# Intoduction to <br> Optimization (Part 2) 

Computer Graphics<br>CMU 15-462/15-662

## Last week we talked about how to set up optimization problems and determine whether they could be solved.

How do we solve optimization problems in general?

## Descent Methods

## An idea as old as the hills:



## Gradient Descent (1D)

- Basic idea: follow the gradient "downhill" until it's zero
- (Zero gradient was our 1st-order optimality condition)

- Do we always end up at a (global) minimum?
- How do we compute gradient descent in practice?


## Gradient Descent Algorithm (1D)

- Did you notice that gradient descent equation is an ODE?
- Q: How do we solve it numerically? $\quad \frac{d}{d t} x(t)=-f_{0}^{\prime}(x(t))$
- One way: forward Euler:

$$
x_{k+1}=x_{k}+\tau f_{0}^{\prime}\left(x_{k}\right)
$$

■ Q: How do we pick the time step?

- If wére not careful, we'll go zipping all over the place; won't make any progress.


■ Basic idea: use "step control" to determine step size based on value of objective \& derivatives.

- A careful strategy (e.g., Armijo-Wolfe) can guarantee convergence at least to a local minimum.
■ For now we will do something simpler: make t really small!


## Gradient Descent Algorithm (nD)

■ Q: How do we write gradient descent equation in general?

$$
\frac{d}{d t} x(t)=-\nabla f_{0}(x(t))
$$

- Q: What's the corresponding discrete update?

$$
x_{k+1}=x_{k}-\tau \nabla f_{0}\left(x_{k}\right)
$$

- Basic challenge in nD:
- solution can "oscillate"
- takes many, many small steps
- very slow to converge



## Higher Order Descent

- General idea: apply a coordinate transformation so that the local energy landscape looks more like a "round bowl"
- Gradient now points directly toward nearby minimizer

■ Most basic strategy: Newton's method:

$$
x_{k+1}=x_{k}-\tau\left(\underset{\text { Hessian inverse }}{2} f_{0}\left(x_{k}\right)\right)^{-1} \nabla f_{0}\left(x_{k}\right)
$$

- Great for convex problems (even proofs about \# of steps!)
- For nonconvex problems, need to be more careful
- In general, nonconvex optimization is a BLACK ART

■ Meta-strategy: try lots of solvers, see what works!

- quasi-Newton, trust region, L-BFGS, ...


## Example: Inverse Kinematics

## Example 12: IK-driven robot claw



## Forward Kinematics

- Many systems well-described by a kinematic chain
- collection of rigid bodies, connected by joints
- joints have various behaviors (ball, piston, ...)
- also have constraints (e.g., range of angles)
- hierarchical structure (body $\rightarrow$ leg $\rightarrow$ foot)
- In animation, often called a rig
- How do we specify the configuration of a "rig"?
- One way: artist sets each joint individually
- Another way: ...optimization!



## Simple Kinematic Chain



- Consider a simple path-like chain in 2D
- Q: How do we write $p_{1}$ in terms of the root position $p_{0}$, angles, $\&$ vectors $u:=c_{i+1}-c_{i}$ ?

$$
p_{1}=p_{0}+\left[\begin{array}{rr}
\cos \theta_{0} & \sin \theta_{0} \\
-\sin \theta_{0} & \cos \theta_{0}
\end{array}\right] u_{0}
$$

- (For brevity, can use complex numbers:)


$$
p_{1}=p_{0}+e^{\imath \theta_{0}} u_{0}
$$

- Q: How about $p_{2}$ ?

$$
p_{2}=p_{0}+e^{\imath \theta_{0}} u_{0}+e^{\imath \theta_{0}} e^{\imath \theta_{1}} u_{1}
$$

## Simple IK Algorithm

- Basic idea behind our IK algorithm:
- write down distance between final point and "target"
- compute gradient with respect to angles
- apply gradient descent

■ Objective?

$$
f_{0}(\theta)=\frac{1}{2}\left|\tilde{p}_{n}-p_{n}\right|^{2}
$$

- Constraints?
- None! The joint angle can take any value.
- Though we could limit joint angles (for instance)


# Physically-Based Animation and PDEs 

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## Partial Differential Equations (PDEs)

- ODE: Implicitly describe function in terms of its time derivatives
- Like any implicit description, have to solve for actual function
- PDE: Also include space derivatives in description

ODE—rock flies through air
PDE—rock lands in pond


## To make a long story short...

- Solving ODE looks like "add a little velocity each time"

$$
q_{k+1}=q_{k}+\tau f(q)
$$

■ Solving a PDE looks like"take weighted combination of neighbors to get velocity (...and add a little velocity each time)"

|  | 1 |  |
| :---: | :---: | :---: |
| 1 | -4 | 1 |
|  | 1 |  |
| $f(q)$ |  |  |

$$
q_{k+1}=q_{k}+\tau f(q)
$$

## Liquid Simulation in Graphics



Losasso, F., Shinar, T. Selle, A. and Fedkiw, R., "Multiple Interacting Liquids"

## Smoke Simulation in Graphics


S. Weißmann, U. Pinkall. "Filament-based smoke with vortex shedding and variational reconnection"

## Cloth Simulation in Graphics

Zhili Chen, Renguo Feng and Huamin Wang, "Modeling friction and air effects between cloth and deformable bodies"

## Elasticity in Graphics



Irving, G., Schroeder, C. and Fedkiw, R., "Volume Conserving Finite Element Simulation of Deformable Models"

## Hair Simulation in Graphics



Danny M. Kaufman, Rasmus Tamstorf, Breannan Smith, Jean-Marie Aubry, Eitan Grinspun, "Adaptive Nonlinearity for Collisions in Complex Rod Assemblies"

## Fracture in Graphics



James F. O'Brien, Adam Bargteil, Jessica Hodgins, "Graphical Modeling and Animation of Ductile Fracture"

## Viscoelasticity in Graphics



Chris Wojtan, Greg Turk, "Fast Viscoelastic Behavior with Thin Features"

## Snow Simulation in Graphics



Alexey Stomakhin, Craig Schroeder, Lawrence Chai, Joseph Teran, Andrew Selle, "A Material Point Method For Snow Simulation"

## Definition of a PDE

- Want to solve for a function of time and space

$$
u(\underset{\substack{\uparrow \\ \text { time }}}{t}, \underset{\substack{\uparrow \\ \text { space }}}{x})
$$

- Function given implicitly in terms of derivatives:
$\dot{u}, \ddot{u}, \frac{d}{d t^{3}} u, \frac{d}{d t^{4}} u, \ldots$
any combination of time derivatives
$\frac{\partial u}{\partial x_{1}}, \frac{\partial u}{\partial x_{2}}, \frac{\partial^{2} u}{\partial x_{1} \partial x_{2}}, \frac{\partial^{m}+n u}{\partial x_{i}^{m} \partial x_{j}^{n}}, \ldots$ plus any combination of space derivatives
■ Example:


## Anatomy of a PDE

■ Linear vs. nonlinear: how are derivatives combined?
nonlinear!

$$
\begin{aligned}
& \dot{u}+u u^{\prime}=a u^{\prime \prime} \\
& \dot{u}=a u^{\prime \prime}
\end{aligned}
$$

(Burgers' equation)
(diffusion equation)

- Order: how many derivatives in space \& time?

1st order in time
2nd order in space

$$
\dot{u}+u u^{\prime}=a u^{\prime \prime}
$$

(Burgers' equation)
2nd order in time

(wave equation)
■ Nonlinear / higher order $\Rightarrow$ HARDER TO SOLVE!

## Model Equations

- Fundamental behavior of many important PDEs is wellcaptured by three model linear equations:



## HEAT EQUATION ("PARABOLIC") $\dot{u}=\Delta u$

"how does an initial distribution

Solve numerically?

"if you throw a rock into a pond, how does the wavefront evolve over time?"
[ NONLINEAR + HYPERBOLIC + HIGH-ORDER ]

## Elliptic PDEs / Laplace Equation

- "What's the smoothest function interpolating the given boundary data?"

- Conceptually: each value is at the average of its "neighbors"

■ Roughly speaking, why is it easier to solve?
■ Very robust to errors: just keep averaging with neighbors!

## Parabolic PDEs / Heat Equation

■ "How does an initial distribution of heat spread out over time?"


- After a long time, solution is same as Laplace equation!

■ Models damping / viscosity in many physical systems

## Hyperbolic PDEs / Wave Equation

- "If you throw a rock into a pond, how does the wavefront evolve over time?"

- Errors made at the beginning will persist for a long time! (hard)


## How did we do that?

## Numerical Solution of PDEs—Overview

- Like ODEs many interesting PDEs are difficult/impossible to solve analytically-especially if we want to incorporate data (e.g., user interaction)
- Must instead use numerical integration
- Basic strategy:
- pick a time discretization (forward Euler, backward Euler...)
- pick a spatial discretization (TODAY)
- as with ODEs, run a time-stepping algorithm
- Historically, very expensive-only for "hero shots" in movies
- Computers are ever faster...
- More \& more use of PDEs in games, interactive tools, ...


## Real Time PDE-Based Simulation (Fire)

Invibia
GAMEWDRKS

## Real Time PDE-Based Simulation (Water)

Nuttapong Chentanez, Matthias Müller, "Real-time Eulerian water simulation using a restricted tall cell grid"

## Lagrangian vs. Eulerian

- Two basic ways to discretize space: Lagrangian \& Eulerian
- E.g., suppose we want to encode the motion of a fluid

track position \& velocity of moving particles

EULERIAN

track velocity (or flux) at fixed grid locations

## Lagrangian vs. Eulerian—Trade-Offs

- Lagrangian
- conceptually easy (like polygon soup!)
- resolution/domain not limited by grid
- good particle distribution can be tough
- finding neighbors can be expensive
- Eulerian
- fast, regular computation
- easy to represent, e.g., smooth surfaces
- simulation "trapped" in grid
- grid causes "numerical diffusion" (blur)
- need to understand PDEs (but you will!)



## Mixing Lagrangian \& Eulerian

- Of course, no reason you have to choose just one!
- Many modern methods mix Lagrangian \& Eulerian:
- PIC/FLIP, particle level sets, mesh-based surface tracking, Voronoi-based, arbitrary Lagrangian-Eulerian (ALE), ...
■ Pick the right tool for the job!


## Aside: Which Quantity Do We Solve For?

- Many PDEs have mathematically equivalent formulations in terms of different quantities
- E.g., incompressible fluids:
- velocity—how fast is each particle moving?
- vorticity—how fast is fluid "spinning" at each point?
- Computationally, can make a big difference
- Pick the right tool for the job!



## Ok, but we're getting way ahead of ourselves. How do we solve easy PDEs?

## Numerical PDEs—Basic Strategy

- Pick PDE formulation
- Which quantity do we want to solve for?
- E.g., velocity or vorticity?
- Pick spatial discretization
- How do we approximate derivatives in space?
- Pick time discretization
- How do we approximate derivatives in time?
- When do we evaluate forces?
- Forward Euler, backward Euler, symplectic Euler, ...
- Finally, we have an update rule
- Repeatedly solve to generate an animation


## The Laplace Operator

- All of our model equations used the Laplace operator
- Different conventions for symbol:

$\nabla^{2}$
■ Unbelievably important object showing up everywhere across physics, geometry, signal processing, ...
- Ok, but what does it mean?
- Differential operator: eats a function, spits out its "2nd derivative"
- What does that mean for a function $\mathrm{u}: \mathrm{R}^{\mathrm{n}} \rightarrow \mathrm{R}$ ?
- divergence of gradient
- sum of second derivatives

$$
\Delta u=\frac{\partial u^{2}}{\partial x_{1}^{2}}+\cdots+\frac{\partial u^{2}}{\partial x_{n}^{2}}
$$

## Discretizing the Laplacian

- How do we approximate the Laplacian?

■ Depends on discretization (Eulerian, Lagrangian, grid, mesh, ...)

- Two extremely common ways in graphics:

- Also not too hard on point clouds, polygon meshes, ...


## Numerically Solving the Laplace Equation

- Want to solve $\Delta u=0$
- Plug in one of our discretizations, e.g.,


$$
\begin{array}{r}
\frac{4 a-b-c-d-e}{h}=0 \\
\Longleftrightarrow a=\frac{1}{4}(b+c+d+e)
\end{array}
$$

- Oh: if we have a solution, then each value must be the average of the neighboring values.
- How do we solve this?
- One idea: keep averaging with neighbors! ("Jacobi method")

■ Correct, but slow. Much better to use modern linear solver

## Solving the Heat Equation

- Back to our three model equations, want to solve heat eqn.

$$
\dot{u}=\Delta u
$$

- Just saw how to discretize Laplacian
- Also know how to do time (forward Euler, backward Euler, ...)
- E.g., forward Euler:

$$
u^{k+1}=u^{k}+\Delta u^{k}
$$

■ Q: On a grid, what's our overall update now at $\mathrm{u}_{\mathrm{i}, \mathrm{j}}$ ?

$$
u_{i, j}^{k+1}=u^{k}+\frac{\tau}{h^{2}}\left(4 u_{i, j}^{k}-u_{i+1, j}^{k}-u_{i-1, j}^{k}-u_{i, j+1}^{k}-u_{i, j-1}^{k}\right)
$$

■ Not hard to implement! Loop over grid, add up some neighbors.

## Solving the Wave Equation

- Finally, wave equation:

$$
\ddot{u}=\Delta u
$$

- Not much different; now have 2nd derivative in time
- By now we've learned two different techniques:
- Convert to two 1st order (in time) equations:

$$
\dot{u}=v, \quad \dot{v}=\Delta u
$$

- Or, use centered difference (like Laplace) in time:

$$
\frac{u^{k+1}-2 u^{k}+u^{k-1}}{\tau^{2}}=\Delta u^{k}
$$

- Plus all our choices about how to discretize Laplacian.
- So many choices! And many, many (many) more we didn't discuss.


## Wave Equation on a Triangle Mesh

Credit: Alec Jacobson (http://www.alecjacobson.com/weblog/?p=4363)


# Wait, what about all those cool fluids and stuff? 

## Want to Know More? <br> - There are some good books: <br> - And papers:

http://www.physicsbasedanimation.com/
Physics-Based Animation
 ablumplor


Blomechanical Simulation and Control of Hands and Tendinous Systems


Search
 Sinngle hary tom

## Also, what did the folks who wrote these books \& papers read?



## Also not covered: solving linear equations



