

Lec 22 - Animation Cont.

Given the forces / physics / theory, how to simulate actual movements
Euler

Single Particle Simulation

have: (for every single particle) $v(t_0)$ & $x(t_0)$

want: $x(t_1)$

- Later, generalize to a multitude of particles

To start, assume motion of particle determined by a velocity vector field that is a function of position and time

速度场: $v(x, t)$

Ordinary Differential Equation (ODE) 常微分方程

计算速度场内粒子的位置需要计算一阶常微分方程:

$$\frac{dx}{dt} = \dot{x} = v(x, t)$$

解一阶常微分方程:

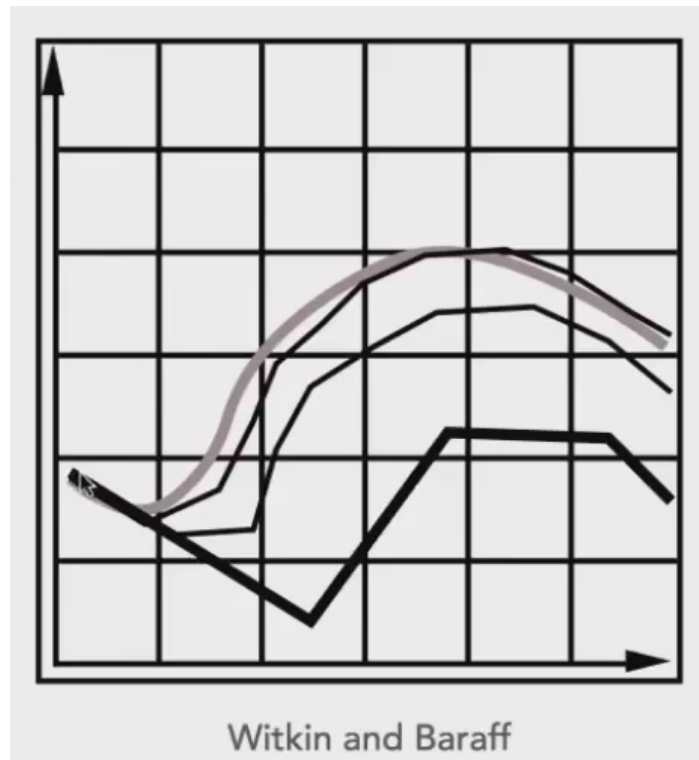
- 连续: 积分
- 离散: Euler's Method 欧拉方法
 - Explicit Euler method (forward 前向、显式)
 - 始终用前一帧的状态来更新后一帧

$$\mathbf{x}^{t+\Delta t} = \mathbf{x}^t + \Delta t \dot{\mathbf{x}}^t$$

$$\dot{\mathbf{x}}^{t+\Delta t} = \dot{\mathbf{x}}^t + \Delta t \ddot{\mathbf{x}}^t$$

- Simple iterative method
- Commonly used
- Very inaccurate 很不准确
 - With numerical integration, errors accumulate
 - Euler integration is particularly bad
- Most often goes unstable 不稳定

- 容易出现正反馈，离正确结果越来越远



Errors and Instability

Solving by numerical integration with finite differences leads to two problems: 数值方法解微分方程都会面临

Errors 误差 不是特别大的问题

- Errors at each time step accumulate. Accuracy decreases as simulation proceeds
- Accuracy may not be critical in graphics applications

Instability 不稳定性 很要命!

- Errors can compound, causing the simulation to **diverge** even when the underlying system does not 收敛很重要!
- Lack of stability is a fundamental problem in simulation, and cannot be ignored

How to determine / quantize “stability”?

- We use the local truncation error (every step) / total accumulated error (overall)
- Absolute values do not matter, but the orders w.r.t. step 研究误差和步长的关系（几次方？）
- Implicit Euler has order 1, which means that
 - Local truncation error: $O(h^2)$ and
 - Global truncation error: $O(h)$ (h is the step, i.e. Δt)
- Understanding of $O(h)$
 - If we halve h , we can expect the error to halve as well

一些对抗不稳定的方法:

Midpoint method / Modified Euler (中点法)

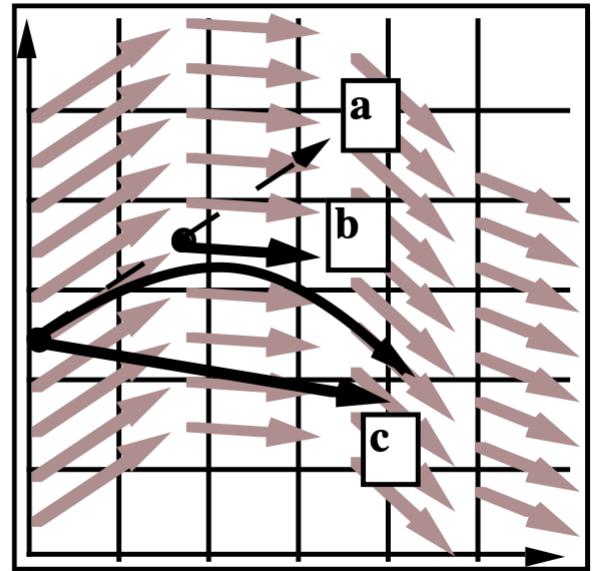
- Average velocities at start and endpoint

Midpoint method

- Compute Euler step (a)
- Compute derivative at midpoint of Euler step (b)
- Update position using midpoint derivative (c)

$$x_{\text{mid}} = x(t) + \Delta t/2 \cdot v(x(t), t)$$

$$x(t + \Delta t) = x(t) + \Delta t \cdot v(x_{\text{mid}}, t)$$



Witkin and Baraff

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

$$\dot{x}^{t+\Delta t} = \dot{x}^t + \Delta t \ddot{x}^t$$

$$x^{t+\Delta t} = x^t + \Delta t \dot{x}^t + \frac{(\Delta t)^2}{2} \ddot{x}^t$$

- 多了一个二次项

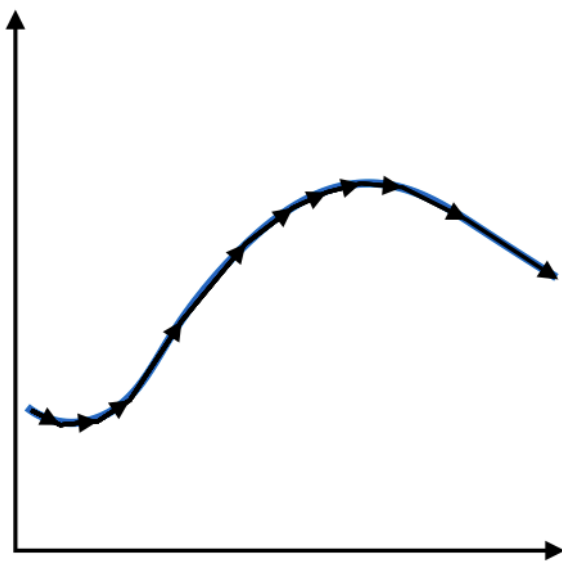
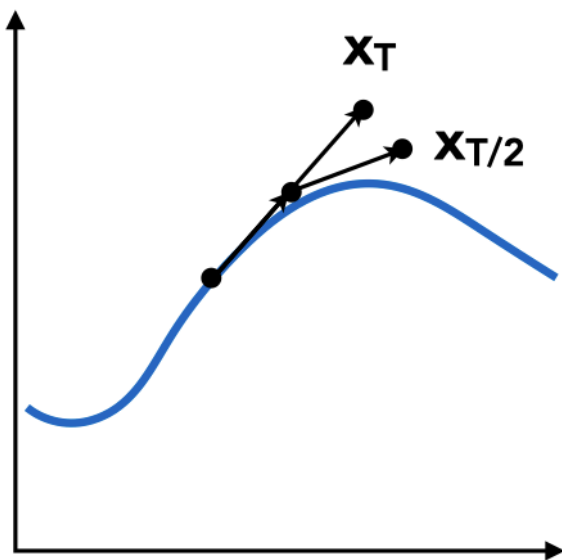
Adaptive step size

- Compare one step and two half-steps, recursively, until error is acceptable
- Repeat until error is below threshold:
 - Compute x_T an Euler step, size T
 - Compute $x_{T/2}$ two Euler steps, size $T/2$
 - Compute error $\|x_T - x_{T/2}\|$
 - If (error > threshold) reduce step size and try again

如果两者相差很远，再缩小步长

- Technique for choosing step size based on error estimate
- Very practical technique

- But may need very small steps!



Implicit methods (backward 隐式、后向)

- Use the velocity at the next time step (hard)

$$\mathbf{x}^{t+\Delta t} = \mathbf{x}^t + \Delta t \dot{\mathbf{x}}^{t+\Delta t}$$

$$\dot{\mathbf{x}}^{t+\Delta t} = \dot{\mathbf{x}}^t + \Delta t \ddot{\mathbf{x}}^{t+\Delta t}$$

- 是一个方程组，有三个未知数，只能假设一个已知（猜）
- Use root-finding algorithm, e.g. Newton's method
- Offers much better stability
- Implicit Euler has order 1, which means that
 - Local truncation error: $O(h^2)$ and
 - Global truncation error: $O(h)$ (h is the step, i.e. Δt)

$O(h)$ 的理解

- If we halve h , we can expect the error to halve as well
- 阶数越高越好，减小步长的情况下降低更快

Runge-Kutta Families (龙格库塔方法)

A family of advanced methods for solving ODEs(常微分)

Especially good at dealing with non-linearity

It's order-four version is the most widely used, a.k.a. **RK4**

Initial condition:

$$\frac{dy}{dt} = f(t, y), \quad y(t_0) = y_0.$$

RK4 solution:

$$y_{n+1} = y_n + \frac{1}{6}h(k_1 + 2k_2 + 2k_3 + k_4),$$
$$t_{n+1} = t_n + h$$

where

$$k_1 = f(t_n, y_n), \quad k_3 = f\left(t_n + \frac{h}{2}, y_n + h\frac{k_2}{2}\right),$$
$$k_2 = f\left(t_n + \frac{h}{2}, y_n + h\frac{k_1}{2}\right), \quad k_4 = f(t_n + h, y_n + hk_3).$$

更多: **Numerical Analysis** 对图形学有用 (其他的: 信号处理)

Position-based / Verlet integration

- Constrain positions and velocities of particles after time step

假设弹簧劲度系数无限大-->恢复

Idea:

- After modified Euler forward-step, constrain positions of particles to prevent divergent, unstable behavior
- Use constrained positions to calculate velocity
- Both of these ideas will dissipate energy, stabilize

Pros / cons

- Fast and simple
- Not physically based, dissipates energy (error)

Rigid body simulation

不会形变

Simple case

- Similar to simulating a particle

- Just consider a bit more properties 拓展

$$\frac{d}{dt} \begin{pmatrix} X \\ \theta \\ \dot{X} \\ \omega \end{pmatrix} = \begin{pmatrix} \dot{X} \\ \omega \\ F/M \\ \Gamma/I \end{pmatrix}$$

X : positions

θ : rotation angle

ω : angular velocity

F : forces

Γ : torque

I : momentum of inertia

Fluid simulation

A Simple Position-Based Method

模拟只需要输出物体的位置，其他的就是渲染的问题了

Key idea

- Assuming water is composed of small rigid-body spheres 水是由小球组成的
- Assuming the water cannot be compressed (i.e. const. density) 不可压缩
- So, as long as the density changes somewhere, it should be "corrected" via changing the positions of particles 密度有变化，就要想着改回去，移动小球位置
- You need to know the gradient of the density anywhere w.r.t. each particle's position

一个小球位置的变化对其周围密度的影响

- Update? Just gradient descent! 梯度下降

非物理

流体模拟中两种不同的思路：Eulerian vs. Lagrangian

Lagrangian: 质点法，以每个元素为单位模拟

Eulerian: 网格法，以空间为单位分割模拟

Material Point Method (MPM)

Hybrid, combining Eulerian and Lagrangian views

- Lagrangian: consider particles carrying material properties 物质由粒子组成，粒子有属性
- Eulerian: use a grid to do numerical integration 网格上计算如何运动
- Interaction: particles transfer properties to the grid, grid performs update, then interpolate back to particles 网格属性写回网格内粒子上