Abnormal Activity Detection and Tracking

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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**: $h_t : S \times \mathbb{R}^2 \times \mathbb{R}^+ \times S0(2) \rightarrow \mathbb{R}^{2k}$, 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*
Let $z_t = [\cos \theta, \sin \theta]^T$,
$\Delta v_{t+1} = \Delta c_{t+1}[- \sin \theta, \cos \theta]^T$,
$\Delta c_{t+1} = |AB|$ is a scalar in $\mathcal{R}^2$.
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 $\pi^N_{t-1}$, perform importance sampling/weighting, followed by resampling to approx. the Bayes’ recursion: $\pi^N_t$

\[\tilde{x}_t^i \sim q_t\]

\[\pi^N_{t-1} \rightarrow \pi^N_{t|t-1} \rightarrow \pi^N_t\]

Imp. Samp. Weight Resample

\[Y_t \sim g_t(Y_t|\tilde{x}_t^i)\]

\[w_t^i \propto g_t(Y_t|\tilde{x}_t^i)\]

- 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

\[ \begin{align*}
X_{t-1} & \xrightarrow{q_t} X_t \\
Y_{t-1} & \xrightarrow{g_{t-1}} Y_t \\
X_t & \xrightarrow{g_t} Y_t
\end{align*} \]

- **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:** \( ^0 \) (unchanged system), \( ^c \) (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, $r^2 = b^T \Sigma_{sys}^{-1} b$. 

Abnormal Activity Detection and Tracking
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)**

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

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

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

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

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

Particle Filter

\[ \tilde{x}_t^i \sim q_t \]

\[ \pi_{t-1}^N \rightarrow \pi_{t|t-1}^N \rightarrow \tilde{\pi}_t^N \rightarrow \pi_t^N \]

\[ Y_t \] (Observation)

\[ w_t^i \propto g_t(Y_t|\tilde{x}_t^i) \]

\[ OL > Th_{OL}? \]

Yes

Change (Sudden)

\[ ELL > Th_{ELL}? \]

Yes

Change (Slow)
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
Abnormal Activity Detection and Tracking
Abnormality (one person stopped in path) begins at $t = 5$
ROC Curves: “Slow” Abnormality Detection

ELL Detects

TE: Takes much longer
Human Actions: Tracking

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

Abnormal Activity Detection and Tracking
Human Actions: Abnormality Detection

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