Person detection, tracking and human body analysis in multi-camera scenarios

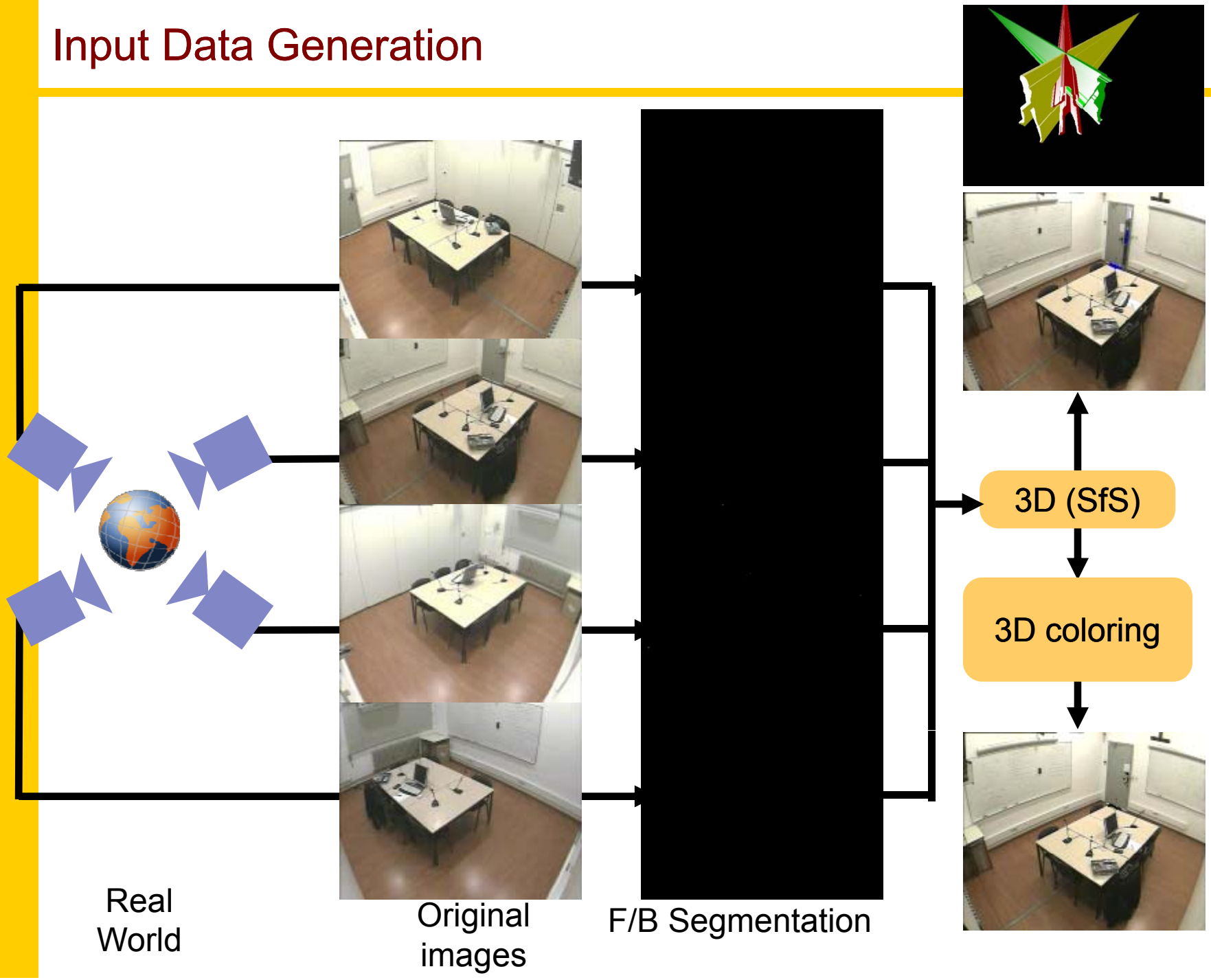
Montse Pardàs (UPC)

ACV, Bilkent University, MTA-SZTAKI, Technion-ML, University of Surrey, University of Amsterdam, UPC

Summary

- Multi-camara scenarios definition and applications.
- Multi-level foreground segmentation and tracking
- 3D person tracking with particle filters
- Human motion capture
  - Marker-based
  - Hierarchical annealing
  - Latent-space based
- Examples of other works in the e-team:
  - Moving object detection and classification
  - Eye tracking

Input Data Generation



Applications

Multi-person tracking

Activity recognition

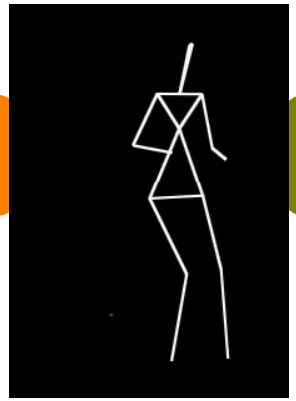
3D (SfS)

3D coloring

Head orientation

Focus of attention

Human motion capture



Gesture/Gait recognition

Raw features

High semantinc level

Foreground detection: multi-level fg segmentation

- Based on a statistical modeling of the pixels' value Xt in the (i,j) coordinates,using Gaussian models.

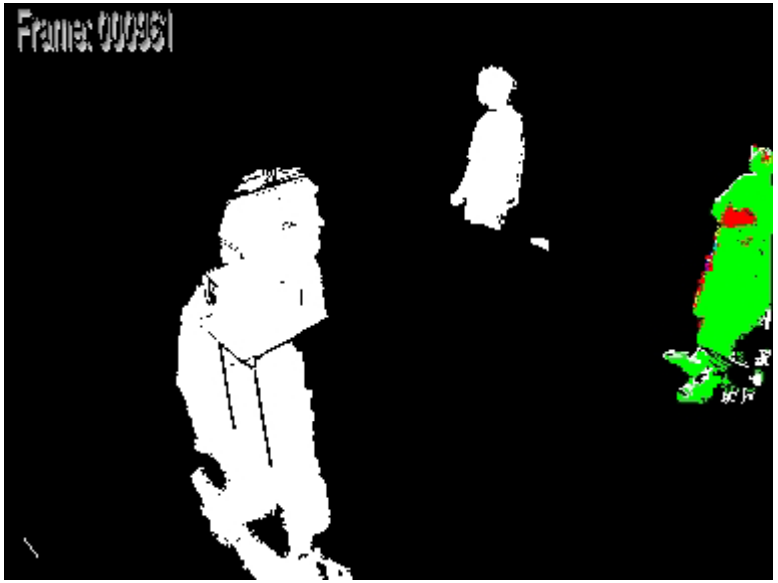
$$P(X_t) = \frac{1}{\sigma\sqrt{(2\pi)}} e^{\left(-\frac{(X_t-\mu_t)^2}{2\sigma^2}\right)}$$

A pixel will be classified as belonging to a Gaussian model if $|X_t - \mu_t| < k\sigma_t$

- Background model
- Moving foreground model:
  - A pixel not classified as bg or static fg is classified as moving fg.
- Static foreground model:
  - When a moving foreground model has been observed during a certaint time T, the model is transferred to the static foreground.

- An incoming pixel can:
  - Match the current foreground model: it is updated and its counter is increased
  - Match the background or static foreground models: it is updated and the counter of the foreground model is decreased
  - Not match any existing model: The foreground model and its counter are re-initialized.

Multi-level foreground segmentation



Mean-shift tracking with multi-level foreground

- Double register, for static and moving objects: centroid position, size, color histogram and counter of appearance

- Foreground objects detection
  - Filtering of the multi-level foreground detection to generate Connected Components if minsize.
- Temporal association of static objects
  - Check if there is a static CC in the position of a static object.
    - Update the corresponding static object register
  - Otherwise:
    - The object has re-started its motion if in the area of the static object there is at least 70% background. The static object is transferred to the moving objects register.
    - The static object has been occluded: a moving CC is detected in the area of the static object. No action is taken.

Mean-shift tracking with multi-level foreground

- Mean-shift tracking of moving foreground objects
  - The estimation of the position of the objects in the moving object register is performed using mean-shift.
  - The foreground mask is applied to the original image before performing the mean shift
  - All the CC in an area of the size of the object around the mean shift estimation are assigned to the object. The object features are updated.
  - If two or more moving objects share the same CC, we enter an occlusion situation and the update is done only on the centroid value using the mean shift estimation.
- Detection of new Static and Moving objects
  - The CC which have not been associated to any object are introduced as new objects.

Mean shift tracking with multi level foreground

Person tracking in multi camera scenarios

- Perform multi-person tracking in an indoor scenario employing 3D information (SfS+color)
- Particle Filters based solution
- Evaluate the performance of this method by using a standardized database (CLEAR 2007)

- **Particle filters:**

  Key idea: represent the posterior p(xk|z1:k) by a set of random samples.

  Four steps are followed: resampling, propagation, evaluation and estimation

  When implementing a PF, two issues are to be taken into account:

  Likelihood evaluation: how to assign weights to our particles

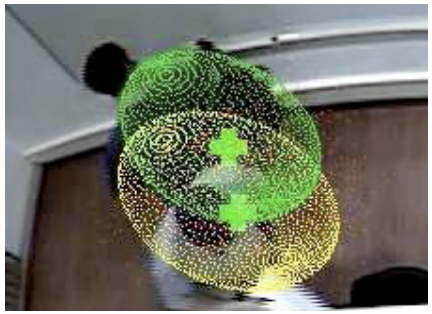
  Propagation model: how to “move” our particles to efficiently sample the state space

Particle Filter implementation

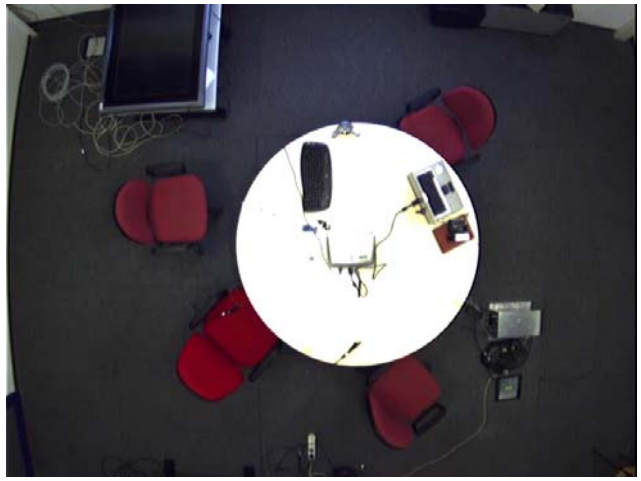
- Likelihood evaluation:
  - Every particle defines a possible location of the person represented by an ellipsoid
  - For every person a reference color histogram is built up
  - Weight assigned to a particle is a function of its overlap with the binary 3D reconstruction and its color similarity with the reference histogram (Battacharyia distance)

Multi-Person Issue

- Multiple targets may be tracked using a PF with a state containing the 3D position of each of them. However, complexity makes it unfeasible
- A PF is assigned to every target and an interaction model is defined

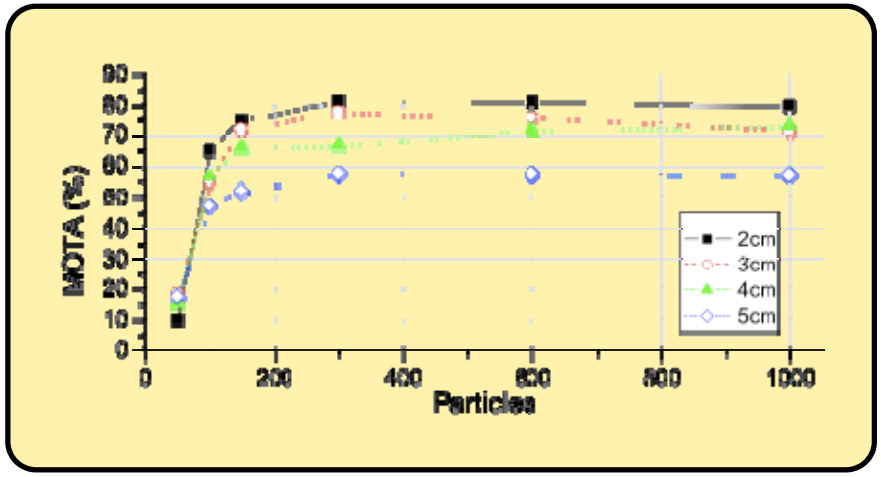


Results

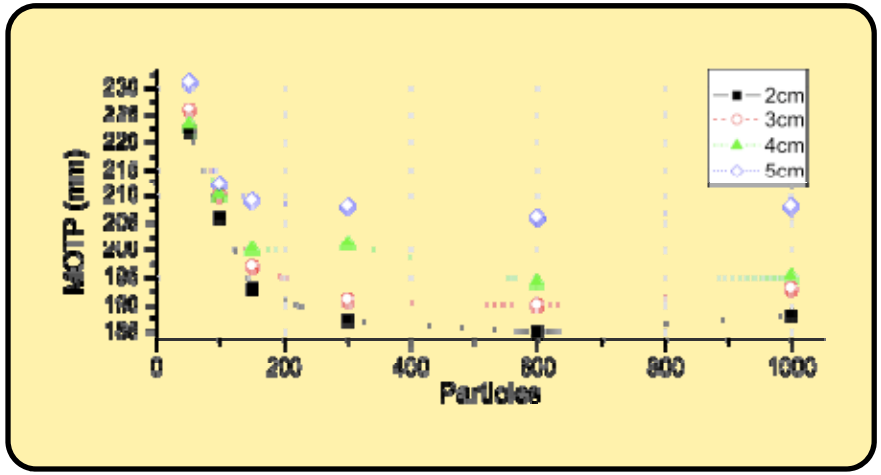


Results

Accuracy



Precision



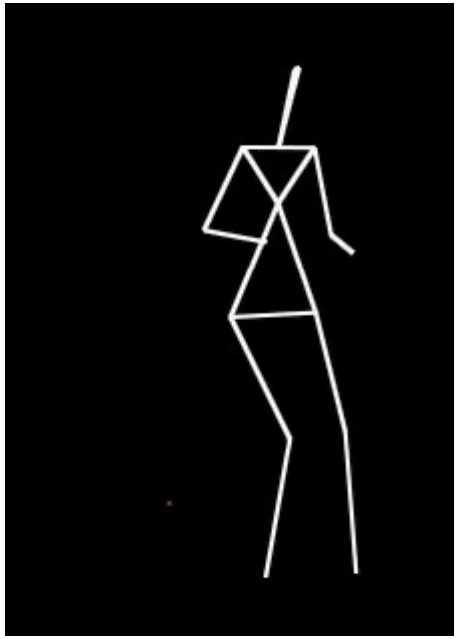
Best performing tracking algorithm at CLEAR 2007 Evaluation Campaing

Multimodal integration

- Audio information was added to produce a more robust tracker
- However, only information fusion at feature level has been conducted so far, giving slightly better results (5%)
- Information fusion at data level is under study

Human Motion Capture

- Two approaches are widely employed: marker and makerless
- It provides information related with the pose of the person. A human body model is assumed
- It poses a technology challenge due to the high dimensionality of the state space (~22 DOF). Moreover, this space is highly non-convex



Marker based capture

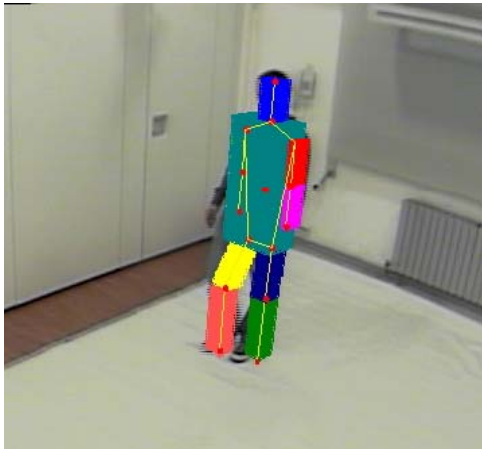
- Intrusive but provides very precise results
- Widely used by the cinema industry. Quite expensive equipment (>10K$) and requires dedicated hardware
- An annealing PF together with off-the-shelf hardware solution has been developed

Markerless based capture (I)

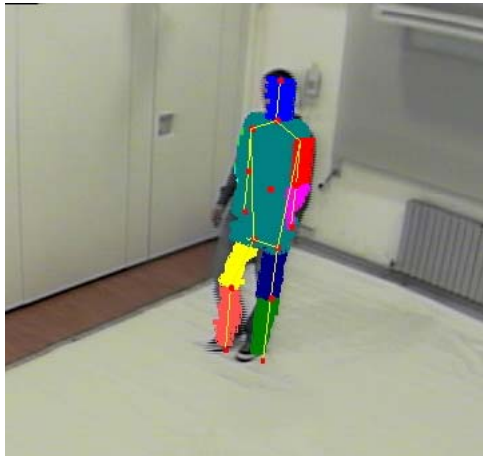
- Non intrusive but more challenge since there are no artificial aid (markers)
- Still an open problem for unconstrained motion
- PF definition: every particle represents a possible pose of the person
- Likelihood evaluation: defining a fitness function matching the input data against the particle pose taking into account 3D information and color

Markerless based capture (II)

Original images

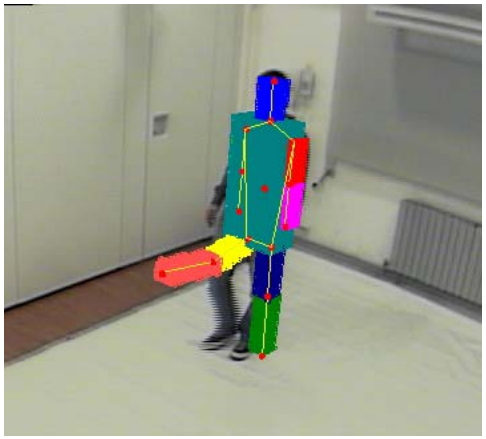


Particle $\mathbf{x}_t^m - \beta(\mathbf{x}_t^m)$

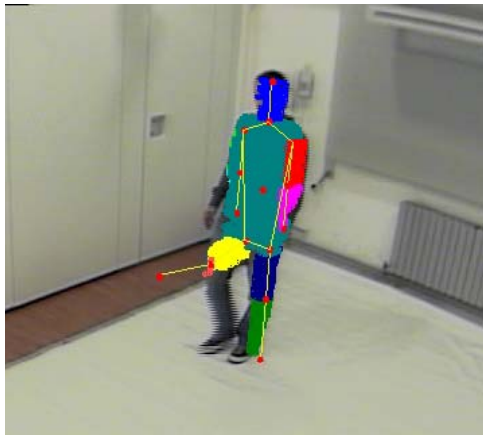


$\beta(\mathbf{x}_t^m) \cup \mathbf{z}_t = 0.84$

Voxel reconstruction



Particle $\mathbf{x}_t^n - \beta(\mathbf{x}_t^n)$

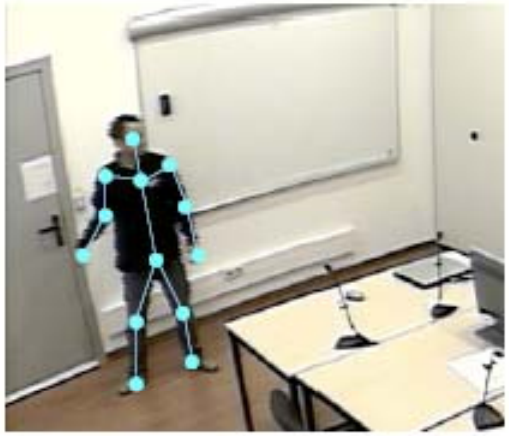


$\beta(\mathbf{x}_t^n) \cup \mathbf{z}_t = 0.62$

Markerless based capture (III)

- Structural annealing PF technique that performs a layered fitting of a hierarchical model to the input data

Input data is very corrupted: a simple body model is used



Data is more complete: the full articulated model is used

Legs are not visible, hence they are removed from the analysis model

Markerless based capture (IV)

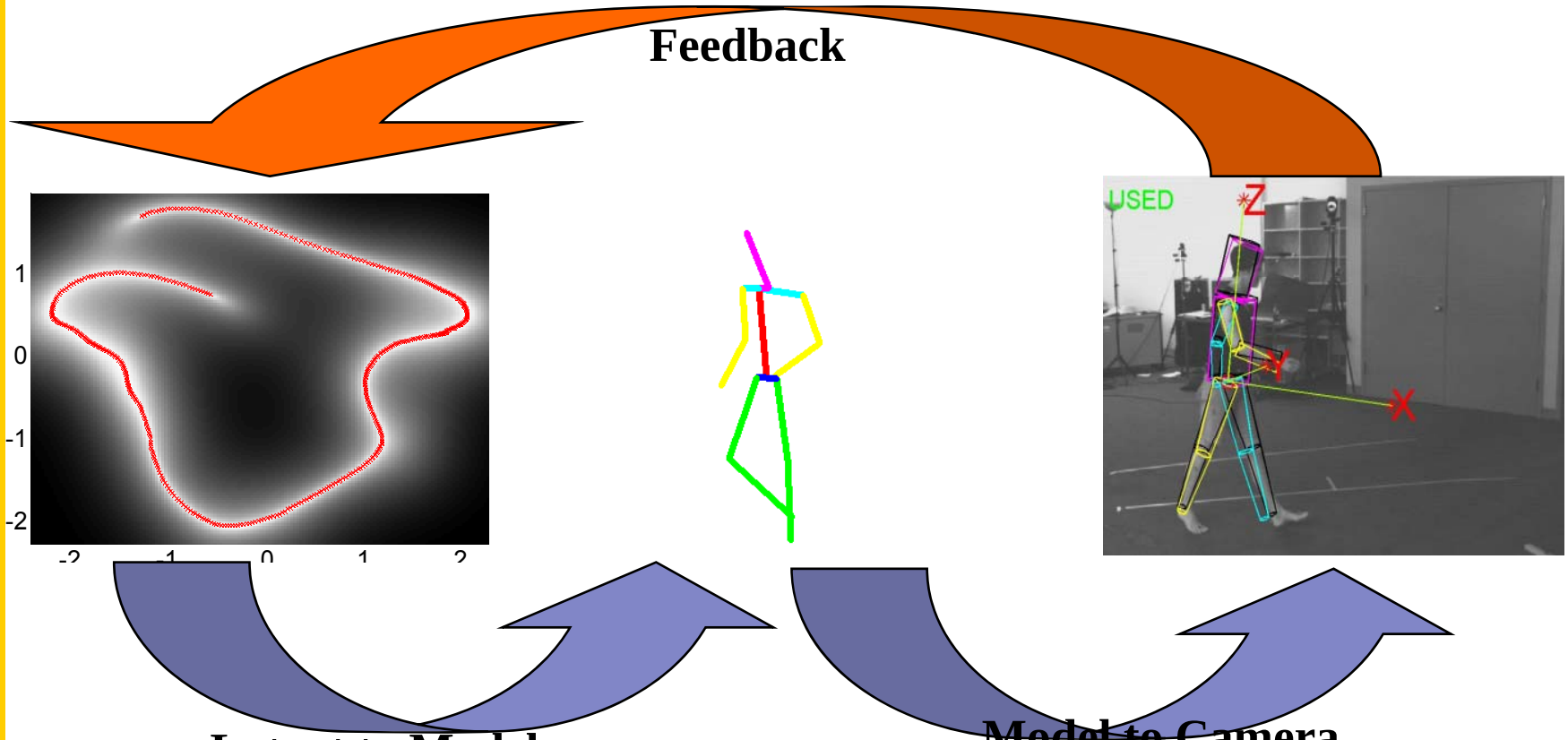
Learning

- The drawback in the annealing particle filter tracker is that a high dimensionality of the state space causes an exponential increase in the number of particles that is needed to be generated in order to preserve the same density of particles.

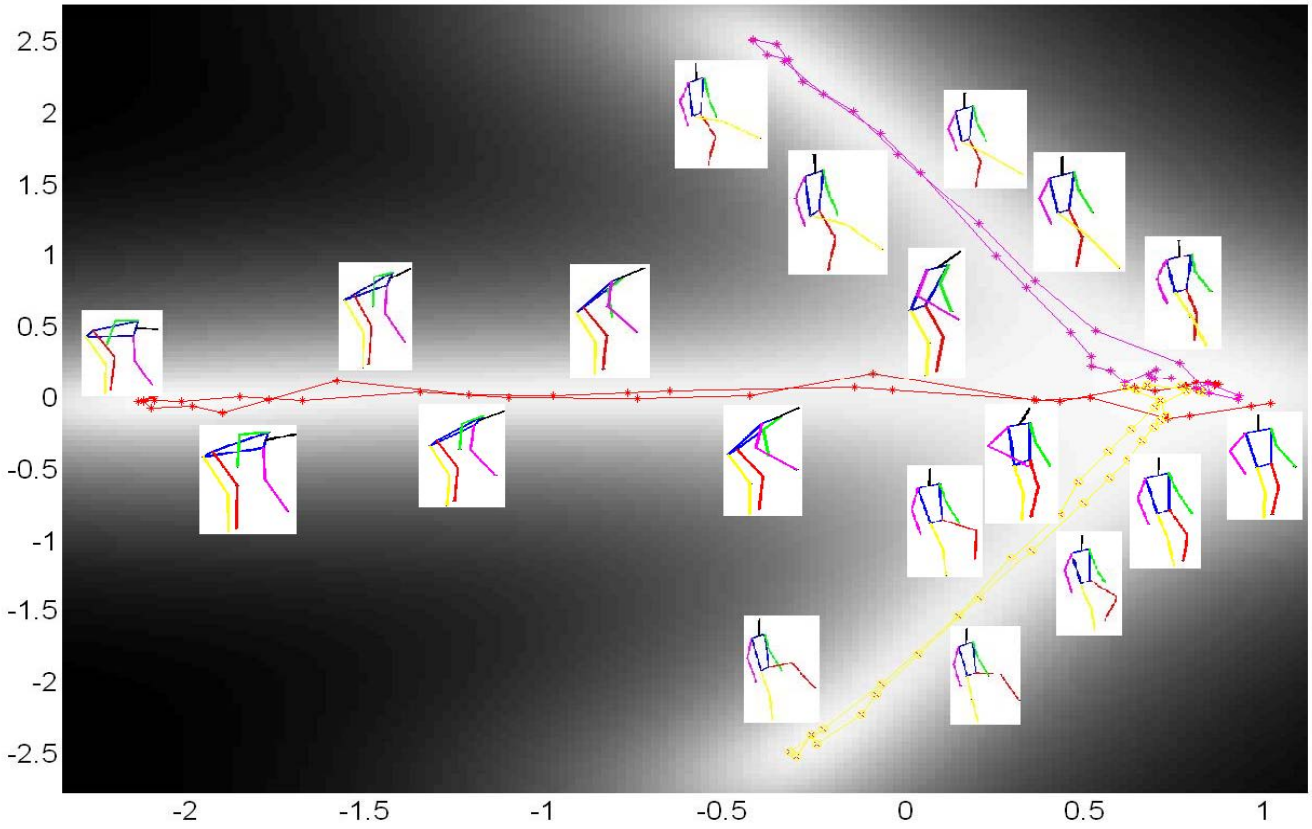
- We use a set of poses in order to create a latent space with a low dimensionality. The poses are taken from different sequences:
  - Walking
  - Running
  - Punching
  - Kicking

- We perform non linear dimensionality reduction using Gaussian Process Dynamic Model (GPDM) and construct a latent space.

The Tracking Scheme

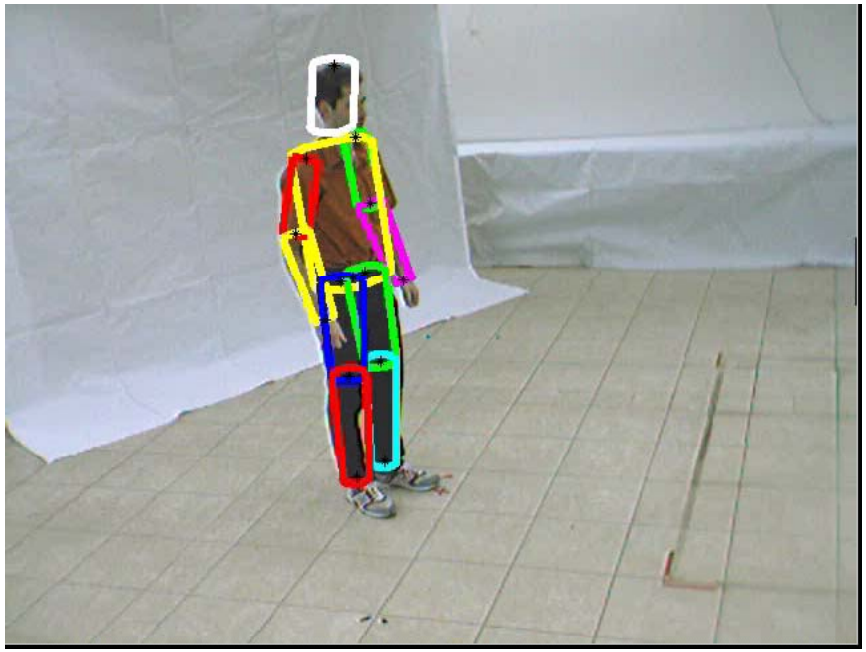


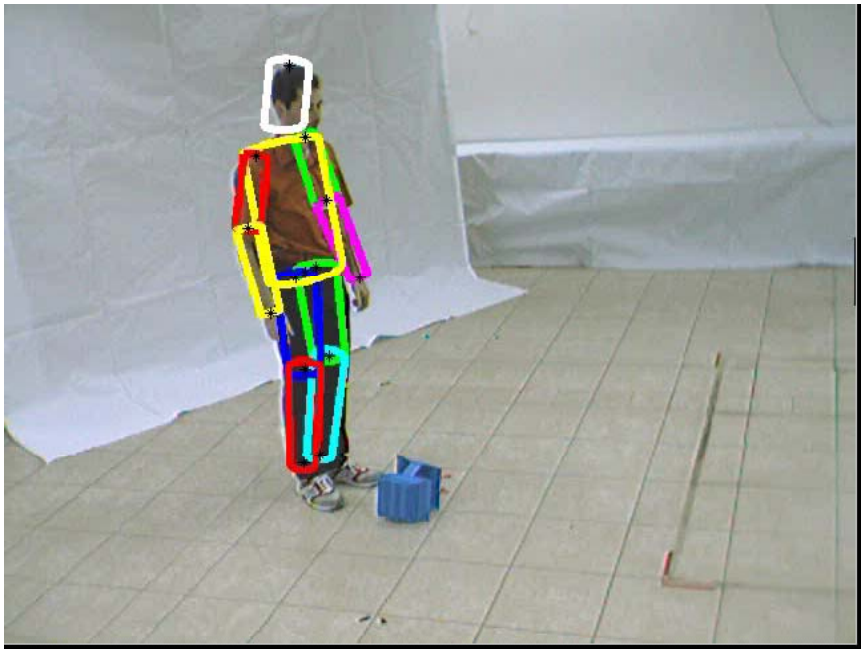
Multi-Action Learning



2D latent space from 3 different motions: lifting an object (red), kicking with the left (green) and the right (magenta) legs.

Results





Other works:

Moving object detection and classification

Other works:

- Eye tracking