

# **Abnormal Activity Detection and Tracking**

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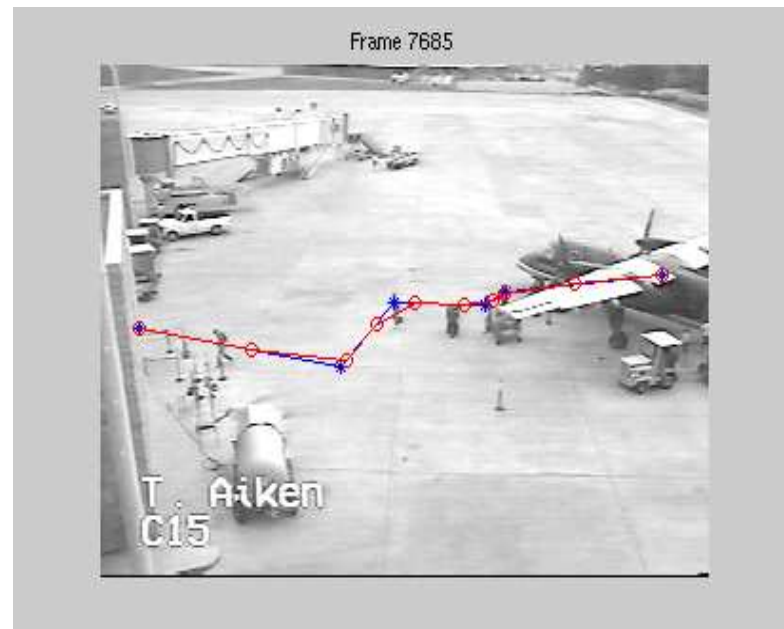
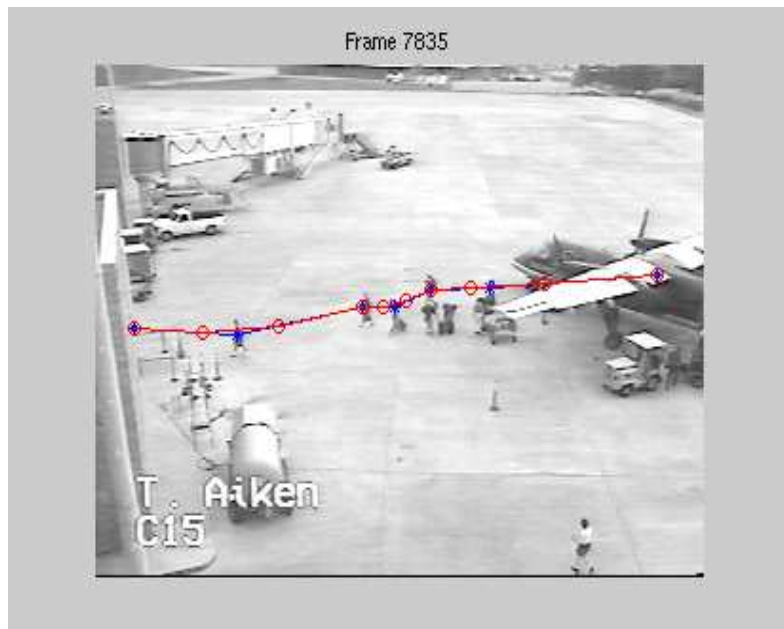
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## The Problem

- **Goal: To track activities performed by a group of moving and interacting objects and detect abnormal activity.**
- Treat each object in an image as a point object (“landmark”)
- **Dynamics of configuration of objects: moving and deforming shape**
- Observations: Vector of measured object locations (Noisy)
- **“Abnormality”: Change in the learnt shape dynamical model**

## Group of People Example

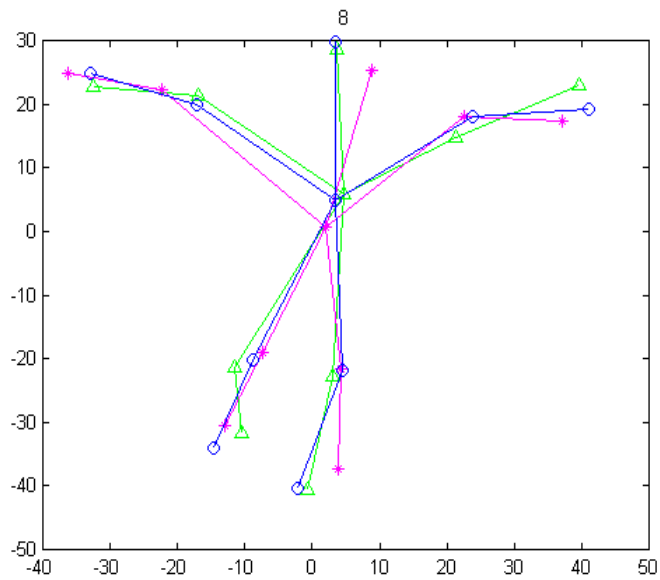


A 'normal activity' frame

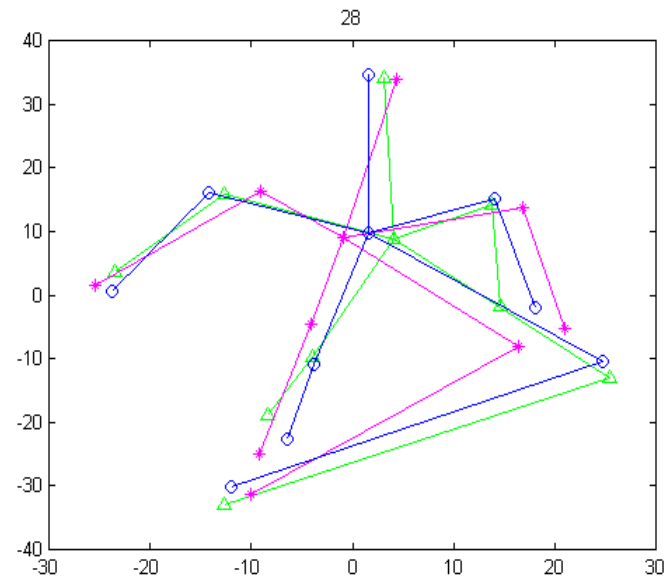
Abnormality

Figure 1: Airport example: Passengers deplaning

# Landmark Representation of Human Actions



Normal action



Abnormality

## What is Shape?

- **Shape: geometric information that remains when location, scale & rotation effects are filtered out [Kendall]**
- Shape of  $k$  landmarks in 2D
  - Represent the  $X$  and  $Y$  coordinates of the  $k$  points as a  $k$ -dimensional complex vector: **Configuration**
  - Translation Normalization: **Centered Configuration**
  - Scale Normalization: **Pre-shape**
  - Rotation Normalization: **Shape**

## Dynamical Model for Landmark Shapes

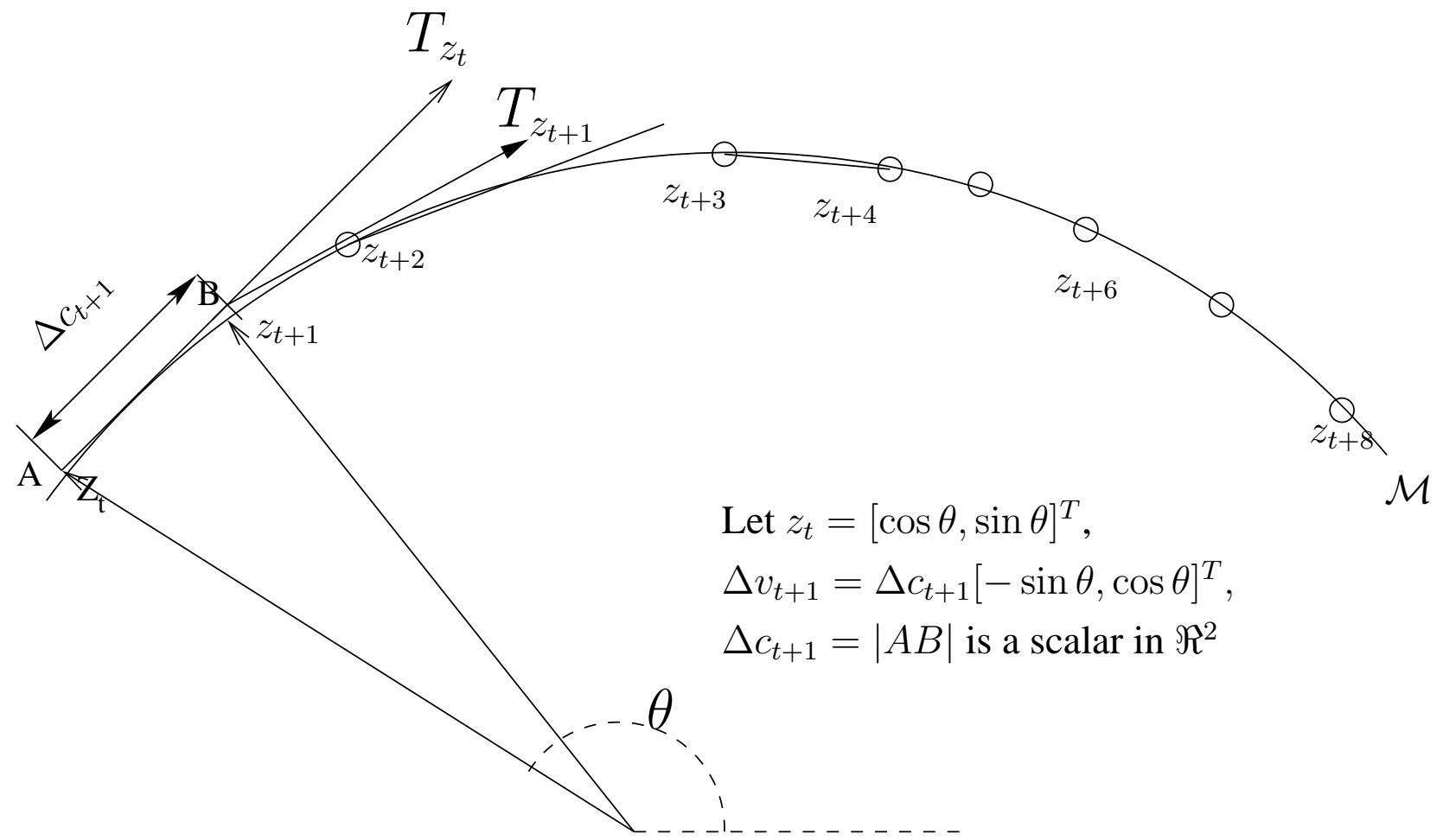
[Vaswani, RoyChowdhury, Chellappa, IEEE Trans. Image Processing, Sept'05]

- **Observation:** Vector of observed object locations (Configuration)
- **State:** [Shape, Similarity group (Trans., Scale, Rotation), Velocities]
- **Observation model:**  $h_t : \mathcal{S} \times \mathbb{R}^2 \times \mathbb{R}^+ \times SO(2) \rightarrow \mathbb{R}^{2k}$ , Gaussian noise
- **System model:**
  - Gauss-Markov model on shape velocity, parallel transported to tangent space of the current shape
  - Gauss-Markov model on the similarity group velocities

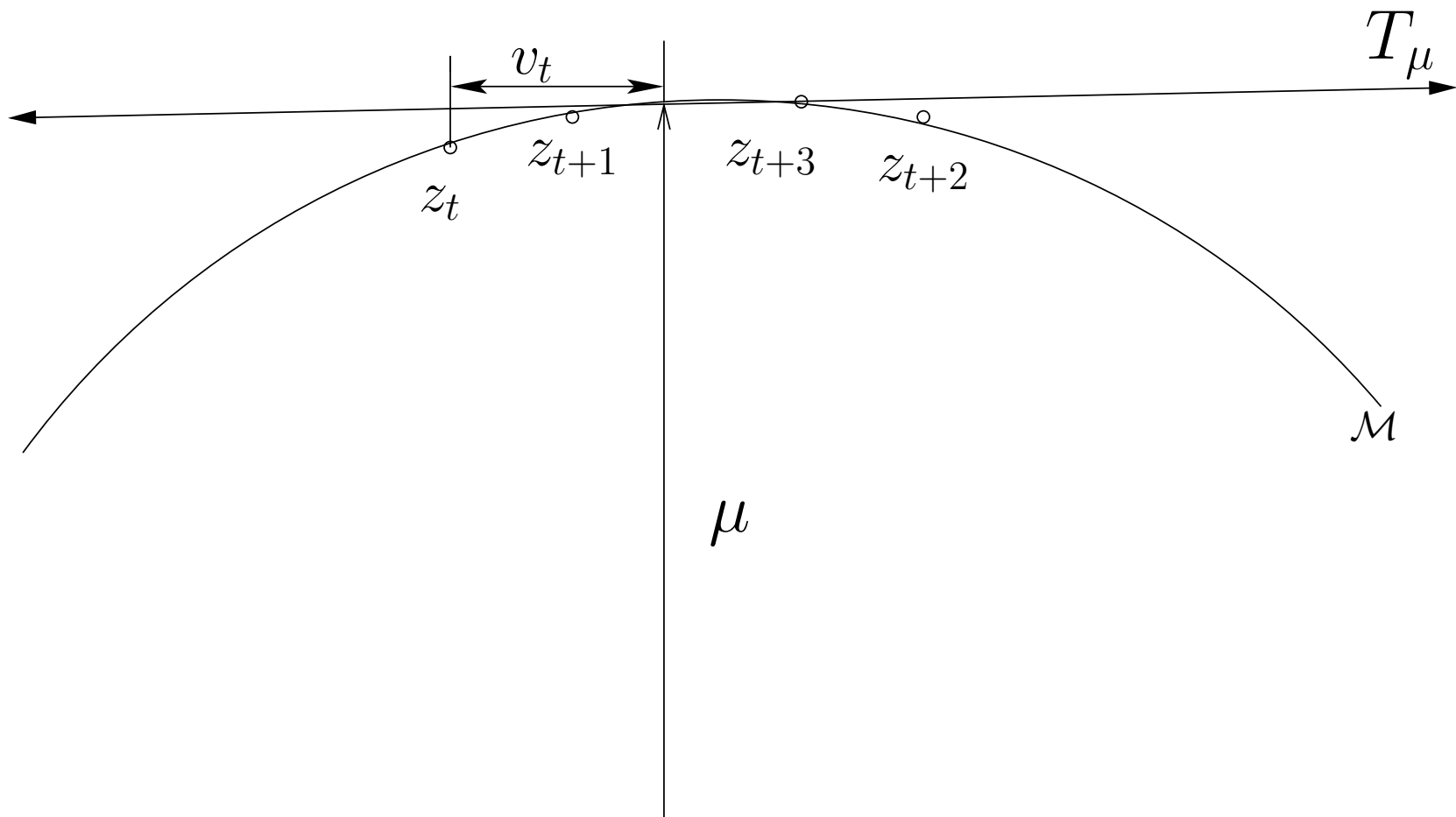
## Nonstationary and Stationary Shape Dynamics

- **Nonstationary Shape Activity** [Vaswani,Chellappa, CDC'05]
  - No single average shape
  - **Most flexible: Detect abnormality and also track it**
- **Stationary Shape Activity** [Vaswani et al, CVPR'03]
  - Assumes normal activity has stationary shape dynamics
  - **Detects abnormality faster, Good model for normalcy**
- **Piecewise Stationary Shape Activity** [Vaswani,Chellappa, CDC'05]
  - Slow shape variation modeled by a p.w. stationary model
  - **Use along with ELL for Activity Segmentation**

# NonStationary Shape Activity

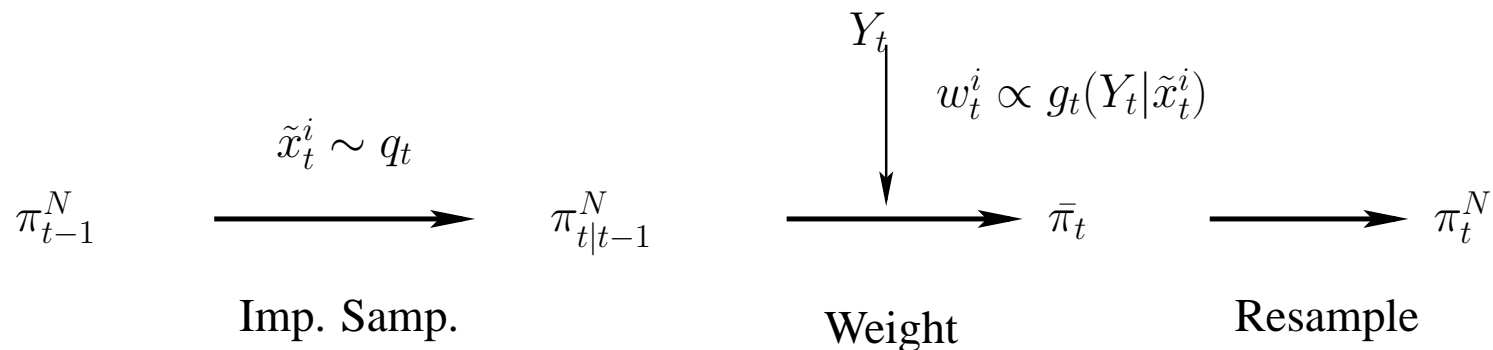


# Stationary Shape Activity



## Tracking using a Particle Filter [Gordon et al'93]

- **Sequential Monte Carlo method, approx. true filter as number of Monte Carlo samples (“particles”),  $N \rightarrow \infty$**
- **Given  $\pi_{t-1}^N$ , perform importance sampling/ weighting, followed by resampling to approx. the Bayes’ recursion:  $\pi_t^N$**

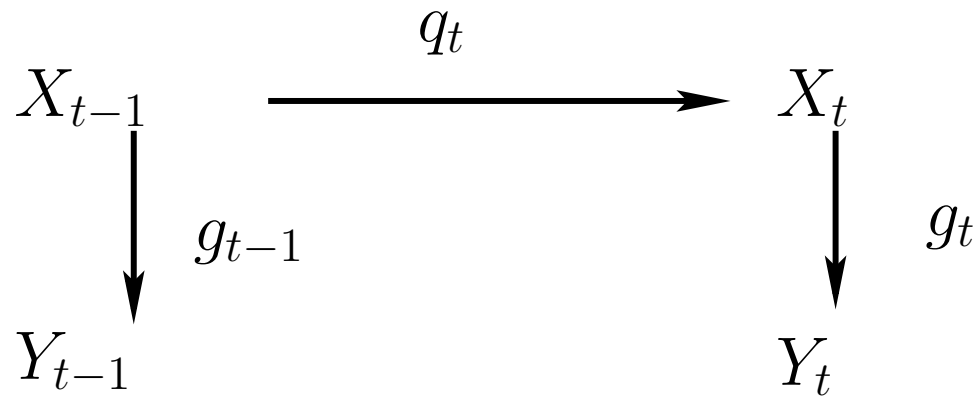


- Using  $\gamma_t(x_t | x_{1:t-1}^{(i)}, Y_{1:t}) = q_t(x_t | x_{t-1}^{(i)})$  as importance density

## Abnormal Activity Detection

- **“Normal Activity”**: Modeled as a landmark shape dynamical model
  - *Partially Observed and Nonlinear System satisfying HMM property*
- **“Abnormal Activity”**: Change in learned shape dynamical model
  - *Parameters of changed system unknown*
  - *Change can be slow or sudden*
- **Detect changes in shape using posterior distribution of shape given observed object locations**

## Notation



- **State:**  $X_t$ , **Observation:**  $Y_t$
- **Prior:** Given no observations,  $X_t \sim p_t(\cdot)$
- **Posterior:**  $X_t | Y_{1:t} \sim \pi_t(\cdot)$
- **Superscripts:** <sup>0</sup> (unchanged system), <sup>c</sup> (changed system)

## Slow v/s Sudden Change

- **Slow change:** small change magnitude per unit time, gets “tracked” by the particle filter
- **Sudden change:** gets “filtered out” (“loses track”)
  - Duration much smaller than “response time” of filter.
  - **Easy to detect using Tracking Error or Observation Likelihood**
- **Quantify “rate of change”,  $r$ :** For an additive change with magnitude  $b$  per unit time,  $r^2 = b^T \Sigma_{sys}^{-1} b$ .

## Slow change detection, Unknown parameters

- Tracking Error, Observation Likelihood: miss slow changes

- **Fully observed state:**  $X_t = h_t^{-1}(Y_t)$

- Log Likelihood of state of unchanged system,

$$-\log p_t^0(X_t) = -\log p_t^0(h_t^{-1}(Y_t))$$

- **Partially observed state (significant observation noise):**

- Why not use Min. Mean Square Error estimate of this ?

- **Our statistic is exactly this MMSE estimate:**

$$ELL(Y_{1:t}) \triangleq E[-\log p_t^0(X)|Y_{1:t}]$$

## Computing the Statistics [Vaswani, ACC'2004]

- **Expected (negative) Log Likelihood of state (ELL)**

$$ELL = E[-\log p_t^0(X_t)|Y_{1:t}] = E_{\pi_t}[-\log p_t^0(X)] \approx \frac{1}{N} \sum_{i=1}^N -\log p_t^0(x_t^{(i)})$$

- For sudden changes, can use
  - **(negative) log of Observation Likelihood (OL)**

$$OL = -\log p_Y(Y_t|Y_{1:t-1}) = -\log E_{\pi_{t|t-1}}[g_t(Y_t|X)] \approx \sum_{i=1}^N w_t^{(i)}$$

- **Tracking Error (TE)** [Bar-Shalom]

$$TE = \|Y_t - \hat{Y}_t\|^2, \hat{Y}_t = E[Y_t|Y_{1:t-1}] = E_{\pi_{t|t-1}}[h_t(X)]$$

## Computing $p_t^0$

- Consider a linear and Gaussian system model:

$$X_0 \sim \mathcal{N}(0, \sigma_0^2)$$

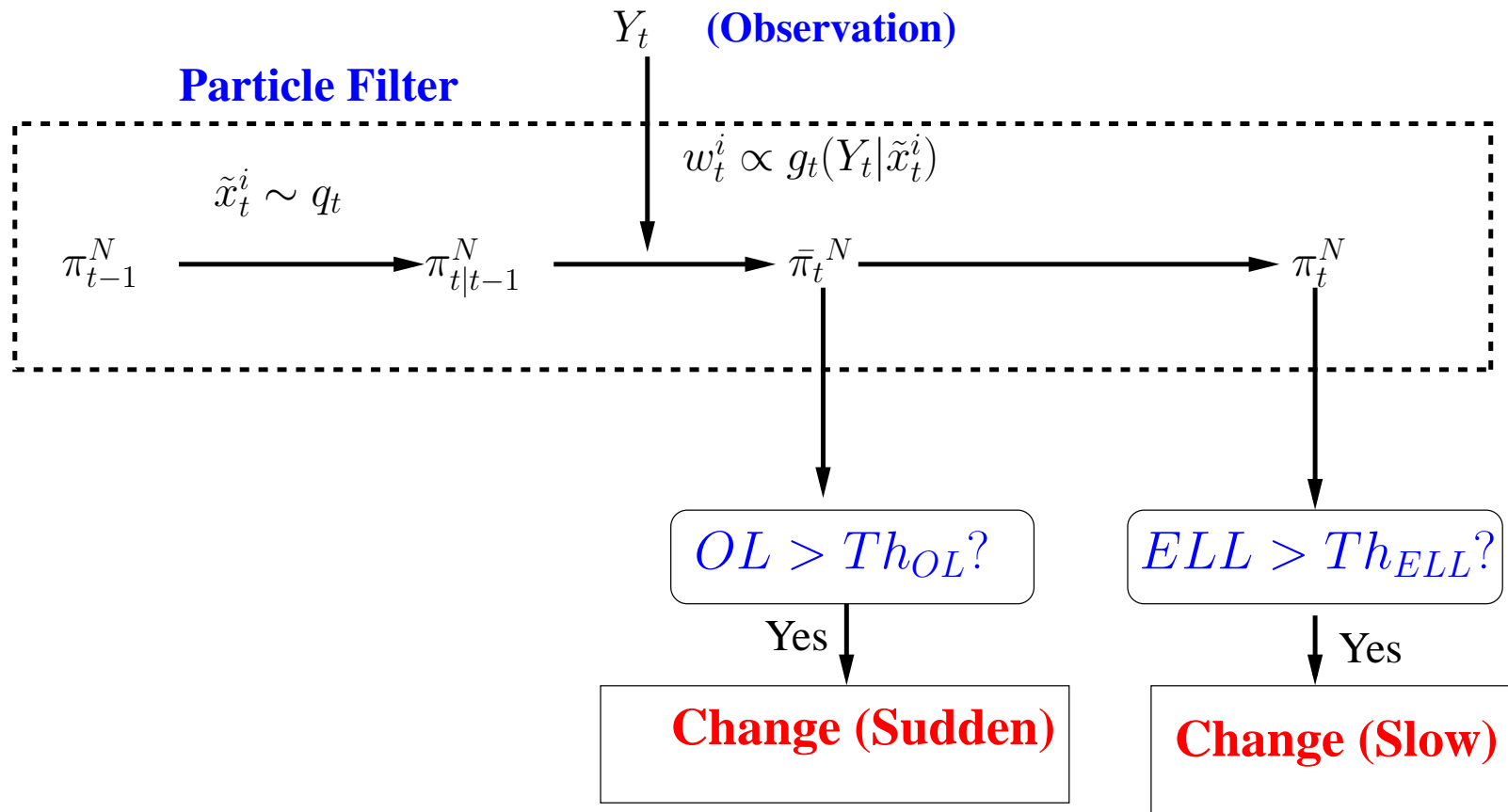
$$X_t = X_{t-1} + n_t, \quad n_t \sim \mathcal{N}(0, \sigma_n^2)$$

Then  $X_t \sim \mathcal{N}(0, \sigma_0^2 + t\sigma_n^2) \triangleq p_t^0(x)$ . Thus

$$-\log p_t^0(X) = \frac{X^2}{2(\sigma_0^2 + t\sigma_n^2)} + \text{const}$$

- For the general case: use Taylor series to get an approximation to  $p_t^0$  or use prior knowledge

# Change Detection Algorithm



## ELL v/s OL (or TE)

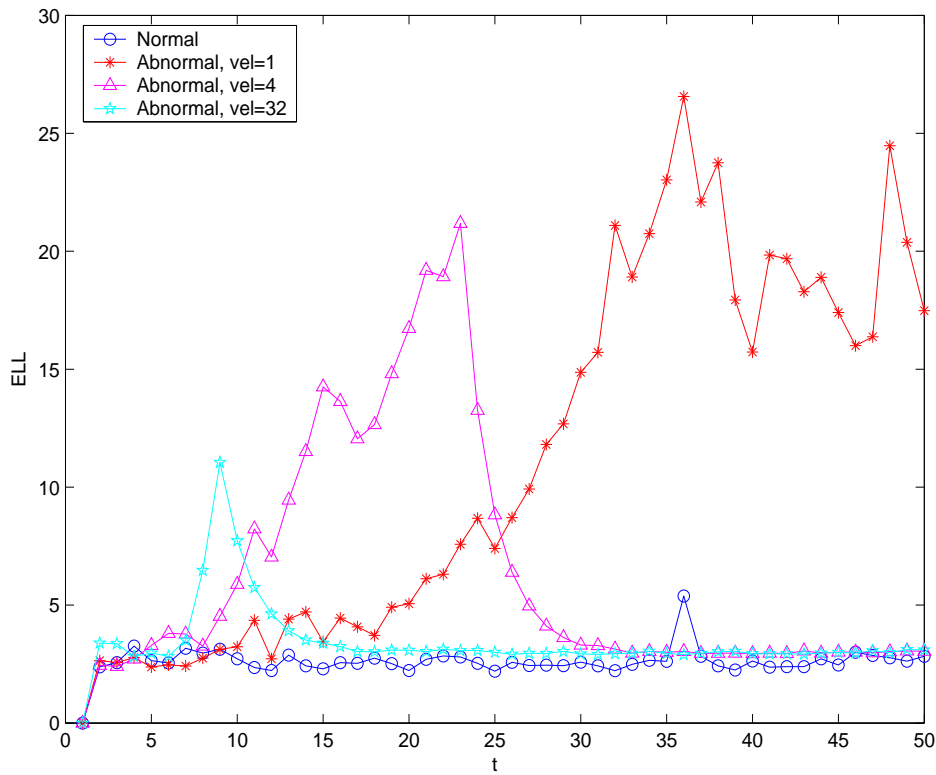
- **Slow Change:**
  - PF: stable under mild assumptions, tracks slow change well
  - **OL & TE rely on error introduced by change to detect**
  - **Error due to change small: OL, TE fail or take longer to detect**
  - Estimate of posterior close to true posterior of changed system
  - **ELL detects as soon as change magnitude becomes detectable**
- **Sudden Change:**
  - **PF loses track: OL & TE detect immediately**
  - **ELL detects based on “tracked part of the change”**
  - **ELL fails or takes longer**

## Summarizing [Vaswani, ACC'04, ICASSP'04,'05]

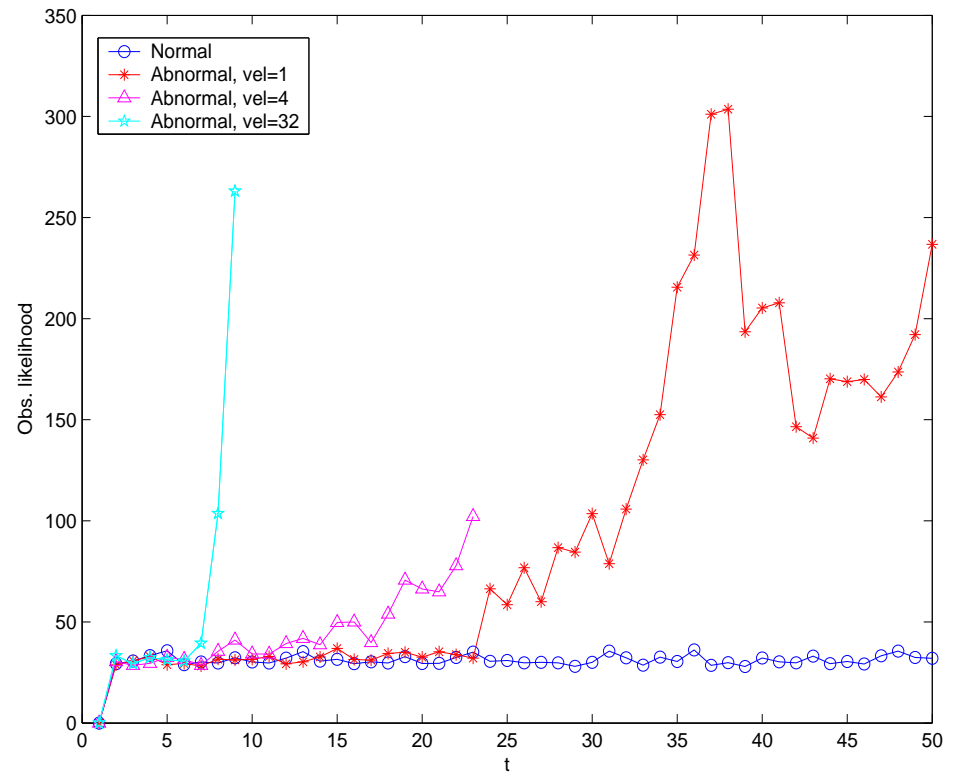
- **ELL detects a change before loss of track (very useful). OL or Tracking Error detect after partial loss of track.**
- **Have shown:**
  - Complementariness of ELL & OL for slow & sudden changes
  - Stability of the total ELL approximation error for large  $N$
  - ELL error upper bounded by increasing function of “rate of change”
  - Relation to Kerridge Inaccuracy and a sufficient condition for the class of detectable changes using ELL

# Group of People: Abnormality Detection

Abnormality (one person walking away) begins at  $t = 5$



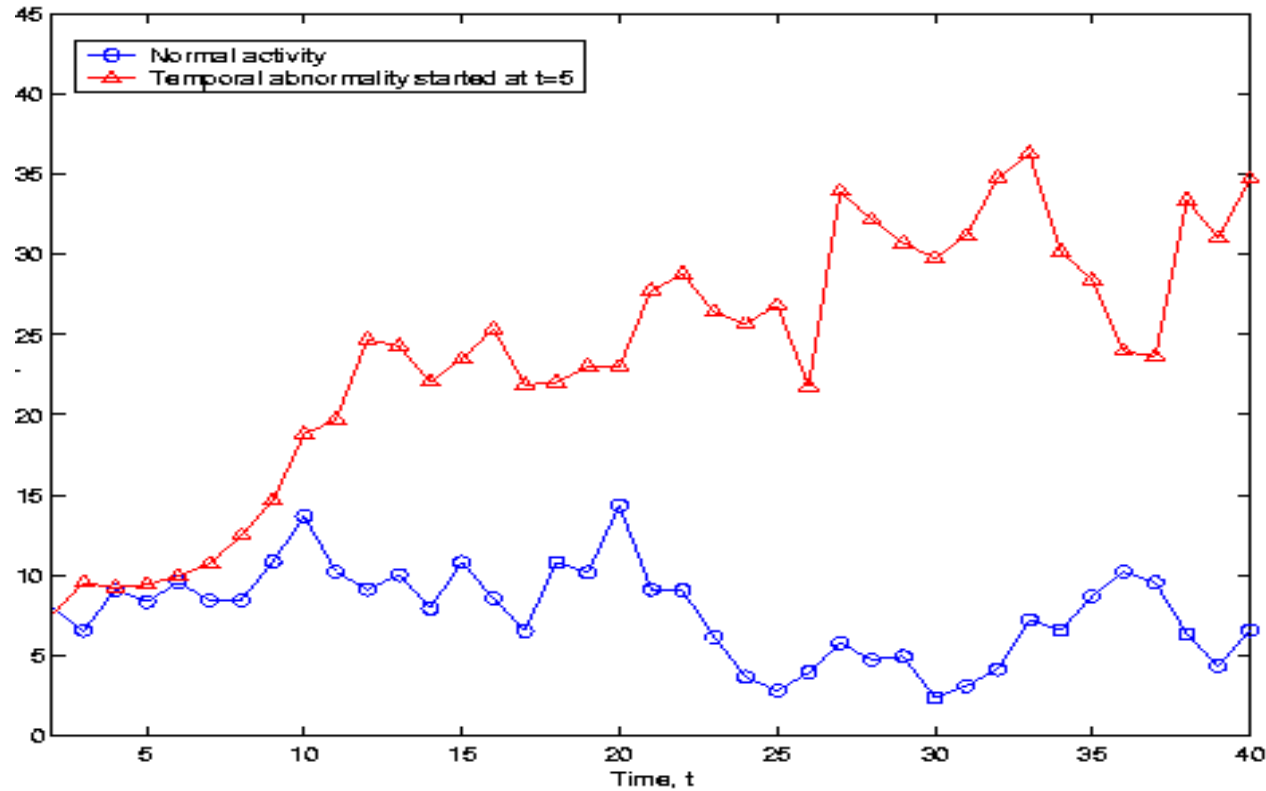
ELL



OL

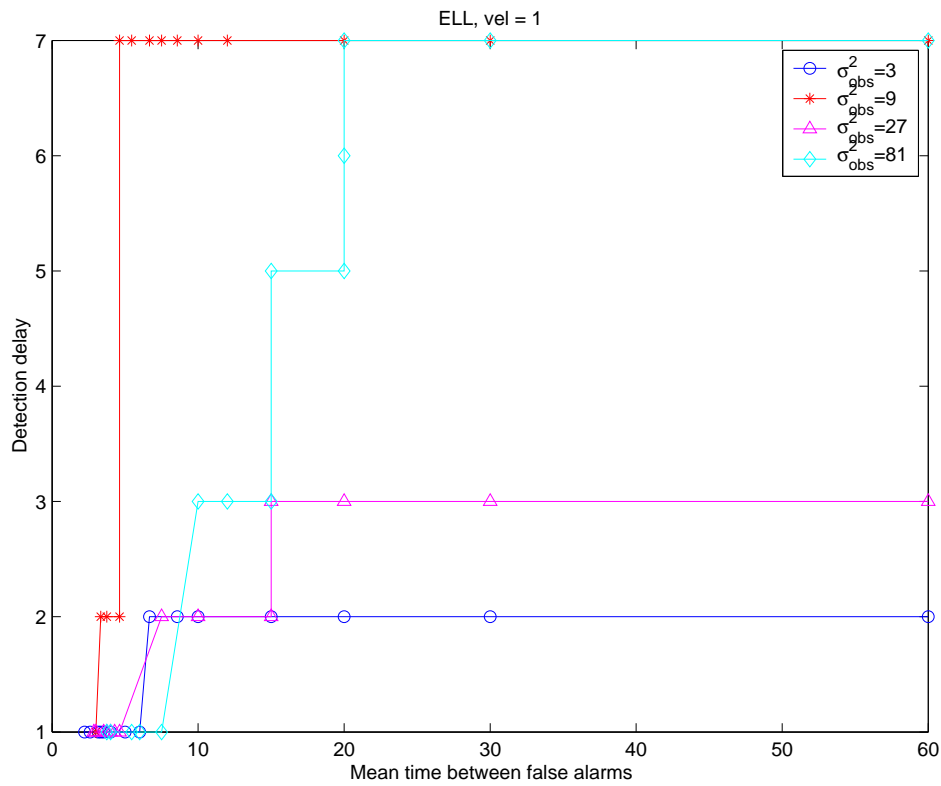
# Group of People: “Temporal Abnormality” Detection

Abnormality (one person stopped in path) begins at  $t = 5$

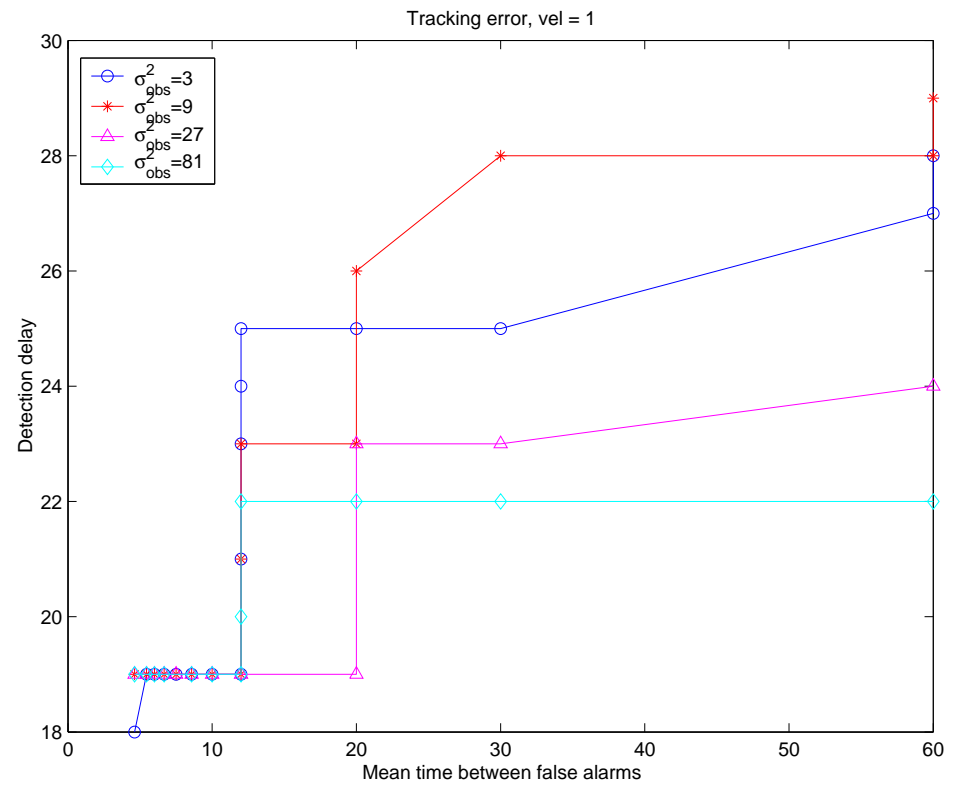


ELL Plot

# ROC Curves: “Slow” Abnormality Detection

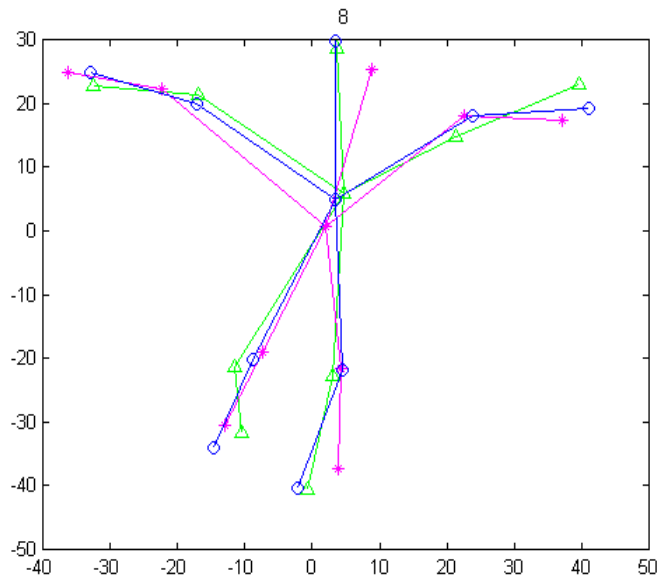


**ELL Detects**

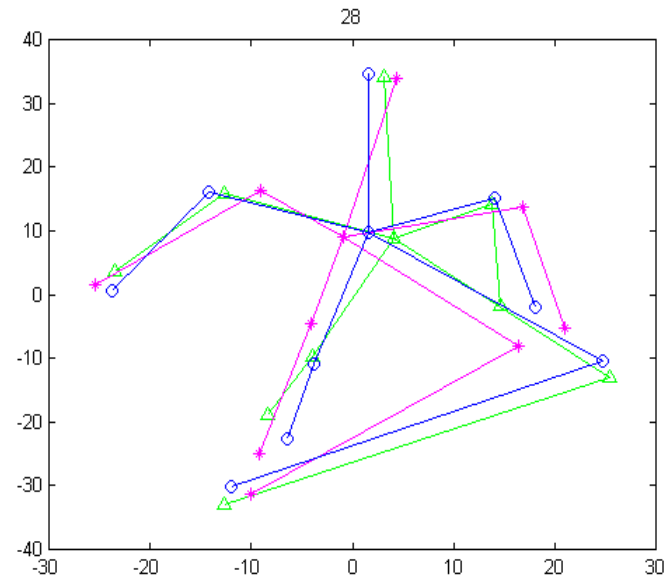


**TE: Takes much longer**

# Human Actions: Tracking



Normal action



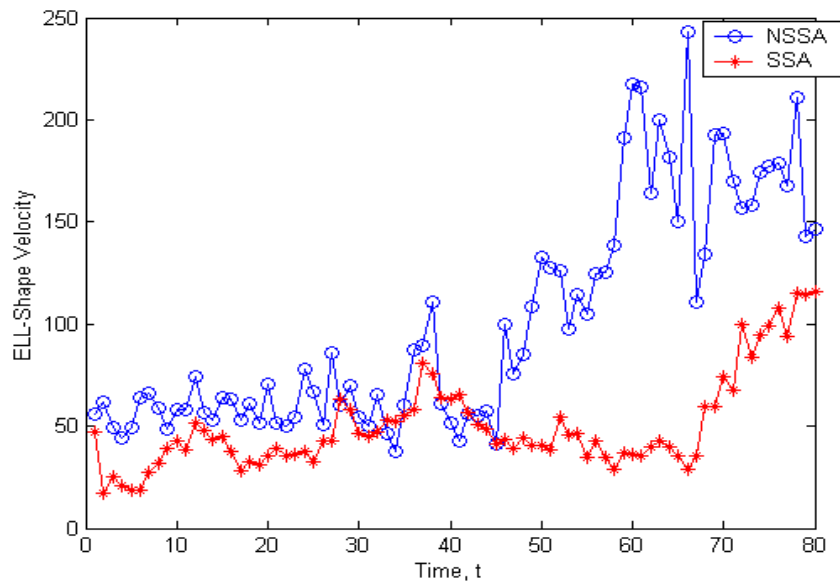
Abnormality

## Legend:

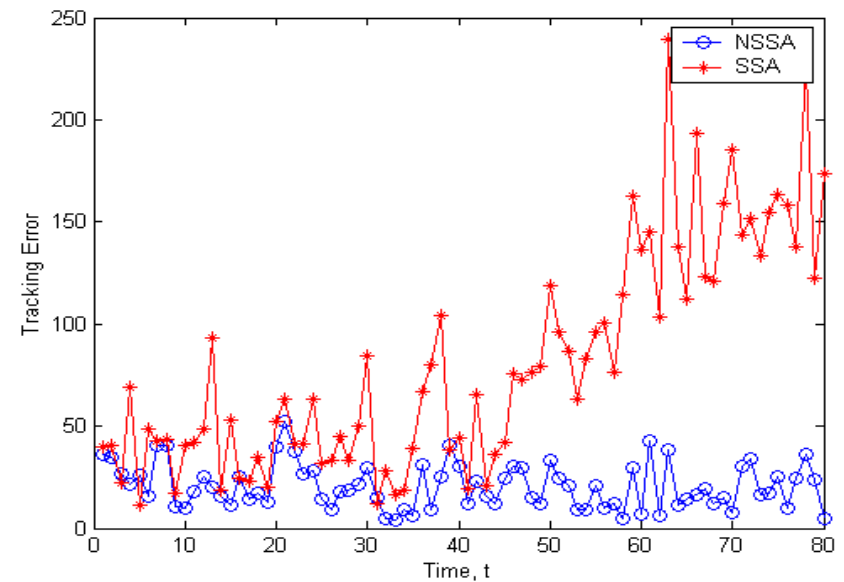
**Green: Observation, Blue: Ground Truth, Magenta: Tracked**

# Human Actions: Abnormality Detection

- Abnormality begins at  $t = 20$
- NSSA detects using ELL without loss of track



ELL



Tracking Error

## A Common Framework for...

- **Abnormal Activity Detection**
  - Suspicious behavior detection, Lane change detection in traffic
  - Abnormal action detection
- **Tracking**
  - Groups of people or vehicles
  - Articulated human body tracking
  - Biomedical applications e.g. human heart tracking
- **Activity Sequence Segmentation**
- **Sensor independent approach: Replace video by audio, infra-red or radar sensors, fuse different sensors**

## Ongoing and Future Research

- **Tracking to get observations**
- **Activity Sequence Segmentation**
- **Changed Parameter Estimation**
- **Practical implications of results for improved particle filter design**
- **Other Applications**
  - **Neural signal processing** (changes in STRFs of auditory neurons)
  - **Acoustic tracking** (changes in target motion model)
  - **Communications applications:** tracking slowly varying channels, congestion detection in networks
  - **Any system model change detection w/o PF losing track**