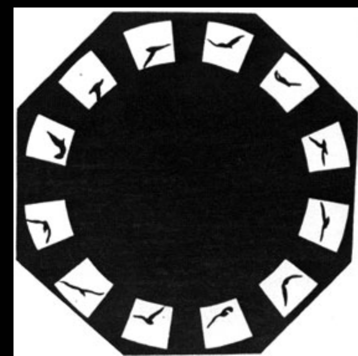
Inferring 3D from 2D

- History
- Monocular vs. multi-view analysis
- Difficulties
  - structure of the solution and ambiguities
  - static and dynamic ambiguities
- Modeling frameworks for inference and learning
  - top-down (generative, alignment-based)
  - bottom-up (discriminative, predictive, exemplar-based)
  - Learning joint models
- Take-home points

History of Analyzing Humans in Motion

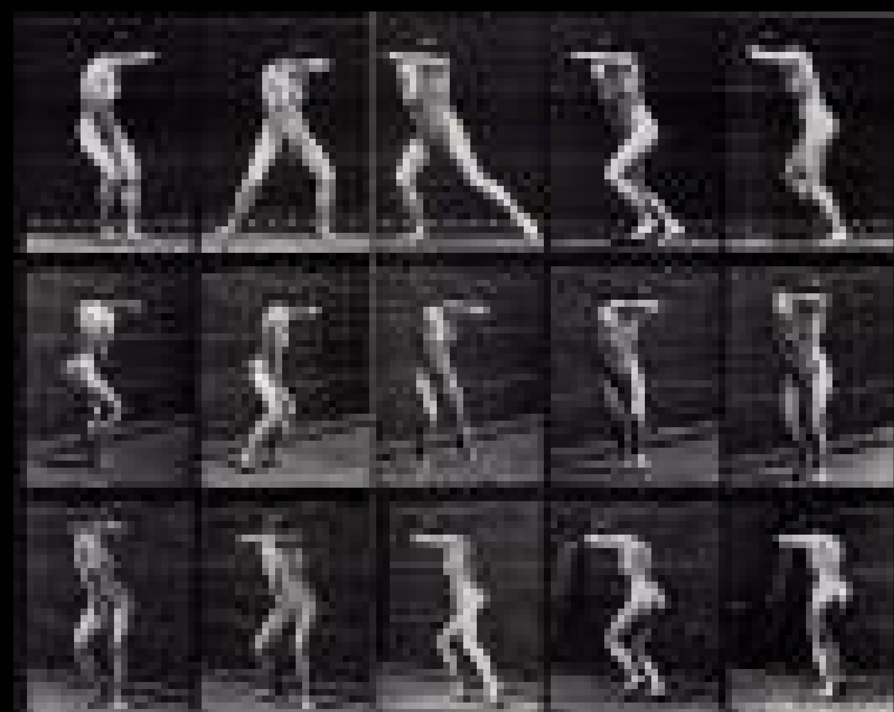
- Markers (*Etienne Jules Marey, 1882)*



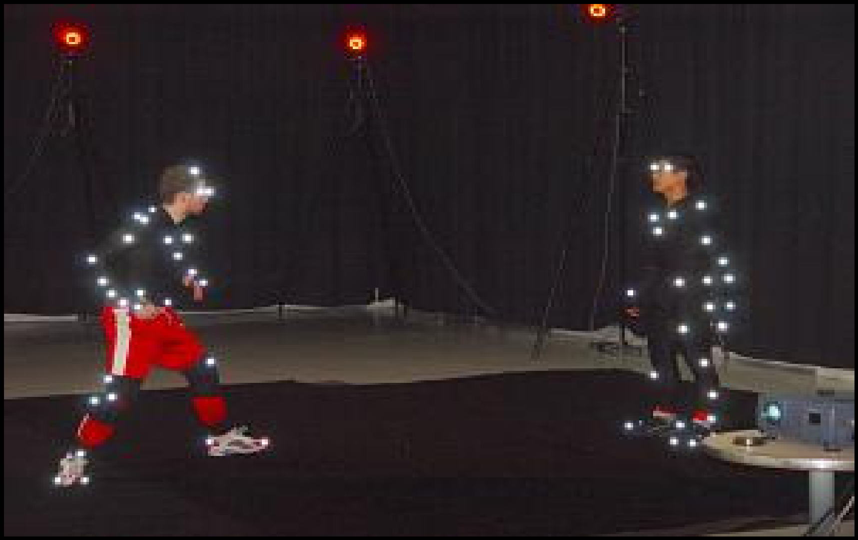
chronophotograph

- Multiple Cameras

(Eadweard Muybridge , 1884)



Human motion capture today
120 years and still fighting …



- VICON ~ 100,000 $
  - Excellent performance, *de-facto* standard for special effects, animation, *etc*
- But heavily instrumented
  - Multiple cameras
  - Markers in order to simplify the image correspondence
  - Special room, simple background

Major challenge: Move from the laboratory to the real world

What is so different between multi-view and single-view analysis?

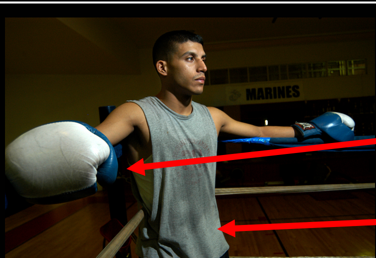
- Different emphasis on the relative importance of measurement and prior knowledge
  - Depth ambiguities
  - Self-occluded body parts
- Similar techniques at least one-way
  - Transition monocular->multiview straightforward
- Monocular as the `robust limit' of multi-view
  - Multiple cameras unavailable, or less effective in real-world environments due to occlusion from other people, objects, etc.

3D Human Motion Capture Difficulties

General poses

Self-occlusions

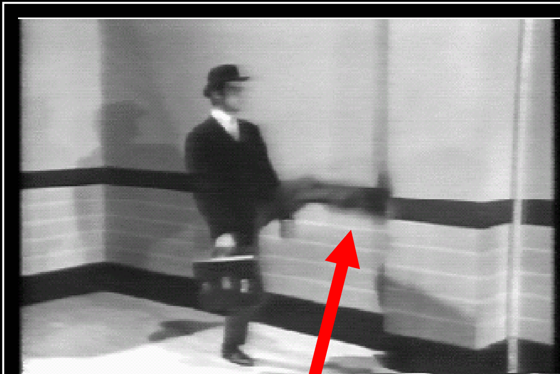
Difficult to segment the individual limbs



Loss of 3D information in the monocular projection

Partial Views

Different body sizes



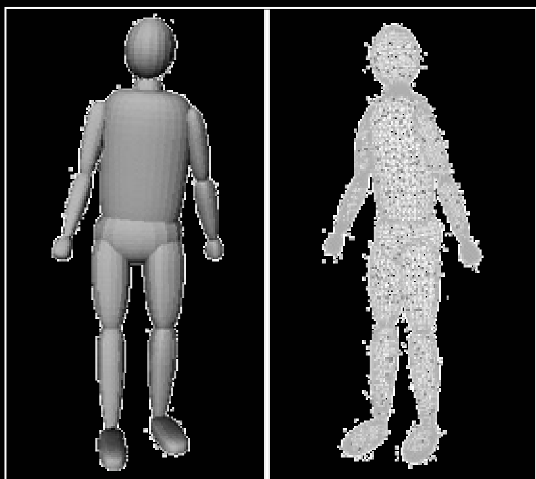
Accidental allignments
Motion blur

Several people, occlusions

Reduced observability of body parts due to loose fitting clothing

Levels of 3d Modeling

This section



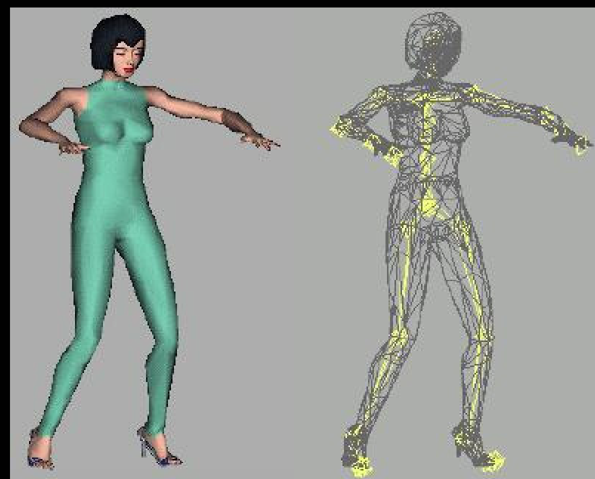


Photo Synthetic

- Coarse body model
- 30 - 35 d.o.f
- Simple appearance (implicit texture map)

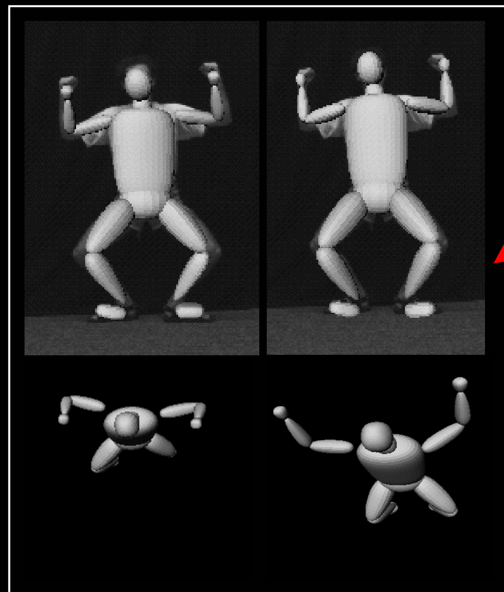
- Complex body model
- 50 - 60 d.o.f
- Simple appearance (edge histograms)

- Complex body model
- ? (hundreds) d.o.f
- Sophisticated modeling of clothing and lighting

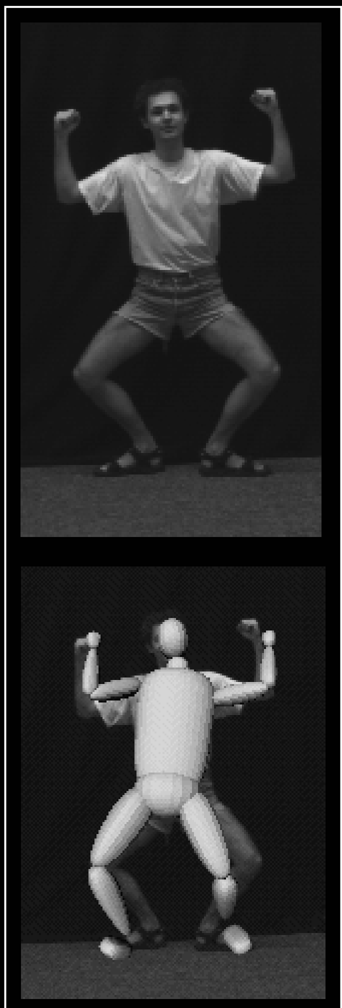
Difficulties

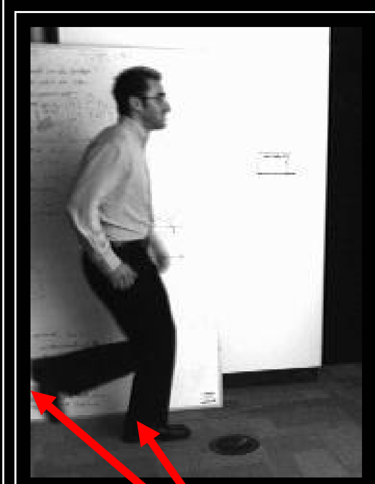
- High-dimensional state space (30-60 dof)
- Complex appearance due to articulation, deformation, clothing, body proportions
- Depth ambiguities and self-occlusion
- Fast motions, only vaguely known a-priori
  - External factors, objects, sudden intentions…
- Data association (what is a human part, what is background – *see the Data Association section*)

Difficulties, more concretely



Depth ambiguities





Data association ambiguities

Left / right leg ?

Occlusions

(missing data)

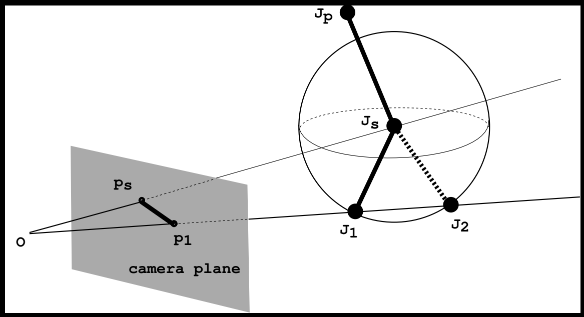
Left arm

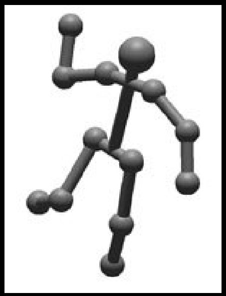
Preservation of physical constraints

Articulated 3d from 2d Joint Positions

Structure of the monocular solution: *Lee and Chen, CVGIP* ***1985*** ***(!)***

- Characterizes the space of solutions, assuming
  - 2d joint positions + limb lengths
  - internal camera parameters
- Builds an interpretation tree of projection-consistent hypotheses (3d joint positions)
  - obtained by forward-backward flips in-depth
  - $O(2^{\text{\# of body parts}})$ solutions
  - In principle, can prune some by physical reasoning
  - But no procedure to compute joint angles, hence difficult to reason about physical constraints
- Not an automatic 3d reconstruction method
  - select the true solution (out of many) manually
- Adapted for orthographic cameras *(Taylor 2000)*

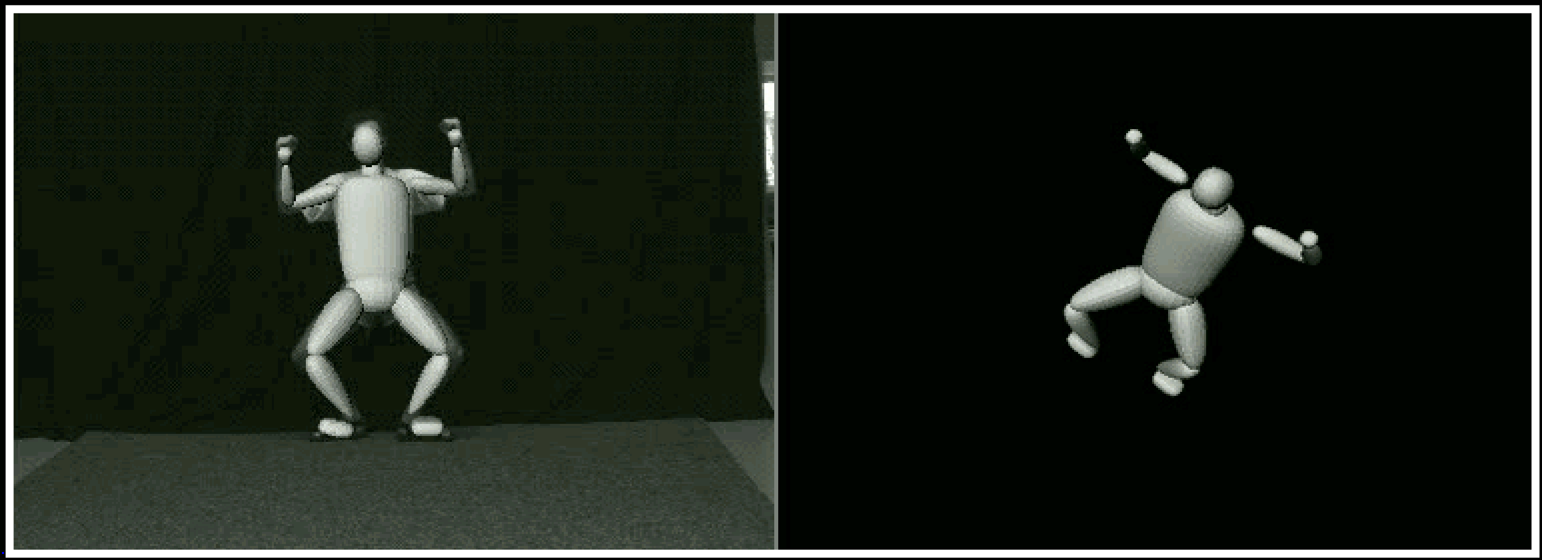




Taylor, CVIU 2000

Why is 3D-from-monocular hard? <v>

Static, Kinematic, Pose Ambiguities



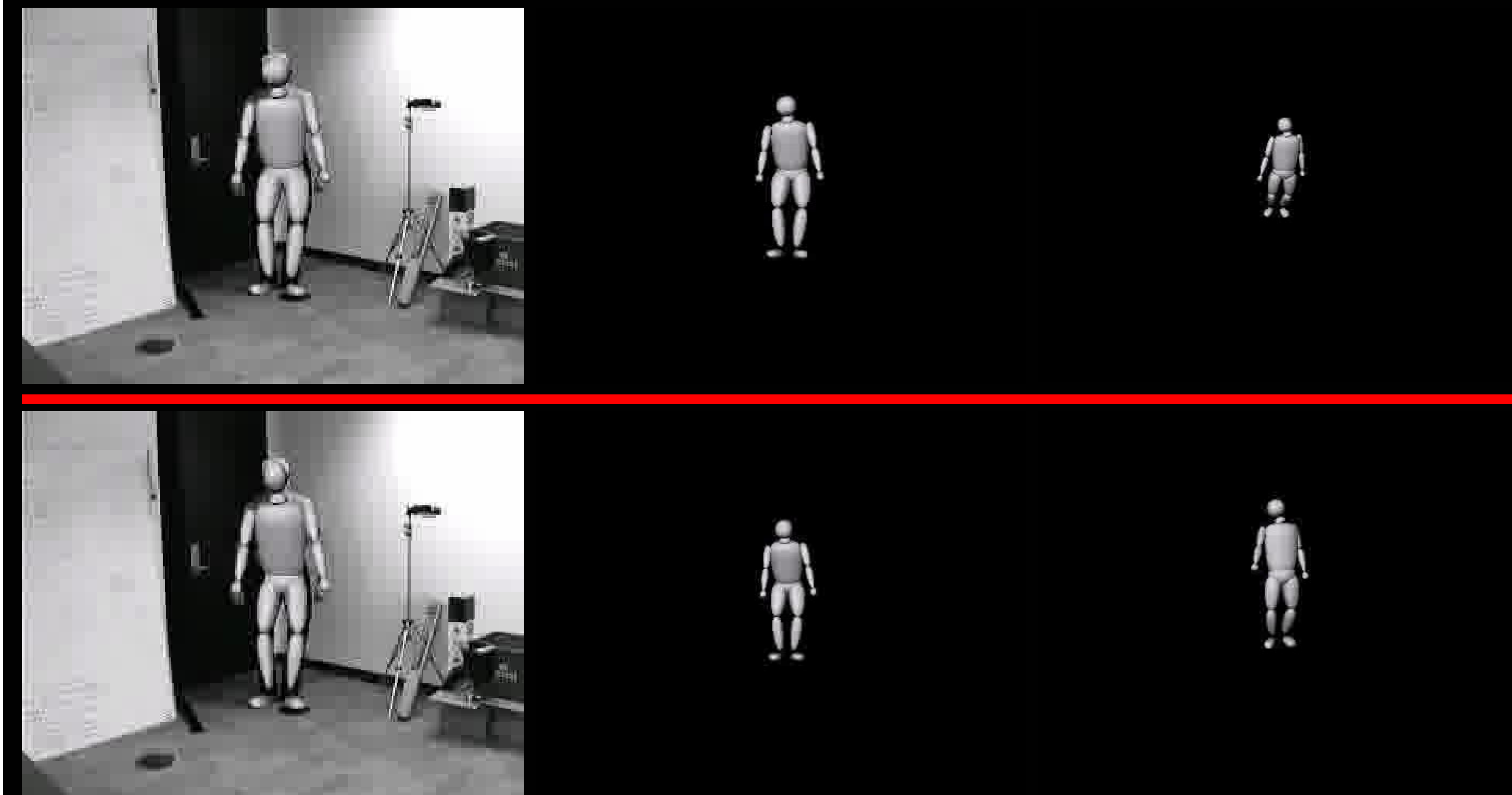
- Monocular static pose optima
  - ~ $2^{\text{Nr of Joints}}$, some pruned by physical constraints
  - Temporally persistent

Sminchisescu and Triggs '02

Trajectory Ambiguities <v>

General smooth dynamics

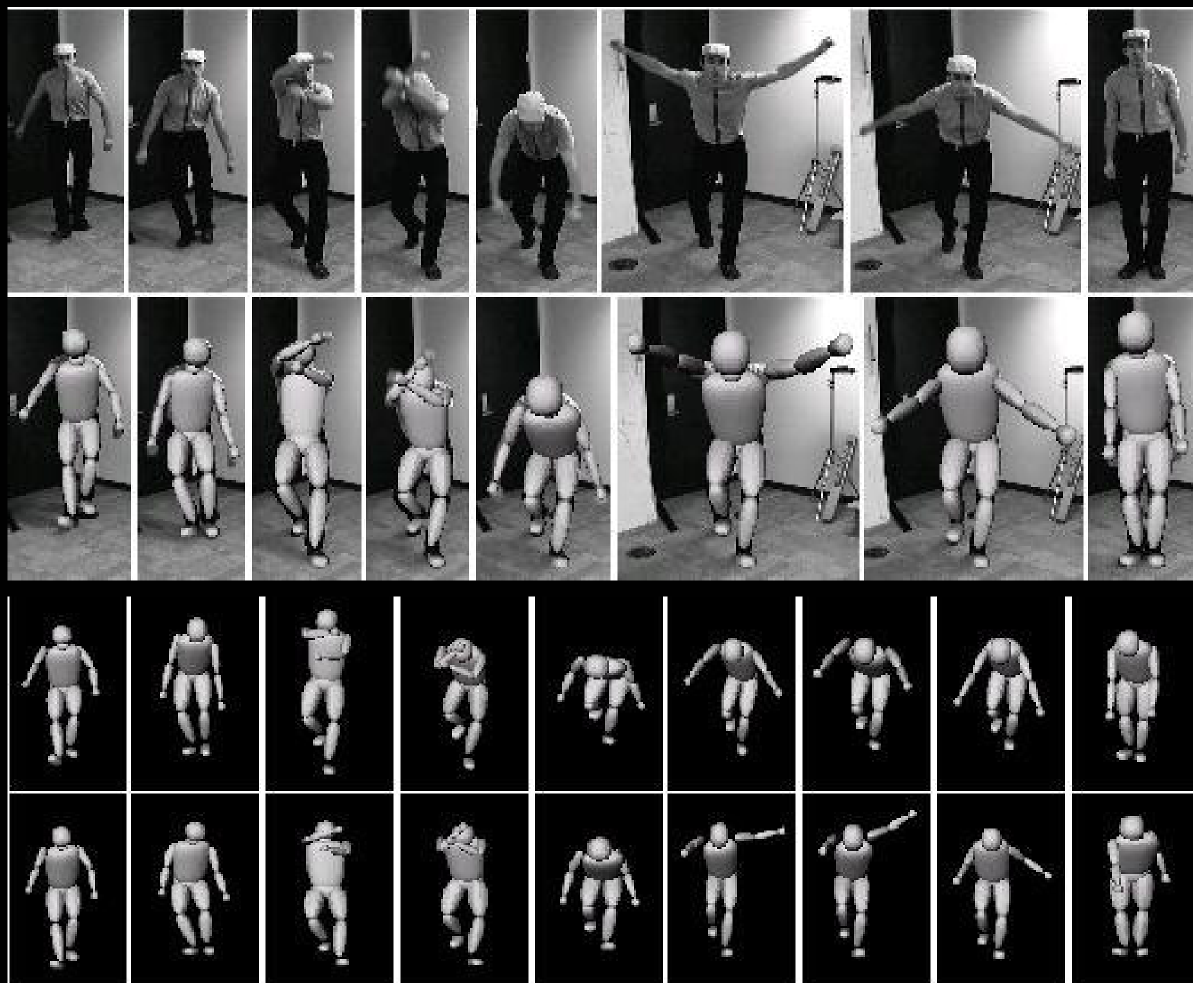
Model / image | Filtered | Smoothed



2 (out of several) plausible trajectories

Sminchisescu and Jepson '04

Trajectory Ambiguities
Smooth dynamics



2 (out of several) plausible trajectories

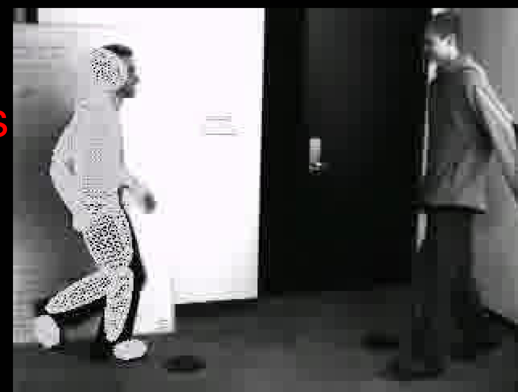
Trajectory Ambiguities <v>

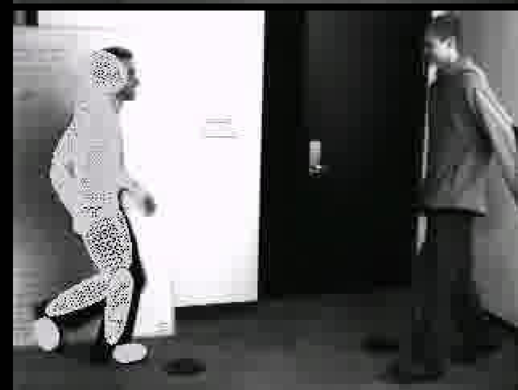
Learned latent space and smooth dynamics

Interpretation #1

Says `salut' when conversation ends

(before the turn)





Interpretation #2

Points at camera when conversation ends

(before the turn)

- Image consistent, smooth, typically human…

Sminchisescu and Jepson '04

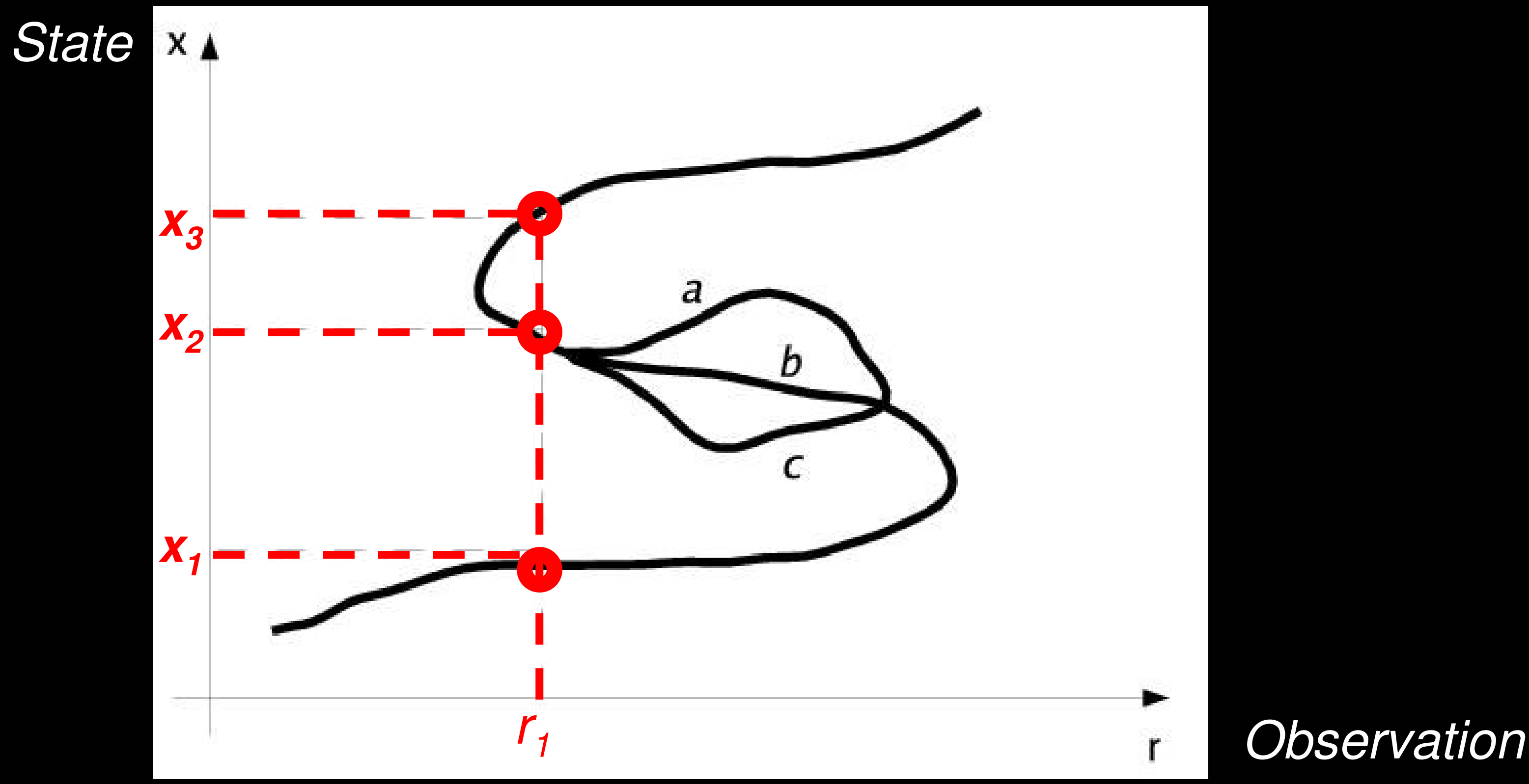
Visual Inference in a 12d Space

6d rigid motion + 6d learned latent coordinate

Interpretation #1
Points at camera when conversation ends (before the turn)

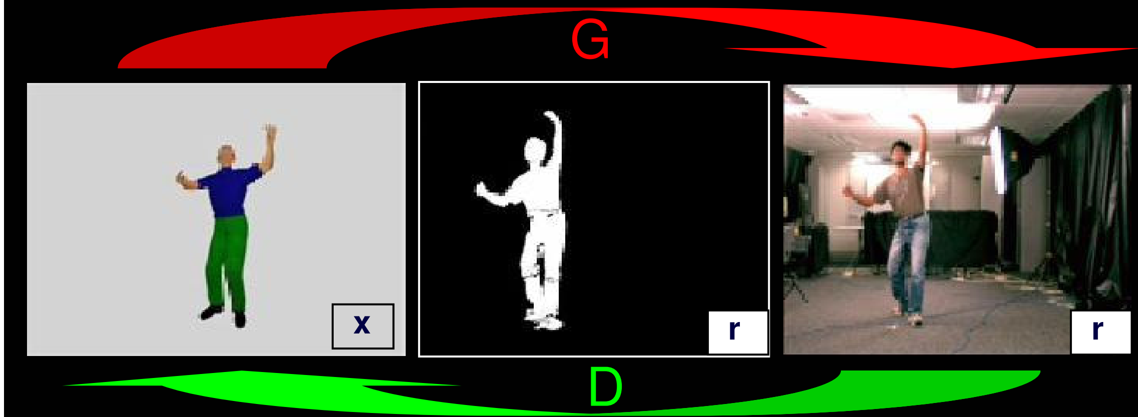
Interpretation #2
Says `salut' when conversation ends (before the turn)

The Nature of 3D Ambiguities



- Persistent over long time-scales (each S-branch)
- Loops (*a, b, c*) have limited time-scale support, hence ambiguity cannot be resolved by extending it

Generative vs. Discriminative Modelling



x is the model state

r are image observations

Goal: $p_\theta(\mathbf{x} \mid \mathbf{r})$

θ are parameters to learn given training set of (**r**,**x**) pairs

$$p_\theta(\mathbf{x} \mid \mathbf{r}) \propto p_\theta(\mathbf{r} \mid \mathbf{x}) \cdot p(\mathbf{x})$$

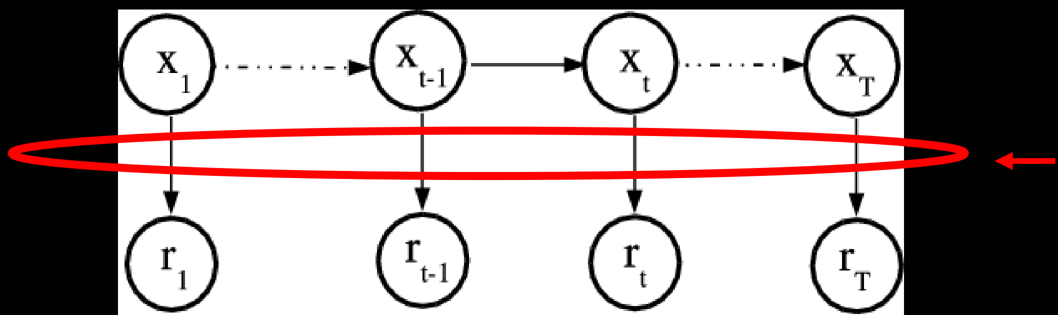
- Predict state distributions from image features
- Learning to `invert' perspective projection and kinematics is difficult and produces multiple solutions
  - *Multivalued mappings ≡ multimodal conditional state distributions*
- Temporal extensions necessary

- Optimize alignment with image features
- Can learn state representations, dynamics, observation models; but difficult to model human appearance
- State inference is expensive, need effective optimization

Temporal Inference (tracking)

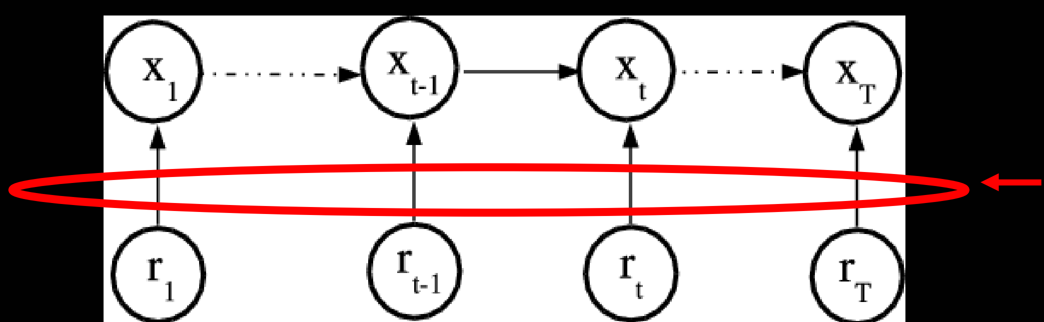
- Generative (top-down) chain models

  (Kalman Filter, Extended KF, Condensation)



- Discriminative (bottom-up) chain models

  (Conditional Bayesian Mixture Of Experts Markov Model - BM^{3}E, Conditional Random Fields -CRF, Max. Entropy Models - MEMM)



Temporal Inference

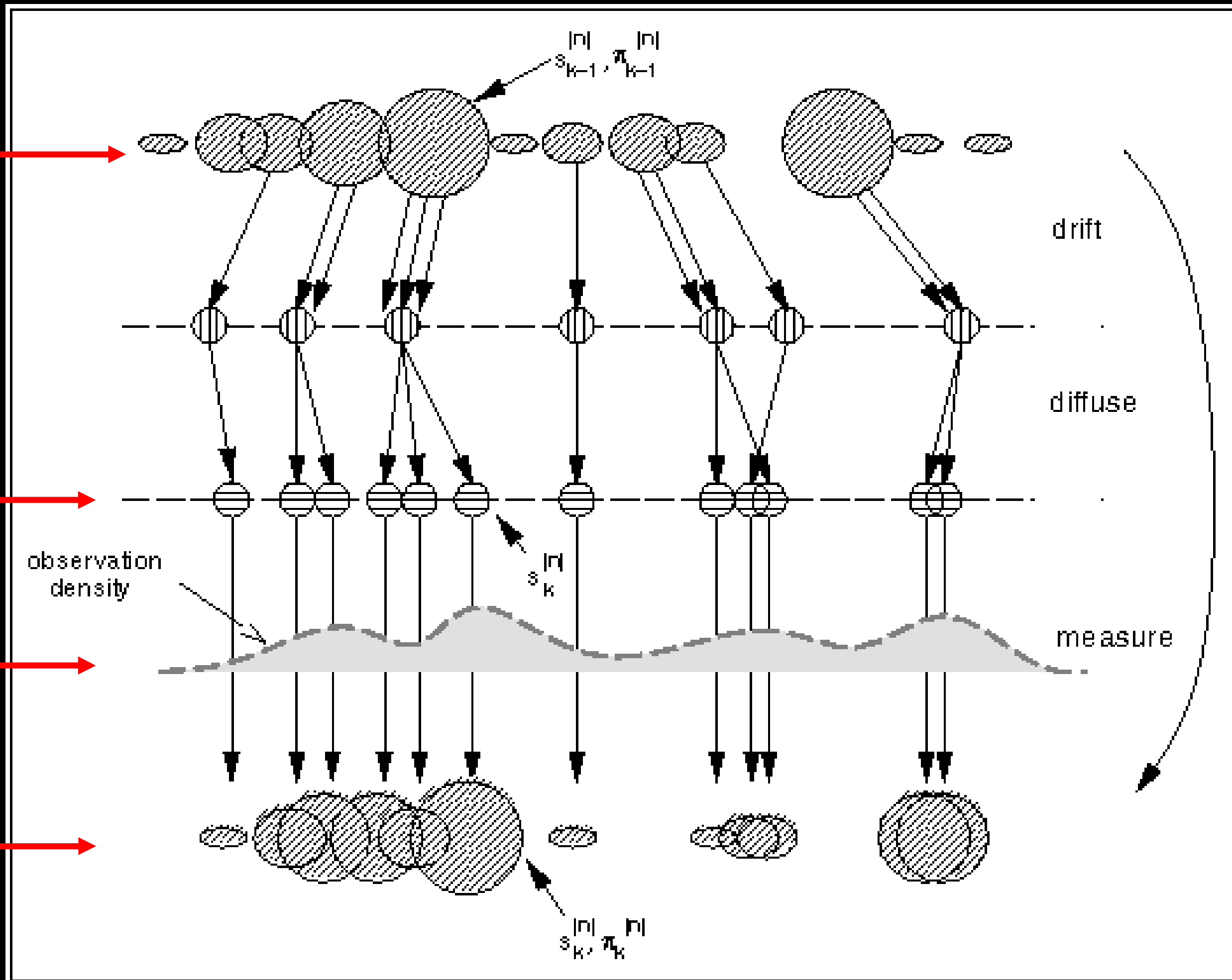
- x_t state at time t
- $O_t = (o_1, o_2, \ldots o_t)$ observations up to time t

$p(x_t | O_t)$

$p(x_{t+1} | O_t)$

$p(o_{t+1} | x_{t+1})$

$p(x_{t+1} | O_{t+1})$



time t

time t+1

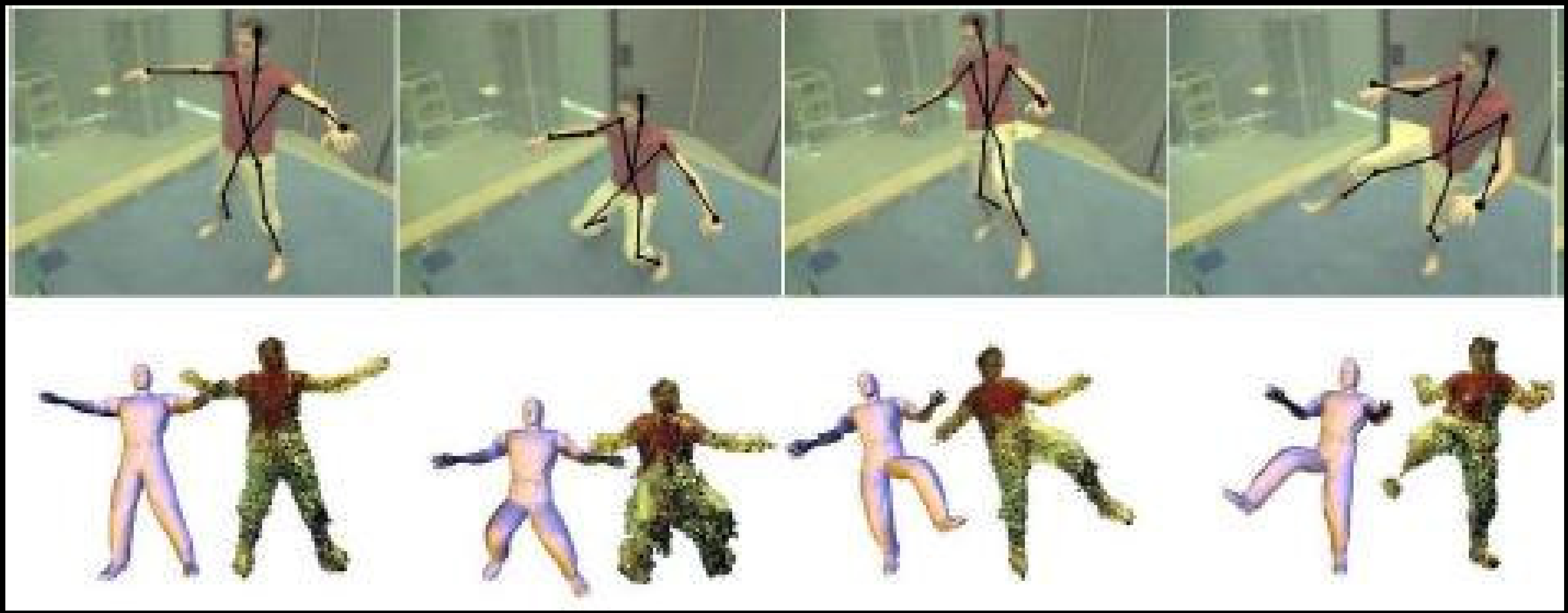
cf. CONDENSATION, *Isard and Blake, 1996*

Generative / Alignment Methods

- Modeling
- Methods for temporal inference
- Learning low-dimensional representations and parameters

Model-based Multiview Reconstruction

Kehl, Bray and van Gool '05



- Body represented as a textured 3D mesh
- Tracking by minimizing distance between 3d points on the mesh and volumetric reconstruction obtained from multiple cameras

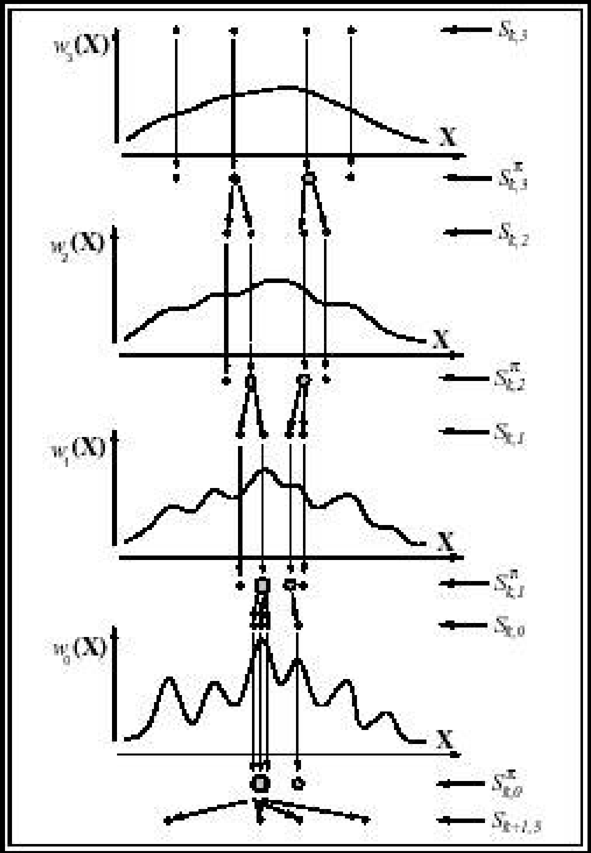
Generative 3D Reconstruction
Annealed Particle Filter

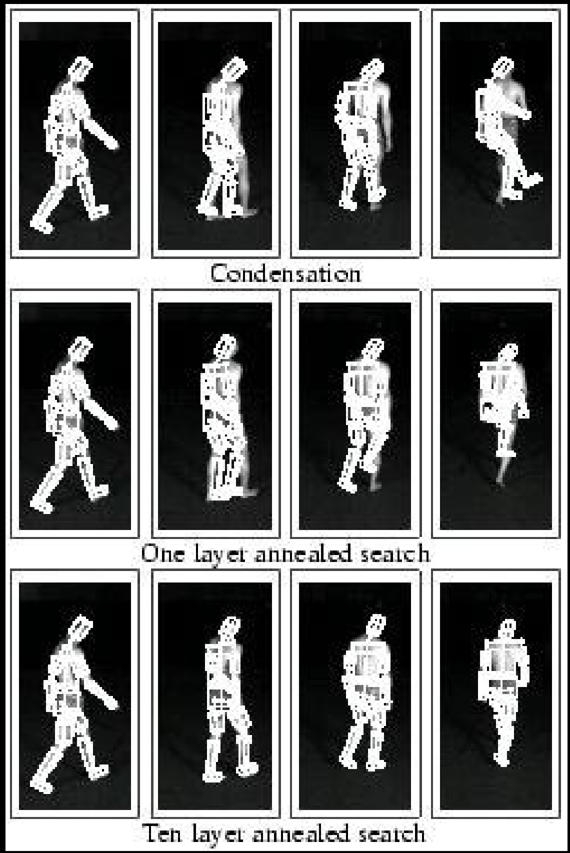
(Deutscher, Blake and Reid, '99-01)

monocular

Careful design

- Dynamics
- Observation likelihood
  - edge + silhouettes
- Annealing-based search procedure, improves over particle filtering
- Simple background and clothing



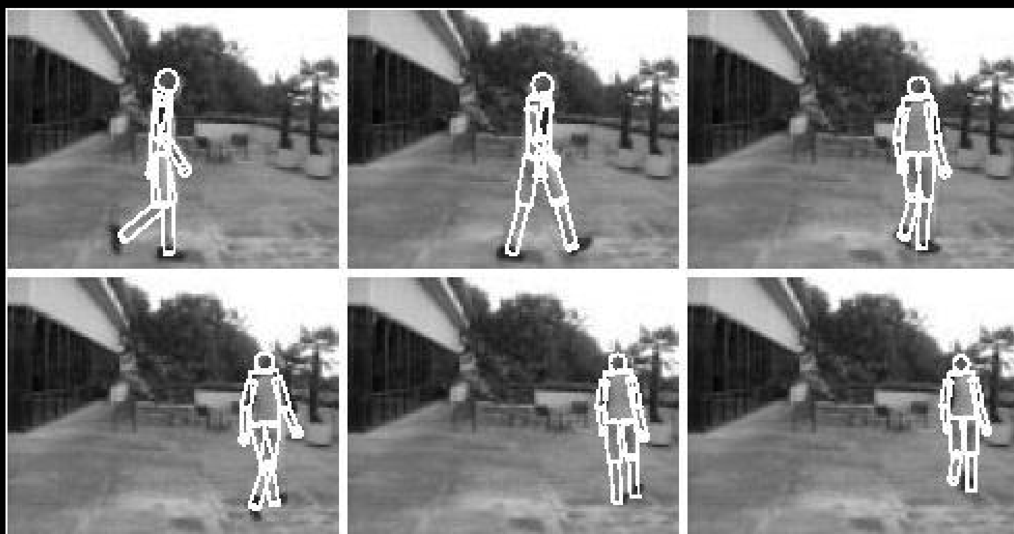


Improved results (complex motions) when multiple cameras (3-6) were used

Generative 3D Reconstruction

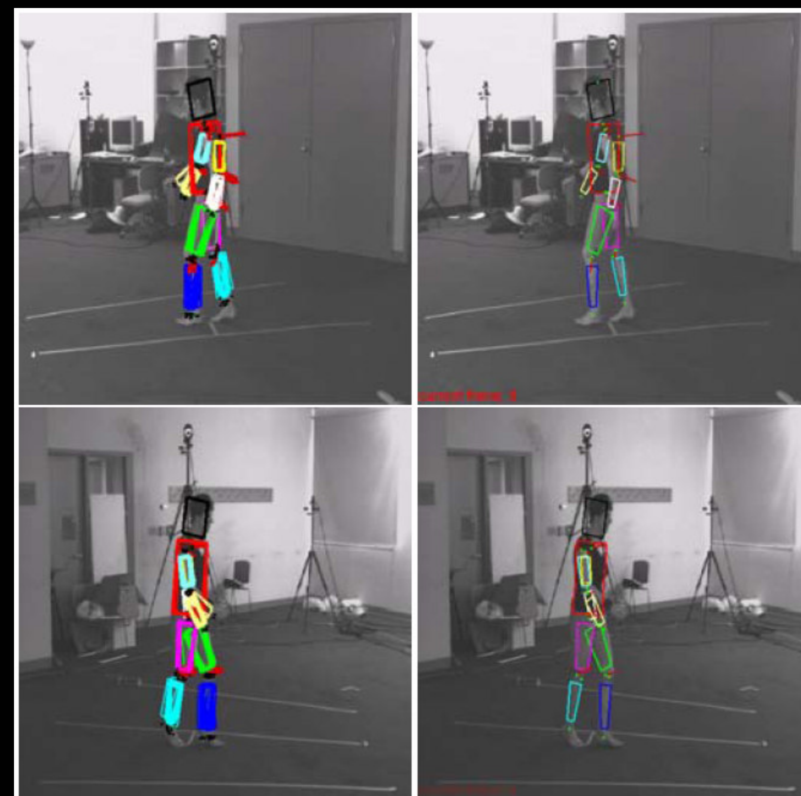
Sidenbladh, Black and Fleet, ’00-02; Sigal et al ‘04

Monocular



- Condensation-based filter
- Dynamical models
  - walking, snippets
- Careful learning of observation likelihood distributions

Multi-camera

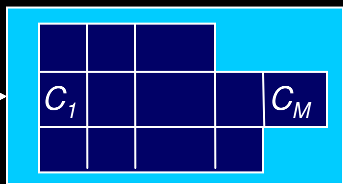


- Non-parametric belief propagation, initialization by limb detection and triangulation

Kinematic Jump Sampling

Sminchisescu & Triggs '03

$C \rightarrow$

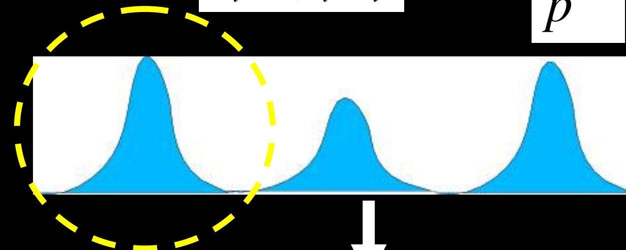


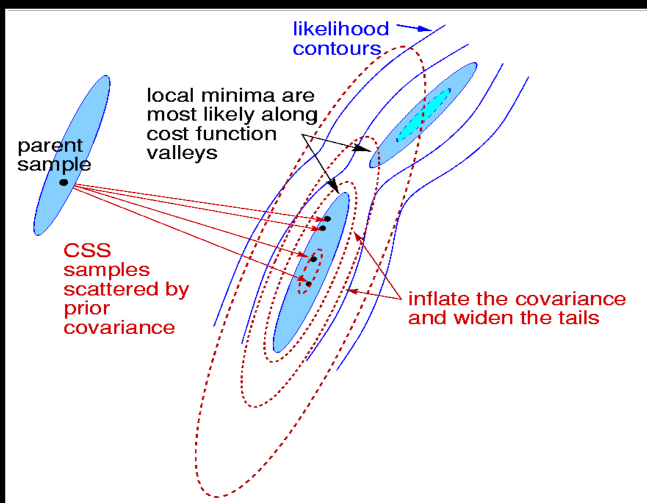
C=SelectSamplingChain(m_i)

Candidate Sampling Chains

$m_i = (\mu_i, \Sigma_i)$

p^{t-1}



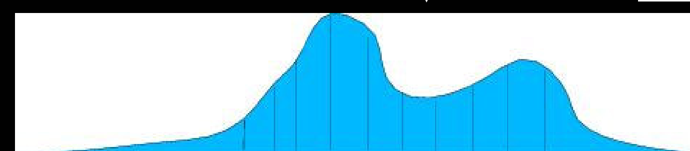


s=CovarianceScaledSampling(m_i)

T=BuildInterpretationTree (s,C)

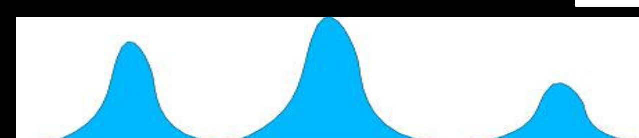
E=InverseKinematics(T)

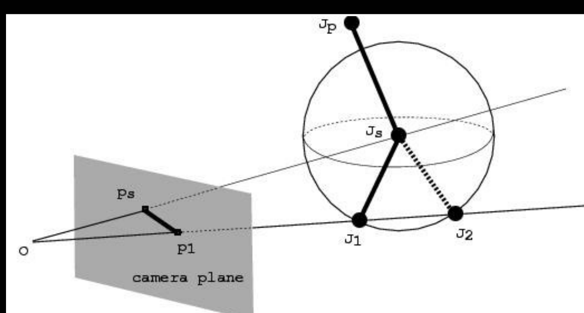
E

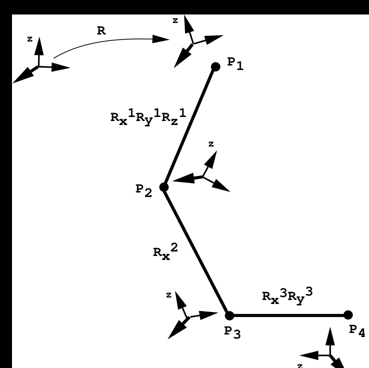


Prune and locally optimize *E*

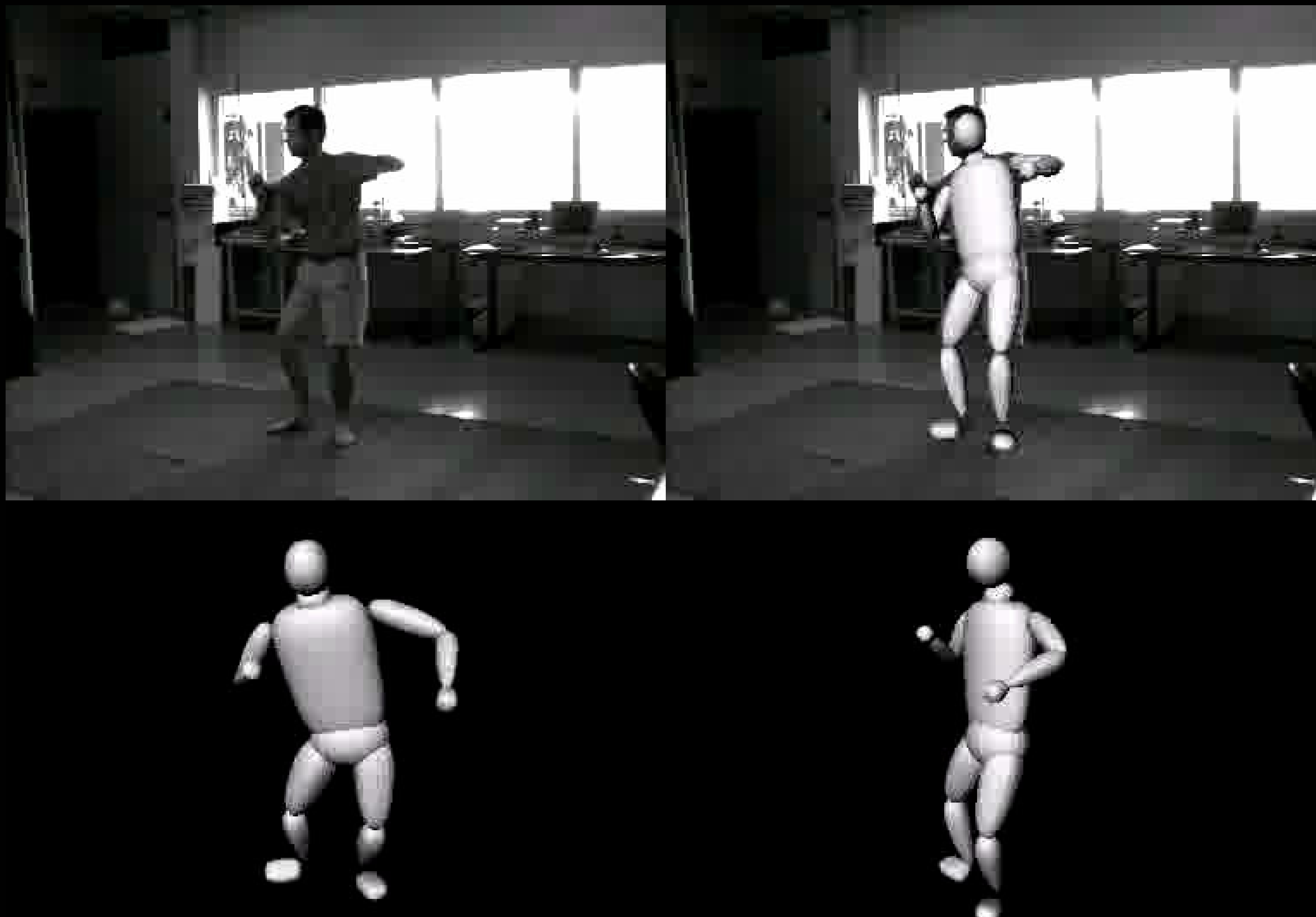
p^t







Kinematic Jump Sampling <v>



Sminchisescu and Triggs '03

What can we learn?

- Low-dimensional perceptual representations, dynamics (unsupervised)
  - What is the intrinsic model dimensionality?
  - How to preserve physical constraints?
  - How to optimize efficiently?

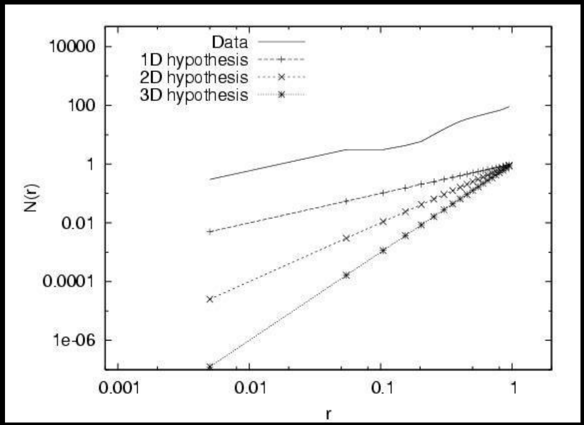
- Parameters (typically supervised)
  - Observation likelihood (noise variance, feature weighting)
  - Can learn separately (easier) but how well we do?
  - Best to learn by doing (i.e. inference)
    - Maximize the probability of the right answer on the training data, hence learning = inference in a loop
    - Need efficient inference methods

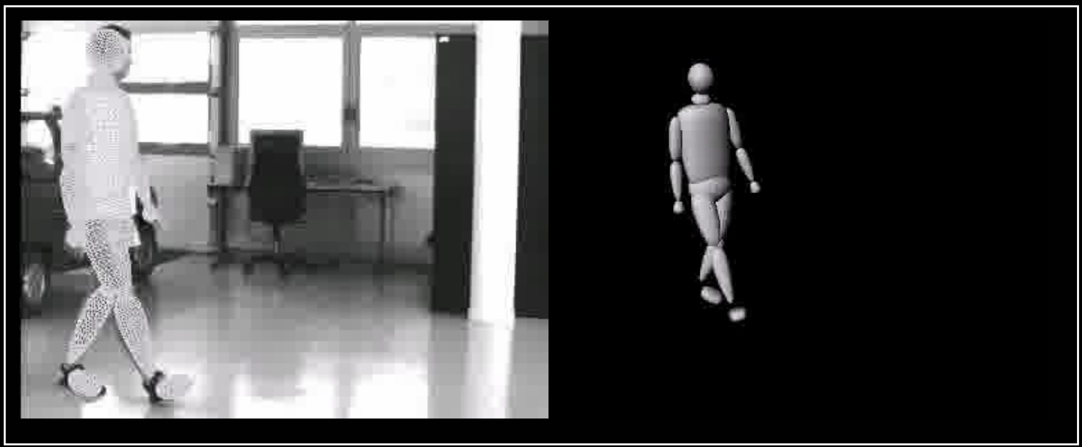
Intrinsic Dimension Estimation <v> and Latent Representation for Walking

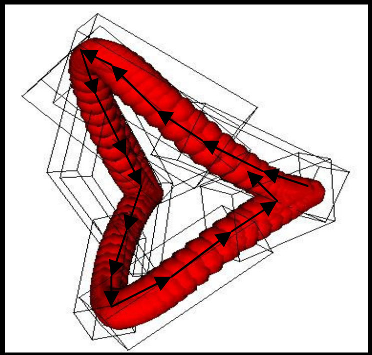
- 2500 samples from motion capture
- The Hausdorff dimension (*d*) is effectively 1, lift to 3 for more flexibility
- Use non-linear embedding to learn the latent 3d space embedded in an ambient 30d human joint angle space

Intrinsic dimension estimation

$$d = \lim_{r \to 0} \frac{\log N(r)}{\log(1/r)}$$





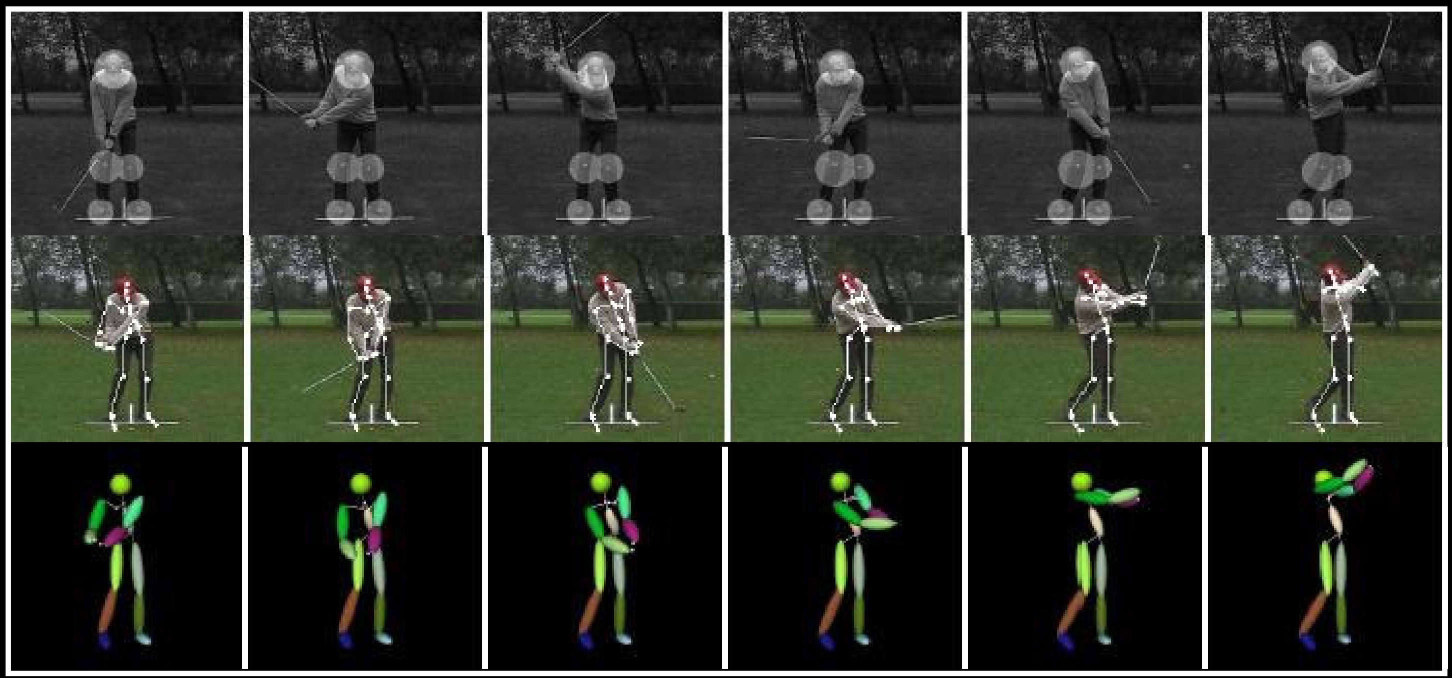


Optimize in 3d latent space

Sminchisescu and Jepson '04

3D Model-Based Reconstruction

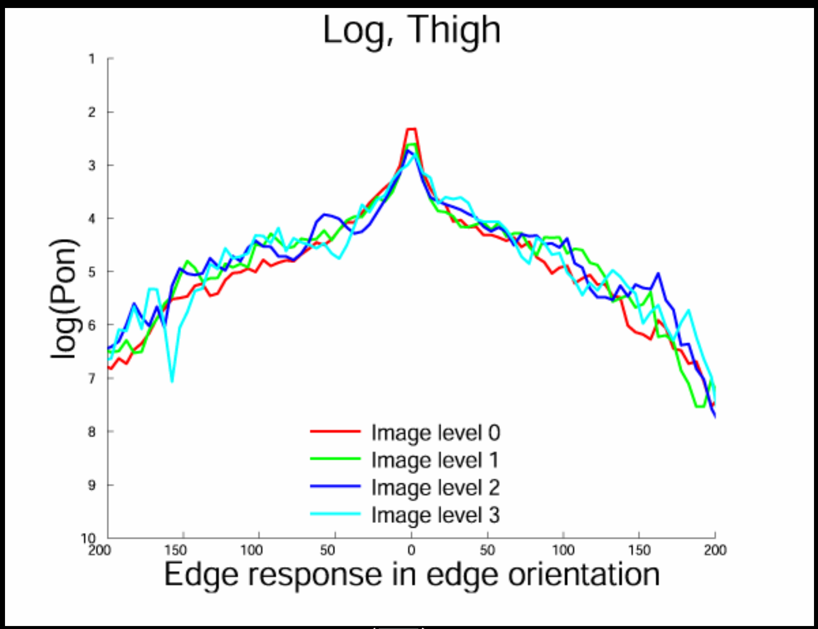
(Urtasun, Fleet, Hertzmann and Fua'05)



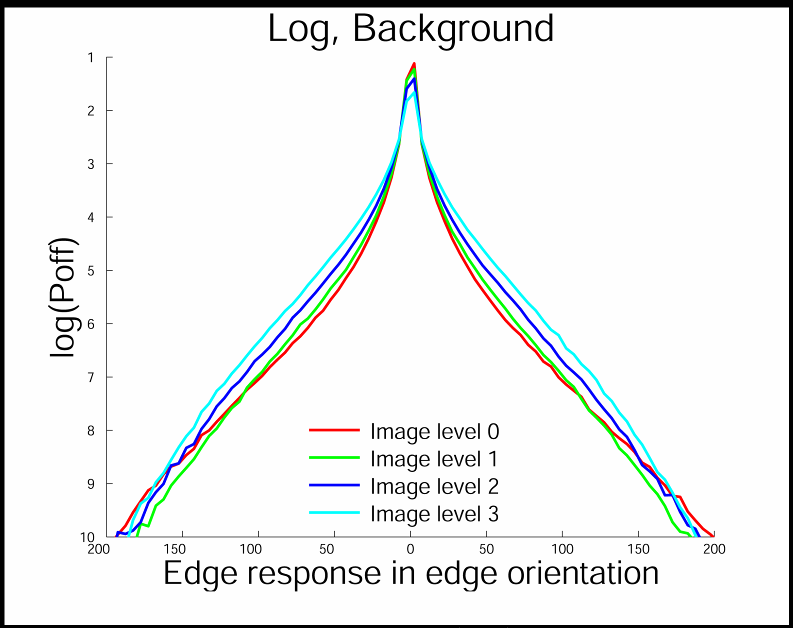
- Track human joints using the *WSL* tracker (*Jepson et al'01*)
- Optimize model joint re-projection error in a low-dimensional space obtained using probabilistic PCA *(Lawrence'04)*

Learning Empirical Distribution of Edge Filter Responses

(original slide courtesy of Michael Black)



$p_{on}(\mathrm{F})$



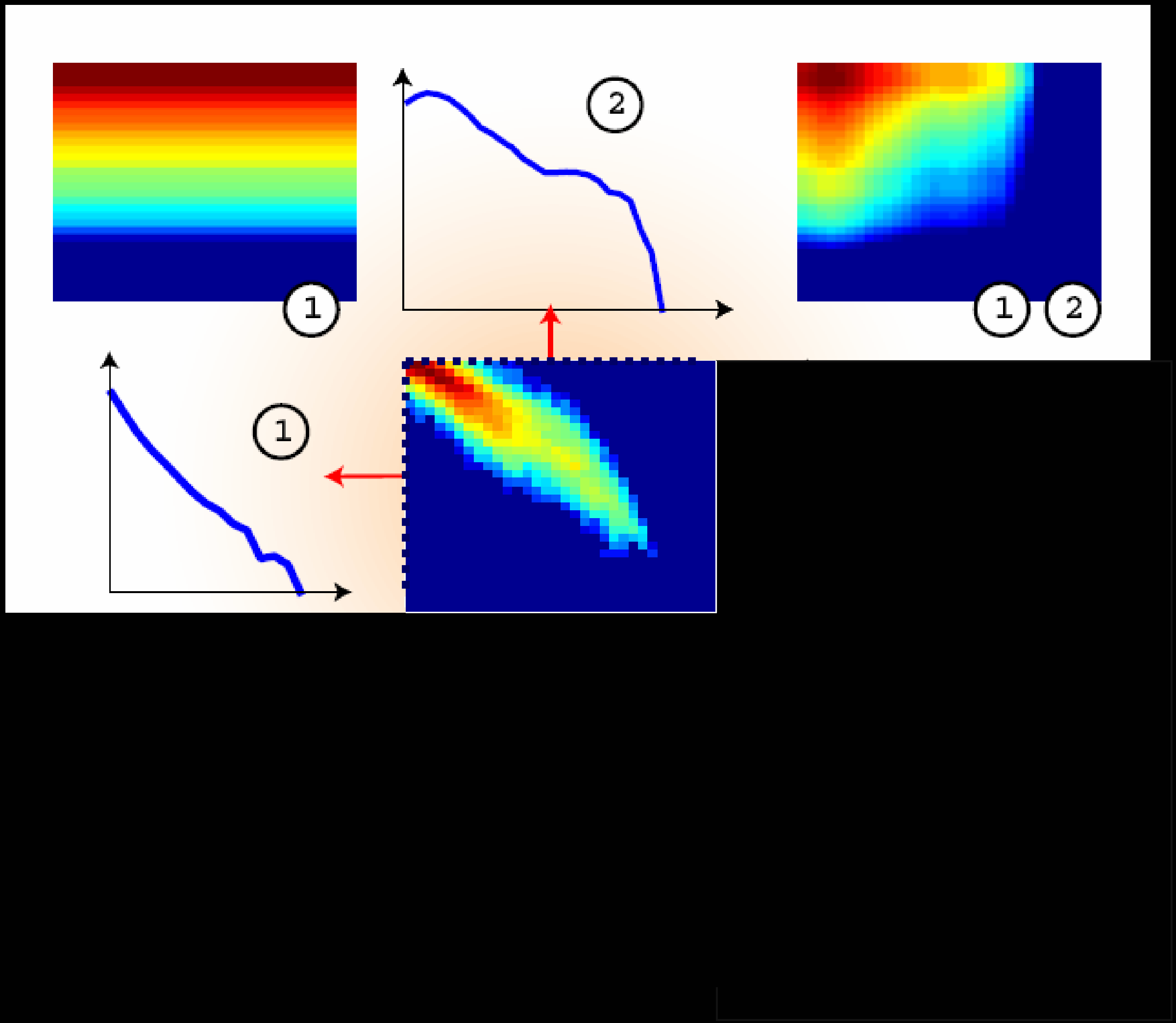
$p_{off}\,(\mathrm{F})$

Likelihood ratio, $p_{on}/\,p_{off}$, used for edge detection

Geman & Jednyak and Konishi, Yuille, & Coughlan

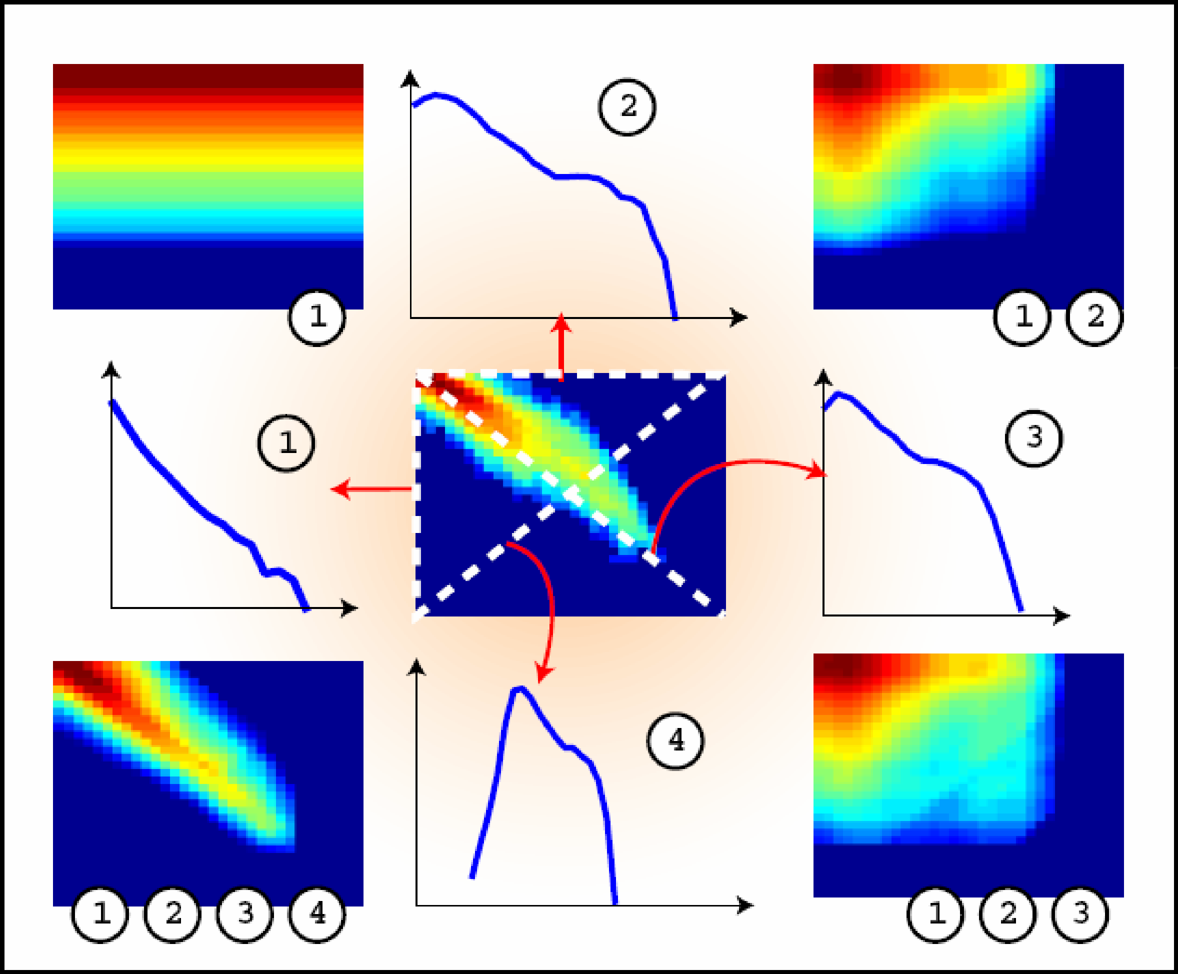
Learning Dependencies

(original slide courtesy of Michael Black); Roth, Sigal and Black'04



Learning Dependencies

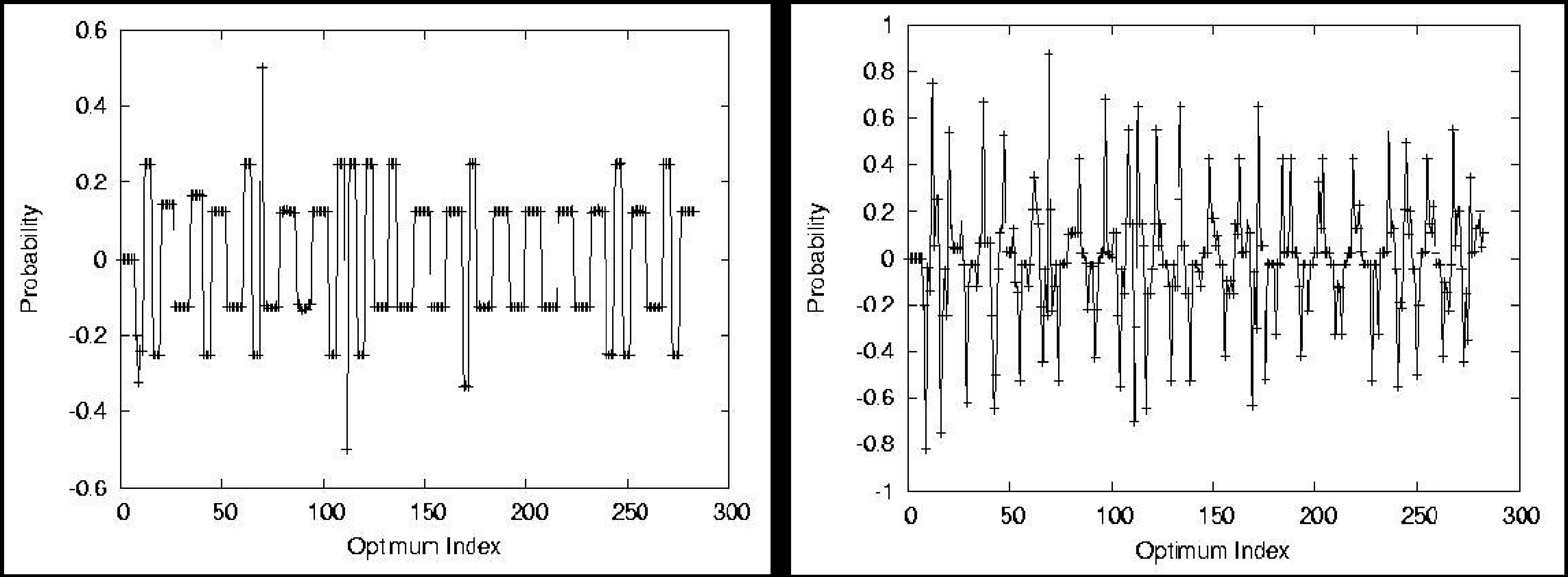
(original slide courtesy of Michael Black); Roth, Sigal and Black '04



Filter responses are not conditionally independent

Leaning by Maximum Entropy

The effect of learning on the trajectory distribution



Before *After*

- Learn body proportions + parameters of the observation model (weighting of different feature types, variances, *etc*)
- Notice reduction in uncertainty
- The ambiguity diminishes significantly but does not disappear

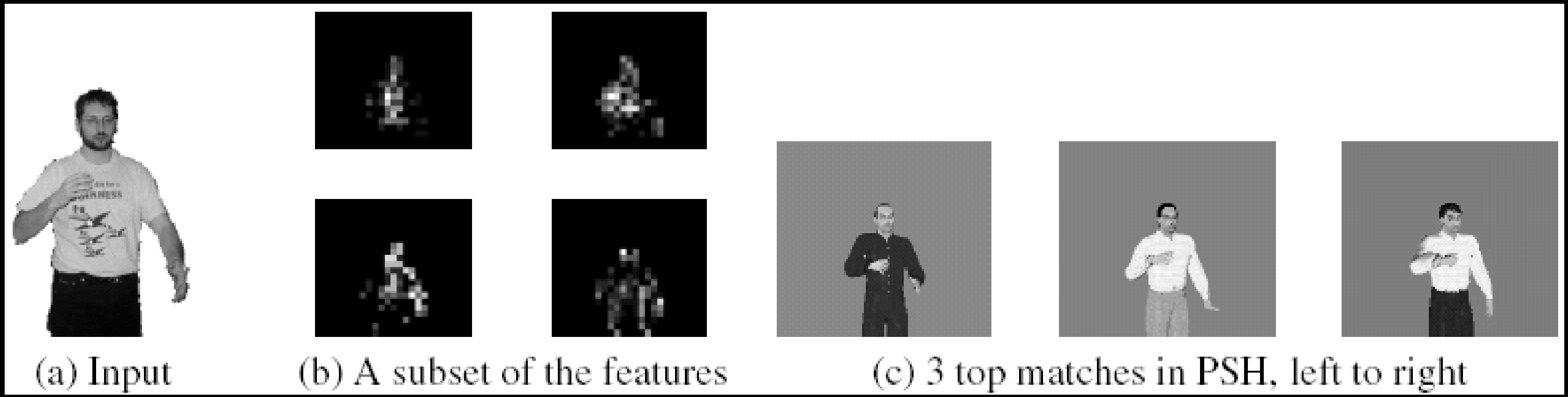
Sminchisescu, Welling and Hinton '03

Conditional /Discriminative/ Indexing Methods

- Nearest-neighbor, snippets
- Regression
- Mixture of neural networks
- Conditional mixtures of experts
- Probabilistic methods for temporal Integration

Discriminative 3d: Nearest Neighbor Parameter Sensitive Hashing (PSH)

Shakhnarovich, Viola and Darell '03



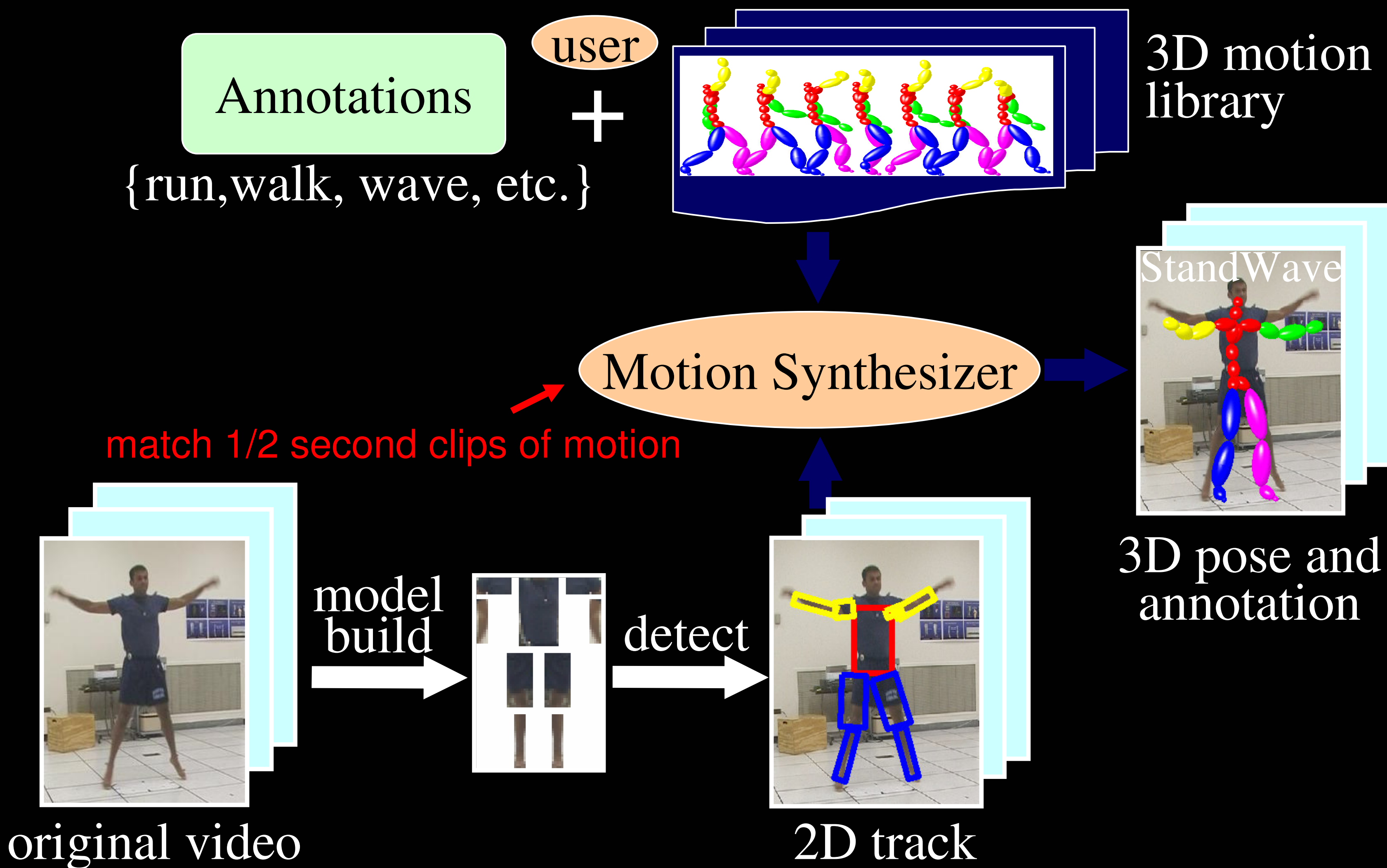
- Relies on database of (observation, state) pairs rendered artificially
  - Locates samples that have observation components similar to the current image data (nearest neighbors) and use their state as putative estimates

- Extension to multiple cameras and tracking by non-linear model optimization (PSH used for initialization *Demirdjan et al, ICCV05*)
  - Foreground / background segmentation from stereo

Discriminative 3d: Nearest Neighbor Matching

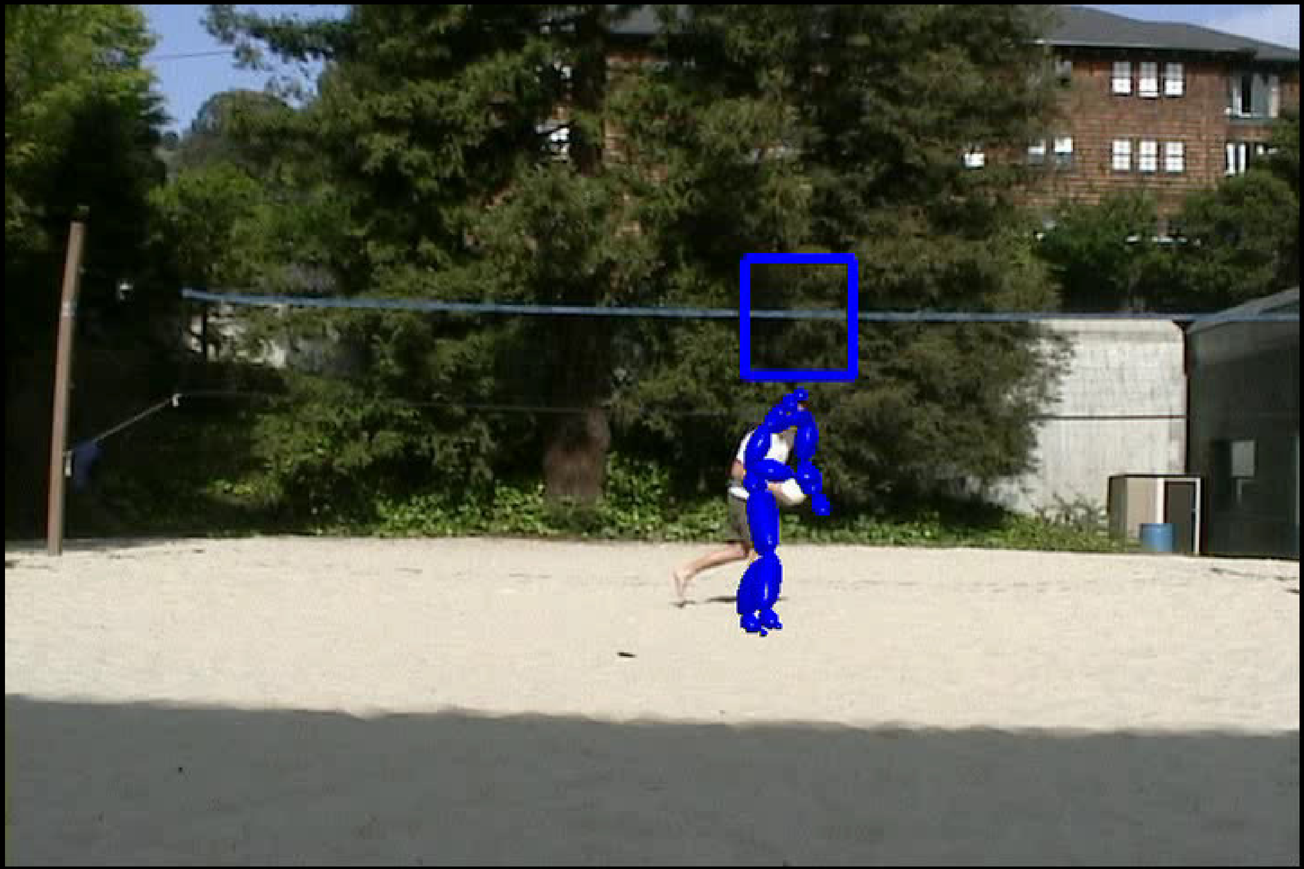
2D->3D Pose + Annotation

Ramanan and Forsyth '03



2D->3D pose + annotation <v>

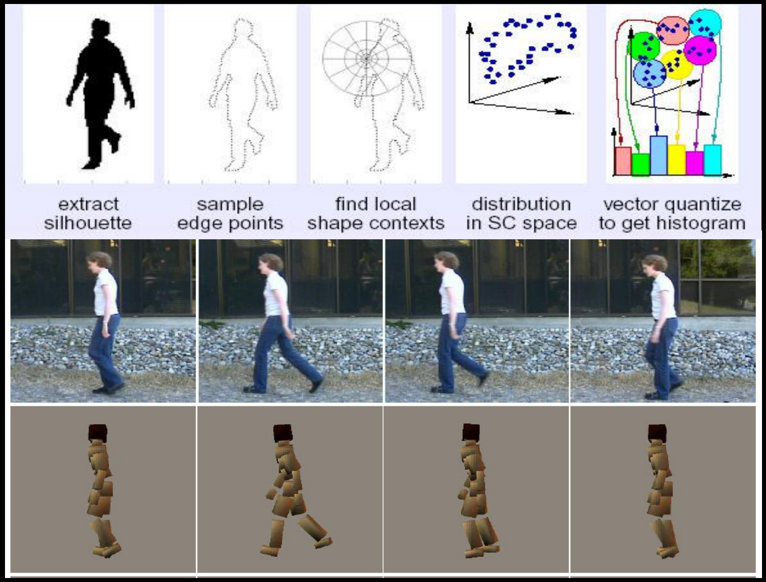
Ramanan and Forsyth'03

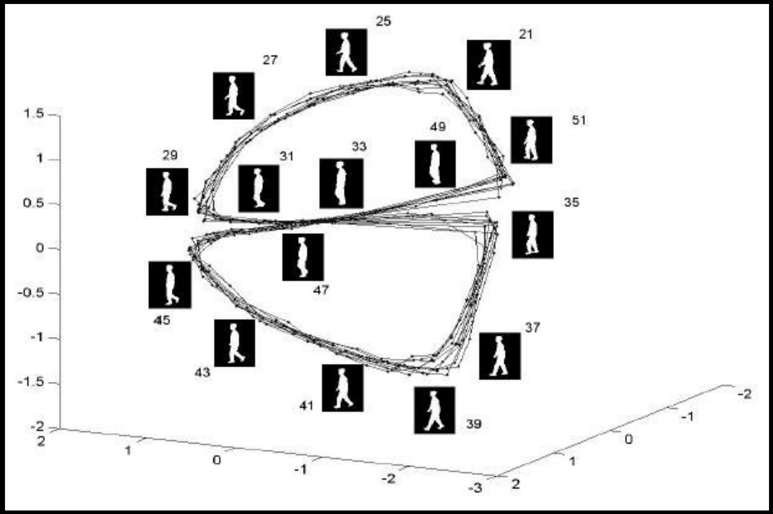


Discriminative 3d: Regression Methods

Aggarwal and Triggs '04, Elgammal & Lee '04

- *(A&T)* 3d pose recovery by non-linear regression against silhouette observations represented as shape context histograms
  - Emphasis on sparse, efficient predictions, good generalization
- *(A&T)* Careful study of dynamical regression-based predictors for walking and extensions to mixture of regressors (HCI'05)
- *(E&L)* pose from silhouette regression where the dimensionality of the input is reduced using non-linear embedding
  - Latent (input) to joint angle (output) state space map based on RBF networks

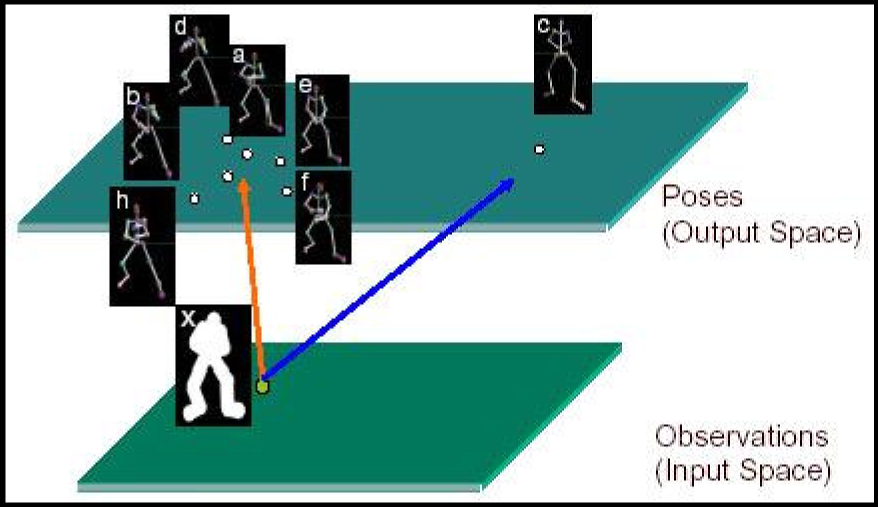


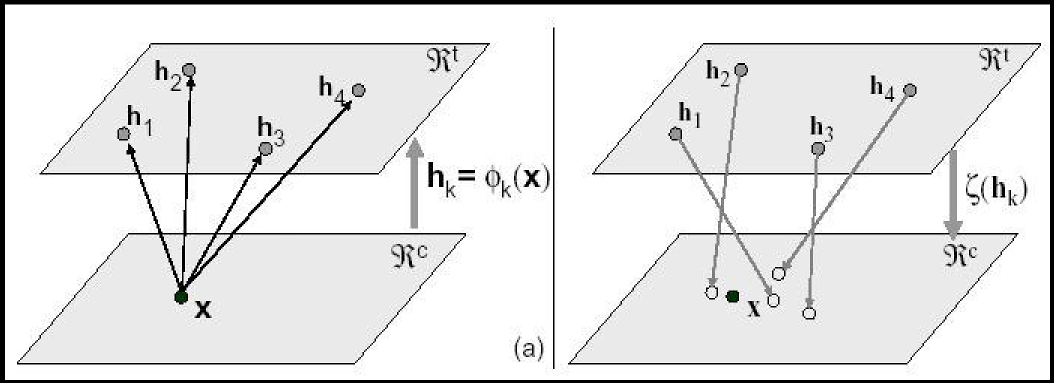


Discriminative 3d:
Specialized Mappings Architecture

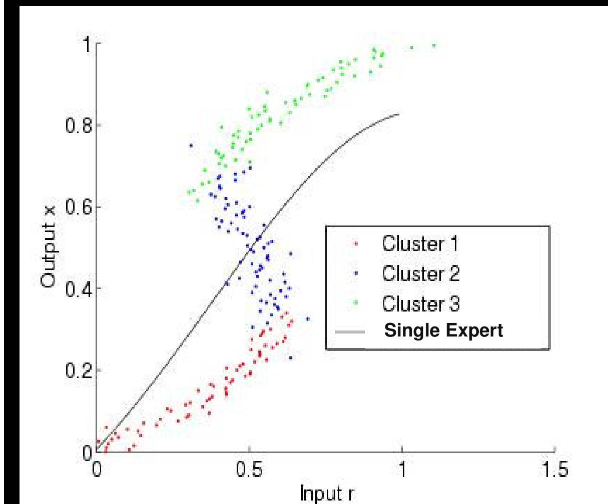
Rosales and Sclaroff '01

- Static 3D human pose estimation from silhouettes (Hu moments)
- Approximates the observation-pose mapping from training data
  - Mixture of neural networks
  - Models the joint distribution
- Uses the forward model (graphics rendering) to verify solutions

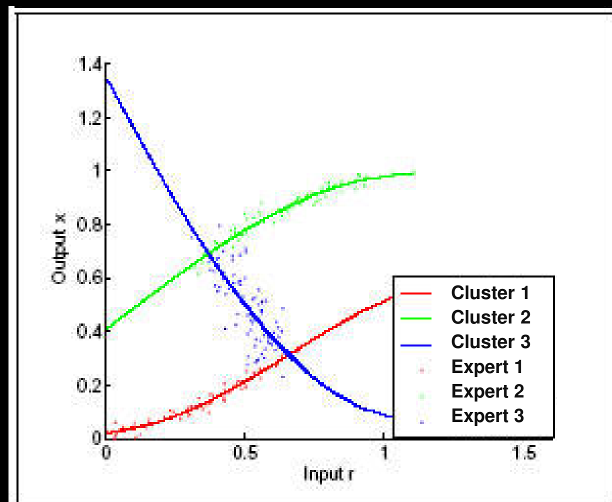




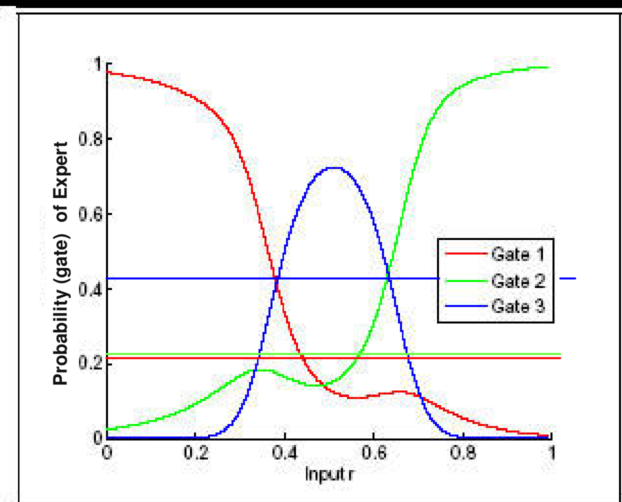
Conditional Bayesian Mixtures of Experts



Data Sample



Multiple Experts



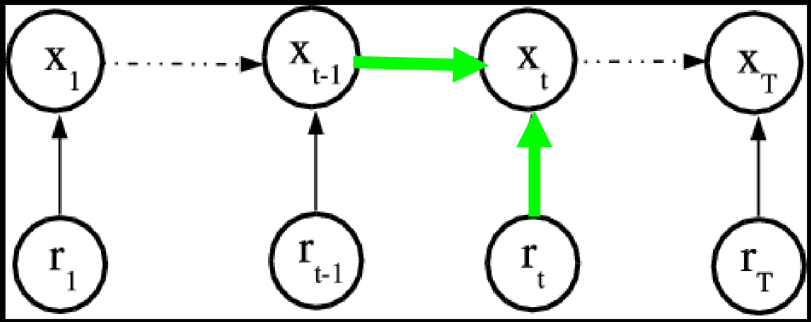
Expert Proportions (Gates) vs. uniform coefficients (Joint)

- A single expert cannot represent multi-valued relations
- Multiple experts can focus on representing parts of the data
- But the expert contribution (importance) is contextual
  - Disregarding context introduces systematic error (invalid extrapolation)
- The experts need observation-sensitive mixing proportions

Discriminative Temporal Inference

BM³E= Conditional Bayesian Mixture of Experts Markov Model

- \`Bottom-up' chain



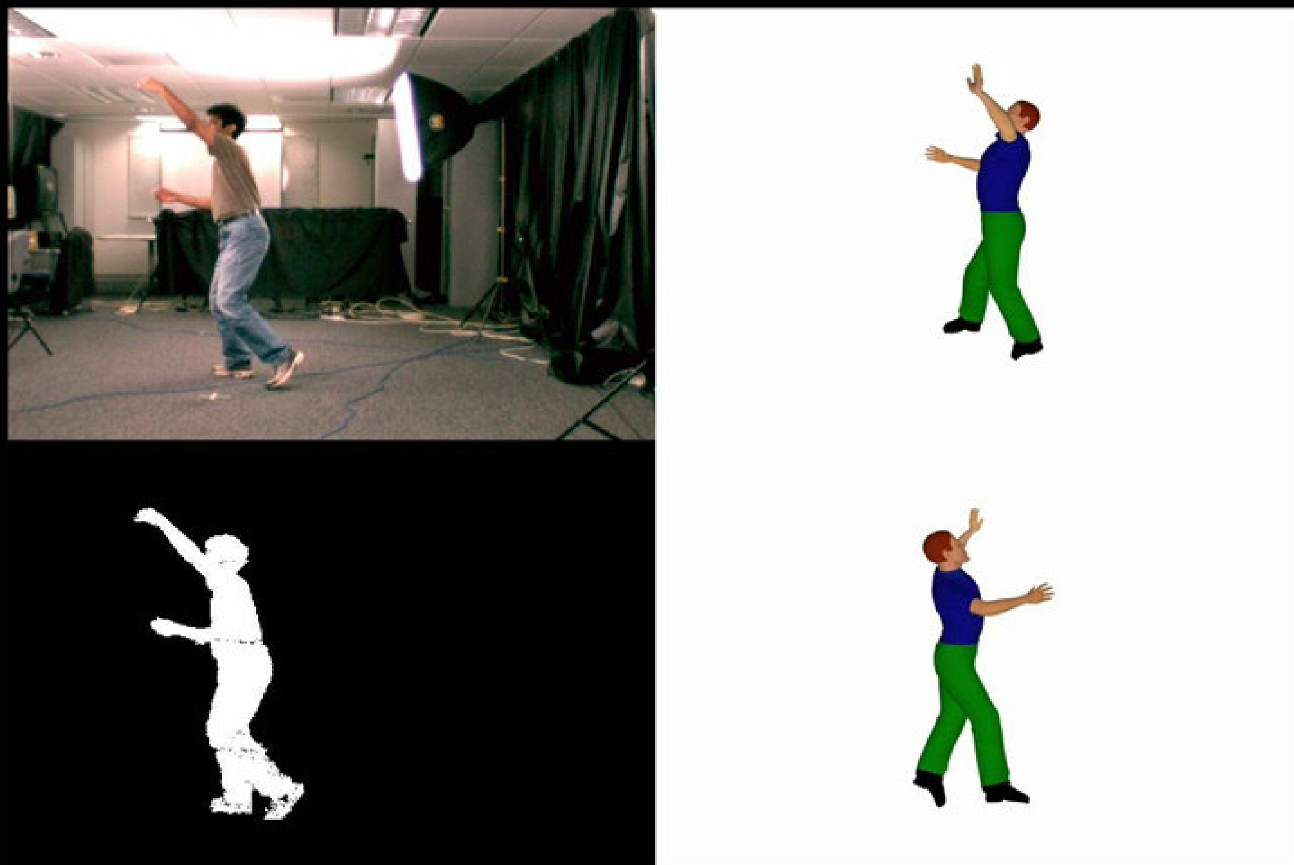
Conditions on the observation

$$p(\mathbf{x}_t \mid \mathbf{R}_t) = \int_{\mathbf{x}_{t-1}} \underbrace{p(\mathbf{x}_t \mid \mathbf{x}_{t-1}, \mathbf{r}_t)}_{\text{Local conditional}} \underbrace{p(\mathbf{x}_{t-1} \mid \mathbf{R}_{t-1})}_{\text{Temporal (filtered) prior}}, \quad where\ \mathbf{R}_t = (\mathbf{r}_1, \ldots, \mathbf{r}_t)$$

- The *temporal prior* is a Gaussian mixture
- The *local conditional* is a Bayesian mixture of Gaussian experts
- Integrate pair-wise products of Gaussians analytically

Sminchisescu, Kanaujia, Li, Metaxas '05

Turn during Dancing <v>

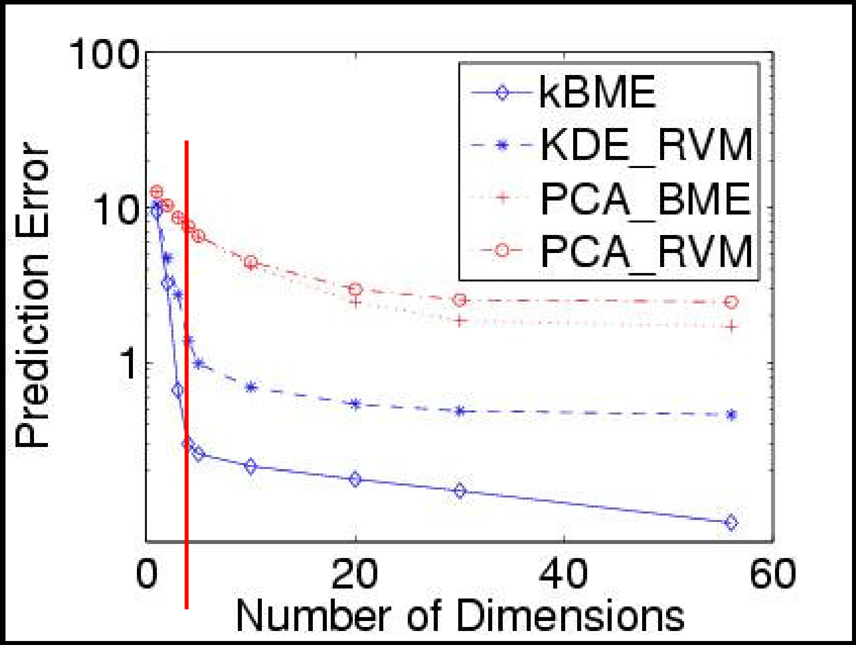


Notice imperfect silhouettes

Sminchisescu, Kanaujia, Li, Metaxas '05

Low-dimensional Discriminative Inference

- The pose prediction problem is highly structured
  - Human joint angles are correlated, not independent
  - Learn conditional mixtures between low-dimensional spaces decorrelated using kernel PCA (kBME)



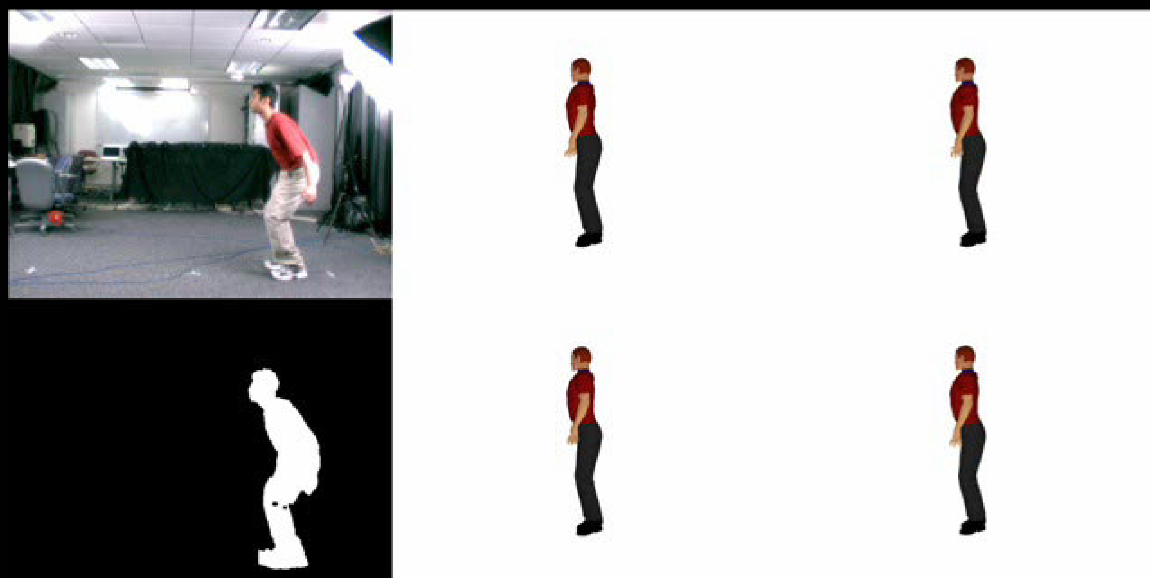
RVM – Relevance Vector Machine
KDE – Kernel Dependency Estimator

Sminchisescu, Kanaujia, Li, Metaxas '05

Low-dimensional Discriminative Inference

(translation removed for better comparison)

4d 10d



6d 56d

Sminchisescu, Kanaujia, Li, Metaxas '05

Evaluation on artificially generated silhouettes with 3d ground truth

(average error / average maximum error, per joint angle)

Sequence	$p(\mathbf{x}_t \mid \mathbf{r}_t)$			$p(\mathbf{x}_t \mid \mathbf{x}_{t-1}, \mathbf{r}_t)$		
	NN	RVM	BME	NN	RVM	BME
NORMAL WALK	4 / 20	2.7 / 12	2 / 10	7 / 25	3.7 / 11.2	2.8 / 8.1
COMPLEX WALK	11.3 / 88	9.5 / 60	4.5 / 20	7.5 / 78	5.67 / 20	2.77 / 9
RUNNING	7 / 91	6.5 / 84	5 / 94	5.5 / 91	5.1 / 108	4.5 / 76
CONVERSATION	7.3 / 26	5.5 / 21	4.15 / 9.5	8.14 / 29	4.07 / 16	3 / 9
PANTOMIME	7 / 36	7.5 / 53	6.5 / 25	7.5 / 49	7.5 / 43	7 / 41

- NN = nearest neighbor
- RVM = relevance vector machine
- BME = conditional Bayesian mixture of experts

Evaluation, low-dimensional models

(average error / joint angle)

	KDE-RR	RVM	KDE-RVM	BME	kBME
Walk and turn back	10.46	4.95	7.57	4.27	4.69
Conversation	7.95	4.96	6.31	4.15	4.79
Run and turn left	5.22	5.02	6.25	5.01	4.92

	KDE-RR	KDE-RVM	kBME
Walk and Turn	7.59	7.15	3.72
Run and Turn	17.7	16.08	8.01

- KDE-RR=ridge regressor between low-dimensional spaces
- KDE-RVM=RVM between low-dimensional spaces
  - Unimodal methods average competing solutions
- kBME=conditional Bayesian mixture between low-dimensional state and observation spaces
  - Training and inference is about 10 time faster

Self-supervised Learning of a Joint Generative-Recognition Model

- Maximize the probability of the (observed) evidence (*e.g.* images of humans)

$$\log p_\theta(\mathrm{r}) = \log \int_{\mathrm{x}} Q_\upsilon(\mathrm{x} \mid \mathrm{r}) \frac{p_\theta(\mathrm{x}, \mathrm{r})}{Q_\upsilon(\mathrm{x} \mid \mathrm{r})} \geq \int_{\mathrm{x}} Q_\upsilon(\mathrm{x} \mid \mathrm{r}) \log \frac{p_\theta(\mathrm{x}, \mathrm{r})}{Q_\upsilon(\mathrm{x} \mid \mathrm{r})} = KL(Q_\upsilon(\mathrm{x} \mid \mathrm{r}) \parallel p_\theta(\mathrm{x}, \mathrm{r}))$$

$$\log p_\theta(\mathrm{r}) - KL(Q_\upsilon(\mathrm{x} \mid \mathrm{r}) \parallel p_\theta(\mathrm{x} \mid \mathrm{r})) = KL(Q_\upsilon(\mathrm{x} \mid \mathrm{r}) \parallel p_\theta(\mathrm{x}, \mathrm{r}))$$

- Hence, the KL divergence between *what the generative model p infers* and *what the recognition model Q predicts*, with tight bound at

$$Q_\upsilon(\mathrm{x} \mid \mathrm{r}) = p_\theta(\mathrm{x} \mid \mathrm{r})$$

Self-supervised Learning of a Joint Generative-Recognition Model

Algorithm for Bidirectional Model Learning

E-step: $\boldsymbol{\nu}^{k+1} = \arg\max_{\boldsymbol{\nu}} \mathcal{L}(\boldsymbol{\nu}, \boldsymbol{\theta}^k)$
Train the *recognition* model using samples from the current *generative* model.

M-step: $\theta^{k+1} = \arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\nu}^{k+1}, \boldsymbol{\theta})$
Train the *generative* model to have state posterior close to the one predicted by the current *recognition* model.

- Local optimum for parameters
- Recognition model is a conditional mixture of *data-driven* mean field experts
  - Fast expectations, dimensions decouple

Generalization under clutter

Mixture of experts

Single expert

Sminchisescu, Kanaujia, Metaxas '06

Take home points

- Multi-view 3d reconstruction reliable in the lab
  - Measurement-oriented
  - Geometric, marker-based
    - correspondence + triangulation
  - Optimize multi-view alignment
    - generative, model-based
  - Data-association in real-world (occlusions) open

- Monocular 3d as robust limit of multi-view
  - Difficulties: depth perception + self-occlusion
  - Stronger dependency on efficient non-convex optimization and good observation models
  - Increased emphasis on prior vs. measurement

Take home points (contd.)

- Top-down / Generative / Alignment Models
  - Flexible, but difficult to model human appearance
  - Difficult optimization problems, local optima
  - Can learn constrained representations and parameters
    - Can handle occlusion, faster search (low-d)
    - Fewer local optima -- the best more likely true solutions
- Discriminative / Conditional / Exemplar–based Models
  - Need to model complex multi-valued relations
  - Replace inference with indexing / prediction
  - Good for initialization, recovery from failure, on-line
  - Still need to deal with segmentation / data association