Motion synthesis

- **Goals:**
  - generate human motions that “look human” and “do what you want”
  - Synthesis
    - with control; with interaction
  - Evaluation
    - what “looks human?”

- **Features**
  - Motion composes across the body and across time
    - so the number of available motions is huge
  - Multiple constraints on the appearance of motion
    - physics;
    - motor control system;
    - internal motion goals;
    - nearby objects;
Key problems

• What makes a motion look human?
  • can we tell good motions from bad?

• How do we describe human activities?
  • with what vocabulary? at what time scales?

• How do nearby objects affect our description
  • interactions and context
Motion synthesis difficulties

- People are good at spotting poor motion
  - and it sometimes matters
- Motions can be very fast and very detailed
  - high accelerations, contacts create major issues
- Authoring is mysterious
  - how does one specify constraints on activity usefully?
- Complexity
  - interactions with objects, etc. create a need for families of motion
  - motion composes in nasty ways
  - motions should interact with objects, users, etc.
- Control
  - character should be manageable
  - have some capability to cope on its own
Motion synthesis, cont

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  - so the number of available motions is huge
- Multiple constraints on the appearance of motion
  - physics;
  - motor control system;
  - internal motion goals;
  - nearby objects;
Motion synthesis

- **Methods**
  - By animator
  - By kinematic control
    - profound difficulties with ambiguity
  - By combining observations
    - old tradition of move trees; also (Kovar et al 02, Lee et al 02, Arikan+Forsyth 02, Arikan et al 03, Gleicher et al 03)
  - By physical models
    - old tradition; (Witkin+Kass, 88; Witkin+Popovic 99; Funge et al 88; Fang+Pollard 03, 04)
  - By biomechanical models
    - old tradition; Liu+Popovic 02; Abe et al 04; Wu+Popovic 03; Liu+Popovic 02)
  - By statistical models
    - old tradition (e.g. Ramsey+Silverman 97); Li et al 02; Safanova et al 04; Mataric et al 99; Mataric 00; Jenkins+Mataric 04;
Variational and Physical Methods

Example 5:
3D Walking

4338 Automatic Constraints (joint angles, footplants)
Data-driven motion synthesis

- Analogies
  - Text synthesis (Shannon)

  “It means that in speaking with you, I am aware of how I think this is one of those questions that exposes a contradiction in our cultural cognitive disconnect the concept of authenticity exposes is, I believe, that we have inner and outer selves, and that the inner self is our real self. I personally find those ideas more misleading than helpful.”

- Texture synthesis (Efros+Leung ‘99; many others since)
Motion graph

• Take measured frames of motion as nodes
  • from motion capture, given us by our friends
• Directed edge from frame to any that could succeed it
  • decide by dynamical similarity criterion
  • see also (Kovar et al 02; Lee et al 02)
• A path is a motion
• Search with constraints
  • root position+orientation
  • length of motion
  • occupy a frame at specified time
  • limb close to a point

Motion Graph:
Nodes = Frames
Edges = Transition
A path = A motion
Search in a motion graph

- Local
  - Kovar et al 02
- With some horizon
  - Lee et al 02; Ikemoto, Arikan+Forsyth 05
- Whole path
  - Arikan+Forsyth 02; Arikan et al 03

Motion Graph:
Nodes = Frames
Edges = Transition
A path = A motion
Local Search methods

- Choose the next edge (Kovar, Gleicher, Pighin 02)
  - ensure that one can’t get stuck locally
  - but can’t guarantee a goal is available on longer scale
Original Motion
On-line control of motion synthesis

Agent travels along *motion graph*. When he reaches a decision point, he must choose which branch to take so he can best meet his objectives.
Value of state $s$ obtained by comparing to a set of example states, encoded using following weighted terms:

- Local geometry
- Visible enemies
- Distance to next waypoint on global path plan
Reinforcement learning

Sample control parameters ($w$) for a random state ($s$)

- $w_1$ → Fix for the motion graph → Generate motion → Reward 1
- $w_2$ → Fix for the motion graph → Generate motion → Reward 2
- $w_{3000}$ → Fix for the motion graph → Generate motion → Reward 3000

Fix control parameters for state $s$ to be the $w$ that yielded maximum reward

Ikemoto+Arikan+Forsyth 05
Characteristic properties of motion

- **Characteristic features**
  - most demands are radically underconstrained
  - motion is simultaneously
    - hugely ambiguous
    - “low entropy”

- Suggests using “summaries”
Limitations

- Can’t synthesize motions one hasn’t seen
  - but see later
- Long term structure of motion is strange
  - running backwards, etc.
- No on-the-fly control of motion or interaction
  - but see later
- Require more detailed control of “type” of motion
  - can deal with this
Synthesis with off-line control

- Annotate motions
  - using a classifier and on-line learning
  - efficient human-in-the loop training
- Produce a sequence that meets annotation demands
  - a form of dynamic programming
Annotation - desirable features

- Composability
  - run and wave;
- Comprehensive but not canonical vocabulary
  - because we don’t know a canonical vocabulary
- Speed and efficiency
  - because we don’t know a canonical vocab.

- Can do this with one classifier per vocabulary item
  - use an SVM applied to joint angles
  - form of on-line learning with human in the loop
  - works startlingly well (in practice 13 bits)
Synthesis by dynamic programming

Walk | P | P | P | P | P
Run  | ● | ● | ● | ● |
Jump | ● | ● | ● | ● |
Wave | P | P | O | O |
Carry| ● | ● | ● | ● |

Motion demand

All frames in the database

Arikan+Forsyth+O’Brien 03
Dynamic programming practicalities

- **Scale**
  - Too many frames to synthesize
  - Too many frames in motion graph
- **Obtain good summary path, refine**
  - Form long blocks of motion, cluster
  - DP on stratified sample
    - split blocks on “best” path
    - find similar subblocks
      - DP on this lot
    - etc. to 1-frame blocks

Arikan+Forsyth+O’Brien 03
Still open

- Local control of synthesis
  - Long term structure of motion is strange
    - running backwards, etc.
    - essential for interaction

- Departing from data?
  - Can’t synthesize motions one hasn’t seen
    - essential for interaction
Transplantation

- MOTIONS CLEARLY HAVE A COMPOSITIONAL CHARACTER
  - WHY NOT CUT LIMBS OFF SOME MOTIONS AND ATTACH TO OTHERS?
    - WE GET SOME BAD MOTIONS
  - BUILD A CLASSIFIER TO TELL GOOD FROM BAD
    - AVOID FOOT SLIDE BY LEAVING LOWER BODY ALONE

Ikemoto+Forsyth 04
Loop {
    Randomly pick a synthesis rule

    \( e^{-\frac{d_{ij}}{(2\sigma_d^2)}} \)

    Djikstra's to find a path

    If successful, output candidate motions
}

Kovar, Gleicher, Pighin 2002

Ikemoto+Forsyth 04
22, 645

Generate

477, 362

Check

340, 596

labelled “human”

Classifier’s total error rate 13%
false positive rate 12%

But what does this mean in practice?

Ikemoto+Forsyth 04
Evaluate

Unreal Tournament 2004

• Position
• Velocity
• Rotation
• Running/Falling

+ 40 hand-generated streams

Ikemoto+Forsyth 04

Motion demands

Original motion graph

Synthesizer

Motion A_i

Synthesizer

Motion B_i

Enriched graph

Proxy
Is the enriched graph better?
Pushes and shoves

• **Natural interaction --- push, pull, hit, shoot, etc**
  • apply an impulse of given strength, direction
  • reaction time precludes much CNS involvement
    • Physics should be important
• **Can’t serve impulse with observed data**
  • too much data required unless you can guarantee limited impulses
• **Strategy**
  • deform each of many data items to serve given impulse
  • blend each to motion sequence
  • build regression model of motion quality to choose which to use
How good are the motions?

\[
P(\text{Human Good} \mid \text{Oracle Bad})
\]

\[
P(\text{Human Good} \mid \text{Oracle Good})
\]

\[
P(\text{Human Good} \mid \text{Motion Capture})
\]
Building Oracles

• Classifier (Ikemoto+Forsyth 04)
• Regression (Arikan+Forsyth 05)
• Ensemble of HMM’s (Ren et al 05)
• Nearest Neighbour (Ikemoto et al, in review)
Slow Motion