

3D Articular Human Tracking from Monocular Video

From Condensation to Kinematic Jumps

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Goal: track human body motion in monocular video and estimate 3D joint motion



Why Monocular ?

- Movies, archival footage
- Tracking / interpretation of actions & gestures (HCI)
- Resynthesis, e.g. change point of view or actor
- How do humans do this so well?

Why is 3D-from-monocular hard?

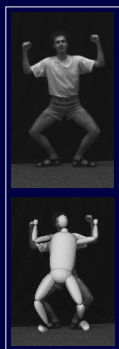
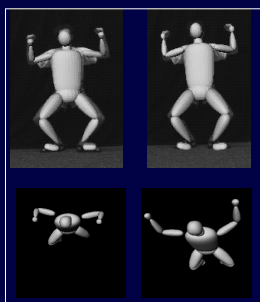


Image matching ambiguities



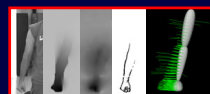
Depth ambiguities



Violations of physical constraints

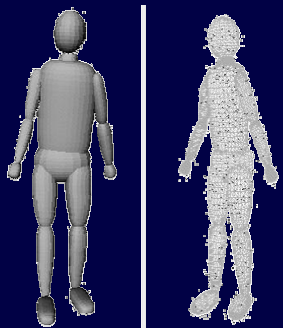
Overall Modelling Approach

1. Generative Human Model
 - Complex, kinematics, geometry, photometry
 - Predicts images or descriptors
2. Model-image matching cost function
 - Associates model predictions to image features
 - Robust, probabilistically motivated
3. Tracking by search / optimization
 - Discovers well supported configurations of matching cost



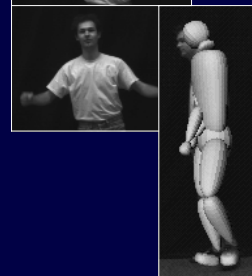
Human Body Model

- Explicit 3D model allows high-level interpretation
- 30-35 d.o.f. articular 'skeleton'
- 'Flesh' of superquadric ellipsoids with tapering & bending
- Model \rightarrow image projection maps points on 'skin' through
 - kinematic chain
 - camera matrix
 - occlusion (z buffer)

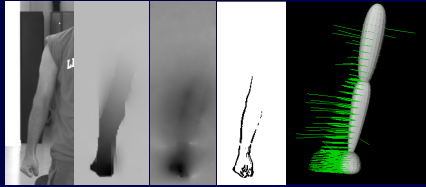


Parameter Space Priors

- Anthropometric prior
 - left/right symmetry
 - bias towards default human
- Accurate kinematic model
 - clavicle (shoulder), torso (twist)
 - robust prior stabilizes complex joints
- Body part interpenetration
 - repulsive inter-part potentials
- Anatomical joint limits
 - hard bounds in parameter space



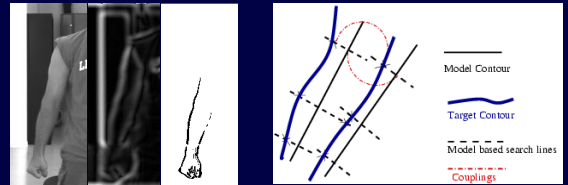
Multiple Image Features, Integrated Robustly



1. Intensity

- The model is 'dressed' with the image texture under its projection (visible parts) in the previous time step
- Matching cost of model-projected texture against current image (robust intensity difference)

2. Contours



- Multiple probabilistic assignment integrates matching uncertainty
- Weighted towards motion discontinuities (robust flow outliers)
- Also accounts for higher order symmetric model/data couplings
 - partially removes local, independent matching ambiguities

Cost Function Minima Caused By Incorrect Edge Assignments



How many local minima are there?

Thousands! – even *without* image matching ambiguities ...

Tracking Approaches We Have Tried

- Traditional CONDENSATION
- Covariance Scaled Sampling
- Direct search for nearby minima
- Kinematic Jump Sampling
- 'Manual' initialization – already requires nontrivial optimization

Properties of Model-Image Matching Cost Function, 1

- High dimension
 - at least 30 – 35 d.o.f.
 - but factorial structure: limbs are quasi-independent
- Very ill-conditioned
 - depth d.o.f. often nearly unobservable
 - condition number $O(1 : 10^4)$
- Many many local minima
 - $O(10^3)$ kinematic minima, times image ambiguity

Properties of Model-Image Matching Cost Function, 2

- Minima are usually well separated
 - fair random samples almost never jump between them
- But they often merge and separate
 - frequent passage through singular / critical configurations – frontoparallel limbs
 - causes mistracking!
- Minima are small, high-cost regions are large
 - random sampling with exaggerated noise almost never hits a minimum

Covariance Scaled Sampling, 1

Mistracking leaves us in the wrong minimum.

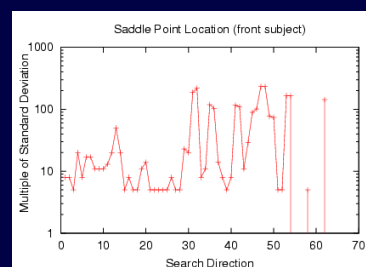
To make particle filter trackers work for this kind of cost function, we need :

- **Broad sampling** to reach basins of attraction of nearby minima
 - in CONDENSATION : exaggerate the dynamical noise
 - robust / long-tailed distributions are best
- Followed by **local optimization** to reach low-cost 'cores' of minima
 - core is small in high dim. problems, so samples rarely hit it
 - CONDENSATION style reweighting will kill them before they get there

Covariance Scaled Sampling, 2

- Sample distribution should be based on **local shape of cost function**
 - the minima that cause confusion are much further in some directions than in others owing to ill-conditioning
 - in particular, kinematic flip pairs are aligned along ill-conditioned depth d.o.f.
- Combining these 3 properties gives **Covariance Scaled Sampling**
 - long-tailed, covariance shaped sampling + optimization
 - represent sample distribution as robust mixture model

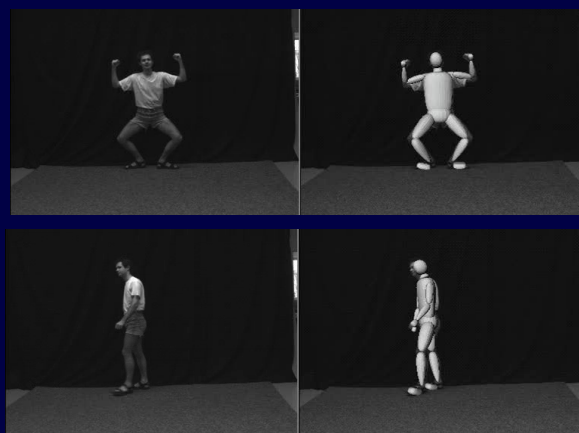
Statistical Separation of Minima



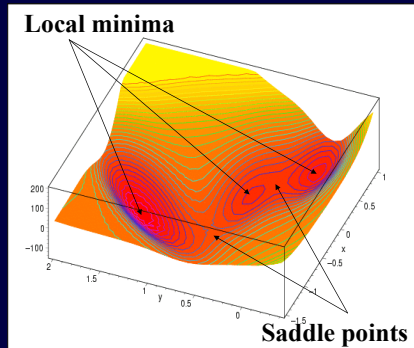
- Minima are usually at least $O(10^1)$ standard deviations away.

Direct Search for Nearby Minima

- Instead of sampling randomly, directly locate nearby cost basins by finding the 'mountain passes' that lead to them
 - i.e. find the saddle point at the top of the path
- Numerical methods for finding saddles :
 - modified Newton optimizers : eigenvector tracking, hypersurface sweeping
 - 'hyperdynamics' : MCMC sampling in a modified cost surface that focuses samples on saddles

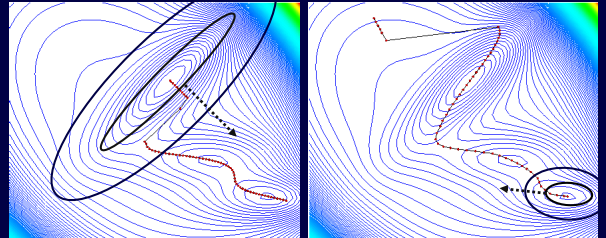


Direct Search for Nearby Minima



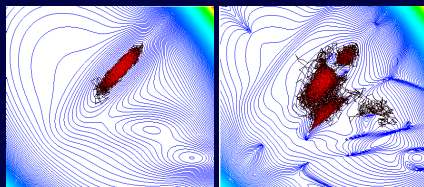
Hypersurface Sweeping

- Track cost minima on an expanding hypersurface
- Moving cost has a local maximum at a saddle point

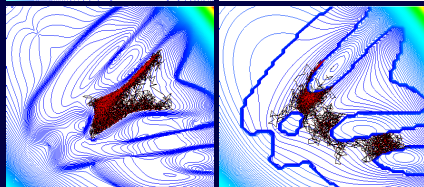


Hyperdynamics

small height



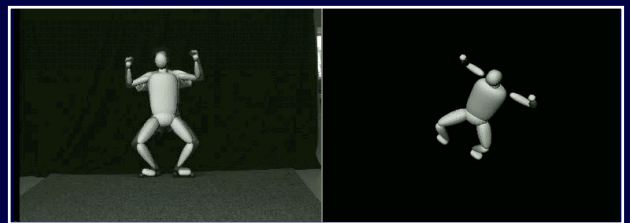
large height



small abruptness

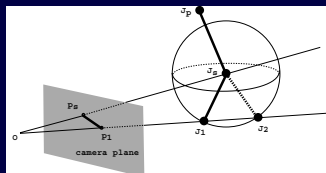
large abruptness

Examples of Kinematic Ambiguities



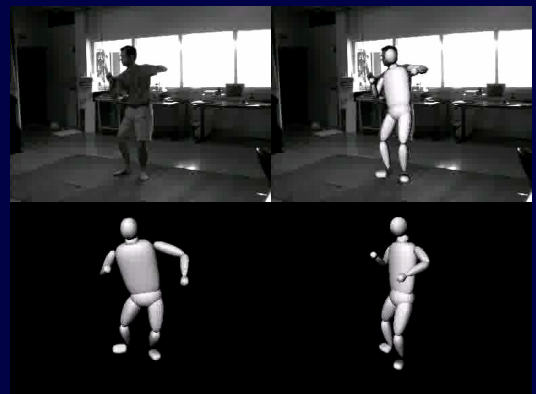
- Eigenvector tracking method
- Initialization cost function (hand specified image positions of joints)

Kinematic Jump Sampling



- Generate tree of all possible kinematic solutions
 - work outwards from root of kinematic tree, recursively evaluating forwards & backwards 'flip' for each body part
 - alternatively, sample by generating flips randomly
 - you can often treat each limb quasi-independently
- Yes, it really does find thousands of minima !
 - quite accurate too – no subsequent minimization is needed
 - random sampling is still needed to handle matching ambiguities

Jump Sampling in Action



Summary

- 3D articular human tracking from monocular video
- A hard problem owing to
 - complex model (many d.o.f., constraints, occlusions...)
 - ill-conditioning
 - many kinematic minima
 - model-image matching ambiguities
- Combine methods to overcome local minima
 - explicit kinematic jumps + sample for image ambiguities
- Current state of the art
 - relative depth accuracy is 10% or 10 cm at best
 - tracking for more than 5 – 10 seconds is still hard
 - still very slow – several minutes per frame

The End

