Mass-Spring Systems

A Basic Tool for Modeling Deformable Objects

Part 2









Outline

- Numerical time integration (continued)
 - Explicit vs. Implicit Euler
 - Solving nonlinear systems: Newton's method
 - The semi-implicit Euler method
 - Solving sparse linear systems
 - Integration Schemes for higher order ODEs
- Towards practical mass spring systems
- Constraints



Mass-Spring Systems



Mass-Spring Systems

- Forces: elastic springs, point damping, gravity
- Dynamics: equations of motion, system of 2nd order ODEs
- **Temporal discretization**: solve 1st order ODE numerically

Numerical Time Integration

- Explicit methods: Euler, Heun, Midpoint, Runge-Kutta 4
- Criteria: accuracy, stability
- Model problem: test equation



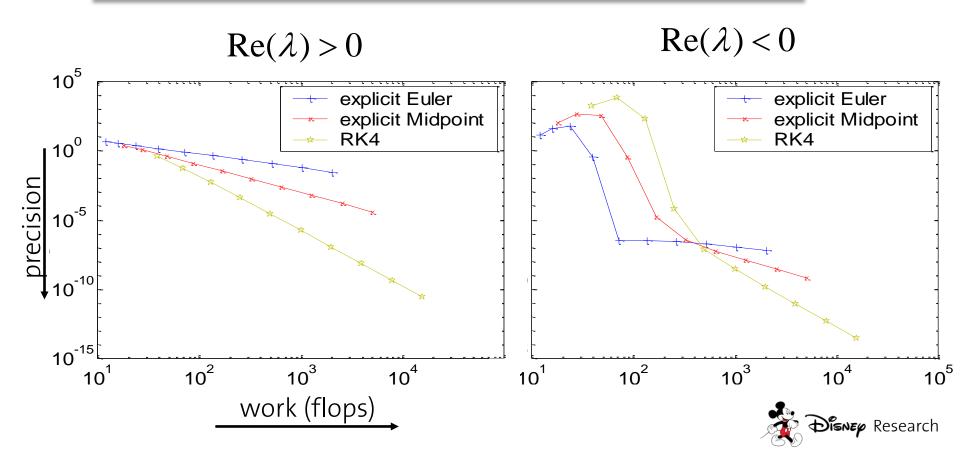
Explicit Methods

Test equation

$$y'(t) = \lambda y(t), \quad \lambda \in \mathbf{C}$$

Analytical solution

$$y(t) = e^{\lambda t} y_0$$



Stiff Problems

Observations from test equation: explicit methods

- require very small time steps for stable integration
- are inefficient since step size is determined by stability, not accuracy requirements

Problems with this characteristic are termed stiff

Don't use explicit methods for stiff problems, use *implicit* methods.



Implicit Euler

• Explicit Euler: step with slope at t_n

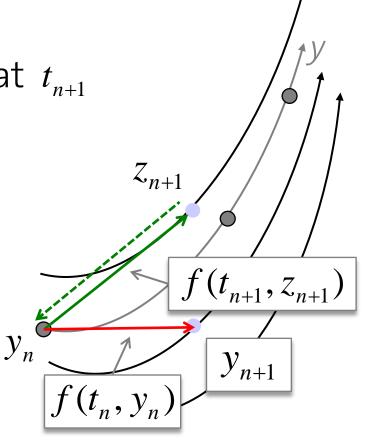
$$y_{n+1} = y_n + hf(t_n, y_n)$$

• Implicit Euler: step with slope at t_{n+1}

$$z_{n+1} = z_n + hf(t_{n+1}, z_{n+1})$$

A.k.a. Backward Euler

$$z_n = z_{n+1} - hf(t_{n+1}, z_{n+1})$$



Numerical Example

Harmonic Oscillator





Explicit vs. Implicit Euler

What about stability?

- Euler step for test equation $y' = \lambda y$, $\lambda < 0$
 - Explicit Euler $y_{n+1} = y_n + h\lambda y_n = y_n(1+h\lambda)$
 - Implicit Euler $y_{n+1} = y_n + h\lambda y_{n+1} = y_n (1 h\lambda)^{-1}$
- Stability conditions for Euler
 - Explicit $y_n = (1 + h\lambda)^n y_0 < \infty \Leftrightarrow |1 + h\lambda| < 1$
 - Implicit $y_n = (1 h\lambda)^{-n} y_0 < \infty \iff |1 h\lambda|^{-1} < 1$



Implicit Euler is stable for all h > 0!

Comparing Integration Schemes

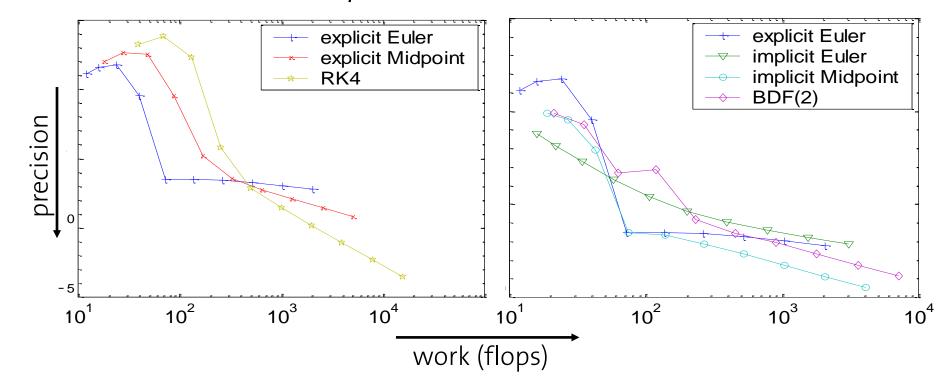
Test equation

$$y'(t) = \lambda y(t), \quad \lambda \in \mathbb{C}$$

Analytical solution

$$y(t) = e^{\lambda t} y_0$$

• $Re(\lambda) < 0$ (damped harmonic oscillator)



Explicit vs. Implicit Euler

Explicit Euler step

$$y_{n+1} = y_n + hf(t_n, y_n)$$

Implicit Euler step

$$y_{n+1} = y_n + hf(t_{n+1}, y_{n+1})$$

Why are these methods called like this?

- Explicit: all quantities are known (given explicitly)
- Implicit: y_{n+1} is unknown (given implicitly)

 \rightarrow solve (nonlinear) equation(s)!



Solving Nonlinear Equations

- Implicit Euler step $y_{n+1} = y_n + hf(t_{n+1}, y_{n+1})$
 - → solve nonlinear system of equations
- Why nonlinear?

1D Spring Force
$$F = -k(l-L)$$

$$F = -k(l-L)$$

3D Spring Force
$$\mathbf{F}_i = -k \left(\mathbf{x}_i - \mathbf{x}_j \right) - L \left(\mathbf{x}_i - \mathbf{x}_j \right)$$

$$\left(|\mathbf{x}| = \sqrt{x^2 + y^2 + z^2} \right)$$

→ linear material law, but nonlinear geometry

How do we solve nonlinear equations?



Outline

- Numerical time integration (continued)
 - Explicit vs. Implicit Euler
 - Solving nonlinear systems: Newton's method
 - The semi-implicit Euler method
 - Solving sparse linear systems
 - Integration Schemes for higher order ODEs
- Towards practical mass spring systems
- Constraints



Newton's Method

$$0 = y_{n+1} - y_n - hf(t_{n+1}, y_{n+1}) =: g(y_{n+1}) \qquad g(y_{n+1}) = 0$$

Solve

$$g(y_{n+1}) = 0$$

Make initial guess

$$\tilde{y}_{n+1} = y_n$$

Define

$$\Delta y = y_{n+1} - \tilde{y}_{n+1}$$

Taylor expansion

$$g(\tilde{y}_{n+1} + \Delta y) = g(\tilde{y}_{n+1}) + g'(\tilde{y}_{n+1}) \cdot \Delta y + O(\Delta y^2) = 0$$

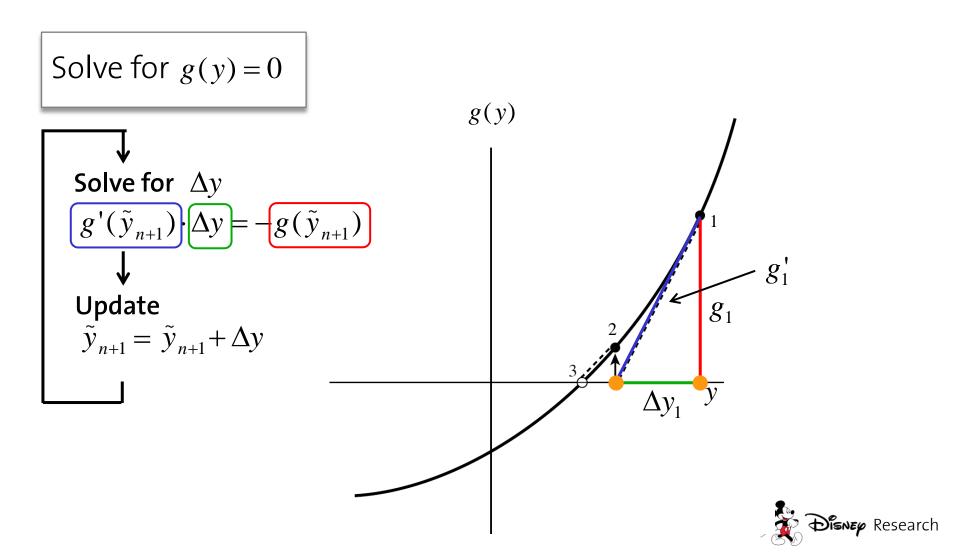
Linearize

$$g'(\tilde{y}_{n+1}) \cdot \Delta y = -g(\tilde{y}_{n+1})$$

Solve for
$$\Delta y$$
 Update — Compute error — $g'(\tilde{y}_{n+1}) \cdot \Delta y = -g(\tilde{y}_{n+1})$ $\tilde{y}_{n+1} = \tilde{y}_{n+1} + \Delta y$ $r = g(\tilde{y}_{n+1})$

Repeat until |r| small enough

Newton's Method Visually

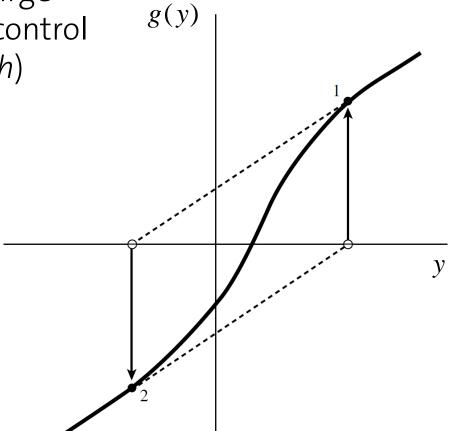


Newton's Method: Problems

Problem: step too large

Solution: step-size control

(line search)

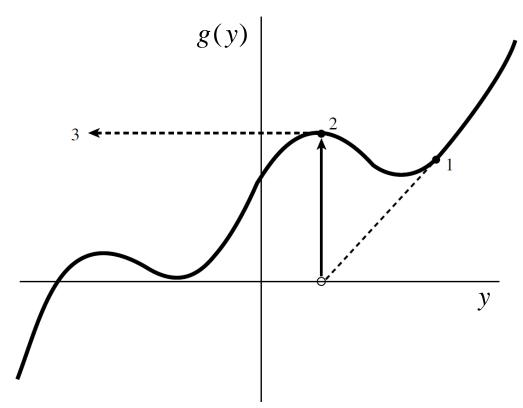




Newton's Method: Problems

Problem: q has local extrema or saddle points

Solution: problem-dependent (more difficult)

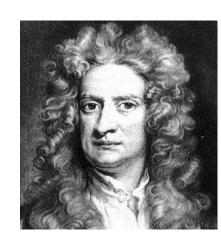




Newton's Method

Powerful, but has to be used with care

- Iterative method, requires solution of linear system in each iteration ← expensive
- Robust implementation needs advanced strategies (line search) ← expensive



Can we sidestep nonlinearities?



Outline - Part 1

- Recap of last lecture
- Numerical time integration (continued)
 - Explicit vs. implicit Euler revisited
 - Solving nonlinear systems: Newton's method
 - The semi-implicit Euler method
 - Solving sparse linear systems
 - Integration Schemes for higher order ODEs



Semi-Implicit Euler

Implicit Euler
$$\mathbf{v}(t_i + h) = \mathbf{v}(t_i) + h \cdot \mathbf{M}^{-1}\mathbf{F}(t_i + h)$$
$$\mathbf{x}(t_i + h) = \mathbf{x}(t_i) + h \cdot \mathbf{v}(t_i + h)$$
Forces
$$\mathbf{F}(t_i + h) = \mathbf{F}(\mathbf{x}(t_i + h), \mathbf{v}(t_i + h))$$

Semi-implicit: linearize forces at current state

$$\mathbf{F}(t_i + h) \approx \mathbf{F}(t_i) + \frac{\partial \mathbf{F}}{\partial \mathbf{x}} \bigg|_{t=t_i} \cdot \left(\mathbf{x}(t_i + h)_i - \mathbf{x}(t_i) \right) + \frac{\partial \mathbf{F}}{\partial \mathbf{v}} \bigg|_{t=t_i} \cdot \left(\mathbf{v}(t_i + h) - \mathbf{v}(t_i) \right) + \frac{\partial \mathbf{F}}{\partial t} \bigg|_{t=t_i} \cdot h$$

$$\frac{\partial \mathbf{F}}{\partial \mathbf{x}}$$
, $\frac{\partial \mathbf{F}}{\partial \mathbf{v}}$ are (3nx3n) Jacobian matrices (derivatives of a vector w.r.t. a vector)



Semi-Implicit Euler

For mass-spring systems

- $\frac{\partial \mathbf{F}}{\partial \mathbf{x}}$ is given by the spring force
- $\frac{\partial \mathbf{F}}{\partial \mathbf{v}}$ is given by the damping force
- $\frac{\partial \mathbf{F}}{\partial t}$ is typically zero (no time-dependent forces)

For exercise

• Task 1: derive Jacobians for a 1-DoF mass-spring system

Semi-Implicit Euler

- Substitute $\mathbf{F}(t_i + h)$ with linearized expression
- Substitute $\mathbf{x}(t_i + h) = \mathbf{x}(t_i) + h \cdot \mathbf{v}(t_i + h)$ in linearized force

$$\mathbf{v}(t_i + h) = \mathbf{v}(t_i) + h\mathbf{M}^{-1} \left(\mathbf{F}(t_i) + h \frac{\partial \mathbf{F}}{\partial \mathbf{x}} \cdot \mathbf{v}(t_i + h) + \frac{\partial \mathbf{F}}{\partial \mathbf{v}} \cdot [\mathbf{v}(t_i + h) - \mathbf{v}(t_i)] \right)$$

Linear system to solve (multiplied by M)

$$\left(\mathbf{M} - h\frac{\partial \mathbf{F}}{\partial \mathbf{v}} - h^2 \frac{\partial \mathbf{F}}{\partial \mathbf{x}}\right) \mathbf{v}(t_i + h) = \left(\mathbf{M} - h\frac{\partial \mathbf{F}}{\partial \mathbf{v}}\right) \cdot \mathbf{v}(t_i) + h\mathbf{F}(t_i)$$

Matrix Structure

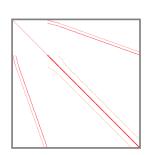
The matrix **A** has a special structure. **A** is

- blocked: (3x3)-blocks relate 3D forces to 3D positions
- sparse: block A_{ij} is only nonzero if i = j or if there is a spring between nodes i and j (-> most entries are zero)
- *symmetric*: force Jacobian is related to Hessian of Energy

$$\frac{\partial^2 E}{\partial \mathbf{x}_i \partial \mathbf{x}_j} = \frac{\partial^2 E}{\partial \mathbf{x}_j \partial \mathbf{x}_i}$$

#v:1448







Outline

- Numerical time integration (continued)
 - Explicit vs. Implicit Euler
 - Solving nonlinear systems: Newton's method
 - The semi-implicit Euler method
 - Solving sparse linear systems
 - Integration Schemes for higher order ODEs
- Towards practical mass spring systems
- Constraints



Solving Sparse Linear Systems

Solve $\mathbf{A}\mathbf{v} = \mathbf{b}$ with direct or iterative methods.

Direct methods

- Factorize $\mathbf{A} = \mathbf{L}\mathbf{L}^t$, with \mathbf{L} lower triangular
- Solve $\mathbf{L}\mathbf{L}^t\mathbf{v} = \mathbf{b}$ via two triangular solves,

$$\mathbf{L}\mathbf{u} = \mathbf{b}, \qquad \mathbf{L}^t \mathbf{v} = \mathbf{u}$$

- + Robust, accuracy to numerical precision
- + Factorization can be reused for different **b**
- Memory requirements L (limits problem size)

Cholesky decomposition

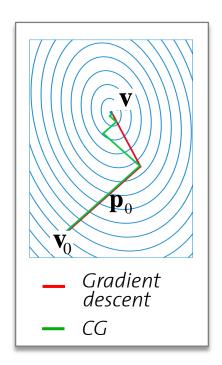


Solving Sparse Linear Systems

Solve $\mathbf{A}\mathbf{v} = \mathbf{b}$ with direct or iterative methods.

Iterative methods

- Jacobi & Gauss-Seidel
 - solve system row by row
 - simple but slow convergence
- Conjugate Gradients
 - minimize $\frac{1}{2} \mathbf{v}^t \mathbf{A} \mathbf{v} \mathbf{v}^t \mathbf{b}$ via sequence of conjugate corrections \mathbf{p}_k , where $\mathbf{p}_i^t \mathbf{A} \mathbf{p}_j = 0$
 - Fast convergence, low memory requirements





Example: Baraff & Witkin '98

[BW98]: cloth animation with semi-Implicit Euler (SIE)

- Cast time integration as a linear problem, $\mathbf{A} \cdot \mathbf{v}(t_i + h) = \mathbf{b}$
- Solve linear system with conjugate gradients







- A step of SIE is far more expensive than explicit Euler
- Better stability of SIE allows (*very*) large time steps, $h\approx 0.01s$ vs. $h\approx 0.0001s$ → much higher performance!



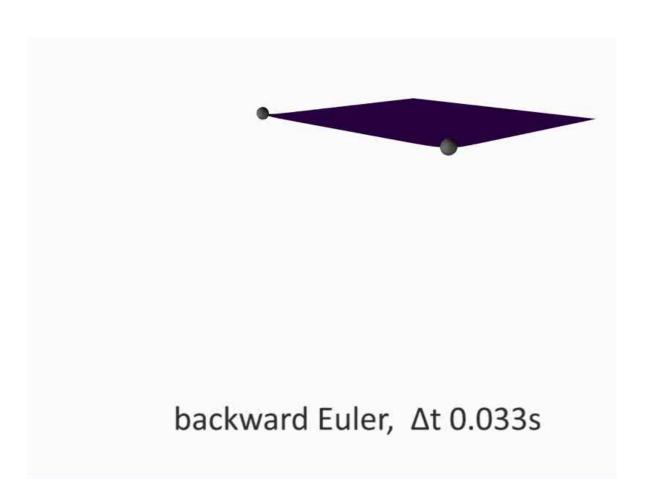
Example: Baraff & Witkin '98

Limitations

- Unconditional stability only for truly linear problems
- 'Semi'-implicit variant leads to severe numerical dissipation (video)



Numerical Dissipation





Example: Baraff & Witkin '98

Limitations

- Unconditional stability only for truly linear problems
- 'Semi'-implicit variant leads to severe numerical dissipation (video)

Alternatives

- Solve full nonlinear equations
- Use more accurate implicit schemes
 - \rightarrow more expensive (in most cases)!



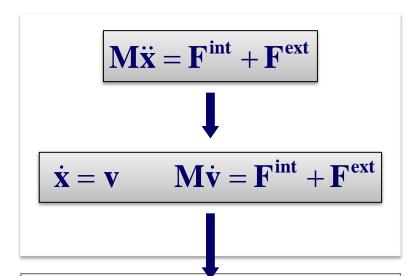
Outline - Part 1

- Recap of last lecture
- Numerical time integration (continued)
 - Explicit vs. implicit Euler revisited
 - Solving nonlinear systems: Newton's method
 - The semi-implicit Euler method
 - Solving sparse linear systems
 - Integration Schemes for higher order ODEs



Higher-Order Numerical Integration

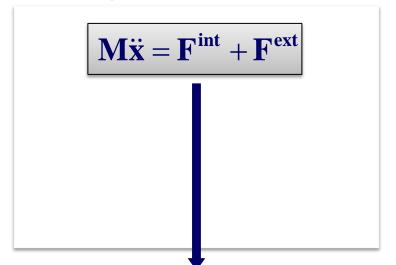
Methods for 1st order ODEs



1st order ODE solver

- Euler, Heun, Midpoint, Runge-Kutta schemes
- Implicit Euler

Methods for higher order ODEs



Higher order ODE solver

- Verlet, Leapfrog,
 Symplectic Euler
- Newmark

Verlet Integration

Combine forward and backward expansions of $\mathbf{x}(t)$

$$\mathbf{x}(t+h) = \mathbf{x}(t) + h\mathbf{x}'(t) + \frac{h^2}{2}\mathbf{a}(t) + \frac{h^3}{6}\mathbf{x}'''(t) + O(h^4)$$

$$\mathbf{x}(t-h) = \mathbf{x}(t) - h\mathbf{x}'(t) + \frac{h^2}{2}\mathbf{a}(t) - \frac{h^3}{6}\mathbf{x}'''(t) + O(h^4)$$

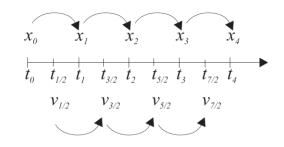
$$\mathbf{v}(t+h) = 2\mathbf{x}(t) - \mathbf{x}(t-h) + h^2\mathbf{a}(t) + O(h^4)$$

- + 2nd order accurate with only one force evaluation
- Two-step method problematic for discontinuities
- Velocities have to be approximated a posteriori

Leapfrog

Compute velocities on staggered grid

Leapfrog
$$\mathbf{v}(t+h/2) = \mathbf{v}(t-h/2) + h \cdot \mathbf{a}(t)$$
$$\mathbf{x}(t+h) = \mathbf{x}(t) + h \cdot \mathbf{v}(t+h/2)$$



- + 2nd order accurate and only one force evaluation
- + One-step method
- Only applicable if a(t) does not depend on velocity → no damping!



Symplectic Euler

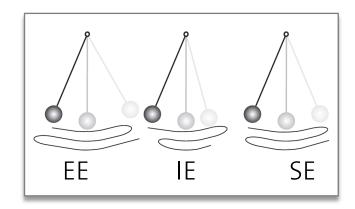
Symplectic Euler (SE) $\mathbf{v}(t+h) = \mathbf{v}(t) + h \cdot \mathbf{a}(t)$ $\mathbf{x}(t+h) = \mathbf{x}(t) + h \cdot \mathbf{v}(t+h)$

Leapfrog
$$\mathbf{v}(t+h/2) = \mathbf{v}(t-h/2) + h \cdot \mathbf{a}(t)$$
$$\mathbf{x}(t+h) = \mathbf{x}(t) + h \cdot \mathbf{v}(t+h/2)$$

- Only 1st order accurate, but
- Good stability for oscillatory motion
- Good conservation properties
 - Exactly conserves momentum
 - Nearly conserves energy over long run times

(unlike EE)

(unlike IE)



Outline – Part 2

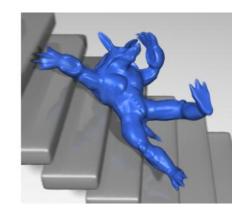
- Towards practical Mass-spring simulations
 - Collision handling
 - Setting up springs for solids and cloth
 - Limitations of mass-spring systems
- Constraints
 - Motivation and definitions
 - Soft constraints and the penalty method
 - Hard constraints
 - Examples



Where We Are...

- Basic mass-spring system
 - Elastic spring forces, point damping
 - Explicit and implicit time stepping

What else do we need to simulate cloth and solids?



- Handle collisions
- Set up springs
- **–** ...

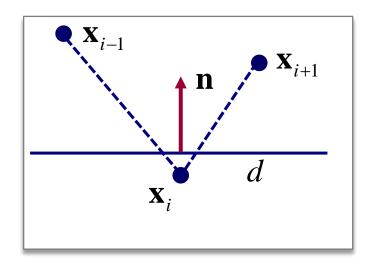




Simple Collision Handling

Details follow in class on Collision Detection and Response (November 21st)

For exercise: Handle collisions between particles and a plane.



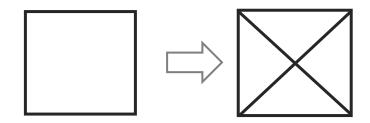
- 1. Step forward in time
- 2. Find particles that are below plane
- 3. For each, set up spring force
 - proportional to penetration depth d
 - in direction of normal n
- 4. Add penalty force in next time step



Setting Up Springs: Solids

Model provided as tetrahedral mesh?

- Yes: springs along edges
- No: find stable topology (shearing)



Problems

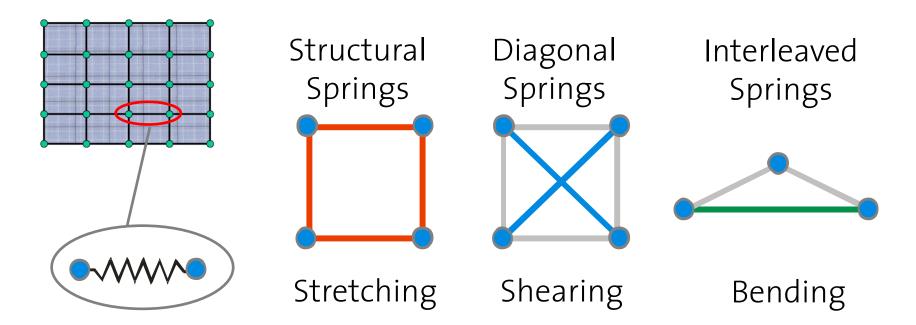
- No control over material properties
- No explicit volume preservation



6888 springs

Setting Up Springs: Cloth

What types of springs are required?

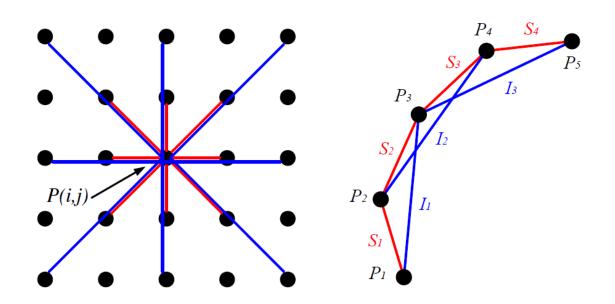




Setting Up Springs: Cloth

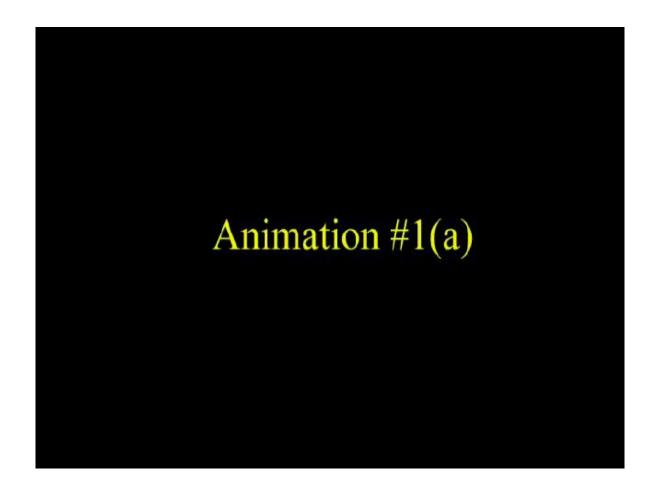
Red: stretch and shear springs

Blue: bending springs





Choi & Ko '02





Choi & Ko '02

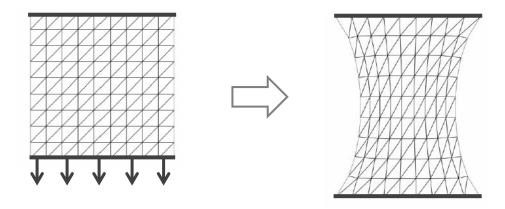




Problems

Springs couple different deformation modes

- Bending and shear springs respond to stretch
- Leads to uncontrollable transverse contraction

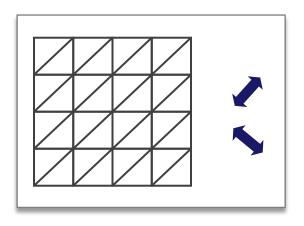




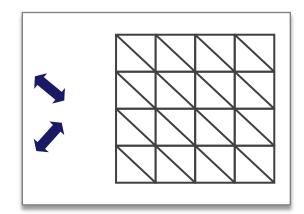
Problems

Material behavior depends strongly on topology.

→ direction-dependent behavior!



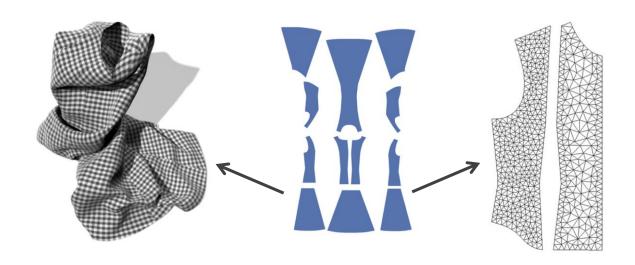
high resistance low resistance





Problems

Curved boundaries require triangle meshes. How to distinguish between stretch and shear?





Mass-Spring Systems

Limitations

- Strong dependence on discretization (topology)
- Limited control over material behavior
- No (explicit) volume preservation (for solids)

Verdict

Simple and efficient, but not very accurate

Alternatives:

- Constraints (next)
- Continuum-mechanics with Finite Elements (November 7th)

Outline – Part 2

- Towards practical Mass-spring simulations
 - Collision handling
 - Setting up springs for solids and cloth
 - Limitations of mass-spring systems
- Constraints
 - Motivation and definitions
 - Soft constraints and the penalty method
 - Hard constraints
 - Examples



Constraints: Motivation

- So far: motion of particles defined by forces
 - Elastic springs, damping, gravity, ...
- Motion is unrestricted (just apply enough force)
- Want to restrict motion sometimes → Condition
 - Bead on a wire (constant length)
 - Incompressible deformations (constant volume)
- Constraints can be used
 - to strictly enforce conditions (unlike elastic forces)
 - to derive general forces (unlike springs)

Constraints: Definition

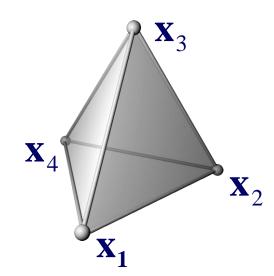
A constraint $C(\mathbf{x}_1,...,\mathbf{x}_n)$ is

- a scalar-valued function of one or several arguments
- an implicit expression for a relation that must hold between its arguments

Convention: a constraint is satisfied if C = 0

Examples of *n*-ary constraints

- constant position $C_1(\mathbf{x}_1)$
- constant length $C_2(\mathbf{x}_1,\mathbf{x}_2)$
- constant area $C_3(\mathbf{x}_1,\mathbf{x}_2,\mathbf{x}_3)$
- constant volume $C_4(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4)$



Outline - Part 2

- Towards practical Mass-spring simulations
 - Collision handling
 - Setting up springs for solids and cloth
 - Limitations of mass-spring systems
- Constraints
 - Motivation and definitions
 - Soft constraints and the penalty method
 - Hard constraints
 - Examples



Penalty Forces

How can we enforce constraints?

Define potential energy for constraint

$$E_C(\mathbf{x}_1,...,\mathbf{x}_n) = \frac{1}{2}kC(\mathbf{x}_1,...,\mathbf{x}_n)^2$$
 k is stiffness coefficient

$$\rightarrow E_C = 0$$
 when constraint met, $E_C > 0$ otherwise

Constraint Force is negative gradient of potential energy

$$\mathbf{F}_{j} = -\frac{\partial E_{C}}{\partial \mathbf{x}_{j}} = -kC(\mathbf{x}_{1},...,\mathbf{x}_{n}) \frac{\partial C(\mathbf{x}_{1},...,\mathbf{x}_{n})}{\partial \mathbf{x}_{j}}$$

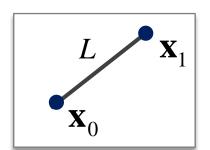


Penalty force, pulls system towards C=0

Example: Distance Preservation

Preserve distance between two points

$$C(\mathbf{x}_0, \mathbf{x}_1) = |\mathbf{x}_1 - \mathbf{x}_0| - L$$



• Constraint force on \mathbf{x}_1 follows as

$$\mathbf{F}_{1}^{C}(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$= -k(|\mathbf{x}_{1} - \mathbf{x}_{0}| - L) \frac{\mathbf{x}_{1} - \mathbf{x}_{0}}{|\mathbf{x}_{1} - \mathbf{x}_{0}|}$$

$$= -k(|\mathbf{x}_{1} - \mathbf{x}_{0}| - L) \frac{\mathbf{x}_{1} - \mathbf{x}_{0}}{|\mathbf{x}_{1} - \mathbf{x}_{0}|}$$

$$\Rightarrow -k(|\mathbf{x}_{1} - \mathbf{x}_{0}| - L) \frac{\mathbf{x}_{1} - \mathbf{x}_{0}}{|\mathbf{x}_{1} - \mathbf{x}_{0}|}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$= -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

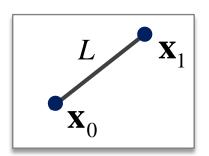
$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$

$$\Rightarrow -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{1}}$$



Simulation with Penalty Forces

• Simulate \mathbf{x}_0 and \mathbf{x}_1 using Newton's law (no spring force!)



Enforce distance constraint with penalty forces

$$\mathbf{F}_{i}^{C}(\mathbf{x}_{0}, \mathbf{x}_{1}) = -kC(\mathbf{x}_{0}, \mathbf{x}_{1}) \frac{\partial C(\mathbf{x}_{0}, \mathbf{x}_{1})}{\partial \mathbf{x}_{i}}$$

Step forward in time (explicit Euler)

$$\mathbf{v}_{n+1} = \mathbf{v}_n + h\mathbf{M}^{-1} \Big(\mathbf{F}^C(\mathbf{x}) + \mathbf{F}^{ext} \Big)$$



More Constraints

- Recipe for constraint forces
 - Define constraint via geometric condition
 - Set up energy and compute gradient (chain rule)
- Preserve area A of triangle $(\mathbf{x}_0, \mathbf{x}_1, \mathbf{x}_2)$

$$C(\mathbf{x_0}, \mathbf{x_1}, \mathbf{x_2}) = \frac{1}{2} |(\mathbf{x_1} - \mathbf{x_0}) \times (\mathbf{x_2} - \mathbf{x_0})| - A$$

• Preserve volume V of tetrahedron $(\mathbf{x}_0, \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3)$

$$C(\mathbf{x_0, x_1, x_2, x_3}) = \frac{1}{6}(\mathbf{x_1 - x_0}) \cdot [(\mathbf{x_2 - x_0}) \times (\mathbf{x_3 - x_0})] - V$$

Constraint Forces

Constraint forces are

- a powerful mechanism to enforce various conditions
- generic: express condition, forces from standard scheme
- n-ary forces as opposed to binary springs

However, constraints can be

- computationally expensive (implicit integration?)
- redundant or conflicting
- penalty forces model soft constraints, not sufficient for strict enforcement (hard constraints)

Outline - Part 2

- Towards practical Mass-spring simulations
 - Collision handling
 - Setting up springs for solids and cloth
 - Limitations of mass-spring systems
- Constraints
 - Motivation and definitions
 - Soft constraints and the penalty method
 - Hard constraints
 - Examples



Hard Constraints

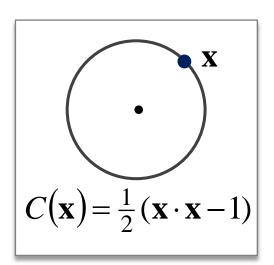
How can we model a hard constraint?

- Consider 2D particle constrained to move on unit circle
- Define legal kinematics

- position
$$C(\mathbf{x}) = 0$$

- velocity
$$\dot{C}(\mathbf{x}) = 0$$

- acceleration
$$\ddot{C}(\mathbf{x}) = 0$$



Idea: start with legal position and velocity, ensure that acceleration remains legal (constraint forces!)



Computing Constraint Forces

Legal acceleration (1)

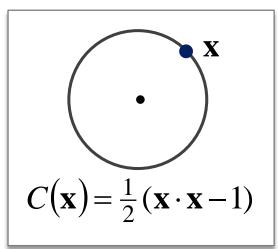
$$\ddot{C}(\mathbf{x}) = \ddot{\mathbf{x}} \cdot \mathbf{x} + \dot{\mathbf{x}} \cdot \dot{\mathbf{x}} = 0$$

Newton's Law

$$\ddot{\mathbf{x}} = \frac{\mathbf{F} + \mathbf{F}^C}{m} \quad (2)$$

• Use (2) in (1)

$$\mathbf{F}^{C} \cdot \mathbf{x} = -\mathbf{F} \cdot \mathbf{x} - m\dot{\mathbf{x}} \cdot \dot{\mathbf{x}} \quad (3)$$



 Require constraint force to act only in gradient direction

$$\mathbf{F}^{C} = \lambda \frac{\partial C}{\partial \mathbf{x}} = \lambda \mathbf{x} \quad (4)$$

• Use (4) in (3)

$$\lambda = -\frac{\mathbf{F} \cdot \mathbf{x} + m\dot{\mathbf{x}} \cdot \dot{\mathbf{x}}}{\mathbf{x} \cdot \mathbf{x}}$$



hard constraint force!

Simulation with Hard Constraints

Use hard constraints with, e.g., explicit Euler

- 1. Solve (LES) for constraint force magnitudes λ_n
- 2. Compute constraint forces $\mathbf{F}_n^C = \frac{\partial C(\mathbf{X}_n)}{\partial \mathbf{X}}^t \lambda_n$
- 3. Step forward in time $\mathbf{v}_{n+1} = \mathbf{v}_n + h\mathbf{M}^{-1}(\mathbf{F}_n^C + \mathbf{F}^{ext})$

Note: using implicit integration with constraints is (much) more complicated!



Hard Constraints

Hard constraint forces

- add just enough force to maintain constraint (exactly)
- require no high stiffness (numerically pleasing)

However,

- Constraints drift (error in ODE solve), needs correction
- General formulation (many constraints) more involved
- Requires solution of systems of equations

A. Witkin and D. Baraff. *Physically-Based Modeling:* Constrained Dynamics. In Siggraph '01 Course Notes.

References & Further Reading

Textbooks (check with library)

 W. Press, S. Teukolsky, W. Vetterling, and B. Flannery: Numerical Recipes. The Art of Scientific Computing. 3rd edition, Cambridge University Press, 2007.

Articles (available from lecture website)

- D. Baraff and A. Witkin. Large Steps in Cloth Simulation.
 In Siggraph '98.
- A. Witkin and D. Baraff. Physically-Based Modeling: Constrained Dynamics. In Siggraph '01 Course Notes.

