or Dynamic?

Position
Velocity
Acceleration

• • • • • •

Mass

F = ma



Force

Torque

• • • • •

Kinematics

Dynamics

Homogeneous or Heterogeneous

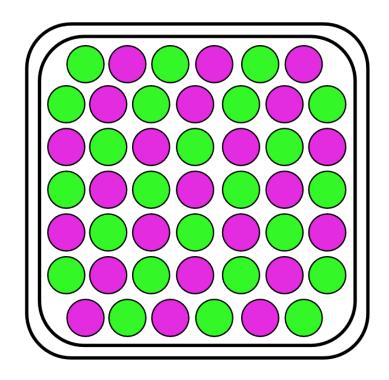


Homogeneous

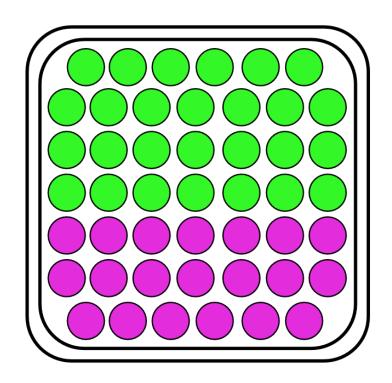


Heterogeneous

Homogeneous or Heterogeneous



Homogeneous



Heterogeneous

Isotropic or Anisotropic?

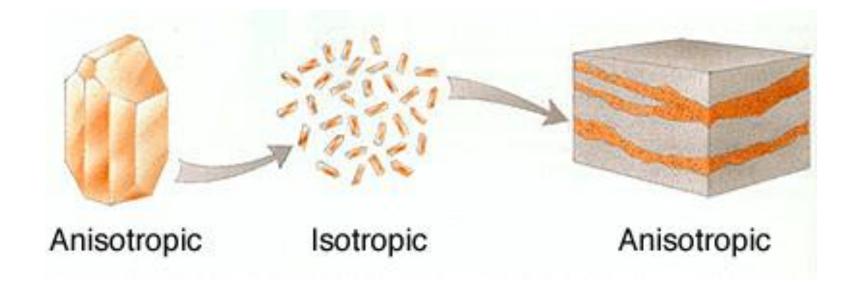


Isotropic



Anisotropic

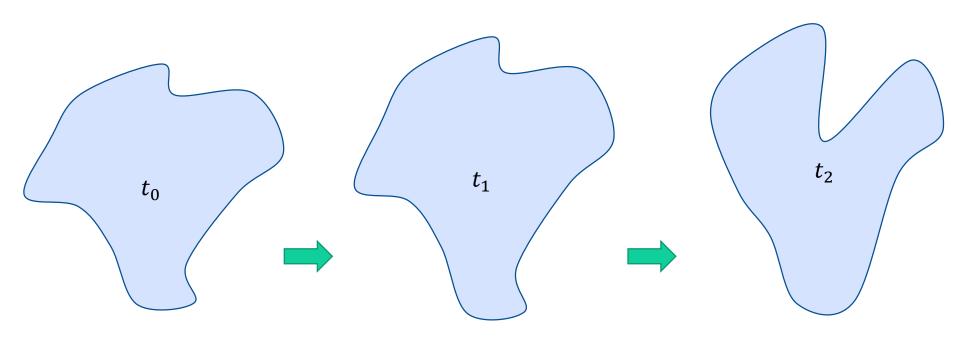
Isotropic or Anisotropic?



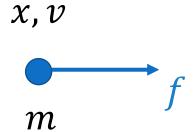
ANISOTROPIC ISOTROPIC HETEROGENEOUS HOMOGENEOUS

What is Simulation

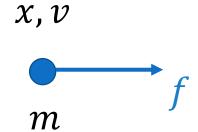
$$X = X(t)$$



$$x = x(t)$$



$$x = x(t)$$



$$f = ma$$

$$a = \dot{v}$$

$$v = \dot{x}$$

$$x = x(t)$$

$$x, v$$

$$m$$

$$f = ma$$

$$a = \dot{v}$$

$$v = \dot{x}$$

$$x = x_0 + \int_{t_0}^{t} adt$$

$$x = x_0 + \int_{t_0}^{t} vdt$$

$$x = x(t)$$

$$x, v$$

$$m$$

$$f = ma$$

$$a = f/m$$

$$a = \dot{v}$$

$$v = v_0 + at$$

$$v = \dot{x}$$

$$x = x_0 + v_0 t + \frac{1}{2}at$$

$$x = x(t)$$

$$x, v$$

$$m$$

$$f = ma$$

$$a = f(x, v, t)/m$$

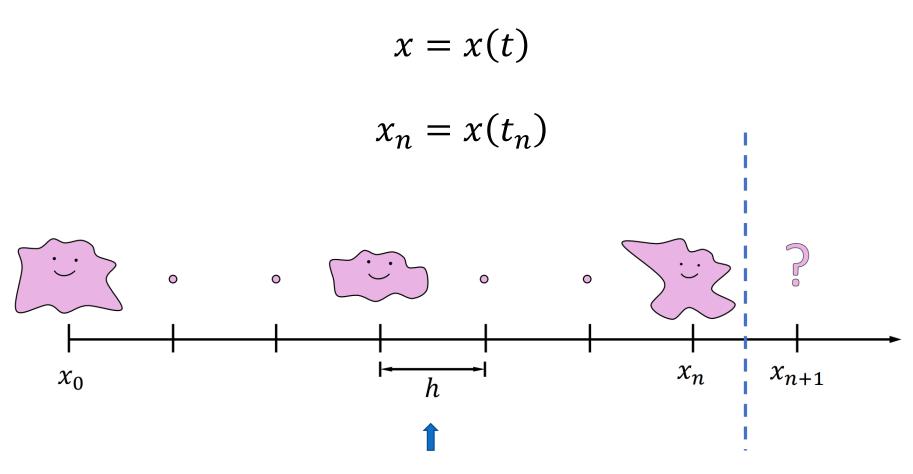
$$a = \dot{v}$$

$$v = v_0 + \int_{t_0}^{t} adt$$

$$v = \dot{x}$$

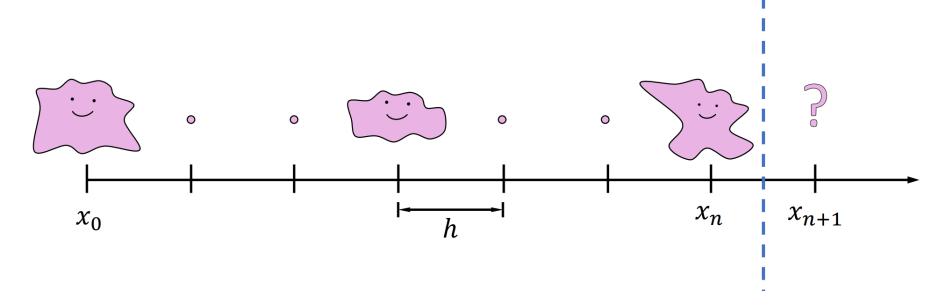
$$x = x_0 + \int_{t_0}^{t} vdt$$

Temporal Discretization



Simulation time step

Temporal Discretization



$$a = f(x, v, t)/m$$

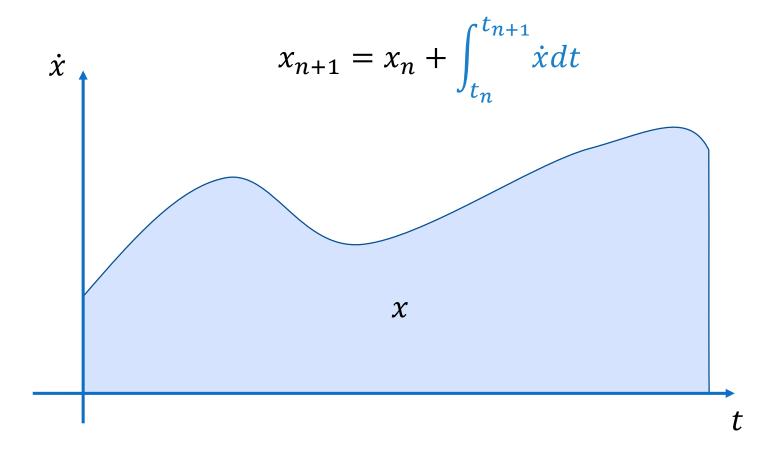
$$v = v_0 + \int_{t_0}^t a dt$$

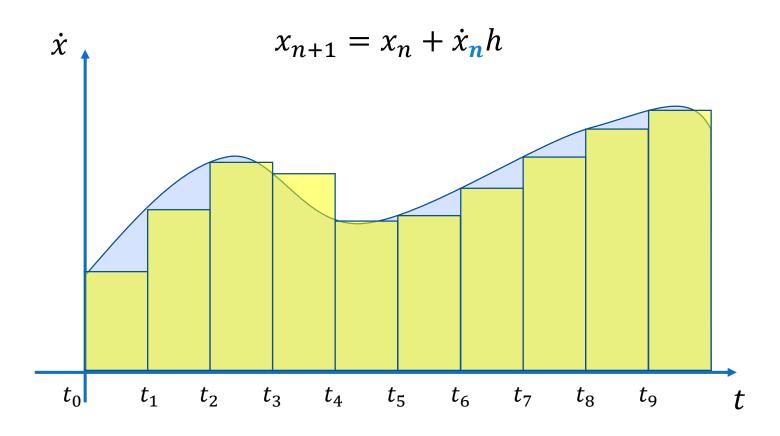
$$x = x_0 + \int_{t_0}^t v dt$$

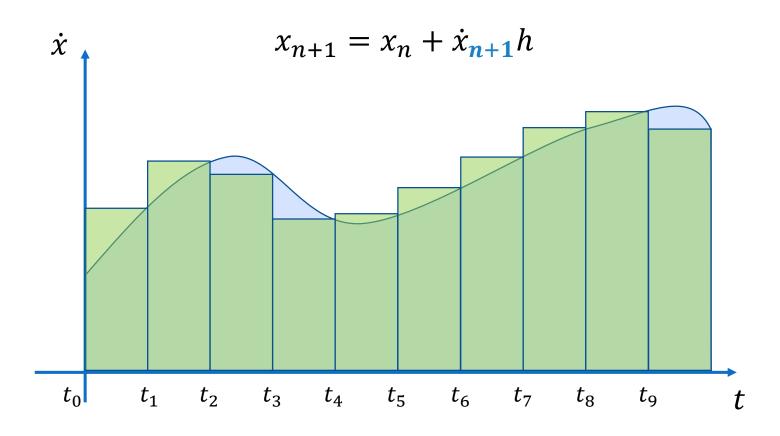
$$a = f(x, v, t)/m$$

$$v_{n+1} = v_n + \int_{t_n}^{t_{n+1}} adt$$

$$x_{n+1} = x_n + \int_{t_n}^{t_{n+1}} v dt$$







Explicit/Forward Euler Integration

$$v_{n+1} = v_n + a_n h$$
$$x_{n+1} = x_n + v_n h$$

Implicit/Backward Euler Integration

$$v_{n+1} = v_n + a_{n+1}h$$
$$x_{n+1} = x_n + v_{n+1}h$$

Explicit/Forward Euler Integration

$$v_{n+1} = v_n + a_n h$$
$$x_{n+1} = x_n + v_n h$$

• Implicit/Backward Euler Integration

$$v_{n+1} = v_n + a_{n+1}h$$

 $x_{n+1} = x_n + v_{n+1}h$

Requires information from the future

Explicit/Forward Euler Integration

$$v_{n+1} = v_n + a_n h$$
$$x_{n+1} = x_n + v_n h$$

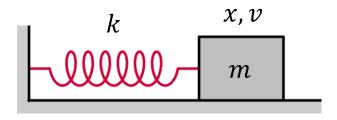
Implicit/Backward Euler Integration

$$v_{n+1} = v_n + a_{n+1}h$$
$$x_{n+1} = x_n + v_{n+1}h$$

Symplectic / Semi-implicit Euler Integration

$$v_{n+1} = v_n + a_n h$$
$$x_{n+1} = x_n + v_{n+1} h$$

Mass on a Spring



$$f = -kx$$

Explicit Euler Integration

$$v_{n+1} = v_n - \frac{kx_n}{m}h$$
$$x_{n+1} = x_n + v_n h$$

Semi-implicit Euler Integration

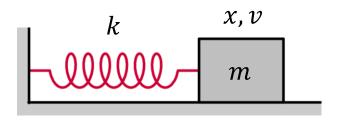
$$v_{n+1} = v_n - \frac{kx_n}{m}h$$
$$x_{n+1} = x_n + v_{n+1}h$$

Implicit Euler Integration

$$v_{n+1} = v_n - \frac{kx_n}{m}h$$
 $v_{n+1} = v_n - \frac{kx_{n+1}}{m}h$ $x_{n+1} = x_n + v_{n+1}h$ $x_{n+1} = x_n + v_{n+1}h$



Mass on a Spring



$$f = -kx$$
$$\hat{k} = k/m$$

$$\hat{k} = k/m$$

Explicit Euler Integration

$$\begin{bmatrix} v_{n+1} \\ x_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & -\hat{k}h \\ h & 1 \end{bmatrix} \begin{bmatrix} v_n \\ x_n \end{bmatrix}$$

$$\det A = 1 + \hat{k}h^2$$

Semi-implicit Euler Integration

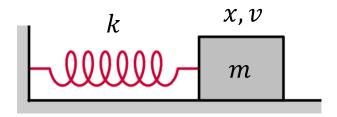
$$\begin{bmatrix} v_{n+1} \\ x_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & -\hat{k}h \\ h & 1 - \hat{k}h^2 \end{bmatrix} \begin{bmatrix} v_n \\ x_n \end{bmatrix}$$

$$\det A = 1$$

$$\begin{bmatrix} v_{n+1} \\ x_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & -\hat{k}h \\ h & 1 \end{bmatrix} \begin{bmatrix} v_n \\ x_n \end{bmatrix} \qquad \begin{bmatrix} v_{n+1} \\ x_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & -\hat{k}h \\ h & 1 - \hat{k}h^2 \end{bmatrix} \begin{bmatrix} v_n \\ x_n \end{bmatrix} \qquad \begin{bmatrix} v_{n+1} \\ x_{n+1} \end{bmatrix} = \frac{1}{1 + \hat{k}h^2} \begin{bmatrix} 1 & -\hat{k}h \\ h & 1 \end{bmatrix} \begin{bmatrix} v_n \\ x_n \end{bmatrix}$$

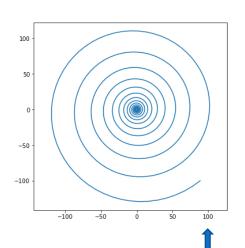
$$\det A = \frac{1}{1 + \hat{k}h^2}$$

Mass on a Spring

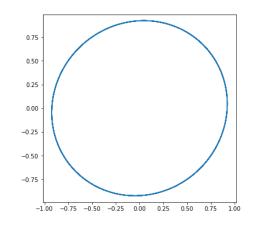


$$f = -kx$$

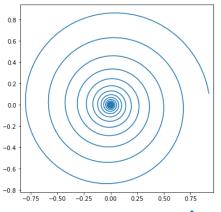
Explicit Euler Integration



Semi-implicit Euler Integration



Implicit Euler Integration





- Explicit/Forward Euler
 Symplectic/Semi-implicit Euler
 - Fast, no need to solve equations
 - Can be unstable under large time step

- Implicit/Backward Euler
 - Rock stable (unconditionally)
 - Slow, need to solve a large problem

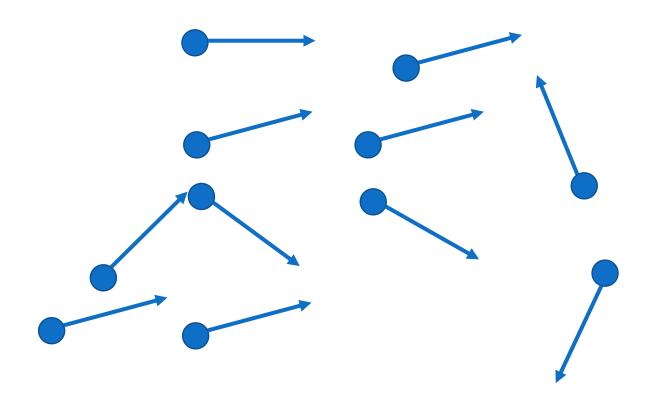
More Advanced Integration

- Runge–Kutta methods
- Variational integration

Particle Systems System

Particle Systems

• A set of (identical) simulated particles $\{x_i\}$



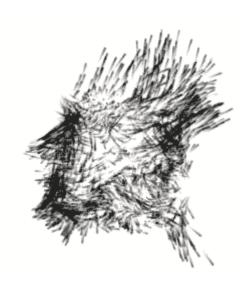
Particle Systems

- Simulation Loop
 - Clear forces
 - Prevent force accumulation
 - Calculate forces
 - Sum all forces into accumulators
 - Update
 - Loop over particles, update x_i and v_i using the corresponding integrator



Particle Systems

- Forces
 - Constant
 - Gravity
 - Position/time dependent
 - Force field
 - Velocity-dependent
 - Damping, dragging
 - Others
 - Contacts, bouncing
 - Spring



Realtime?

- A few related concepts
 - Wall clock / real world time T
 - Simulation clock t
 - Advance h seconds every simulation step
 - $t \ge T \rightarrow$ realtime simualtion

- Synchronization between the two worlds
 - Sleep when necessary

Example: Particle System in Unity

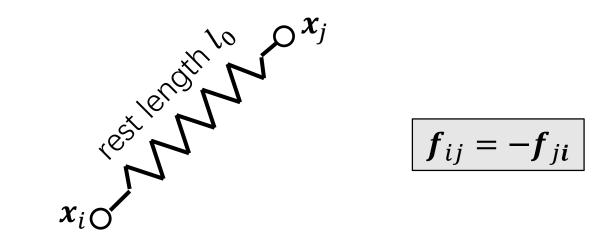
Any Questions?

Mass-Spring System



Huamin Wang. 2021. *GPU-based simulation of cloth wrinkles at submillimeter levels*. *ACM Trans. Graph.* 40, 4 (July 2021)

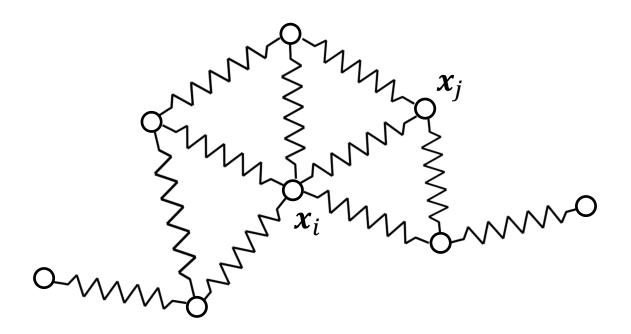
Mass Spring System



$$f_{ij} = -k(||x_i - x_j|| - l_0) \frac{x_i - x_j}{||x_i - x_j||}$$

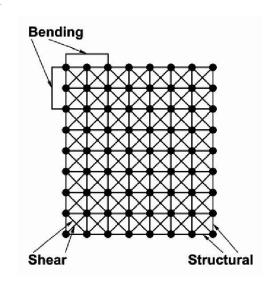
$$f_{ji} = -k(||x_j - x_i|| - l_0) \frac{x_j - x_i}{||x_j - x_i||}$$

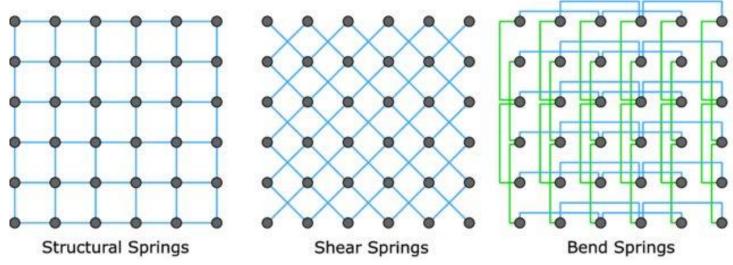
Mass Spring System



$$f_i = \sum_{j \in N(i)} f_{ij}$$

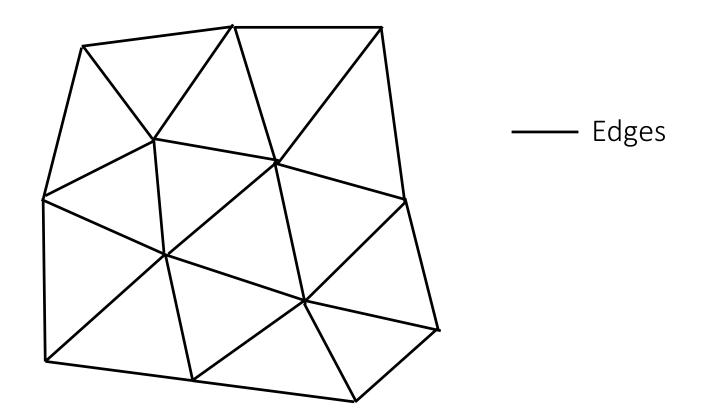
Structured Network





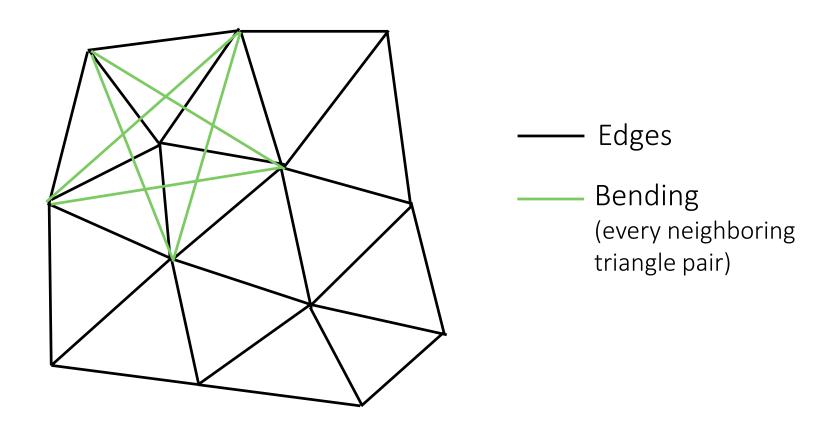
Structured Network

For a triangle mesh



Structured Network

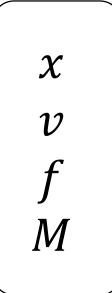
For a triangle mesh



Mass Spring System

Simulation Loop

- Clear forces
 - Prevent force accumulation
- Calculate forces
 - For every edge *ij*
 - Compute f_{ij}
 - $f_i += f_{ij}$, $f_j -= f_{ij}$
- Update
 - Loop over particles, update x_i and v_i using the corresponding integrator



Update

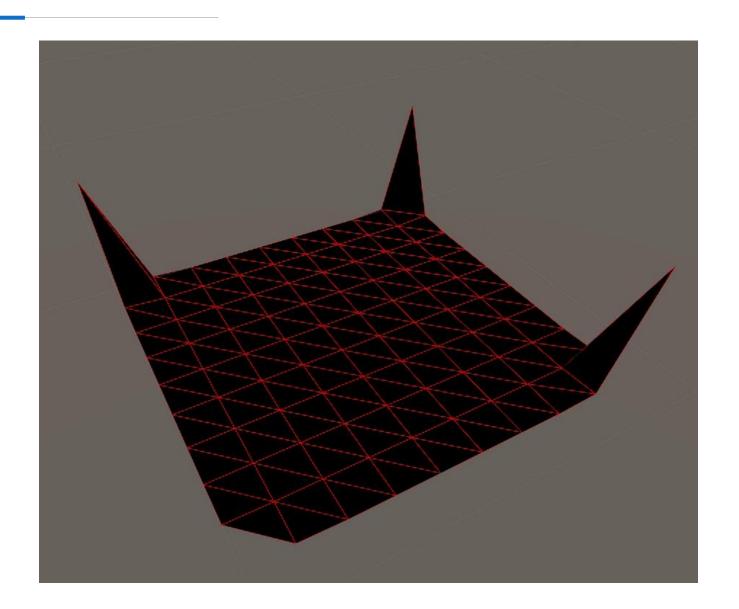
- (Semi-) Explicit Euler Integration
 - Need small time step

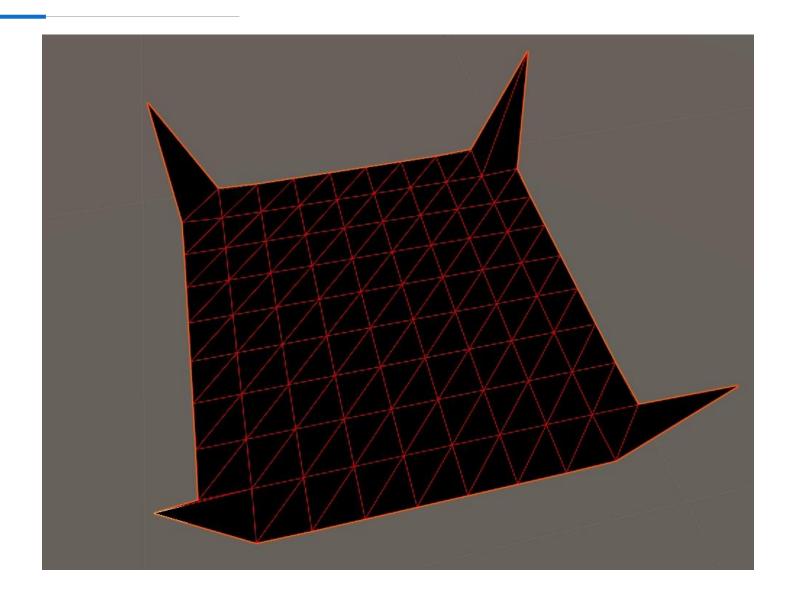
Explicit Euler Integration

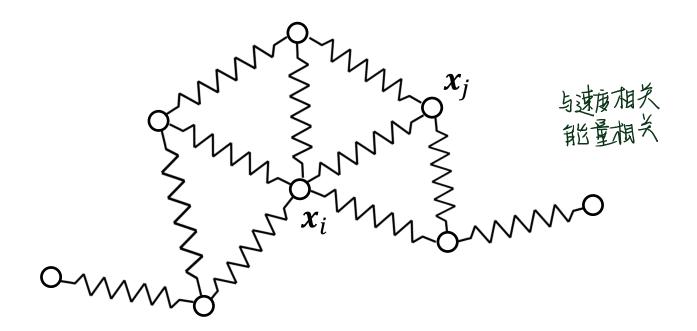
$$v_{n+1} = v_n + hM^{-1}f_nh$$
$$x_{n+1} = x_n + v_nh$$

Semi-implicit Euler Integration

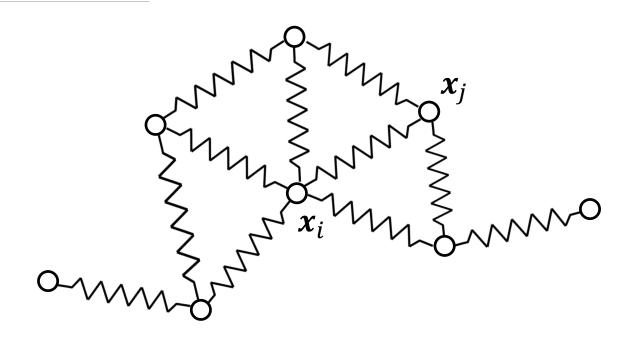
$$v_{n+1} = v_n + hM^{-1}f_n$$
$$x_{n+1} = x_n + v_{n+1}h$$



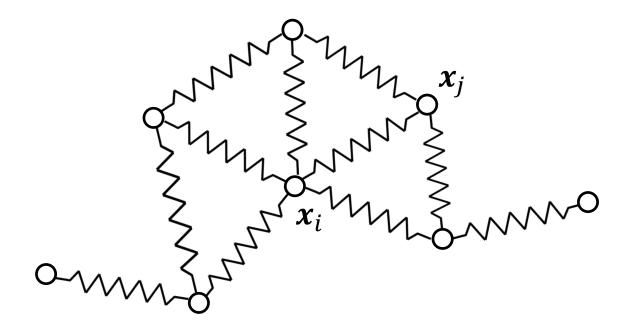




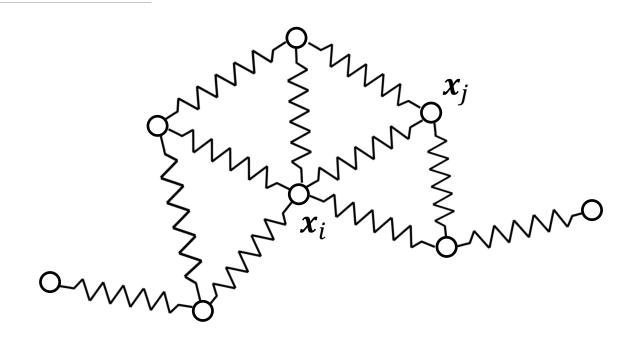
$$f_i = \sum_{j \in N(i)} f_{ij} - k_d v_i$$
 类似空



$$f_i = \sum_{j \in N(i)} f_{ij} - k_d(v_i - v_j)$$
 不抖动 阻止相对运动 写外力为 f_{ij} 但有为形式的最重要 f_{ij} 现的代



$$f_i = \sum_{j \in N(i)} f_{ij} - k_d (v_i - v_j) \cdot \frac{x_i - x_j}{\|x_i - x_j\|}$$



每个小三角形的质心

$$f_i = \sum_{j \in N(i)} f_{ij} - f_d(v)$$

Update

- (Semi-) Explicit Euler Integration
 - Need small time step h
 - ullet May be very small when k is large

Explicit Euler Integration

$$v_{n+1} = v_n + hM^{-1}f_nh$$
$$x_{n+1} = x_n + v_nh$$

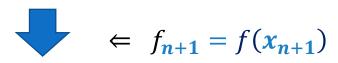
Semi-implicit Euler Integration

$$v_{n+1} = v_n + hM^{-1}f_n$$
$$x_{n+1} = x_n + v_{n+1}h$$

Implicit Integration

Implicit Euler Integration

$$v_{n+1} = v_n + M^{-1} f_{n+1} h$$
$$x_{n+1} = x_n + v_{n+1} h$$

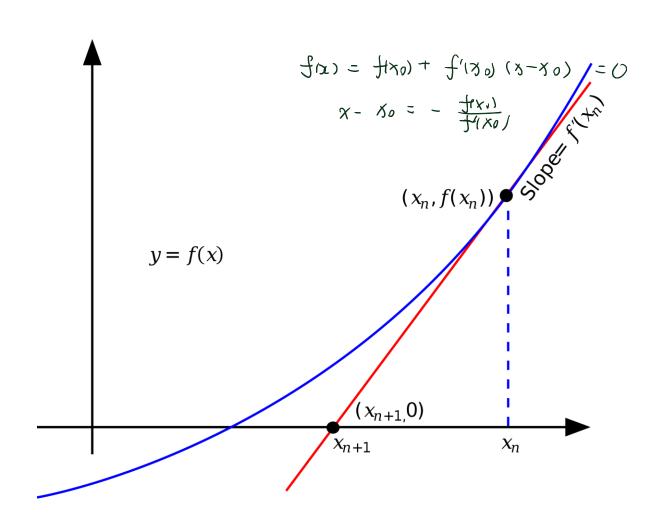


$$x_{n+1} = x_n + hv_n + h^2 M^{-1} f(x_{n+1})$$

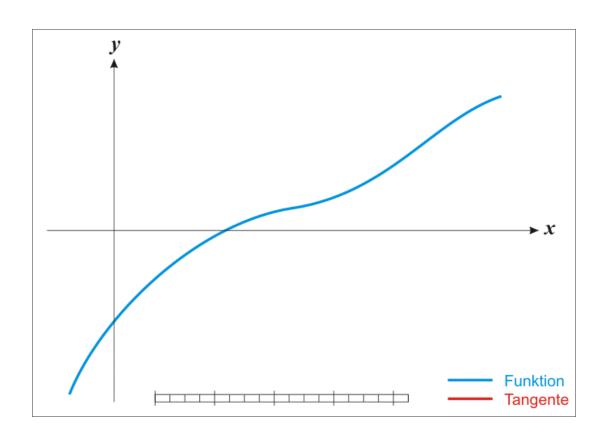
$$f_{ij} = -k \left(\| \delta_{i} \cdot j \| - v_{i} \right) \frac{\gamma_{i} \cdot j}{|||\alpha_{ij}||}$$

$$\pi_{ij} = \gamma_{i} \cdot \gamma_{j}$$

Newton-Raphson Method



Newton-Raphson Method



$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$$

初始值进择

Simulation by Newton's Method

$$x_{n+1} = x_n + hv_n + h^2 M^{-1} f(x_{n+1})$$

$$F\left(x_{n}^{(k)}\right)$$

$$F'\left(x_{n}^{(k)}\right)$$

$$+ hv_{n} + h^{2}M^{-1}f(x_{n+1})$$

$$+ f(x_{n+1}^{(k)}) = \frac{1}{h^{2}}M(x_{n+1}^{(k)} - x_{n} - hv_{n}) - f(x_{n+1}^{(k)})$$

$$+ f'(x_{n+1}^{(k)}) = \frac{1}{h^{2}}M - f'(x_{n+1}^{(k)})$$

Initialize $x_{n+1}^{(0)}$, often as x_n or $x_n + hv_n$

For
$$k = 0 \dots K$$

Solve
$$\left(\frac{1}{h^2}M - f'\left(x_{n+1}^{(k)}\right)\right)\Delta x = -\frac{1}{h^2}M\left(x_{n+1}^{(k)} - x_n - hv_n\right) + f(x_{n+1}^{(k)})$$

$$\boldsymbol{x}_{n+1}^{(k+1)} \leftarrow \boldsymbol{x}_{n+1}^{(k)} + \Delta \boldsymbol{x}$$

If $\|\Delta x\|$ is small then break

$$x_{n+1} \leftarrow \mathbf{x}^{(k+1)}$$

$$v_{n+1} \leftarrow \frac{(x_{n+1} - x_n)}{h}$$

Implicit Integration as Optimization

$$x_{n+1} = x_n + hv_n + h^2 M^{-1} f(x_{n+1})$$



$$x_{n+1} = \operatorname{argmax}_{x} F(x)$$

$$= \operatorname{argmax}_{x} \frac{1}{2h^{2}} \|x - x_{n} - hv_{n}\|_{M}^{2} + E(x)$$

$$\|\mathbf{x}\|_{\mathbf{M}}^2 = \mathbf{x}^{\mathrm{T}}\mathbf{M}\mathbf{x}$$

Elastic Energy

Newton-Raphson Method for Optimization

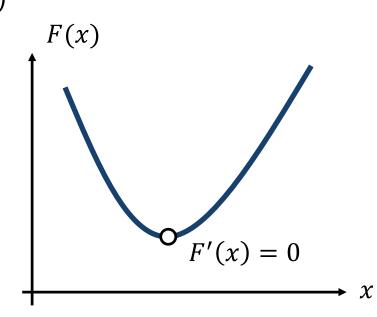
域状の段 : 求子(x) =0 M
$$x$$

$$x_{n+1} = \operatorname{argmax}_{x} F(x) = \operatorname{argmax}_{x} \frac{1}{2h^{2}} \|x - x_{n} - hv_{n}\|_{M}^{2} + E(x)$$

Optimality condition:

$$\lambda - \lambda_{(k)} = -\frac{\pm_{(\lambda_{(k)})}}{\pm_{(\lambda_{(k)})}}$$

$$0 = F'(x) \approx F'(x^{(k)}) + F''(x^{(k)})(x - x^{(k)})$$



Newton-Raphson Method for Optimization

$$x_{n+1} = \operatorname{argmax}_{x} F(x) = \operatorname{argmax}_{x} \frac{1}{2h^{2}} ||x - x_{n} - hv_{n}||_{M}^{2} + E(x)$$

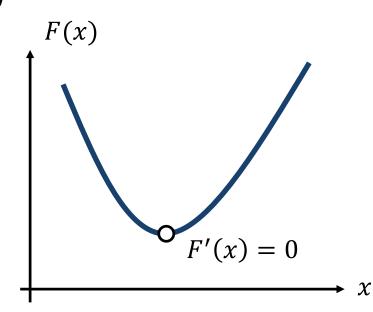
Optimality condition:

$$0 = F'(x) \approx F'(x^{(k)}) + F''(x^{(k)})(x - x^{(k)})$$



$$\Delta x \leftarrow -\left(F''(x^{(k)})\right)^{-1} F'(x^{(k)})$$

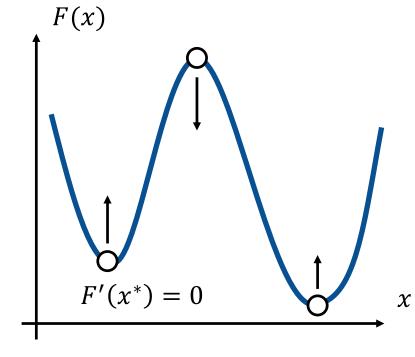
$$x^{(k+1)} \leftarrow x^{(k)} + \Delta x$$



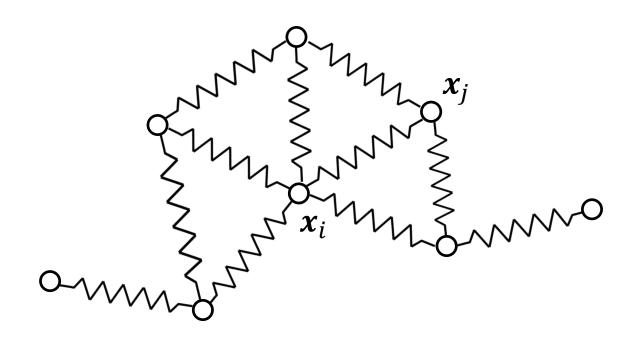
Hessian Matrix

$$0 = F'(x) \approx F'(x^{(k)}) + F''(x^{(k)})(x - x^{(k)})$$

$$H(x) = F''(x) = \left[\frac{\partial^2 F}{\partial x_i \partial x_j}\right]$$



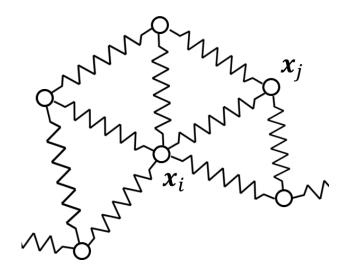
- minimum $x^* \Rightarrow H(x^*) > 0$ (SPD)
- maximum $x^* \Rightarrow H(x^*) < 0$ (SND)
- If F''(x) > 0 for any $x \Rightarrow F(x)$ has no maximum.
- $\Rightarrow F(x)$ has only one minimum.



$$f_i = \sum_{j \in N(i)} f_{ij} = \sum_{j \in N(i)} -k(||x_i - x_j|| - l_0) \frac{x_i - x_j}{||x_i - x_j||}$$

Elastic Energy

$$E(x) = \sum_{(i,j)\in\mathcal{E}} \frac{k}{2} (\|x_i - x_j\| - l_0)^2$$



Force

$$f_i(x) = \frac{\partial E}{\partial x_i} = \sum_{j \in N(i)} -k(||x_i - x_j|| - l_0) \frac{x_i - x_j}{||x_i - x_j||}$$

$$H(x) = \left[\frac{\partial E}{\partial x_i \partial x_j} \right]$$

$$H(x) = \left[\frac{\partial E}{\partial x_i \partial x_j}\right]$$

$$= \sum_{e=(i,j)\in\mathcal{E}} \begin{bmatrix} \ddots & \vdots & \vdots & \ddots \\ \frac{\partial^2 E}{\partial x_i^2} & \frac{\partial^2 E}{\partial x_i \partial x_j} & \dots \\ \frac{\partial^2 E}{\partial x_i \partial x_j} & \frac{\partial^2 E}{\partial x_j^2} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

$$= \sum_{e=(i,j)\in\mathcal{E}} \begin{bmatrix} \ddots & \vdots & \vdots & \ddots \\ \cdots & H_e & -H_e & \cdots \\ \cdots & -H_e & H_e & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

$$H(x) = \left[\frac{\partial E}{\partial x_i \partial x_j}\right] = \sum_{e=(i,j) \in \mathcal{E}} \begin{vmatrix} \vdots & \vdots & \vdots & \vdots \\ \cdots & H_e & -H_e & \cdots \\ \cdots & -H_e & H_e & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{vmatrix}$$

$$x_{ij} = x_i - x_j$$

$$\boldsymbol{H}_{e} = k \frac{x_{ij} x_{ij}^{T}}{\|x_{ij}\|^{2}} + k \left(1 - \frac{l_{0}}{\|x_{ij}\|}\right) \left(\boldsymbol{I} - \frac{x_{ij} x_{ij}^{T}}{\|x_{ij}\|^{2}}\right)$$

$$H(x) = \left[\frac{\partial E}{\partial x_i \partial x_j}\right] = \sum_{e=(i,j) \in \mathcal{E}} \begin{vmatrix} \vdots & \vdots & \vdots & \vdots \\ \cdots & H_e & -H_e & \cdots \\ \cdots & -H_e & H_e & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{vmatrix}$$

$$x_{ij} = x_i - x_j$$

$$\boldsymbol{H}_{e} = k \frac{x_{ij} x_{ij}^{T}}{\left\|x_{ij}\right\|^{2}} + k \left(1 - \frac{l_{0}}{\left\|x_{ij}\right\|}\right) \left(\boldsymbol{I} - \frac{x_{ij} x_{ij}^{T}}{\left\|x_{ij}\right\|^{2}}\right)$$
SPD
SPD

$$H(x) = \left[\frac{\partial E}{\partial x_i \partial x_j}\right] = \sum_{e=(i,j) \in \mathcal{E}} \begin{bmatrix} \vdots & \vdots & \vdots & \vdots \\ \cdots & H_e & -H_e & \cdots \\ \cdots & -H_e & H_e & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$$x_{ij} = x_i - x_j$$

$$H_e = k \frac{x_{ij} x_{ij}^T}{\|x_{ij}\|^2} + k \left(1 - \frac{l_0}{\|x_{ij}\|}\right) \left(I - \frac{x_{ij} x_{ij}^T}{\|x_{ij}\|^2}\right)$$
SPD
SPD
SPD

$$H_{e} = k \frac{x_{ij} x_{ij}^{T}}{\left\|x_{ij}\right\|^{2}} + k \left(1 - \frac{l_{0}}{\left\|x_{ij}\right\|}\right) \left(I - \frac{x_{ij} x_{ij}^{T}}{\left\|x_{ij}\right\|^{2}}\right)$$

$$SPD \quad \text{positive} \quad SPD$$

$$\text{when } \left\|x_{ij}\right\| > l_{0}$$

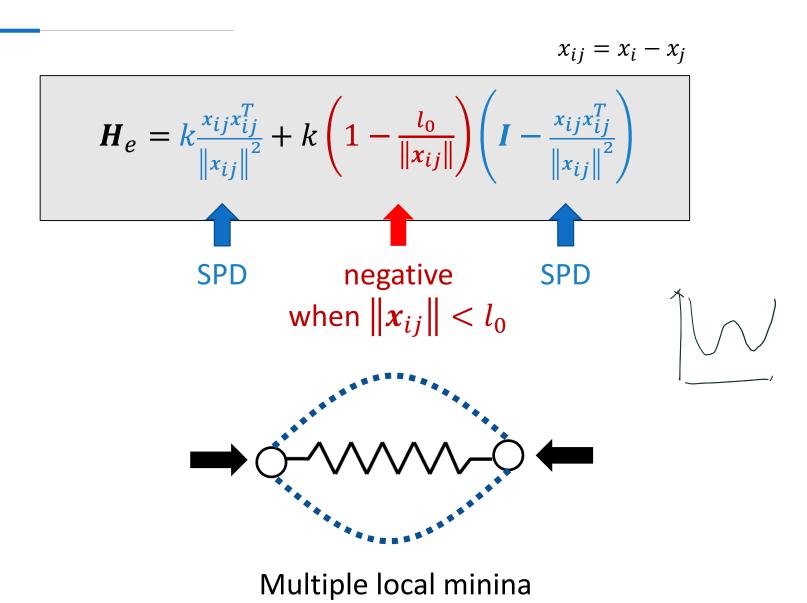


$$H_e = k \frac{x_{ij} x_{ij}^T}{\|x_{ij}\|^2} + k \left(1 - \frac{l_0}{\|x_{ij}\|}\right) \left(I - \frac{x_{ij} x_{ij}^T}{\|x_{ij}\|^2}\right)$$

$$\text{SPD} \quad \text{negative} \quad \text{SPD}$$

$$\text{when } \|x_{ij}\| < l_0$$





- Why positive definiteness is important?
 - Newton's method: $F''(x^{(k)})\Delta x = -F'(x^{(k)})$
 - Some linear solvers can fail when A in $A\Delta x = b$ is not positive definite

$$H_{e} = k \frac{x_{ij} x_{ij}^{T}}{\|x_{ij}\|^{2}} + k \left(1 - \frac{l_{0}}{\|x_{ij}\|}\right) \left(I - \frac{x_{ij} x_{ij}^{T}}{\|x_{ij}\|^{2}}\right)$$

Linear Solvers

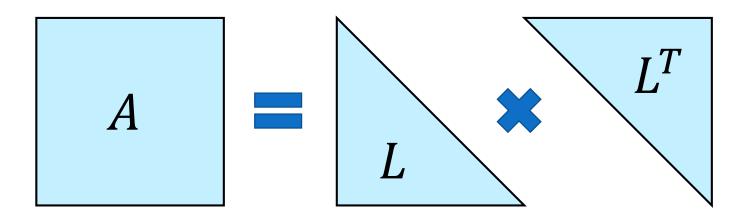
- Direct solvers
 - LU, LDLT, Cholesky, ...
 - Solve Ax = b in one shot
 - Slow when A is large, inaccurate when cond(A) is large
- Iterative solvers
 - Gauss–Seidel method, Jacobi method, ...
 - Iteratively approaching the true solution
 - Easy to implement
 - Convergence often rely on positive definiteness of A



Cholesky Decomposition

ullet A positive definite matrix A can be decomposed as

$$A = LL^T \text{ or } A = LDL^T$$



Cholesky Decomposition

半 服分解不惟一

• A positive definite matrix \hat{A} can be decomposed as

$$A = LL^{T} \text{ or } A = LDL^{T}$$

$$L^{T}$$

$$\tilde{a}_{21} \tilde{a}_{22}$$

$$\tilde{a}_{01} \tilde{y}_{1}$$

$$\tilde{a}_{21} \tilde{y}_{22}$$

$$\tilde{a}_{11} \tilde{y}_{1} \tilde{a}_{22} \tilde{y}_{2}$$

$$\tilde{a}_{11} \tilde{y}_{1} \tilde{a}_{22} \tilde{y}_{2}$$

$$\tilde{a}_{11} \tilde{y}_{1} \tilde{a}_{21} \tilde{y}_{12} \tilde{a}_{22}$$

$$\tilde{a}_{11} \tilde{y}_{11} \tilde{a}_{22} \tilde{y}_{2}$$

$$\tilde{a}_{11} \tilde{y}_{12} \tilde{a}_{22} \tilde{a}_{22} \tilde{a}_{22} \tilde{a}_{22} \tilde{a}_{22}$$

$$\tilde{a}_{11} \tilde{y}_{11} \tilde{a}_{22} \tilde{y}_{22}$$

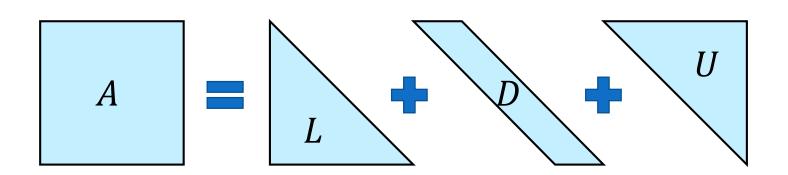
$$\tilde{a}_{11} \tilde{y}_{12} \tilde{a}_{22} \tilde{$$

$$Ax = b \longrightarrow L(L^T x) = b \longrightarrow L^T x = y$$

Jacobi Method

$$Ax = b$$

• A can be decomposed as



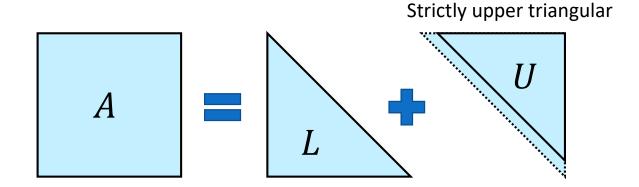
Then

$$x^{(k+1)} = D^{-1} (b - (L+U)x^{(k)})$$

Gauss-Seidel Method

$$Ax = b$$

• A can be decomposed as



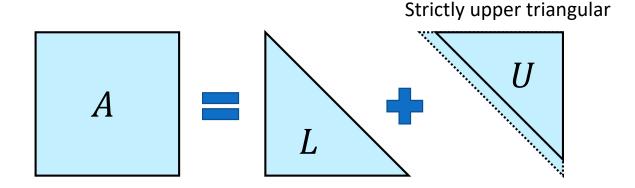
Then

$$x^{(k+1)} = L^{-1}(b - Ux^{(k)})$$

Gauss-Seidel Method

$$Ax = b$$

• A can be decomposed as



Then

Forward substitution

$$x_i^{(k+1)} = \frac{1}{a_{ii}} \left(b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij} x_j^{(k)} \right)$$

Positive Definiteness of Hessian

- Why positive definiteness is important?
 - Newton's method: $F''(x^{(k)})\Delta x = -F'(x^{(k)})$
 - Some linear solvers can fail when A in $A\Delta x=b$ is not positive definite
- Drop the last term when $||x_{ij}|| < l_0$

$$H_{e} = k \frac{x_{ij} x_{ij}^{T}}{\|x_{ij}\|^{2}} + k \left(1 - \frac{t_{0}}{\|x_{ij}\|}\right) \left(1 - \frac{x_{ij} x_{ij}^{T}}{\|x_{ij}\|^{2}}\right)$$

- Other solutions, for example:
 - Choi and Ko. 2002. Stable But Responive Cloth. TOG (SIGGRAPH)

Get Rid of Hessian?

Get rid of Hessian?

• Newton's method $x^{(k+1)} = x^{(k)} + \alpha \Delta$ $\Delta \leftarrow -\left(H(x^{(k)})\right)^{-1} F'(x^{(k)})$ $H(x) = F''(x) \otimes$

Quasi-Newton method

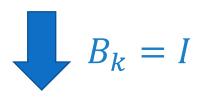
$$\Delta \leftarrow -(B_k)^{-1} F'(x^{(k)})$$

$$B_k \approx H(x^{(k)}) \quad \odot$$

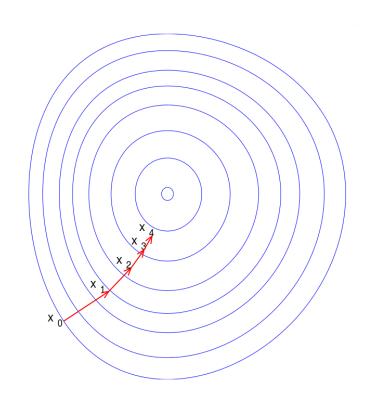
Gradient Descent

$$x^{(k+1)} = x^{(k)} + \alpha \Delta$$

$$\Delta = -(B_k)^{-1} F'(x^{(k)})$$



$$\Delta = -F'(x^{(k)})$$



Diagonal Hessian

$$x^{(k+1)} = x^{(k)} + \alpha \Delta$$

$$\Delta = -(B_k)^{-1} F'(x^{(k)})$$

$$B_k = \operatorname{diag}\left(\frac{\partial^2 F}{\partial x_i \partial x_i}\right)$$



Huamin Wang. 2015. A chebyshev semi-iterative approach for accelerating projective and position-based dynamics. ACM Trans. Graph. 34, 6, Article 246 (November 2015)

BFGS Algorithm

Broyden-Fletcher-Goldfarb-Shanno Algorithm



BFGS Algorithm

$$x^{(k+1)} = x^{(k)} + \Delta$$

Newton's method

$$H(x^{(k)})\Delta = -F'(x^{(k)})$$

Quasi-Newton method

$$B_k \Delta = -F'(\mathbf{x}^{(k)})$$

• BFGS Algorithm

$$\Delta_k \leftarrow B_k \Delta = -F'(x^{(k)})$$

$$y_k \leftarrow F'(x^{(k+1)}) - F'(x^{(k)})$$

$$B_{k+1} \leftarrow B_k + \frac{y_k y_k^T}{y_k^T \Delta_k} - \frac{B_k \Delta_k \Delta_k^T B_k^T}{\Delta_k^T B_k \Delta_k}$$

BFGS Algorithm

$$x^{(k+1)} = x^{(k)} + \Delta$$

Newton's method

$$H(x^{(k)})\Delta = -F'(x^{(k)})$$

Quasi-Newton method

$$B_k \Delta = -F'(\mathbf{x}^{(k)})$$

• BFGS Algorithm

$$\Delta_k \leftarrow -B_k^{-1} F'(x^{(k)})$$

$$y_k \leftarrow F'(x^{(k+1)}) - F'(x^{(k)})$$

$$B_{k+1}^{-1} \leftarrow \left(I - \frac{\Delta_k y_k^T}{y_k^T \Delta_k}\right) B_k^{-1} \left(I - \frac{y_k \Delta_k^T}{y_k^T \Delta_k}\right) + \frac{\Delta_k \Delta_k^T}{y_k^T \Delta_k}$$

L-BFGS Algorithm

Limited-memory BFGS

$$B_{k+1}^{-1} \leftarrow \left(I - \frac{\Delta_k y_k^T}{y_k^T \Delta_k}\right) B_k^{-1} \left(I - \frac{y_k \Delta_k^T}{y_k^T \Delta_k}\right) + \frac{\Delta_k \Delta_k^T}{y_k^T \Delta_k}$$

- $B \in \mathbb{R}^{n \times n}$ can be very big...
- $\Delta_k, y_k \in \mathbb{R}^n$ is small

L-BFGS Algorithm

Limited-memory BFGS

$$B_{k+1}^{-1} \leftarrow \left(I - \frac{\Delta_k y_k^T}{y_k^T \Delta_k}\right) B_k^{-1} \left(I - \frac{y_k \Delta_k^T}{y_k^T \Delta_k}\right) + \frac{\Delta_k \Delta_k^T}{y_k^T \Delta_k}$$

- $B \in \mathbb{R}^{n \times n}$ can be very big...
- Δ_k , $y_k \in \mathbb{R}^n$ is small
- A possible solution
 - Record $\rho_k = \left(y_{\mathbf{k}}^{\mathrm{T}} \Delta_k\right)^{-1}$, Δ_k , y_k
 - Then unroll up to $m \ll n$ steps of the above equation
 - Many different implementations

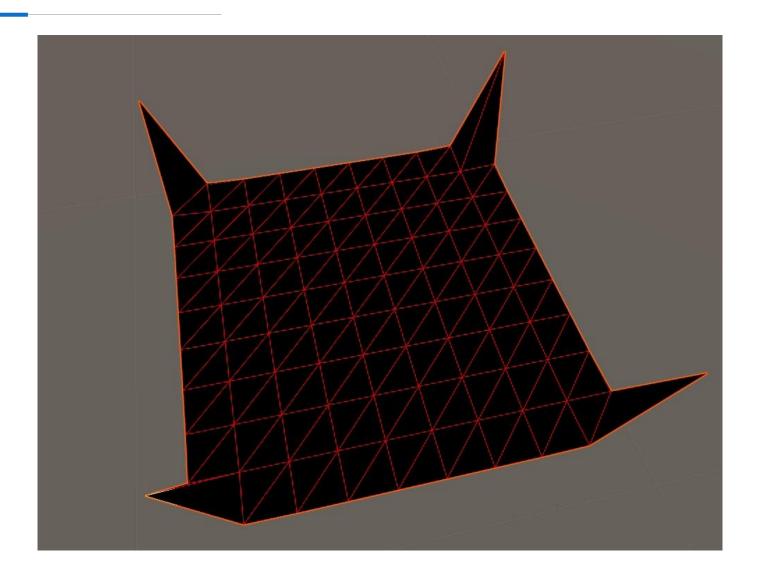
Outline

- Basic concepts of simulation
 - Types of simulation
 - Discretization in time
 - Forward/Backward/Symplectic Euler integration
- Particle System
- Mass-Spring System
- Numerical Methods
 - Newton's method
 - Linear solvers
 - Quasi-Newton methods

Constraints and Contacts

Some simple cases, we will discuss this topic again later

System with Constraints



Inverse Mass in System Dynamics

$$v_{n+1} = v_n + h \mathbf{M}^{-1} f$$

$$v_{n+1} = v_n + h \begin{bmatrix} 1/m \\ 1/m \\ 1/m \end{bmatrix} f$$

Modified Inverse Mass

$$v_{n+1} = v_n + h \mathbf{M}^{-1} f$$

What does this mean?

Modified Inverse Mass

$$v_{n+1} = v_n + h \mathbf{M}^{-1} f$$

$$v_{n+1} = v_n + h \frac{1}{m} (I - pp_{\text{nxn}}^T) f$$
 约束不在中的方向上移动

A more general case: no change is allowed in direction p

Modified Inverse Mass

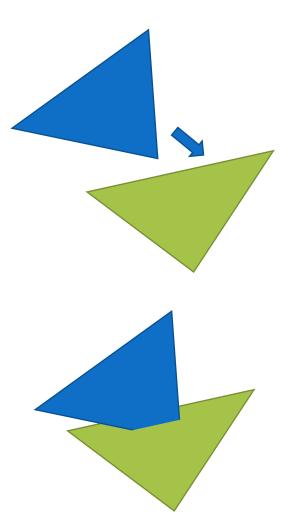
$$v_{n+1} = v_n + h \mathbf{M}^{-1} f$$

$$v_{n+1} = v_n + h \frac{1}{m} (I - pp^T - qq^T) f$$

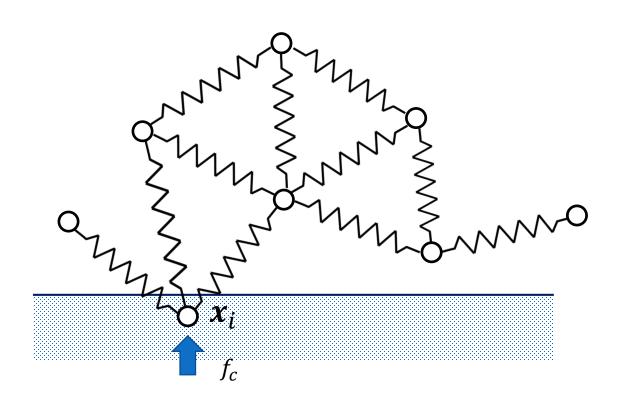
A more general case: no change is allowed in directions p and q

Contacts

- Contact handling is a BIG topic in simulation
 - Collision detection
 - Discrete Collision Detection (DCD)
 - Continuous Collision Detection (CCD)
 - Contact models
 - Penalty-based methods
 - Constraint-based methods

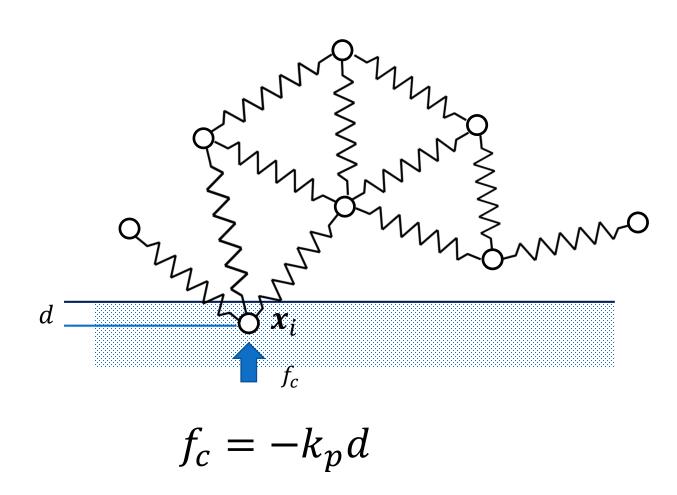


Penalty-based Methods

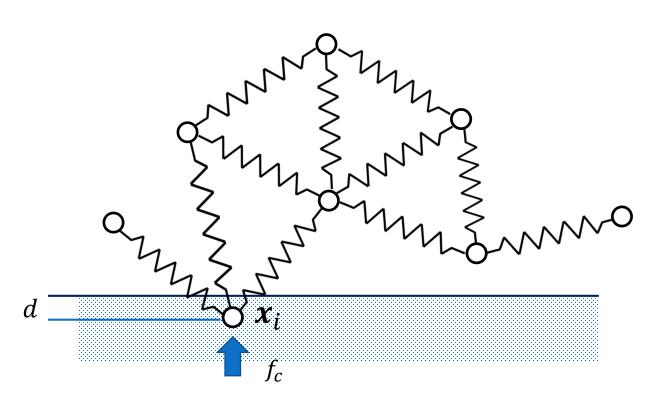


$$f_i = \sum_{j \in N(i)} f_{ij} + f_c$$

Penalty-based Methods



Penalty-based Methods



$$f_c = -k_p d - k_d v_i$$
 dang 能量扱耗

Any Questions?