

Animation

← BACK Lecture 10 Slide 1 6.837 Fall 2003 Next →

Conventional Animation

Draw each frame of the animation

- great control
- tedious

Reduce burden with cel animation

- layer
- keyframe
- inbetween
- cel panoramas (Disney's Pinocchio)
- ...

← BACK Lecture 10 Slide 2 6.837 Fall 2003 Next →

Computer-Assisted Animation

Keyframing

- automate the inbetweening
- good control
- less tedious
- creating a good animation still requires considerable skill and talent

ACM © 1987 "Principles of traditional animation applied to 3D computer animation"

Procedural animation

- describes the motion algorithmically
- express animation as a function of small number of parameters
- Example: a clock with second, minute and hour hands
 - hands should rotate together
 - express the clock motions in terms of a "seconds" variable
 - the clock is animated by varying the seconds parameter
- Example 2: A bouncing ball
 - $Abs(\sin(\omega t + \theta_0)) * e^{-\lambda t}$

← BACK Lecture 10 Slide 3 6.837 Fall 2003 Next →

Computer-Assisted Animation

Physically Based Animation

- Assign physical properties to objects (masses, forces, inertial properties)
- Simulate physics by solving equations
- Realistic but difficult to control

ACM © 1988 "Spacetime Constraints"

Motion Capture

- Captures style, subtle nuances and realism
- You must observe someone do something

← BACK Lecture 10 Slide 4 6.837 Fall 2003 Next →

Overview

Hermite Splines
Keyframing
Traditional Principles

Articulated Models
Forward Kinematics
Inverse Kinematics
Optimization
Differential Constraints

← BACK Lecture 10 Slide 5 6.837 Fall 2003 Next →

Keyframing

ACM © 1987 "Principles of traditional animation applied to 3D computer animation"

Describe motion of objects as a function of time from a set of key object positions. In short, compute the inbetween frames.

← BACK Lecture 10 Slide 6 6.837 Fall 2003 Next →

Interpolating Positions

Given positions: $(x_i, y_i, t_i), i = 0, \dots, n$
 find curve $C(t) = \begin{bmatrix} x(t) \\ y(t) \end{bmatrix}$ such that $C(t_i) = \begin{bmatrix} x_i \\ y_i \end{bmatrix}$

(x_2, y_2, t_2)
 (x_0, y_0, t_0)
 (x_1, y_1, t_1)
 $C(t)$

BAW Lecture 10 Slide 7 6.837 Fall 2003

Linear Interpolation

(x_2, y_2, t_2)
 (x_0, y_0, t_0)
 (x_1, y_1, t_1)

Simple problem: linear interpolation between first two points assuming $t_0=0$ and $t_1=1$: $x(t) = x_0(1-t) + x_1t$
 The x-coordinate for the complete curve in the figure:

$$x(t) = \begin{cases} \frac{t_1-t}{t_1-t_0} x_0 + \frac{t-t_0}{t_1-t_0} x_1, & t \in [t_0, t_1] \\ \frac{t_2-t}{t_2-t_1} x_1 + \frac{t-t_1}{t_2-t_1} x_2, & t \in [t_1, t_2] \end{cases}$$

Derivation?

BAW Lecture 10 Slide 8 6.837 Fall 2003

Polynomial Interpolation

(x_2, y_2, t_2)
 (x_0, y_0, t_0)
 (x_1, y_1, t_1)
 parabola

An n-degree polynomial can interpolate any n+1 points. The Lagrange formula gives the n+1 coefficients of an n-degree polynomial that interpolates n+1 points. The resulting interpolating polynomials are called Lagrange polynomials. On the previous slide, we saw the Lagrange formula for n = 1.

BAW Lecture 10 Slide 9 6.837 Fall 2003

Spline Interpolation

Lagrange polynomials of small degree are fine but high degree polynomials are too wiggly.

$x(t)$
 t
 8-degree polynomial

How many n-degree polynomials interpolate n+1 points?

BAW Lecture 10 Slide 10 6.837 Fall 2003

Spline Interpolation

Lagrange polynomials of small degree are fine but high degree polynomials are too wiggly.
Spline (piecewise cubic polynomial) interpolation produces nicer interpolation.

$x(t)$
 t
 t
 t
 8-degree polynomial spline spline vs. polynomial

BAW Lecture 10 Slide 11 6.837 Fall 2003

Spline Interpolation

A cubic polynomial between each pair of points:
 $x(t) = c_0 + c_1t + c_2t^2 + c_3t^3$

Four parameters (degrees of freedom) for each spline segment.

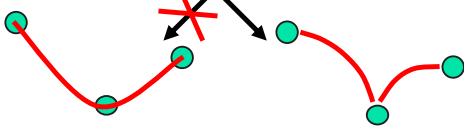
Number of parameters:
 n+1 points \hat{y} n cubic polynomials \hat{y} 4n degrees of freedom

Number of constraints:
 ■ interpolation constraints
 n+1 points \hat{y} 2 + 2(n-1) = 2n interpolation constraints
 "endpoints" + "each side of an internal point"
 ■ rest by requiring smooth velocity, acceleration, etc.

BAW Lecture 10 Slide 12 6.837 Fall 2003

Hermite Splines

We want to support general constraints: not just smooth velocity and acceleration. For example, a bouncing ball does not always have continuous velocity:



Solution: specify position AND velocity at each point
Derivation? $c_0, c_1, c_2, c_3 = ?$ for $x_0, v_0 : t = t_0$ and $x_1, v_1 : t = t_1$

Keyframing

Given keyframes $K_i = (p_i^0, p_i^1, \dots, t_i)$, $i = 0, \dots, n$

find curves $K(t) = \begin{bmatrix} p^0(t) \\ p^1(t) \\ \vdots \end{bmatrix}$ such that $K(t_i) = K_i$

What are parameters p_i^0, p_i^1, \dots ?

- position, orientation, size, visibility, ...

Interpolate each curve separately

Interpolating Key Frames

Interpolation is not fool proof. The splines may undershoot and cause interpenetration. The animator must also keep an eye out for these types of side-effects.



Traditional Animation Principles

The in-betweening, was once a job for apprentice animators. We described the automatic interpolation techniques that accomplish these tasks automatically. However, the animator still has to draw the key frames. This is an art form and precisely why the experienced animators were spared the in-betweening work even before automatic techniques.

The classical paper on animation by John Lasseter from Pixar surveys some of the standard animation techniques:

"Principles of Traditional Animation Applied to 3D Computer Graphics," SIGGRAPH'87, pp. 35-44.

Squash and stretch

Squash: flatten an object or character by pressure or by its own power

Stretch: used to increase the sense of speed and emphasize the squash by contrast

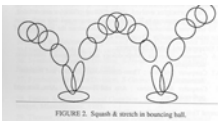


FIGURE 2. Squash & stretch in bouncing ball.

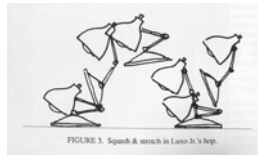


FIGURE 3. Squash & stretch in Lasso Jr.'s legs.

Timing

Timing affects weight:

- Light object move quickly
- Heavier objects move slower

Timing completely changes the interpretation of the motion. Because the timing is critical, the animators used the draw a time scale next to the keyframe to indicate how to generate the in-between frames.

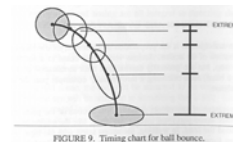


FIGURE 9. Timing chart for ball bounce.

Anticipation

An action breaks down into:

- Anticipation
- Action
- Reaction

Anatomical motivation: a muscle must extend before it can contract. Prepares audience for action so they know what to expect. Directs audience's attention. Amount of anticipation can affect perception of speed and weight.

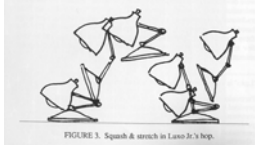


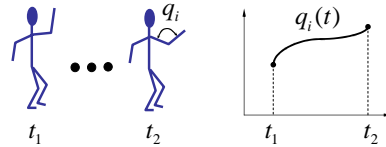
FIGURE 3. Squash & stretch in Lasso Jr.'s hop.

Articulated Models

Articulated models:

- rigid parts
- connected by joints

They can be animated by specifying the joint angles as functions of time.



Forward Kinematics

Describes the positions of the body parts as a function of the joint angles.

1 DOF: knee



2 DOF: wrist

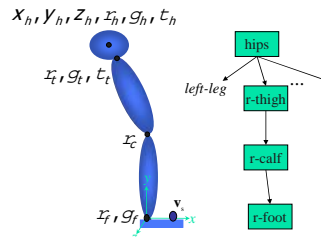


3 DOF: arm



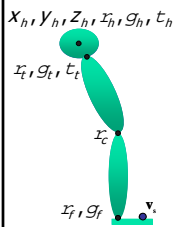
Skeleton Hierarchy

Each bone transformation described relative to the parent in the hierarchy:



Derive world coordinates V_w for an effector with local coordinates V_s ?

Forward Kinematics



Transformation matrix for an effector v_s is a matrix composition of all joint transformation between the effector and the root of the hierarchy.

$$V_w = T(x_h, y_h, z_h) R(\alpha_h, \beta_h, \gamma_h) TR(\alpha_i, \beta_i, \gamma_i) TR(\alpha_c, \beta_c, \gamma_c) V_s$$

$$V_w = S \left(\underbrace{x_h, y_h, z_h, \theta_h, \phi_h, \sigma_h, \theta_i, \phi_i, \sigma_i, \theta_c, \phi_c, \sigma_c, \theta_f, \phi_f, \sigma_f}_{\rho} \right) V_s = S(\rho) V_s$$

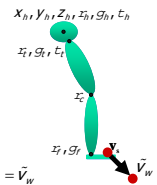
Inverse Kinematics

Forward Kinematics

- Given the skeleton parameters (position of the root and the joint angles) ρ and the position of the effector in local coordinates V_s , what is the position of the sensor in the world coordinates V_w ?
- Not too hard, we can solve it by evaluating $S(\rho)V_s$

Inverse Kinematics

- Given the position of the effector in local coordinates V_s and the desired position \tilde{V}_w in world coordinates, what are the skeleton parameters ρ ?



- Much harder requires solving the inverse of the non-linear function: ρ ? such that $S(\rho)V_s = \tilde{V}_w$
- Underdetermined problem with many solutions

Real IK Problem

Find a "natural" skeleton configuration for a given collection of pose constraints.

Definition: A scalar objective function $g(p)$ measures the quality of a pose. The objective $g(p)$ reaches its minimum for the most natural skeleton configurations p .

Definition: A vector constraint function $C(p) = 0$ collects all pose constraints:

$$\begin{bmatrix} S_0(p)v_0 - \bar{v}_0 \\ S_1(p)v_1 - \bar{v}_1 \\ \vdots \end{bmatrix} = 0$$

$C(p)$

BAUW Lecture 10 Slide 25 6.837 Fall 2003 MIT

Optimization

Compute the optimal parameters p^* that satisfy pose constraints and maximize the natural quality of skeleton configuration:

$$p^* = \underset{p}{\operatorname{argmin}} g(p)$$

s.t. $C(p) = 0$

Example objective functions $g(p)$:

- deviation from natural pose: $g(p) = (p - \bar{p})^T M(p - \bar{p})$
- joint stiffness
- power consumption
- ...

BAUW Lecture 10 Slide 26 6.837 Fall 2003 MIT

Unconstrained Optimization

Define an objective function $f(p)$ that penalizes violation of pose constraints:

$$f(p) = g(p) + \sum_i w_i [C_i(p)]^2$$

$$p^* = \underset{p}{\operatorname{argmin}} f(p)$$

Necessary condition:

$$f(p^* + \Delta p) - f(p^*) \geq 0 \quad (p^* \text{ is local minimum})$$

$$\nabla f(p^*)^T \Delta p + \dots \geq 0 \quad (\text{Taylor series})$$

$$\Downarrow$$

$$\nabla f(p^*) = 0 \quad (\Delta p \text{ is arbitrary})$$

BAUW Lecture 10 Slide 27 6.837 Fall 2003 MIT

Numerical Solution

Gradient methods

- Guess initial solution x_0
- Iterate $x_{k+1} = x_k + \alpha_k d_k$, $\alpha_k > 0$, $\nabla f(x_k)^T d_k < 0$
- Until $\nabla f(x_k) = 0$

The conditions $\alpha_k > 0$, $\nabla f(x_k)^T d_k < 0$ guarantee that each new iterate is more optimal $f(x_{k+1}) < f(x_k)$. Derive?

Some choices for direction d_k :

- Steepest descent $d_k = -\nabla f(x_k) = -\frac{\partial g}{\partial p} - 2\sum_i w_i C_i \frac{\partial C_i}{\partial p}$
- Newton's method $d_k = -[\nabla^2 f(x_k)]^{-1} \nabla f(x_k)$
- Quasi-Newton methods $d_k = -D_k \nabla f(x_k)$

BAUW Lecture 10 Slide 28 6.837 Fall 2003 MIT

Gradient Computation

Requires computation of constraint derivatives:

- Compute derivatives of each transformation primitive
- Apply chain rule

Example:

$$C(p) \gg T(x_h, y_h, z_h) \mathbf{R}(x_h, g_h, t_h) \mathbf{TR}(x_t, g_t, t_t) \mathbf{TR}(x_c) \mathbf{TR}(x_f, g_f) v_s \cdot \bar{v}_w$$

$$\frac{\bullet C}{\bullet x_c} \gg T(x_h, y_h, z_h) \mathbf{R}(x_h, g_h, t_h) \mathbf{TR}(x_t, g_t, t_t) \mathbf{T} \frac{\bullet \mathbf{R}(x_c)}{\bullet x_c} \mathbf{TR}(x_f, g_f) v_s$$

Derive $\frac{\bullet \mathbf{R}(x_c)}{\bullet x_c}$ if \mathbf{R} is a rotation around z-axis?

BAUW Lecture 10 Slide 29 6.837 Fall 2003 MIT

Constrained Optimization

Unconstrained formulation has drawbacks:

- Sloppy constraints
- The setting of penalty weights w_i must balance the constraints and the natural quality of the pose

Necessary condition for equality constraints:

- Lagrange multiplier theorem:

$$\nabla f(p^*) + \sum_i \lambda_i \nabla C_i(p^*) = 0$$
- $\lambda_0, \lambda_1, \dots$ are scalars called Lagrange multipliers

Interpretations:

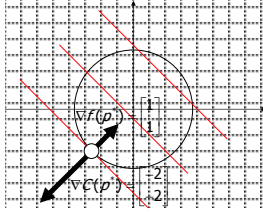
- Cost gradient (direction of improving the cost) belongs to the subspace spanned by constraint gradients (normals to the constraints surface).
- Cost gradient is orthogonal to subspace of feasible variations.

BAUW Lecture 10 Slide 30 6.837 Fall 2003 MIT

Example

$$p^* = \underset{p}{\operatorname{argmin}} \quad p_1 + p_2$$

$$\text{s.t.} \quad p_1^2 + p_2^2 = 2$$



Lecture 10

Slide 31

6.837 Fall 2003



Nonlinear Programming

Use Lagrange multipliers and nonlinear programming techniques to solve the IK problem:

$$p^* = \underset{p}{\operatorname{argmin}} \quad g(p) \quad \left. \vphantom{p^*} \right\} \text{ nonlinear objective}$$

$$\text{s.t.} \quad C(p) = 0 \quad \left. \vphantom{p^*} \right\} \text{ nonlinear constraints}$$

In general, slow for interactive use!



Lecture 10

Slide 32

6.837 Fall 2003



Differential Constraints

Differential constraints linearize original pose constraints.

Rewrite constraints by pulling the desired effector locations to the right hand side

$$\begin{bmatrix} S_0(p)v_0 \\ S_1(p)v_1 \\ \vdots \\ c(p) \end{bmatrix} = \begin{bmatrix} \tilde{v}_0 \\ \tilde{v}_1 \\ \vdots \\ \vdots \end{bmatrix}$$

Construct linear approximation around the current parameter p . Derive with Taylor series.

$$\frac{\partial C(p)}{\partial p} \Delta p = \Delta \tilde{v}$$



Lecture 10

Slide 33

6.837 Fall 2003



IK with Differential Constraints

Interactive Inverse Kinematics

- User interface assembles desired effector variations $\Delta \tilde{v}$
- Solve quadratic program with Lagrange multipliers:

$$\Delta p^* = \underset{\Delta p}{\operatorname{argmin}} \quad \Delta p^T M \Delta p$$

$$\text{s.t.} \quad \frac{\partial C(p)}{\partial p} \Delta p = \Delta \tilde{v}$$

- Update current pose: $p_{k+1} = p_k + \alpha_k \Delta p^*$

Objective function is quadratic, differential constraints are linear.

Some choices for matrix M :

- Identity: minimizes parameter variations
- Diagonal: minimizes scaled parameter variations



Lecture 10

Slide 34

6.837 Fall 2003



Quadratic Program

Elimination procedure

Apply Lagrange multiplier theorem and convert to vector notation:

general form in scalar notation:
 $\nabla f(p^*) + \sum \lambda_i \nabla C_i(p^*) = 0$

$$M \Delta p + \left(\frac{\partial C(p)}{\partial p} \right)^T \lambda = 0$$

Rewrite to expose Δp :

$$\Delta p = -M^{-1} \left(\frac{\partial C(p)}{\partial p} \right)^T \lambda$$

Use this expression to replace Δp in the differential constraint:

$$\frac{\partial C(p)}{\partial p} M^{-1} \left(\frac{\partial C(p)}{\partial p} \right)^T \lambda = -\Delta \tilde{v}$$

Solve for Lagrange multipliers and compute Δp^*



Lecture 10

Slide 35

6.837 Fall 2003



Kinematics vs. Dynamics

Kinematics

Describes the positions of body parts as a function of skeleton parameters.

Dynamics

Describes the positions of body parts as a function of applied forces.



Lecture 10

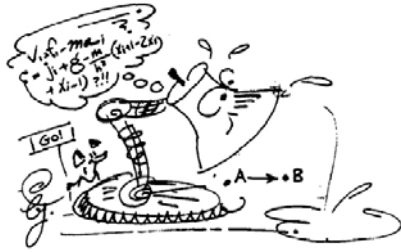
Slide 36

6.837 Fall 2003



Next

Dynamics



ACM© 1988 "Spacetime Constraints"

← Back

Lecture 10

Slide 37

6.837 Fall 2003

Next →