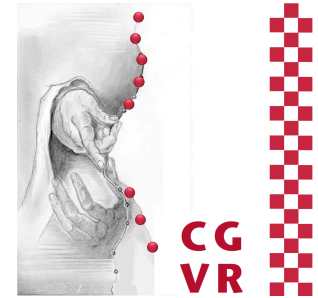
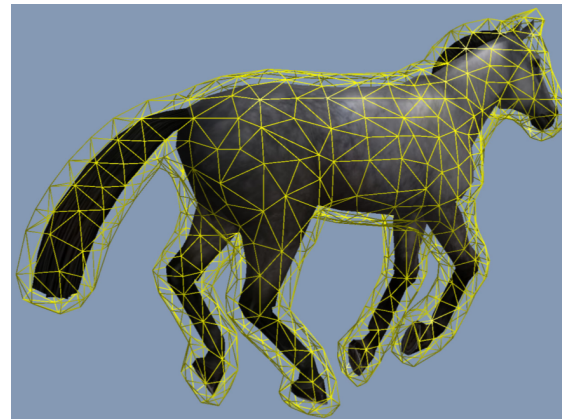


Bremen



Virtual Reality & Physically-Based Simulation Mass-Spring-Systems



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1. Law (law of inertia):

A body, which no forces act upon, continues to move with constant velocity.

- A resting body is just a special case of this law.

2. Law (law of action):

If a force \mathbf{F} acts on a body with mass m , then the body accelerates, and its acceleration is given by

$$\mathbf{F} = m \cdot \mathbf{a}$$

- In other words: force and acceleration are **proportional** to each other; (the proportionality factor happens to be m). In particular, both force and acceleration have the same direction.

3. Law (law of reaction):

If a force \mathbf{F} , that acts on a body, is extended to another body,
Then the opposite force $-\mathbf{F}$ acts on that other body.

- In school, you learn: "action= reaction"

4. Law (law of superposition):

If a number of forces $\mathbf{F}_1, \dots, \mathbf{F}_n$ act on a point or body, then they
can be accumulated by vector addition yielding one resulting
force:

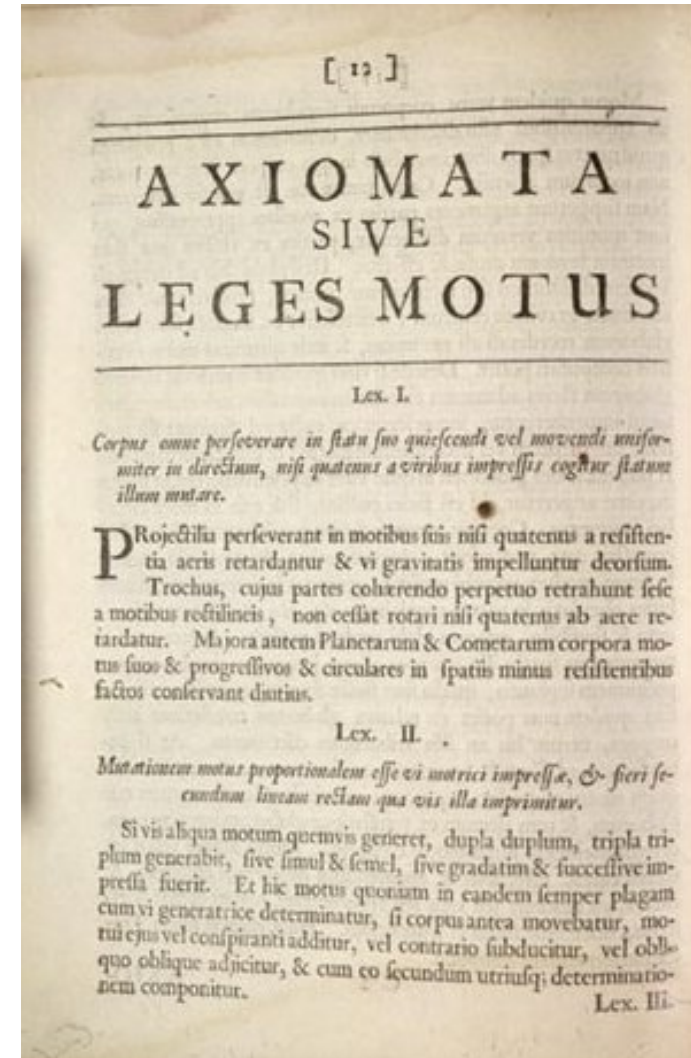
$$\mathbf{F} = \mathbf{F}_1 + \dots + \mathbf{F}_n .$$

- Newton published these laws in his original book

Principia Mathematica

(1687):

- *Lex I. Corpus omne perseverare in statu suo quiescendi vel movendi uniformiter in directum, nisi quatenus illud a viribus impressis cogitur statum suum mutare.*
- *Lex II. Mutationem motus proportionalem esse vi motrici impressae, et fieri secundum lineam rectam qua vis illa imprimitur.*



- Definition:

A **mass-spring system** is a system consisting of:

1. A set of point masses m_i with positions \mathbf{x}_i and velocities $\mathbf{v}_i, i = 1 \dots N$;
2. A set of springs $s_{ij} = (i, j, k_s, k_d)$, where s_{ij} connects masses i and j , with rest length l_0 , spring constant k_s (= stiffness) and the damping coefficient k_d

- Advantages:

- Very easy to program
- Ideally suited to study different kinds of solving methods
- *Ubiquitous in games* (cloths, capes, sometimes also for deformable objects)

- Disadvantages:

- Some parameters (in particular the spring constants) are **not obvious, i.e.**, difficult to derive
- No built-in volumetric effects (e.g., preservation of volume)

A Single Spring (Plus Damper)

- Given: masses m_i and m_j with positions \mathbf{x}_i , \mathbf{x}_j

- Let $\mathbf{r}_{ij} = \frac{\mathbf{x}_j - \mathbf{x}_i}{\|\mathbf{x}_j - \mathbf{x}_i\|}$

- The force between particles i and j :

- Force extended by spring (Hooke's law):

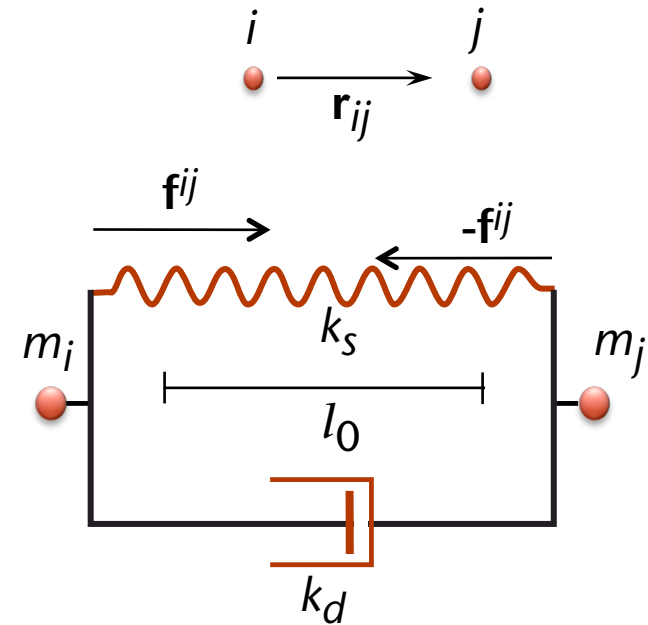
$$\mathbf{f}_s^{ij} = k_s \mathbf{r}_{ij} (\|\mathbf{x}_j - \mathbf{x}_i\| - l_0)$$

acts on mass m_i in direction of m_j

- Force extended by damper : $\mathbf{f}_d^{ij} = k_d ((\mathbf{v}_j - \mathbf{v}_i) \cdot \mathbf{r}_{ij}) \mathbf{r}_{ij}$

- Sum of forces : $\mathbf{f}^{ij} = \mathbf{f}_s^{ij} + \mathbf{f}_d^{ij}$

- Force on m_j : $\mathbf{f}^{ji} = -\mathbf{f}^{ij}$



- Notice: from (4) follows that the **momentum is conserved**
 - I.e., the kinetic energy is conserved
 - Momentum = velocity × mass = $\mathbf{v} \cdot m$
- Note on terminology:
 - German "**Kraftstoß**" = English "**Impulse**" = force × time
 - German "**Impuls**" = English "**momentum**" = force × mass
- Alternative Federkraft: $\mathbf{f}_s^{ij} = k_s \mathbf{r}_{ij} \frac{\|\mathbf{x}_j - \mathbf{x}_i\| - l_0}{l_0}$
- A spring-damper element in reality:



Simulation of a Single Spring

- From Newton's law, we have: $\ddot{\mathbf{x}} = \frac{1}{m} \mathbf{f}$
- Convert differential equation (DE) of order 2 into DE of order 1:

$$\dot{\mathbf{v}}(t) = \frac{1}{m} \mathbf{f}(t)$$

$$\dot{\mathbf{x}}(t) = \mathbf{v}(t)$$

- Initial values (boundary values): $\mathbf{v}(t_0) = \mathbf{v}_0$, $\mathbf{x}(t_0) = \mathbf{x}_0$
- "Simulation" = "Integration of DE's over time"
- By Taylor expansion we get:

$$\mathbf{x}(t + \Delta t) = \mathbf{x}(t) + \Delta t \dot{\mathbf{x}}(t) + O(\Delta t^2)$$

- Analogously: $\mathbf{v}(t + \Delta t) = \mathbf{v}(t) + \Delta t \dot{\mathbf{v}}(t)$

→ This integration scheme is called **explicit Euler integration**


```
forall particles  $i$  :  
    initialize  $\mathbf{x}_i, \mathbf{v}_i, m_i$   
  
loop forever:  
    forall particles  $i$  :  
         $\mathbf{f}_i \leftarrow \mathbf{f}^g + \mathbf{f}_i^{coll} + \sum_{j, (i,j) \in \mathcal{S}} \mathbf{f}(\mathbf{x}_i, \mathbf{v}_i, \mathbf{x}_j, \mathbf{v}_j)$   
  
        forall particles  $i$  :  
             $\mathbf{v}_i += \Delta t \cdot \frac{\mathbf{f}_i}{m_i}$   
             $\mathbf{x}_i += \Delta t \cdot \mathbf{v}_i$   
  
    render system every  $n$ -th time
```

\mathbf{f}^g = gravitational force

\mathbf{f}^{coll} = penalty force exerted by collision (e.g., with obstacles)

- Advantages:
 - Can be implemented very easily
 - Fast execution per time step
- Disadvantages:
 - Stable only for very small time steps
 - Typically $\Delta t \approx 10^{-4} \dots 10^{-3}$ sec!
 - With large time steps, additional energy is generated "out of thin air", until the system explodes 😊
 - Example: overshooting when simulating a single spring
 - Errors accumulate quickly

Example for the Instability of Euler Integration

- Consider the differential equation

$$\dot{x}(t) = -kx(t)$$

- The exact solution:

$$x(t) = x_0 e^{-kt}$$

- Euler integration does this:

$$x^{t+1} = x^t + \Delta t(-kx^t)$$

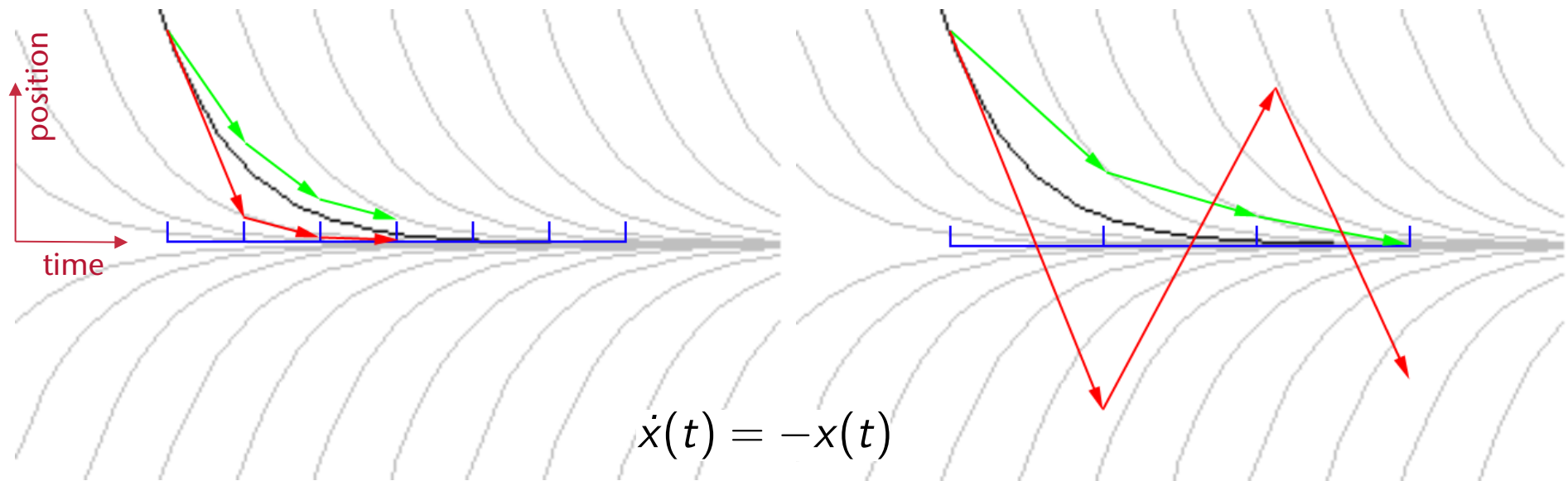
- Case $\Delta t > \frac{1}{k}$:

$$x^{t+1} = x^t \underbrace{(1 - k\Delta t)}_{<0}$$

$\Rightarrow x^t$ oscillates about 0, but approaches 0 (hopefully)

- Case $\Delta t > \frac{2}{k}$: $\Rightarrow x^t \rightarrow \infty$!

■ Visualization:



- Terminology: if k is large \rightarrow the DE is called "*stiff*"
 - The stiffer the DE, the smaller Δt has to be

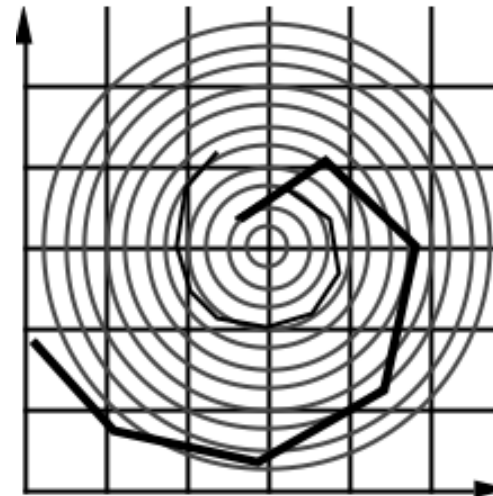
- Consider this DE:

$$\dot{\mathbf{x}}(t) = \begin{pmatrix} -x_2 \\ x_1 \end{pmatrix}$$

- Exact solution:

$$\mathbf{x}(t) = \begin{pmatrix} r \cos(t + \phi) \\ r \sin(t + \phi) \end{pmatrix}$$

- The solution by Euler integration moves in spirals outward, no matter how small Δt !
- Conclusion: Euler integration accumulates errors, no matter how small Δt !

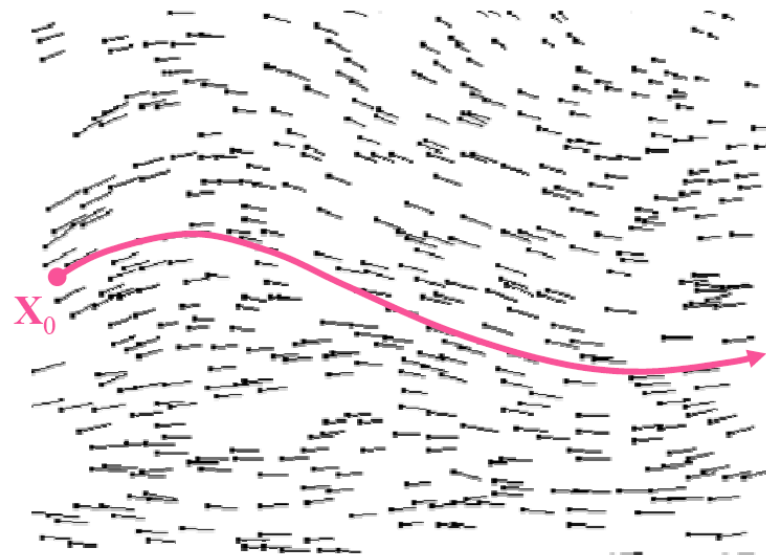


Visualization of Differential Equations

- The general form of a DE:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), t)$$

- Visualization of \mathbf{f} as a vector field:



- Notice: this vector field can vary over time!
- Solution of a boundary value problem = path through this field

- Runge-Kutta of order 2:

- Idea: approximate $f(\mathbf{x}(t), t)$ by a quadratic function that is defined at positions $\mathbf{x}(t)$, $\mathbf{x}(t + \frac{1}{2}\Delta t)$ and $\mathbf{v}(t)$
- The integrator (w/o proof):

$$\mathbf{a}_1 = \mathbf{v}^t \qquad \mathbf{a}_2 = \frac{1}{m} \mathbf{f}(\mathbf{x}^t, \mathbf{v}^t)$$

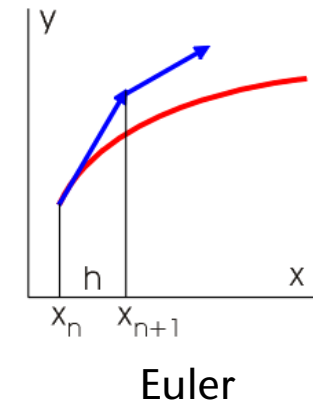
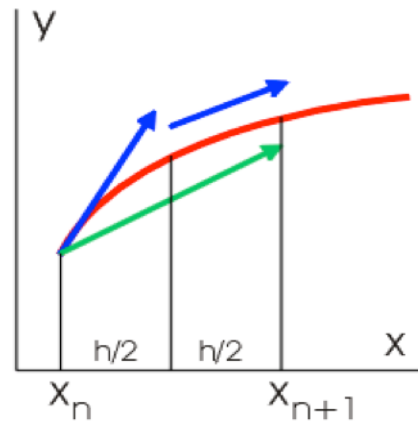
$$\mathbf{b}_1 = \mathbf{v}^t + \frac{1}{2} \Delta t \mathbf{a}_2 \qquad \mathbf{b}_2 = \frac{1}{m} \mathbf{f}\left(\mathbf{x}^t + \frac{1}{2} \Delta t \mathbf{a}_1, \mathbf{v}^t + \frac{1}{2} \Delta t \mathbf{a}_2\right)$$

$$\mathbf{x}^{t+1} = \mathbf{x}^t + \Delta t \mathbf{b}_1 \qquad \mathbf{v}^{t+1} = \mathbf{v}^t + \Delta t \mathbf{b}_2$$

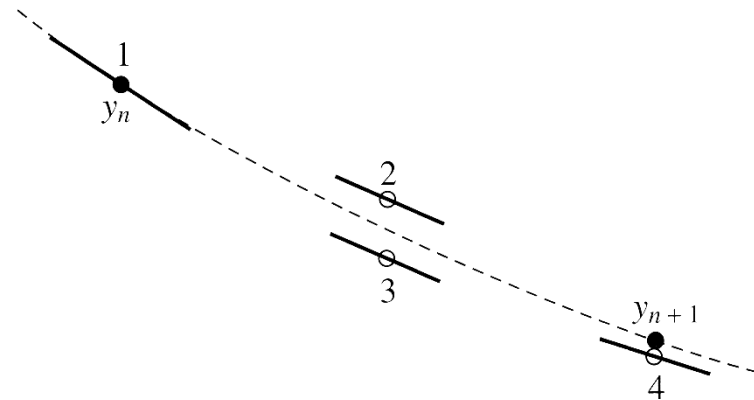
- Runge-Kutta of order 4:

- The standard integrator among the explicit integration schemata
- Needs 4 function evaluations (i.e., force computations) per time step
- Order of convergence is: $e(\Delta t) = O(\Delta t^4)$

- Runge-Kutta of order 2:



- Runge-Kutta of order 4:



- A general, alternative method to increase the order of convergence: utilizes values from **history**
- Verlet: utilize $\mathbf{x}(t - \Delta t)$
- Derivation:
 - Develop the Taylor series in both time directions:

$$\mathbf{x}(t + \Delta t) = \mathbf{x}(t) + \Delta t \dot{\mathbf{x}}(t) + \frac{1}{2} \Delta t^2 \ddot{\mathbf{x}}(t) + \frac{1}{6} \Delta t^3 \dddot{\mathbf{x}}(t) + O(\Delta t^4)$$

$$\mathbf{x}(t - \Delta t) = \mathbf{x}(t) - \Delta t \dot{\mathbf{x}}(t) + \frac{1}{2} \Delta t^2 \ddot{\mathbf{x}}(t) - \frac{1}{6} \Delta t^3 \dddot{\mathbf{x}}(t) + O(\Delta t^4)$$

- Add both:

$$\mathbf{x}(t + \Delta t) + \mathbf{x}(t - \Delta t) = 2\mathbf{x}(t) + \Delta t^2 \ddot{\mathbf{x}}(t) + O(\Delta t^4)$$

$$\mathbf{x}(t + \Delta t) = 2\mathbf{x}(t) - \mathbf{x}(t - \Delta t) + \Delta t^2 \ddot{\mathbf{x}}(t) + O(\Delta t^4)$$

- Initialization:

$$\mathbf{x}(\Delta t) = \mathbf{x}(0) + \Delta t \mathbf{v}(0) + \frac{1}{2} \Delta t^2 \left(\frac{1}{m} \mathbf{f}(\mathbf{x}(0), \mathbf{v}(0)) \right)$$

- Remark: the velocity does not occur any more!
(at least, not explicitly)

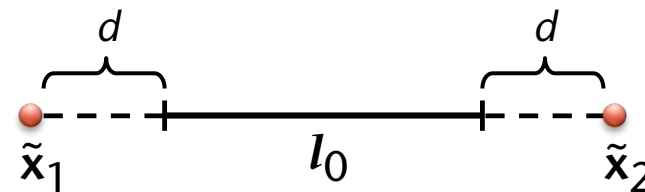
- Big advantage of Verlet over Euler & Runge-Kutta:
it is very easy to handle constraints
- Definition: **constraint** = some condition on the position of one or more mass points
- Examples:
 1. A point must not penetrate an obstacle
 2. The distance between two points must be constant,
or distance must be \leq some specific distance

■ Examples:

- Consider the constraint:

$$\|\mathbf{x}_1 - \mathbf{x}_2\| \stackrel{!}{=} l_0$$

1. Perform one Verlet integration step $\rightarrow \tilde{\mathbf{x}}^{t+1}$
2. Enforce the constraint:



$$\mathbf{x}_1^{t+1} = \tilde{\mathbf{x}}_1^{t+1} + \frac{1}{2} \mathbf{r}_{12} \cdot (\|\tilde{\mathbf{x}}_2^{t+1} - \tilde{\mathbf{x}}_1^{t+1}\| - l_0)$$

$$\mathbf{x}_2^{t+1} = \tilde{\mathbf{x}}_2^{t+1} - \underbrace{\frac{1}{2} \mathbf{r}_{12} \cdot (\|\tilde{\mathbf{x}}_2^{t+1} - \tilde{\mathbf{x}}_1^{t+1}\| - l_0)}_d$$

- Problem: if several constraints are to constrain the same mass point, we need to employ constraint algorithms

- All integration schemes are only *conditionally stable*
 - I.e.: they are only stable for a specific range for Δt
 - This range depends on the stiffness of the springs
- Goal: *unconditionally stability*
- One option: **implicit Euler integration**

explicit

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \Delta t \mathbf{v}_i^t$$

$$\mathbf{v}_i^{t+1} = \mathbf{v}_i^t + \Delta t \frac{1}{m_i} \mathbf{f}(\mathbf{x}^t)$$

implicit

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \Delta t \mathbf{v}_i^{t+1}$$

$$\mathbf{v}_i^{t+1} = \mathbf{v}_i^t + \Delta t \frac{1}{m_i} \mathbf{f}(\mathbf{x}^{t+1})$$

- Now we've got a system of non-linear, algebraic equations, with \mathbf{x}^{t+1} and \mathbf{v}^{t+1} as unknowns on **both** sides → **implicit integration**

- Write all the implicit equations as **one big** system of equations :

$$M\mathbf{v}^{t+1} = M\mathbf{v}^t + \Delta t \mathbf{f}(\mathbf{x}^{t+1}) \quad (1)$$

$$\mathbf{x}^{t+1} = \mathbf{x}^t + \Delta t \mathbf{v}^{t+1} \quad (2)$$

- Plug (2) into (1) :

$$M\mathbf{v}^{t+1} = M\mathbf{v}^t + \Delta t \mathbf{f}(\mathbf{x}^t + \Delta t \mathbf{v}^{t+1}) \quad (3)$$

- Expand \mathbf{f} as Taylor series:

$$\begin{aligned} \mathbf{f}(\mathbf{x}^t + \Delta t \mathbf{v}^{t+1}) &= \mathbf{f}(\mathbf{x}^t) + \frac{\partial}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}^t) \cdot (\Delta t \mathbf{v}^{t+1}) \\ &\quad + O((\Delta t \mathbf{v}^{t+1})^2) \end{aligned} \quad (4)$$

- Plug (4) into (3):

$$\begin{aligned}
 M \mathbf{v}^{t+1} &= M \mathbf{v}^t + \Delta t \left(\mathbf{f}(\mathbf{x}^t) + \underbrace{\frac{\partial}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}^t)}_K \cdot (\Delta t \mathbf{v}^{t+1}) \right) \\
 &= M \mathbf{v}^t + \Delta t \mathbf{f}(\mathbf{x}^t) + \Delta t^2 K \mathbf{v}^{t+1}
 \end{aligned}$$

- K is the Jacobi-Matrix, i.e., the derivative of \mathbf{f} (wrt. \mathbf{x}):

$$K = \begin{pmatrix} \frac{\partial}{\partial x_{11}} f_{11} & \frac{\partial}{\partial x_{12}} f_{11} & \dots & \frac{\partial}{\partial x_{n3}} f_{11} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_{11}} f_{n3} & \dots & \dots & \frac{\partial}{\partial x_{n3}} f_{n3} \end{pmatrix}$$

- K is called the **tangent stiffness matrix**
 - (The normal stiffness matrix is evaluated at the equilibrium of the system: here the matrix is evaluated at an arbitrary "position" of the system in phase space, hence the name "*tangent ...*")

- Reorder terms :

$$(M - \Delta t^2 K) \mathbf{v}^{t+1} = M \mathbf{v}^t + \Delta t \mathbf{f}(\mathbf{x}^t)$$

- Now, this has the form:

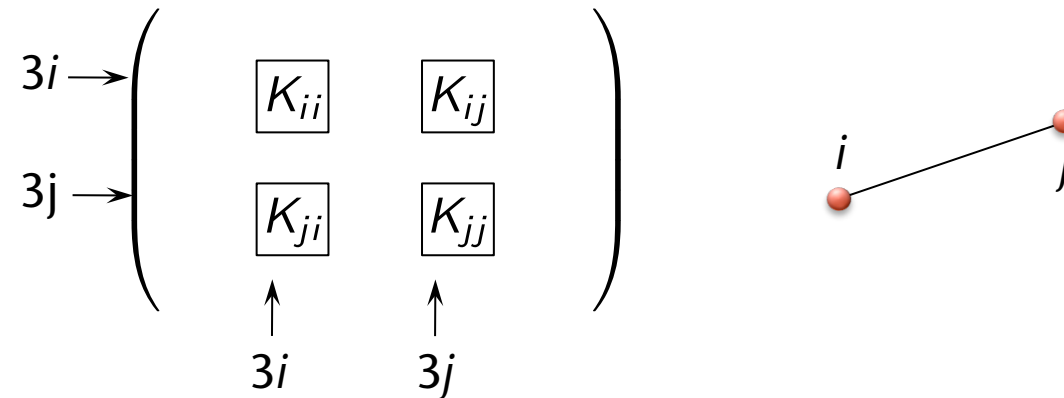
$$A \mathbf{v}^{t+1} = \mathbf{b}$$

$$\text{mit } A \in \mathbb{R}^{3n \times 3n}, \quad b \in \mathbb{R}^{3n}$$

- Solve this system of linear equations with any of the iterative solvers
- Don't use a non-iterative solver, because
 - A changes with every frame (simulation step)
 - We can "warm start" the iterative solver with the solution as of last frame

Computation of the Stiffness Matrix

- First, understand the anatomy of matrix K :
 - A spring (i, j) adds the following four 3×3 block matrices to K :



- Matrix K_{ij} arises from the derivation of $\mathbf{f}_i = (f_{i1}, f_{i2}, f_{i3})$ wrt. $\mathbf{x}_j = (x_{j1}, x_{j2}, x_{j3})$:

$$K_{ij} = \begin{pmatrix} \frac{\partial}{\partial x_{j1}} f_{i1} & \frac{\partial}{\partial x_{j2}} f_{i1} & \frac{\partial}{\partial x_{j3}} f_{i1} \\ \vdots & \vdots & \vdots \\ \frac{\partial}{\partial x_{j1}} f_{i3} & \dots & \frac{\partial}{\partial x_{j3}} f_{i3} \end{pmatrix}$$

- In the following, consider only f^S (spring force)

- First of all, compute K_{ij} :

$$\begin{aligned}
 K_{ij} &= \frac{\partial}{\partial \mathbf{x}_i} f_i(\mathbf{x}_i, \mathbf{x}_j) \\
 &= k_s \frac{\partial}{\partial \mathbf{x}_i} \left((\mathbf{x}_j - \mathbf{x}_i) - l_0 \frac{\mathbf{x}_j - \mathbf{x}_i}{\|\mathbf{x}_j - \mathbf{x}_i\|} \right) \\
 &= k_s \left(-I - l_0 \frac{-I \cdot \|\mathbf{x}_j - \mathbf{x}_i\| - (\mathbf{x}_j - \mathbf{x}_i) \cdot 2 \frac{(\mathbf{x}_j - \mathbf{x}_i)^\top}{\|\mathbf{x}_j - \mathbf{x}_i\|}}{\|\mathbf{x}_j - \mathbf{x}_i\|^2} \right) \\
 &= k_s \left(-I + l_0 \frac{1}{\|\mathbf{x}_j - \mathbf{x}_i\|} I + \frac{2l_0}{\|\mathbf{x}_j - \mathbf{x}_i\|^3} (\mathbf{x}_j - \mathbf{x}_i)(\mathbf{x}_j - \mathbf{x}_i)^\top \right)
 \end{aligned}$$

■ Reminder:

■
$$\left(\frac{f}{g}\right)' = \frac{f'g - fg'}{g^2}$$

■
$$\frac{\partial}{\partial \mathbf{x}} \|\mathbf{x}\| = \frac{\partial}{\partial \mathbf{x}} \left(\sqrt{x_1^2 + x_2^2 + x_3^2} \right) = 2 \frac{\mathbf{x}^T}{\|\mathbf{x}\|}$$

- From some symmetries, we can analogously derive:

- $K_{ij} = \frac{\partial}{\partial \mathbf{x}_j} f_i(\mathbf{x}_i, \mathbf{x}_j) = -K_{ji}$

- $K_{ji} = \frac{\partial}{\partial \mathbf{x}_i} f_j(\mathbf{x}_i, \mathbf{x}_j) = \frac{\partial}{\partial \mathbf{x}_i} (-f_i(\mathbf{x}_i, \mathbf{x}_j)) = -K_{ij}$

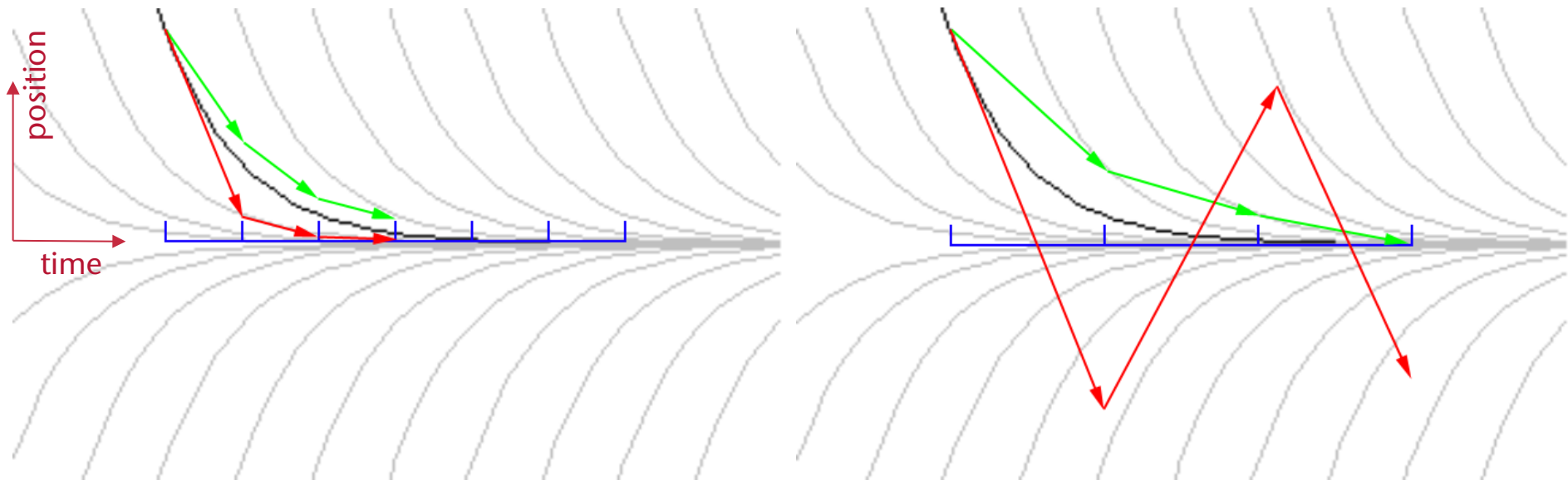
- $K_{ij} = K_{ji}$

Overall Solution Algorithm

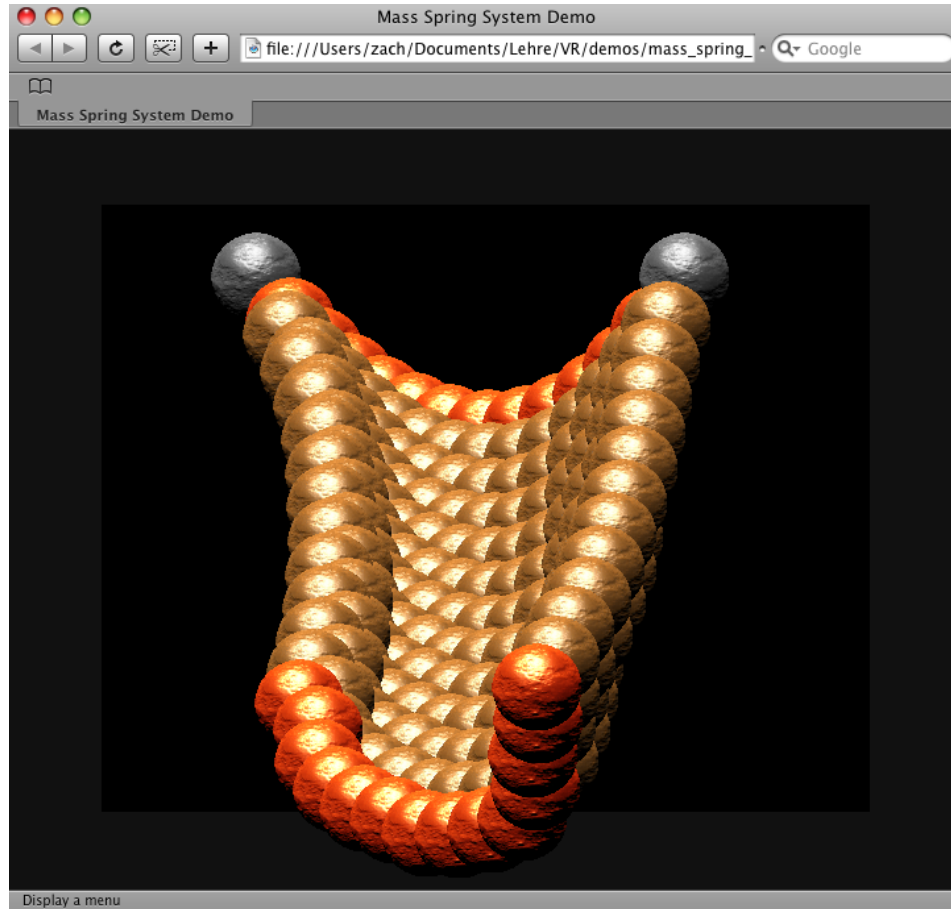
- Initialize $K = 0$
- For each spring (i, j) compute $K_{ij}, K_{ij}, K_{ji}, K_{ji}$ and accumulate it to K at the right places
- Compute $\mathbf{b} = M \mathbf{v}^t + \Delta t f(\mathbf{x}^t)$
- Solve the linear equation system $A \mathbf{v}^{t+1} = \mathbf{b} \rightarrow \mathbf{v}^{t+1}$
- Compute $\mathbf{x}^{t+1} = \mathbf{x}^t + \Delta t \mathbf{v}^{t+1}$

- **Explicit** integration:
 - + Very easy to implement
 - Small step sizes needed
 - Stiff springs don't work very well
 - Forces are propagated only by one spring per time step
- **Implicit** Integration:
 - + Unconditionally stable
 - + Stiff springs work better
 - + Globale solver → forces are being propagated throughout the whole spring-mass system with one time step
 - Large time steps are needed, because one step is much more expensive (if real-time is needed)
 - The integration scheme introduces damping by itself (might be unwanted)

- Visualization of: $\dot{x}(t) = -x(t)$



- Informal Descripiton:
 - **Explicit** jumps forward blindly, based on current information
 - **Implicit** jumps backward and tries to find a future position such that the backwards jump arrives exactly at the current point (in phase space)

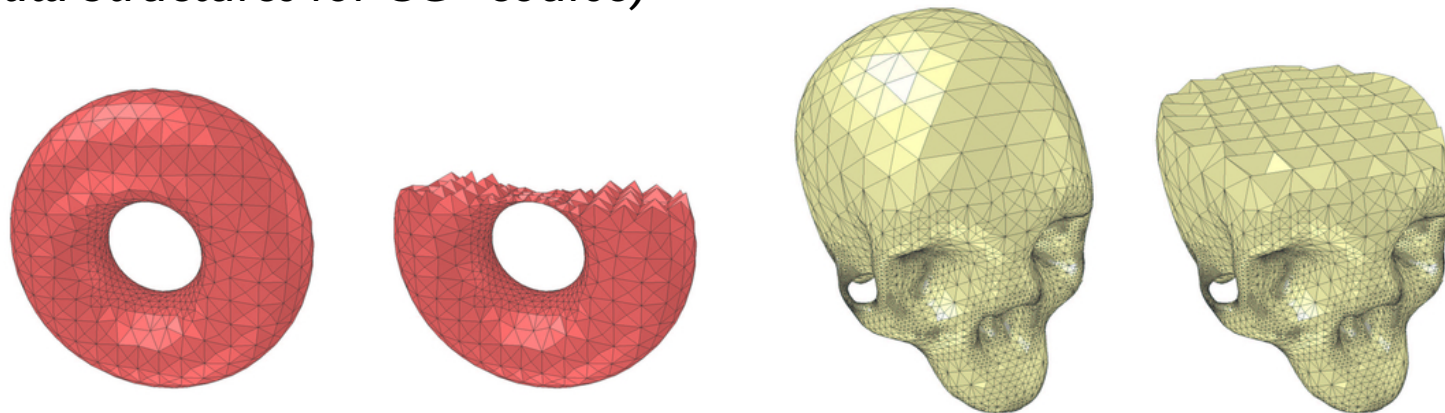


<http://www.dhteumeuleu.com/dhtml/v-grid.html>

Mesh Creation for Volumetric Objects

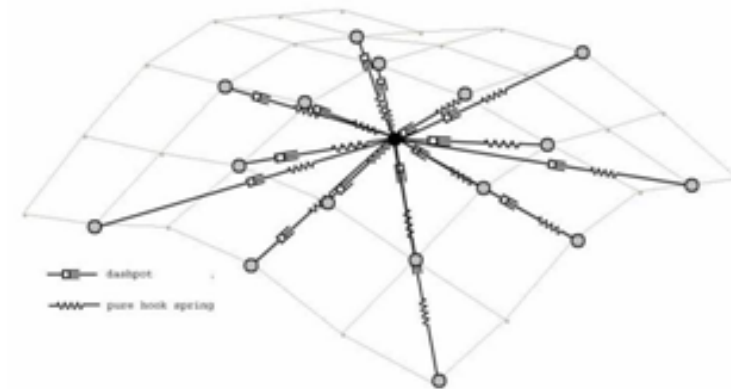
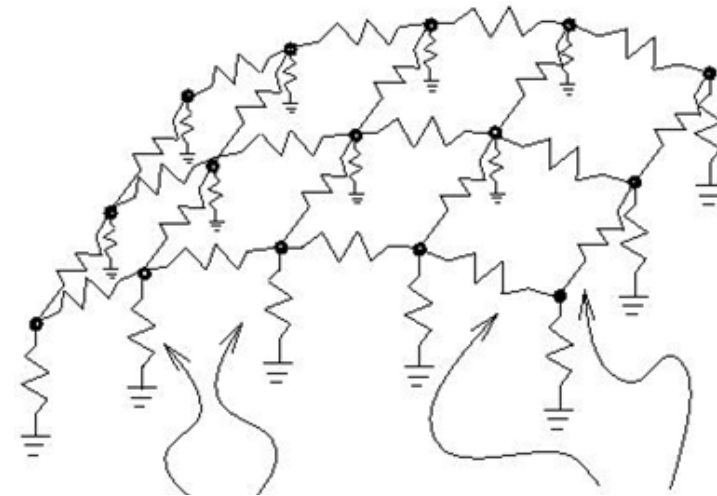
- How to create a mass-spring system for a **volumetric** model?
- Direct conversion of 3D (surface) geometry into spring-mass system does not yield good results:
 - Geometry has too high a complexity
 - Degenerate polygons
- Better (and still simple) idea:
 - Create a tetrahedron mesh out of the geometry (somehow)
 - Each vertex (node) of the tetrahedron mesh becomes a mass point, each edge a spring
 - Distribute the masses of the tetraeder (= density \times volume) equally among the mass point

- Generation of the tetrahedron mesh (simple method):
 - Distribute a number of points uniformly (perhaps randomly) in the interior of the geometry (so called "**Steiner points**")
 - Dito for a sheet/band above the surface
 - Connect the points by Delaunay triangulation (see my "Geometric Data Structures for CG" course)



- Anchor the surface meshes within the tetraeder mesh:
 - Represent each vertex of the surface mesh by the *barycentric combination* of its surrounding tetrahedron vertices

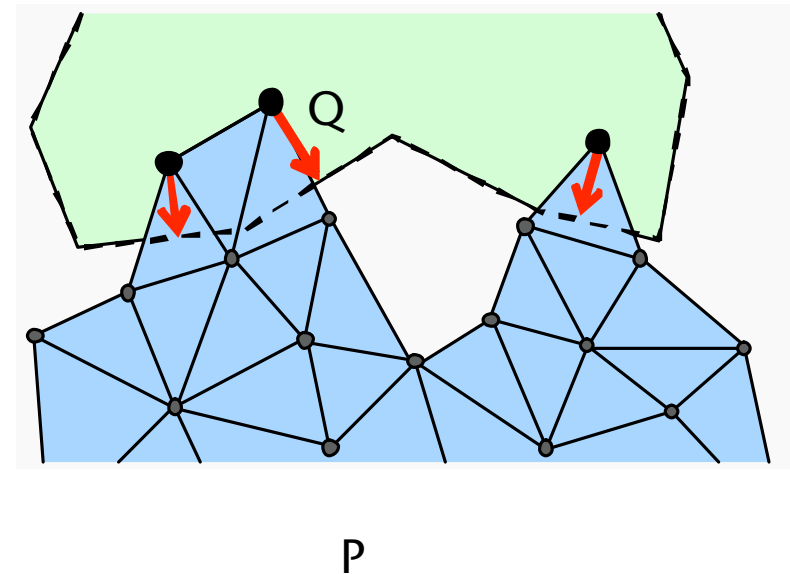
- In addition (optionally):
 - Anchor the outer mass points (of the tetrahedron mesh) at (imaginary) walls
 - Introduce diagonal "struts" (Streben)



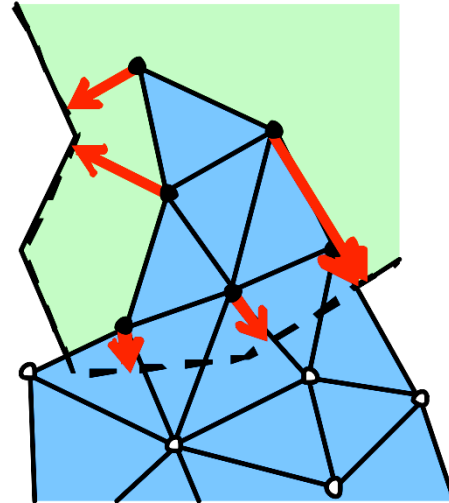
- Put all tetrahedra in a 3D grid (use a hash table!)
- In case of a collision in the hash table:
 - Compute exact intersection between the 2 involved tetrahedra

Collision Response

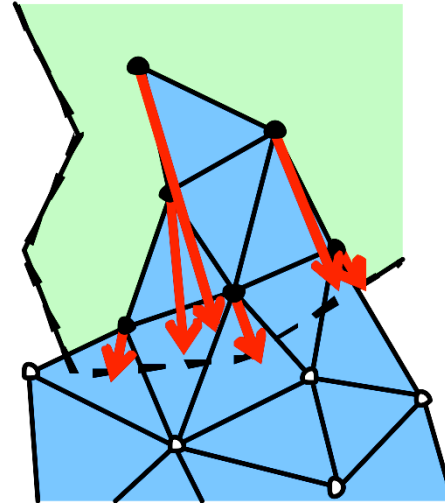
- Task: objects P and Q (= tetrahedral meshes) collide — what is the **penalty force**?
- Naïve approach:
 - For each mass point of P that has penetrated, compute its closest distance from the surface of Q → force (amount + direction)
- Problem:
 - Implausible forces
 - "Tunneling" (s. a. the chapter on force-feedback)



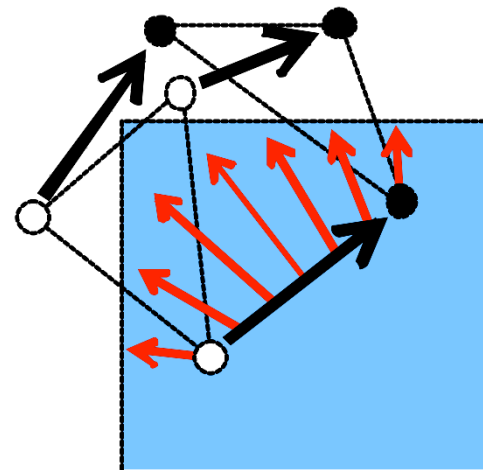
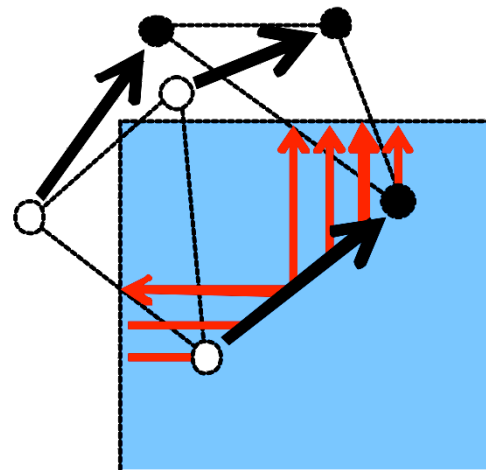
■ Examples:



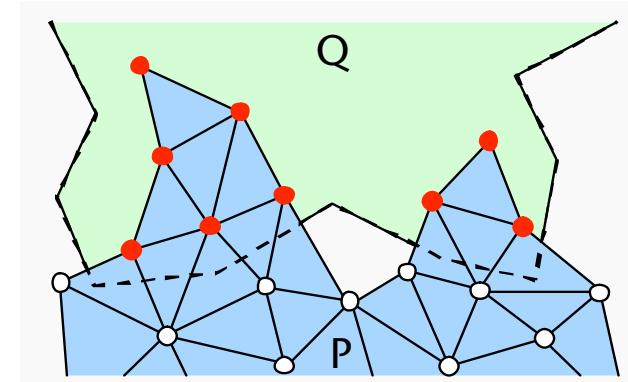
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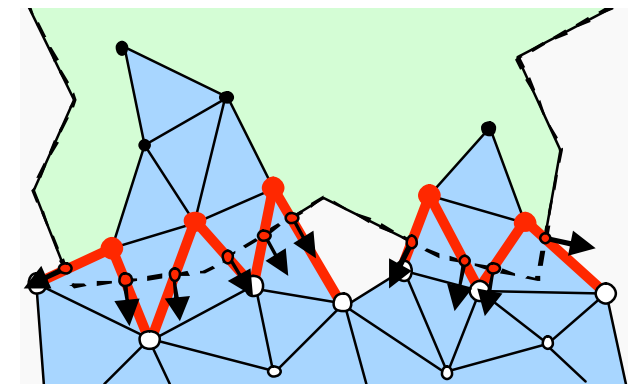


1. Phase: identify all points of P that penetrate Q



2. Phase: determine all edges of P that intersect the surface of Q

- For each such edge, compute the exact intersection point x_i
- For each intersection point, compute a normal n_i
 - E.g., by barycentric interpolation of the vertex normals of Q



3. Phase: compute the approximate force for border points

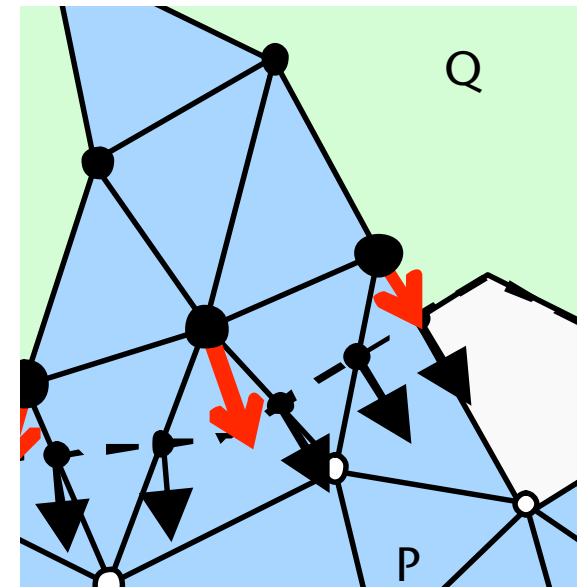
- Border point = a point \mathbf{p} that penetrates Q and is incident to an intersecting edge
- Observation: a border point can be incident to several intersecting edges
- Set the penetration depth for point p

to

$$d(\mathbf{p}) = \frac{\sum_{i=1}^k \omega(\mathbf{x}_i, \mathbf{p}) (\mathbf{x}_i - \mathbf{p}) \cdot \mathbf{n}_i}{\sum_{i=1}^k \omega(\mathbf{x}_i, \mathbf{p})}$$

where $d(\mathbf{p})$ = approx. penetration depth of mass point \mathbf{p} , \mathbf{x}_i = point of the intersection of an edge incident to \mathbf{p} with surface Q , \mathbf{n}_i = normal to surface of Q at point \mathbf{x}_i ,

and $\omega(\mathbf{x}_i, \mathbf{p}) = \frac{1}{\|\mathbf{x}_i - \mathbf{p}\|}$



- Direction of the penalty force on border points:

$$\mathbf{r}(\mathbf{p}) = \frac{\sum_{i=1}^k \omega(\mathbf{x}_i, \mathbf{p}) \mathbf{n}_i}{\sum_{i=1}^k \omega(\mathbf{x}_i, \mathbf{p})}$$

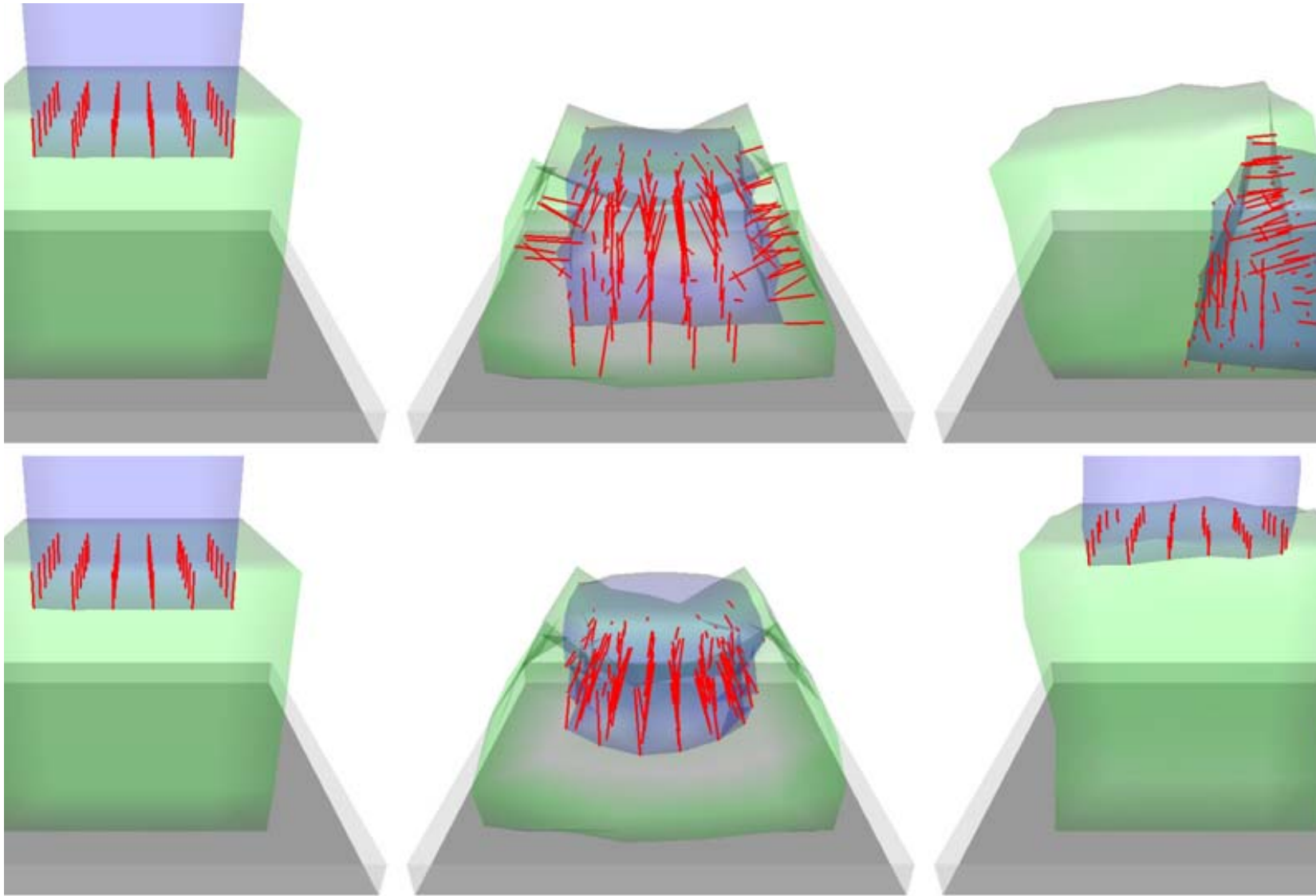
4. Phase: propagate forces by way of breadth-first traversal through the tetrahedron mesh

$$d(\mathbf{p}) = \frac{\sum_{i=1}^k \omega(\mathbf{p}_i, \mathbf{p}) ((\mathbf{p}_i - \mathbf{p}) \cdot \mathbf{r}_i + d(\mathbf{p}_i))}{\sum_{i=1}^k \omega(\mathbf{x}_i, \mathbf{p})}$$

where \mathbf{p}_i = points of P that have been visited already, \mathbf{p} = point not yet visited, \mathbf{r}_i = direction of the estimated penalty force in point \mathbf{p}_i .



Visualization



Consistent Penetration Depth Estimation for Deformable Collision Response

<http://cg.informatik.uni-freiburg.de>