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## Tracking known and unknown human activites

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# Tracking Known and Unknown Human Activites

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#### Introduction

#### Constructing a pose space for analysis-by-synthesis

- ▶ High-D Pose Space
- "Curse of dimensionality"
- ▶ Need efficient search techniques
- ▶ Partitioned Sampling [6], Annealed Particle Filter [2]
- ▶ Potential to cope with any activity

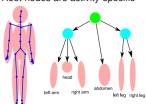
#### ▶ Low-D Pose Space

- As few as 2-3 dimensions
- Limited image evidence sufficient
- Many available techniques
- ▶ PCA [7], GP-LVM [8]
- ▶ Activity specific

### Hierarchical Models: H-GPLVM [5]

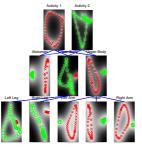
#### Learning

- ▶ Composed of GP-LVMs [4]
- ▶ Represents high-D data through a low-D latent model and a non-linear GP mapping from latent space to data space
- MoCap state space is partitioned between 5 nodes
- Latent variables initialised through application of PCA to joint angles
- ▶ Augmented by further latent models providing coordination
- Non-leaf nodes model joint distribution over latent variables of children
- Latent variables initialised through application of PCA to concatenated latent variables of children
- ▶ Root nodes are activity-specific



#### ▶ Pose Generation

- Given a particular latent position in any node, the H-GPLVM defines Gaussian conditional distributions over
- 1. the children (non-leaf nodes)
- 2. the state space (leaf nodes)
- ▶ These can be used to fully descend the hierarchy to the state space
- ▶ Top level root nodes are akin to global activity models
- ▶ Bottom level leaf nodes are akin to a flat part-based activity model
- ▶ H-GPLVM can be used to produce novel poses depending on the extent to which coordination is respected



#### **Pose Estimation**

- ▶ Recover novel poses by 'backing off' down the hierarchy [5]
- ▶ Applying the models in the next level independently
- ▶ Particle-based approach
- 1. initialised in the root nodes (globally coordinated training poses)
- 2. terminating in leaf nodes (uncoordinated part-based poses)
- ▶ APF used to gradually introduce peaks in the cost function [2]
- ▶ Recombine particle coordinates for each latent space using crossover operator-type approach

for t = 1 to T do

**Reinitialise** from root data + noise:  $\{(\mathbf{x}_{t,R}^{(n)})\}_{n=1}^{N}$ 

for r = R downto 1 do

- 1. **Evaluate** weights  $\pi_{t,r}^{(n)} = w_r(\mathbf{z}_t, \mathbf{x}_{t,r}^{(n)})$
- 2. **Resample** B particles with likelihood  $\propto \pi_{t,r}^{(n)}$  and with replacement
- 3. Back off using mapping from latent coordinates to descend to next level
- 4. Recombine particle coordinates for each node to form new particle set
- 5. Disperse latent coordinates with noise term

end for

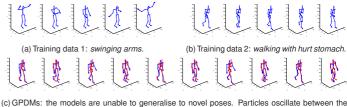
Calculate expected pose for visualisation  $E(\mathbf{x}_t) = \sum_{n=1}^{N} \pi_{t,1}^{(n)} \mathbf{x}_{t,1}^{(n)}$ end for

Figure 1: Pseudocode for pose estimation.

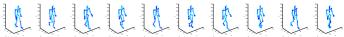
#### **Weighting Function**

- Compare joint locations in observation and hypotheses
- ▶ MoCap: squared 3D Euclidean distance
  - ▶ 15 joint locations on each body model
- ► Monocular: squared 2D Euclidean distance ▶ 9 joint locations on hypothesised body model
- ▶ 9 approximate joint locations in image
- Found by 2D image-based tracker: WSL [3]
- Manually initialised: few mouse clicks
- ▶ Able to handle partial occlusions

#### **Results: MoCap Data**



best compromises in each latent space.



(d) H-GPLVM: back off and the addition of latent space noise allows the recovery of novel poses. Note the opposing swing of the arms

Figure 2: MoCap training data [1] (a, b) and resulting pose estimation results for a walking sequence using GPDMs (c) and H-GPLVM (d).

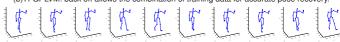
#### **Results: Monocular Data**



(a) GPDMs: neither latent space contains the pose. The waving hand is recovered at the expense of the leas



(b) H-GPLVM: back off allows the combination of training data for accurate pose recovery



(c) H-GPLVM: inferred 3D poses from a different view point

Figure 3: Pose estimation results using 2D WSL joint tracks from a monocular walking whilst waving sequence: GPDMs (a), H-GPLVM (b). Training data is slow walk/stride and stand and wave.

#### **Results: Occlusions**











Figure 4: H-GPLVM: pose estimation for a walking sequence [7] using 2D WSL joint tracks. Position of occluded right arm is inferred from the visible upper body.

#### **Conclusions**

#### Discussion

- ▶ Outperforms global models for novel
- ▶ By modelling correlations between nodes separately we can:
- 1. Disregard them to recover novel poses (back off to leaf nodes)
- 2. Respect them to handle occlusions (terminate descent early)

## ▶ Future Work

- ▶ Find a complimentary set of "basis
- Final dispersion and resampling step in full state space
- ▶ Make backing off a decision
- ▶ Temporal model e.g. cluster and ascend

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