Summarization and Indexing of Human Activity Sequences

Bi Song*, Namrata Vaswani**, Amit K. Roy-Chowdhury*

*EE Dept, UC-Riverside

**ECE Dept, Iowa State University

Goal

- In order to summarize human activity sequences, we need to:
  - Recognize the current activity from a set of known activity types
  - Track using the activity's model
  - Detecting the change to the next activity

Applications

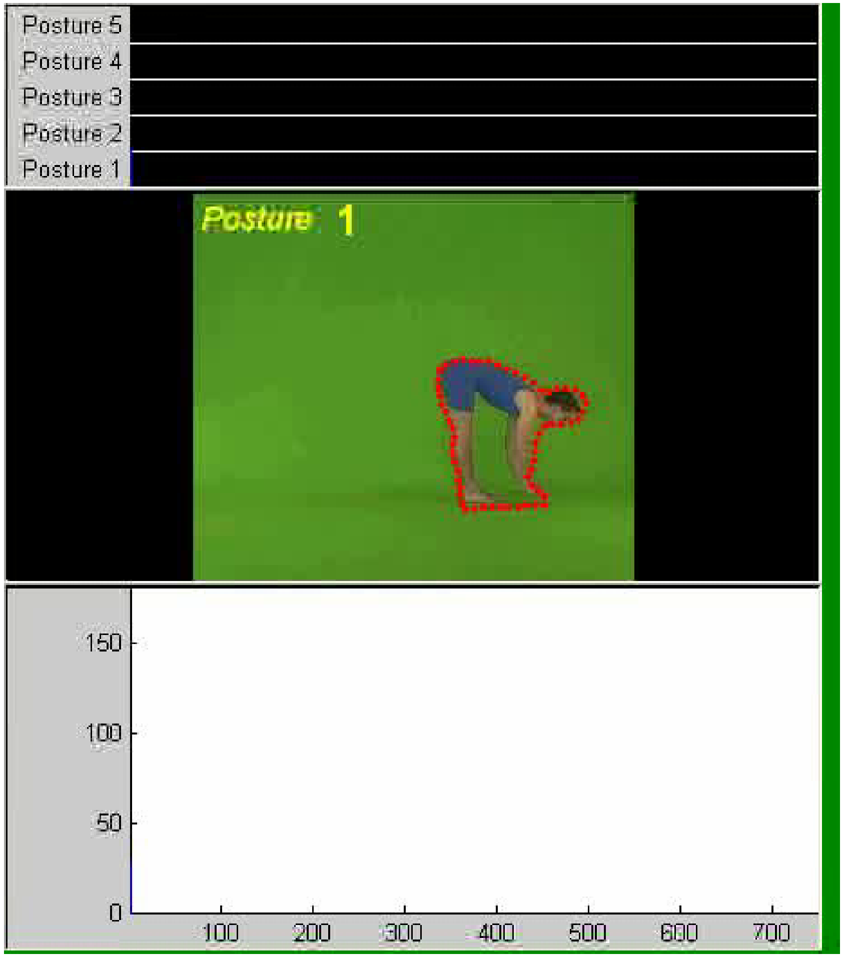
- Summarizing/annotating videos, e.g.
  - Sports videos, Training videos
  - Movies or documentaries
- Surveillance, e.g.
  - Recognizing activities in a parking lot
  - Shop surveillance
  - Airport surveillance

Example

Recognition

Tracking

Tracking Error



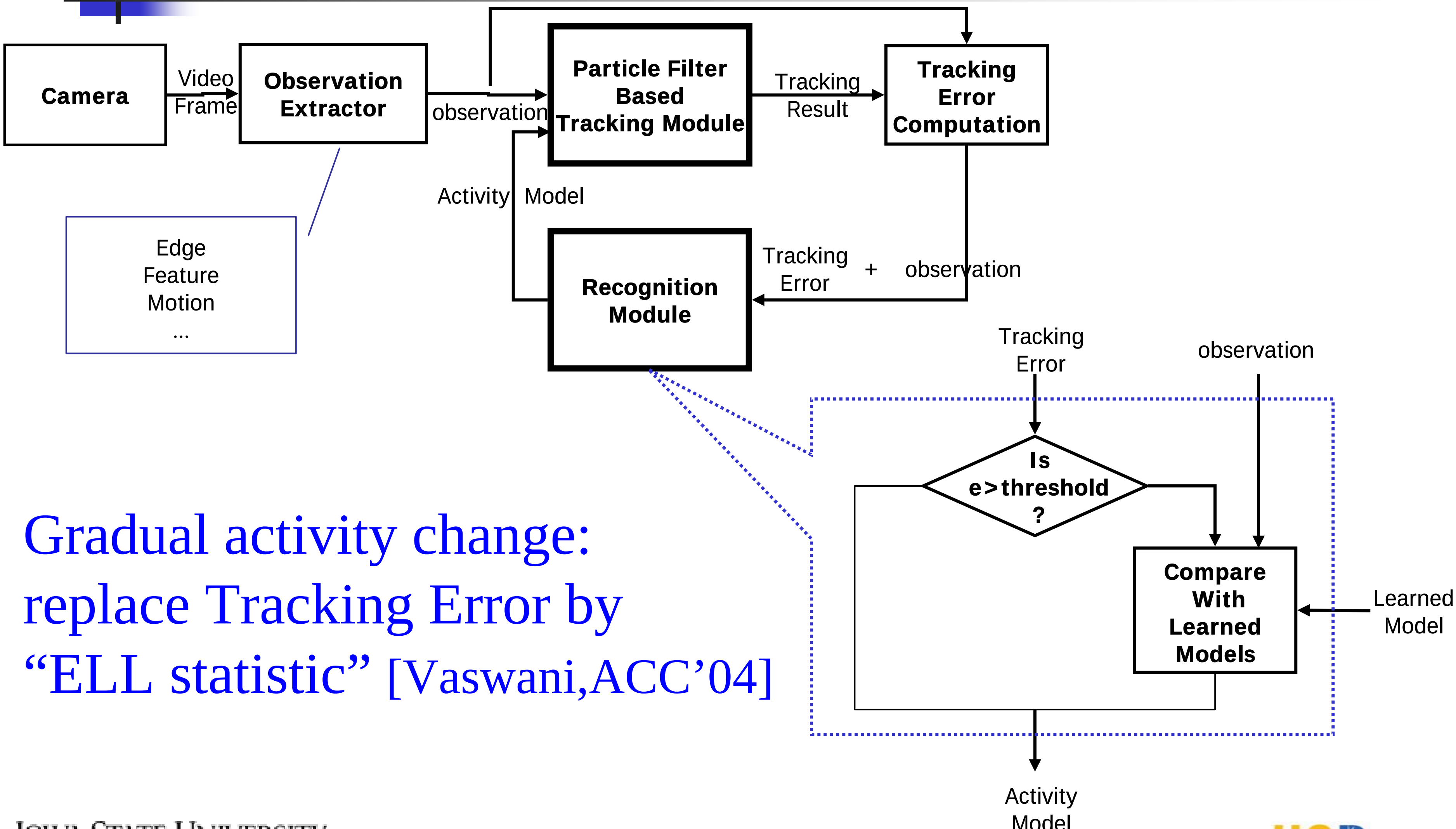
Outline

- Our Approach & Related Work
- State Space Model for Tracking
  - Shape dynamics for an activity
  - Transitioning to next activity model
  - Motion model
  - Observation model
- Change Detection (using ELL & TE), Recognition
- Experimental Results & Future Plans

‘Shape Activity’ (SA) approach

- Recognize activity using a few frames
  - Invariant scaled Euclidean camera motion
- Track with dynamic model of recognized SA
  - Separate dynamics of shape from that of camera motion (allows learning dynamics of activity with one camera and tracking with another, possibly moving, camera, where have a statistical model for camera motion dynamics)
- Keep detecting “change” from current SA model
  - Use a combination of “ELL statistic” & Tracking Error
  - ELL detects “gradual deviations” from current SA model

Closed-loop Framework for Simultaneous Tracking and Recognition



Gradual activity change:
replace Tracking Error by
"ELL statistic" [Vaswani,ACC'04]

Existing Work

- Condensation for gesture recognition
  - Only tracked affine deformations
  - Used a discrete state variable to model current gesture type: needed a set of particles for each gesture type
- DBN on discrete states, LGM on rest: track with RB-PF
  - Need to learn the model for discrete state dynamics
  - SLDS: Markov model for discrete state (special case of DBN)
- All above approaches: not invariant to camera motion

Statistical Shape Analysis [Dryden-Mardia'98]

- Configuration: set of K sampled contour locations
  - or B-spline control points or any other "feature points"
  - Represented as a K-dim complex vector, C

- Shape: C modulo translation, scale, in-plane rotation (scaled Euclid camera motion)
  - lies on a non-Euclidean space (hyper-sphere)
  - represent as tangent coordinate w.r.t. a "pole"

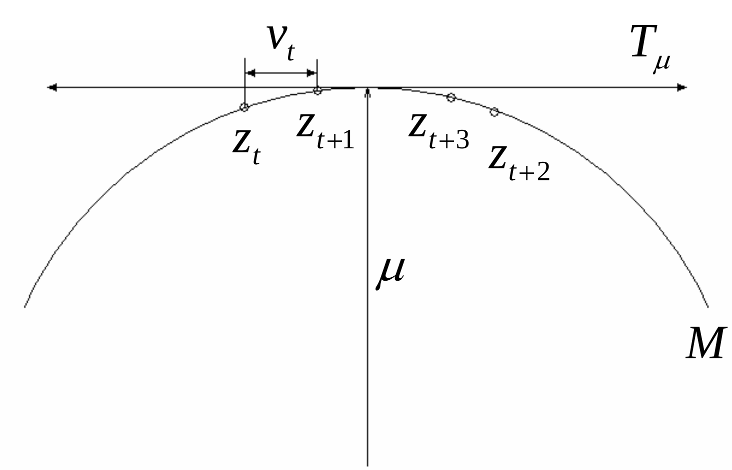
- Motion: trans, scale, in-plane rotation
- Shape X Motion ←→ Configuration

‘Shape Activity’ Model

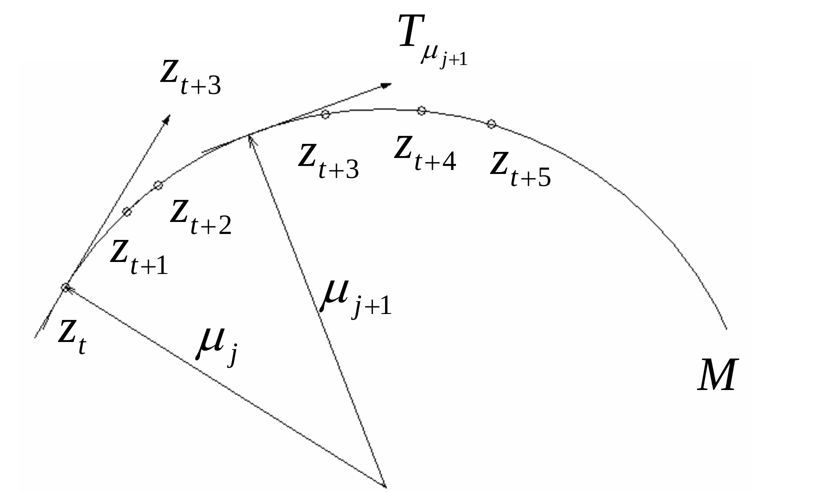
- Each activity represented by a “mean shape” and an AR model for deviations about the “mean”

- State = [motion, shape]
  - Motion = trans, scale, in-plane rotation
  - Dynamics: model for random camera motion
  - Shape = “tangent coordinates” of current shape w.r.t. the activity’s “mean shape” [Dryden-Mardia]
  - Dynamics: AR model on “tangent coordinates”

Modeling Human Activity Dynamics --Details



(a) Stationary Shape Sequence (SSS)



(b) Piecewise-Stationary Shape Sequence (PSSS)

Stationary and Piecewise-Stationary Shape Sequence on the shape manifold. In (a), we show a stationary sequence of shapes; at all times the shapes are close to the mean shape μ and hence the dynamics can be approximated in T_μ (tangent space at). In (b), we show a piecewise-stationary sequence of shapes; the shapes move on the shape manifold.

State Space Model

- μ = mean shape of current activity
- s_t = scale, θ_t = rotation,
- v_t = tangent coordinate of current shape w.r.t. μ
- Motion: $\log s_t = \log s_{t-1} + n_{s,t}$, $\theta_t = \theta_{t-1} + n_{\theta,t}$
- Shape: $v_t = A\, v_{t-1} + n_{v,t}$

- Observed edge map either generated by predicted configuration, C_t or by clutter [Condensation, IJCV'98]
  - Arrange v_t as a complex vector
  - $z_t = (1-v_t^* v_t)^{1/2} \mu + v_t$, $C_t = z_t\, s_t\, e^{j\,\theta_t}$

At Activity Change Time…

- Track using a particle filter (PF)
- Get shape from tangent coordinate and current mean shape, μ
  - $z_t = (1-v_t^* v_t)^{1/2} \mu + v_t$
- Compute its tangent coordinate w.r.t. μ_{new}
  - $v_{t,new} = [I - \mu_{new} \mu_{new}^*] z_t e^{j \theta(z_t, \mu_{new})}$

Change Detection (slow): ELL [Vaswani,ACC'04]

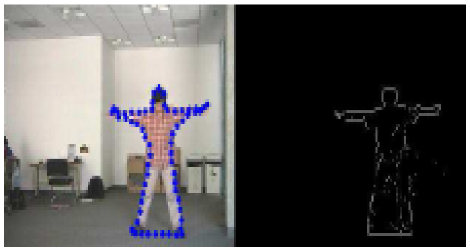
- Tracking Error (TE) relies on "loss of track" of observations to detect changes
- Gradual changes get tracked by a particle filter (PF)
- ELL: measure of KLD b/w the posterior & the t step ahead prediction distribution of state (pdf of state given no observations)
  - uses "tracked part of change" to detect it, detects only gradual changes (which TE misses)

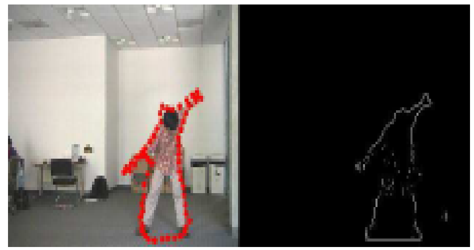
Computing ELL

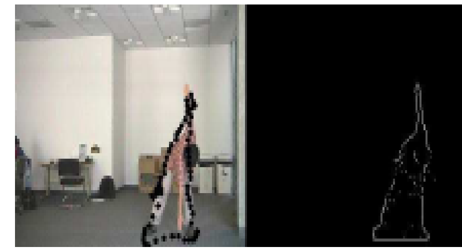
$$ELL_t^N = \frac{1}{N}\sum_{i=1}^{N} v_t^{(i)^T} \Sigma_v^{-1} v_t^{(i)} + constant$$

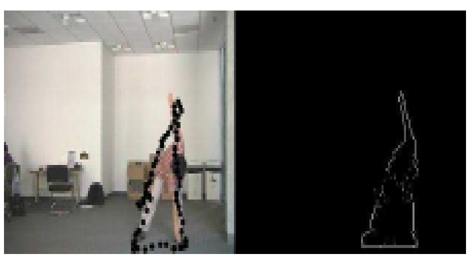
- v_t^i = particles of tangent coordinate of current shape w.r.t. current activity's mean
- ELL = posterior Expectation of the negative Log Likelihood of v_t being generated from $N(0,\Sigma_v)$ which is the prior pdf of v_t

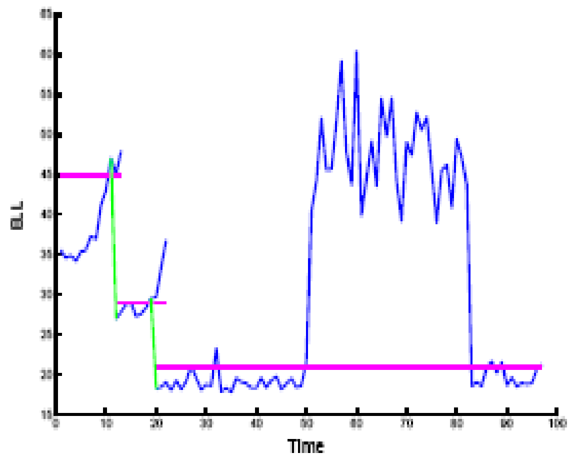
Change Detection (slow): ELL

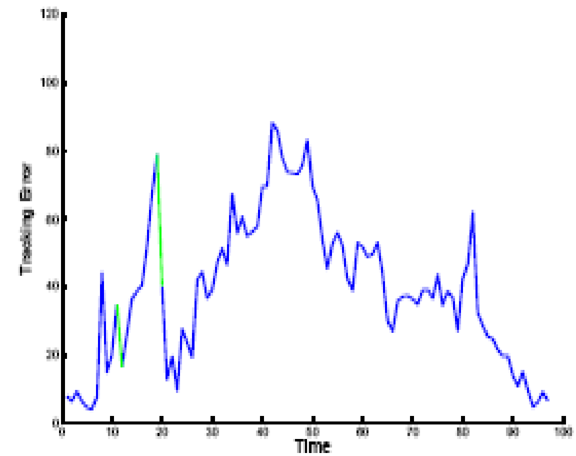




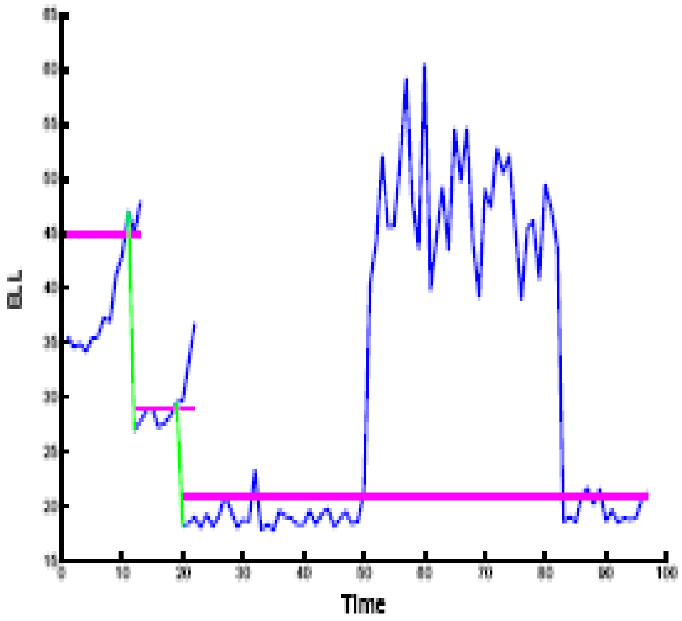


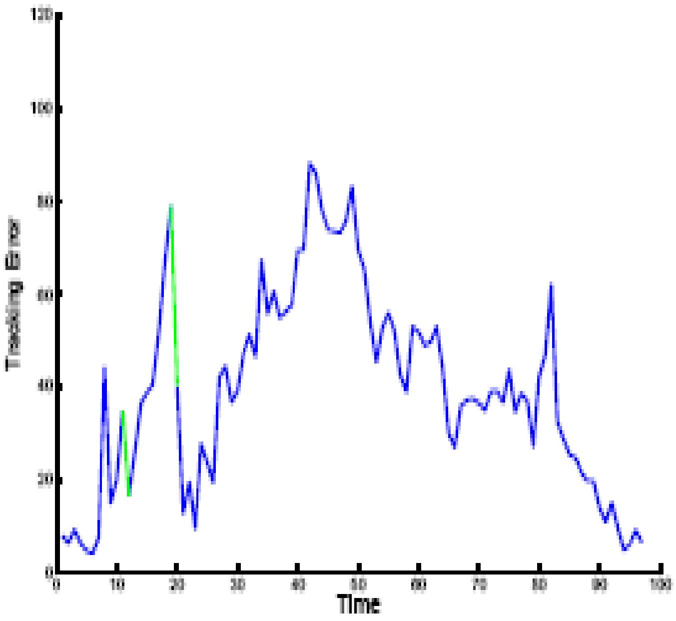






ELL v/s TE for Slow Change





ELL detects faster than TE

Change Detection (Sudden): TE

Sudden activity changes will cause the PF with a large enough number of particles, and tuned to the dynamical model of a particular activity, to lose track. The tracking error (TE) will increase when the activity changes and this can be used to detect the change times. TE is calculated by

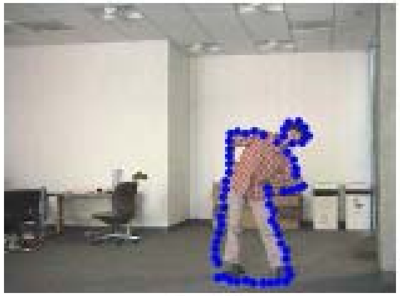
$$TE = \sum_{k=1}^{K} \left\| q_k - f(q_k, G_t) \right\|^2$$

q_k: k^{th} predicted landmark

$f(q_k,G_t)$: the nearest edge point of q^k along its norm direction

Change Detection (Sudden): TE

Act3

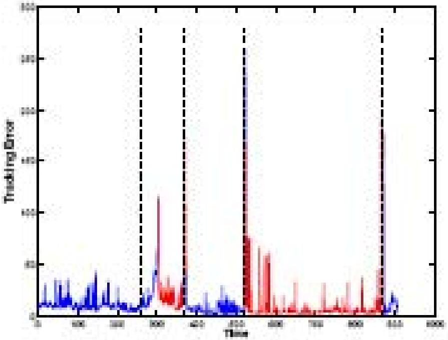


Act4

Act8

Act9

Act7



Tracking Error

Recognition

This is done by projecting the observed shape in a frame onto the mean shape for each of the learned activities and choosing the one with the largest projection.

Specifically, given an observed image I_t, we label this frame as the activity that minimizes

$$\left\| \Gamma_t - s e^{j\theta} \mu_m + (a + jb) \right\|$$

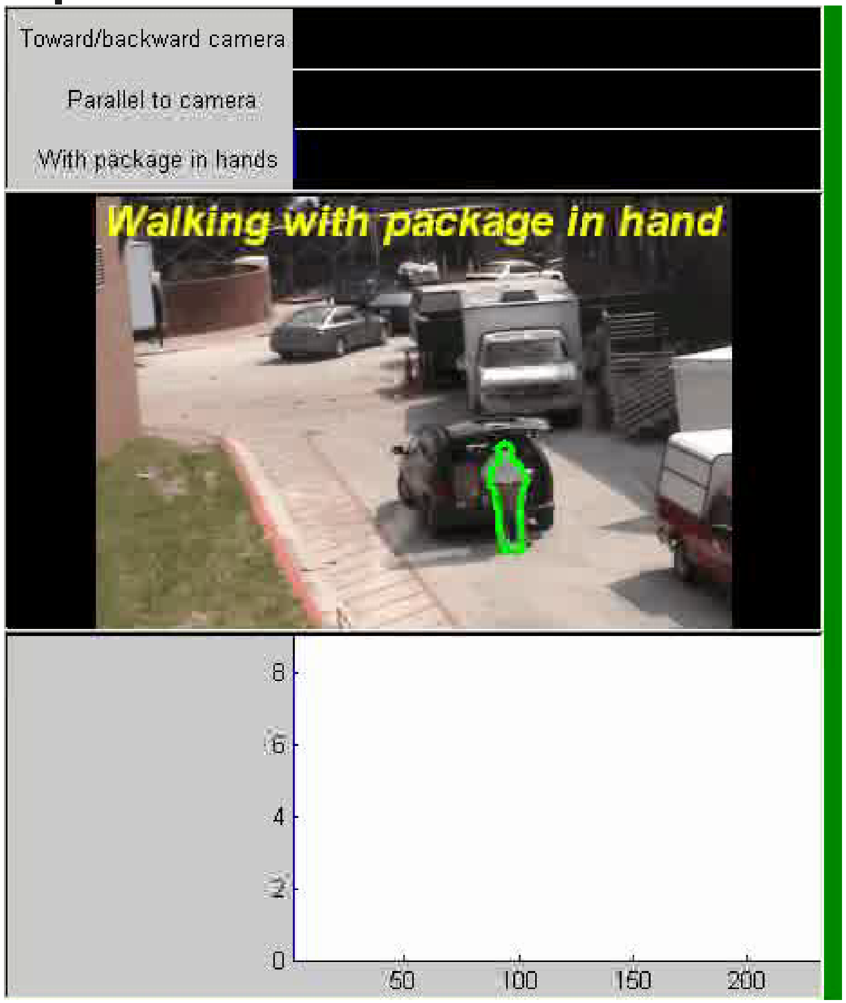
Where s -- scale, θ – rotation, $a+jb$ -- translation

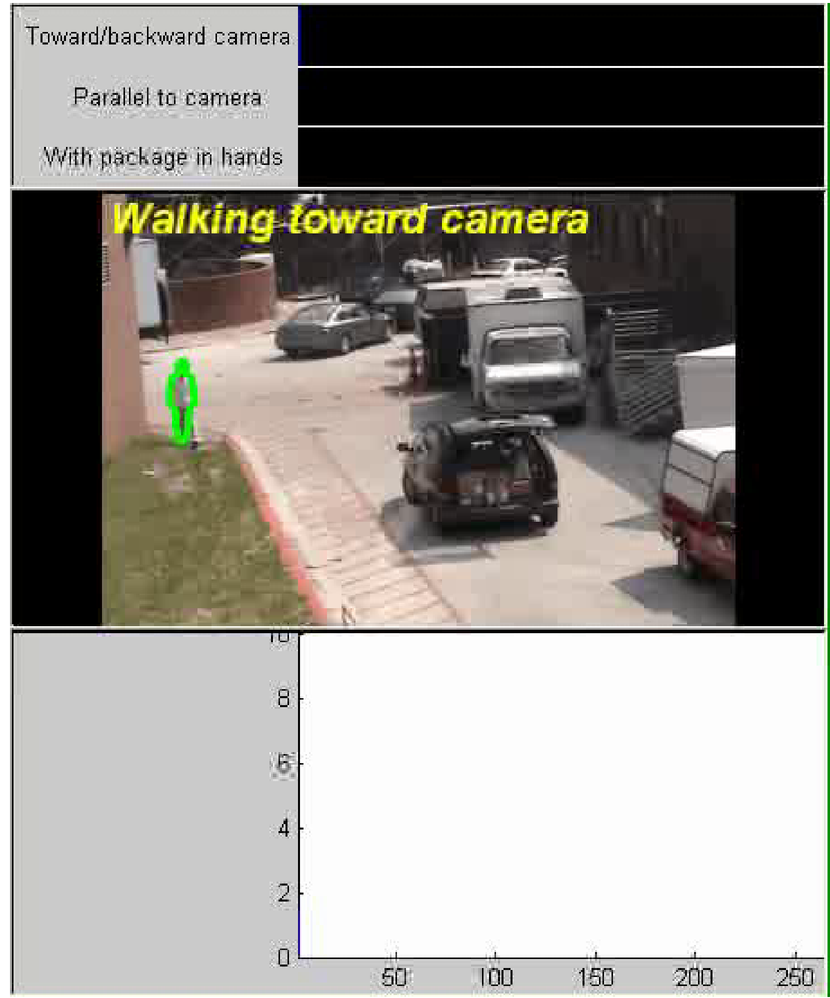
Experiments

- 10 human activities captured indoors
  - 1) bending across,
  - 2) walking toward camera and bending down,
  - 3) leaning forward and backward,
  - 4) leaning sideward,
  - 5) looking around,
  - 6) turning head,
  - 7) turning upper body,
  - 8) squatting,
  - 9) bending with hands outstretched,
  - 10) walking.

Summarizing and Index of Human Activity Sequences

Outdoor Sequence (ongoing work)





Future Work

- Replace PF by PF-MT [Vaswani et al, ICASSP'06]
  - Local shape deformation per frame is small
  - PF-MT: IS only on motion, MT on shape
- Improving observation model by adding more features
- NSSA model for tracking, PSSA for recognition
- Tracking & activity analysis across a network of cameras
- Illumination invariant tracking
- Unsupervised Training: given a time seq. of landmarks, automatically segment it into pieces & learn dynamics