Dynamics Based Video-Analytics

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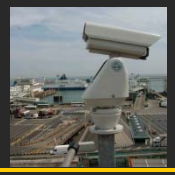
Why video-analytics?



- Inexpensive, easily deployable sensors
  - A very large number already deployed in critical locations
  - Roaming cameras (vehicles, cell phones) maximize area coverage
- Provide standoff detection capabilities:
  - Can identify potential threats with enough lead time to allow for averting/mitigating actions.
- Provide contextual coverage, uncovering threats not apparent to single sensors:
  - Coordinated activities by groups, where each individual behaves “normally”.
- Can cue off and coordinate shorter range sensors
  - Establish target identity across occlusion
  - Coordinate hand-offs across fields of view to guarantee persistent surveillance.

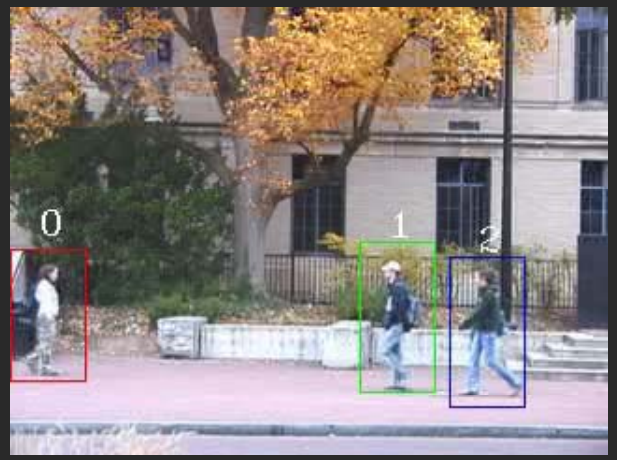
Example of a Goal:

Detect contextually "interesting" events

Challenges:

- **Tracking a very large number of targets:**
  - **Occlusion**
  - **Targets with similar appearance**
  - **Appearance change**

  } ***Normal or malicious***



How many targets?

Who is who?

Challenges:

- **Assessing intentions:**
  - **Distinguishing contextually normal from threatening.**
  - **Eliminating 99.9% of ``clutter" and passing only relevant data to human operators.**

events encoded in 1/100 to less than $1/10^6$ of the data

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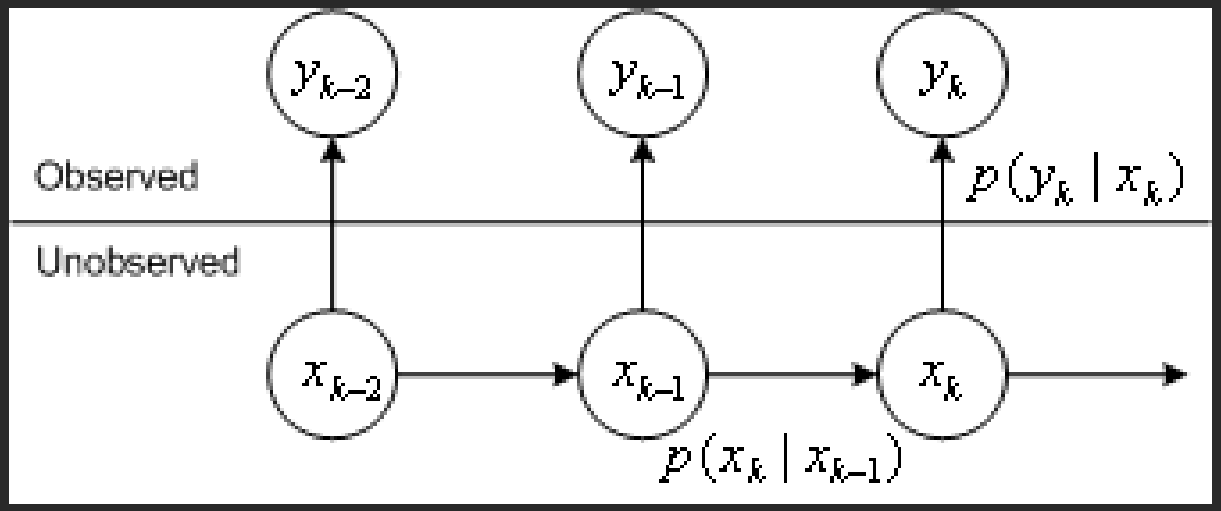
Approach: dynamical models as information encapsulation/prediction paradigms

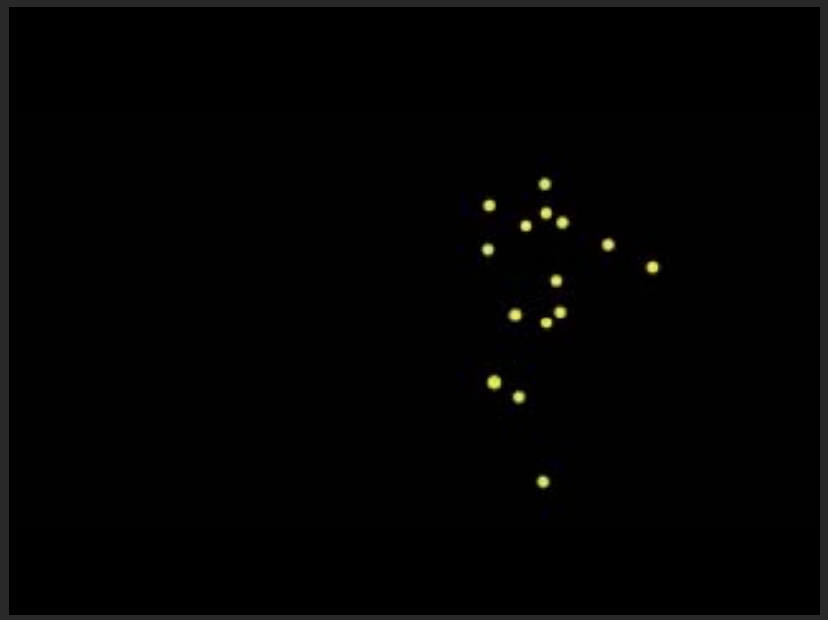
Background: Dynamical Models



A mathematical rule describing the time dependence of a point's position in its ambient space.

Order (rank): number of parameters needed

Why Dynamical Models?



All the information is encapsulated in the dynamics

Dynamical Models in Tracking:

- Model target evolution as the output of an unknown system
- Learn the rule (system id)
- Use this rule to “guess”

y(t-1)...y(t-n) → G → y(t)

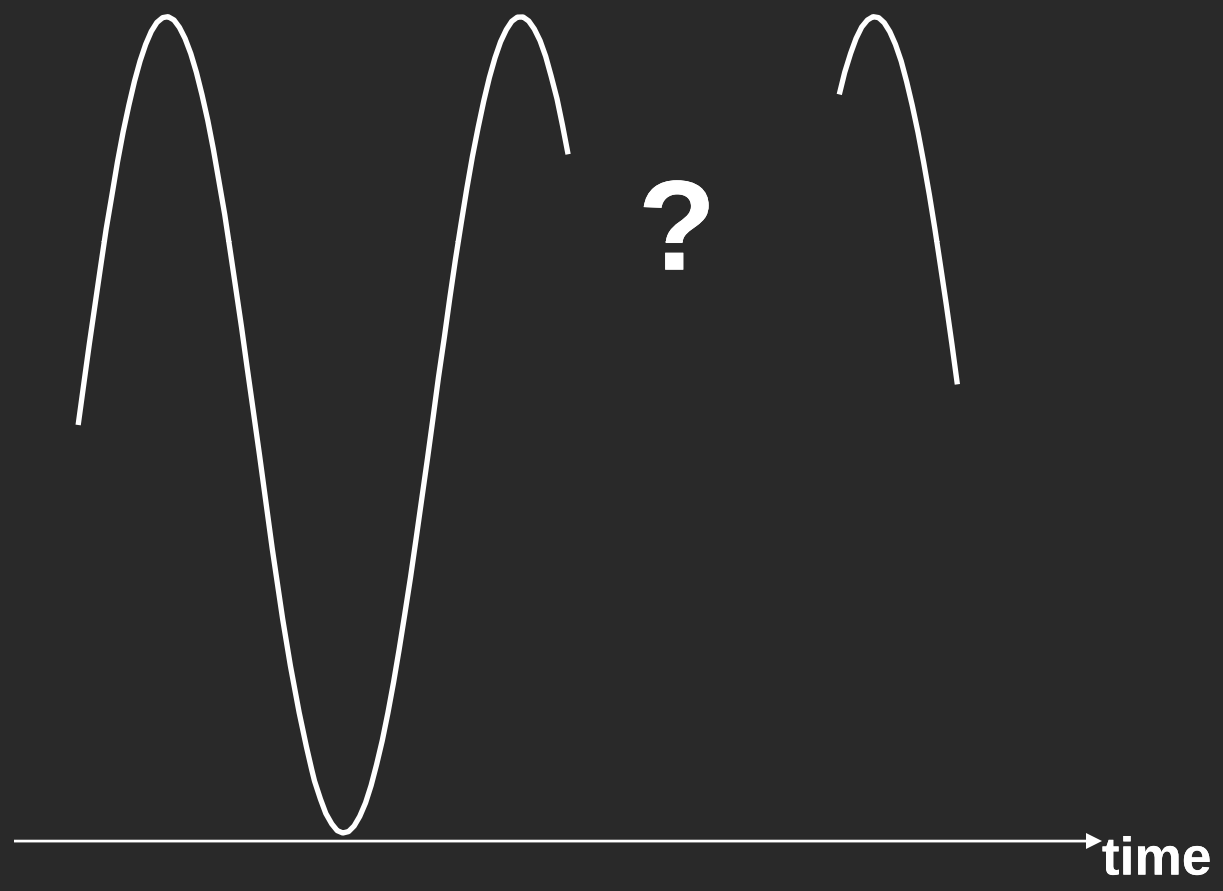
Works, but..
Computationally expensive
Can’t handle time variations

Dynamical Models in Tracking:

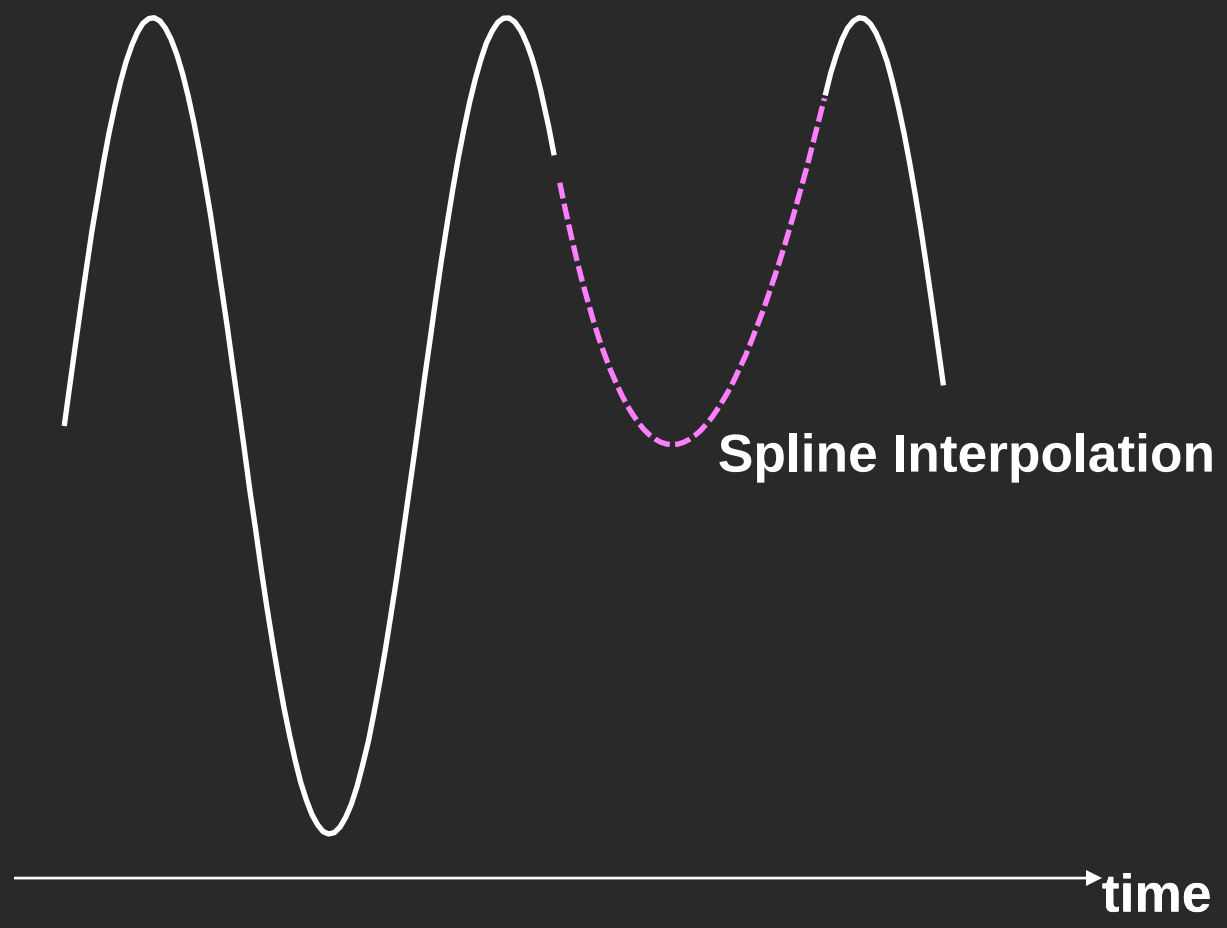
- Model target evolution as the output of an unknown system
- Learn the rule (system id)
- Use this rule to “guess”

Key observation:
We don’t need G, just y !

Detour: Completing missing information



Detour: Completing missing information



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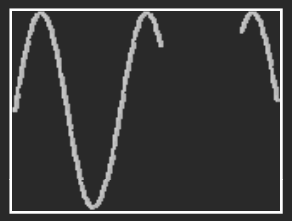
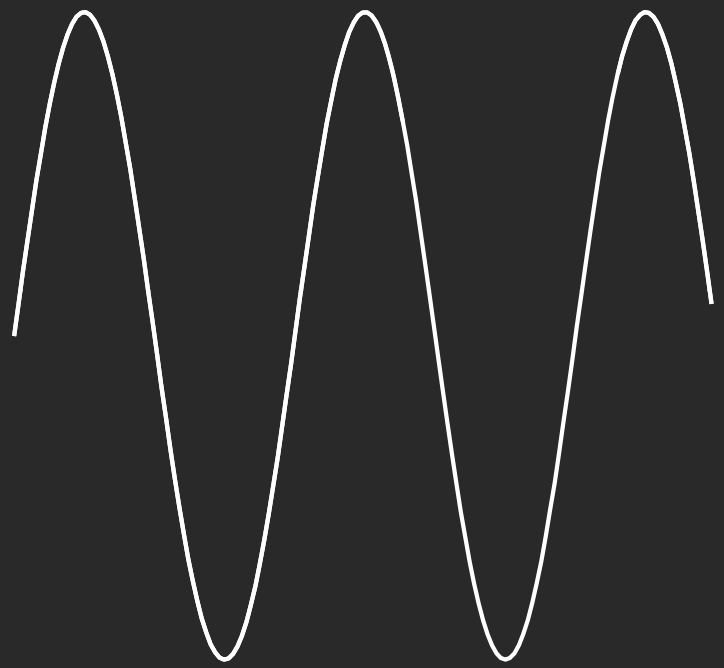
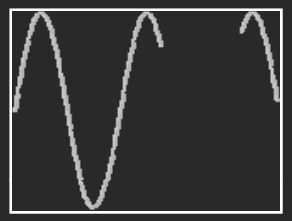


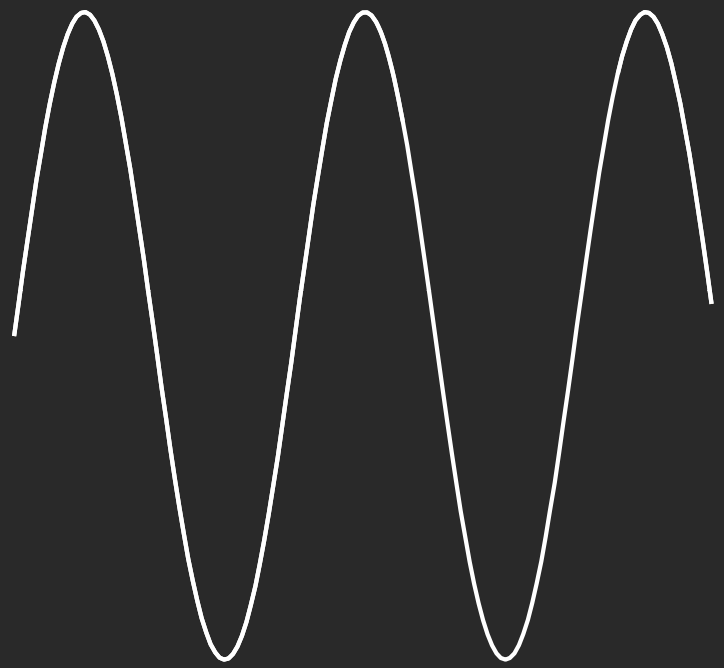


Right Description: maximum smoothness

time

Detour: Completing missing information

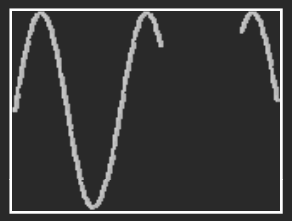


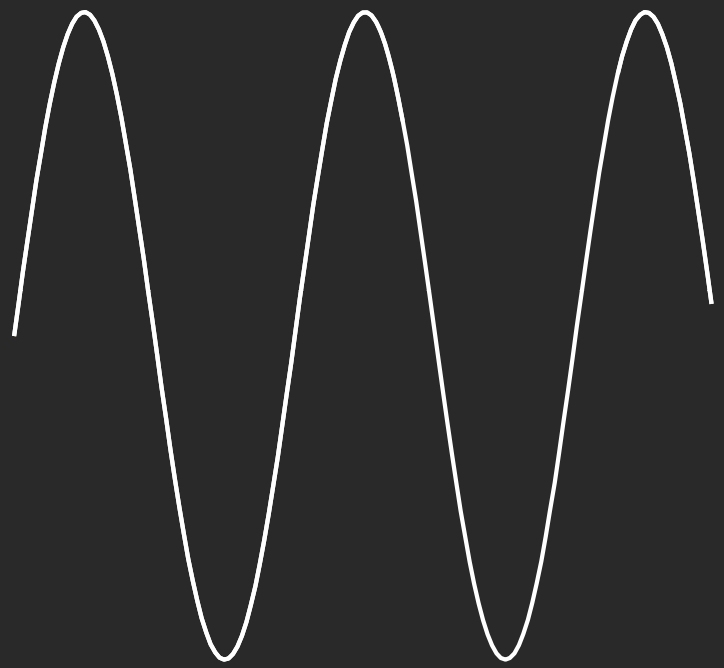


Right Description: don't add *new* rules

time

Detour: Completing missing information

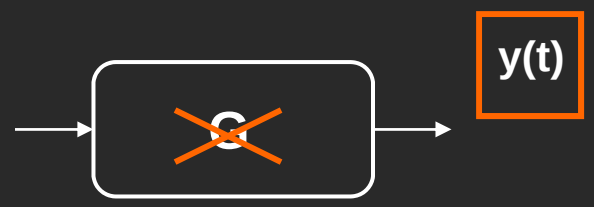




Formally: minimize the rank of the underlying model

time

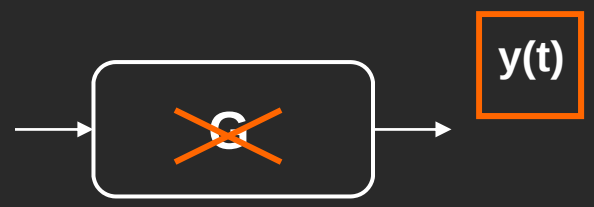
Hankel Based Prediction



$$H = \begin{bmatrix} y_1 & y_2 & . & . & y_n \\ y_2 & . & . & . & y_{n+1} \\ . & & . & & . \\ . & & & . & . \\ y_n & . & . & . & y_{2n-1} \end{bmatrix} \qquad \min_{x} rank(H) = \begin{bmatrix} y_1 & y_2 & . & . & y_n \\ y_2 & . & . & . & y_{n+1} \\ . & & . & & . \\ . & & & . & . \\ y_n & . & . & . & x \end{bmatrix}$$

Fact: $x_o = y_{2n-1}$

Receding Horizon Rank Minimization Filter



$$\min_{\mathbf{v}\in\mathcal{N}} \operatorname{rank} \begin{bmatrix} y_1 + v_1 & y_2 + v_2 & \cdots & y_n + v_n \\ y_2 + v_2 & y_3 + v_3 & \cdots & y_{n+1} + v_{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_n + v_n & y_{n+1} + v_{n+1} & \cdots & y_{2n-1} + v_{2n-1} \end{bmatrix}$$

$$\begin{aligned} \text{minimize} \quad & \operatorname{Trace}(\mathbf{W}) + Tr(\mathbf{Z}) \\ \text{subject to} \quad & \begin{bmatrix} \mathbf{W} & \mathbf{H}_y \\ \mathbf{H}_y{}^T & \mathbf{Z} \end{bmatrix} \geq 0 \end{aligned}$$

$$\hat{y}_k = y_k - v_k$$

Robust Receding Horizon Tracking

Particle

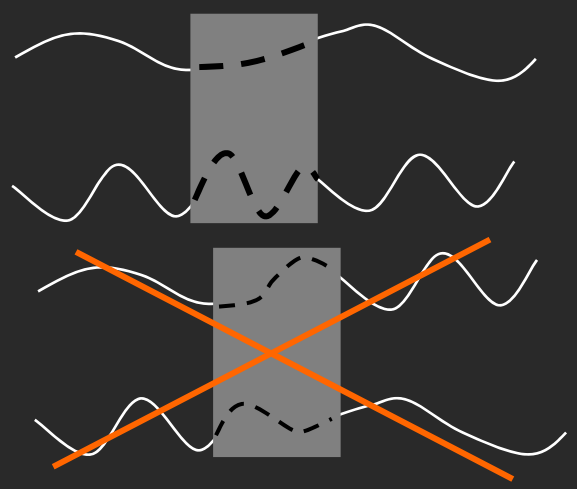
Kalman

RHRM

Establishing identity across occlusion

Automatically stitched tracklets:

Look for lowest complexity joint model.



Fast Event Detection

two parameters: v_1, v_2

one parameter: velocity v_1

one parameter: velocity v_2

Key observation: activity changes increase overall model complexity

Fast Event Detection

two parameters: v_1, v_2

one parameter: velocity v_1

one parameter: velocity v_2

Look for changes in model complexity

Fast Event Detection

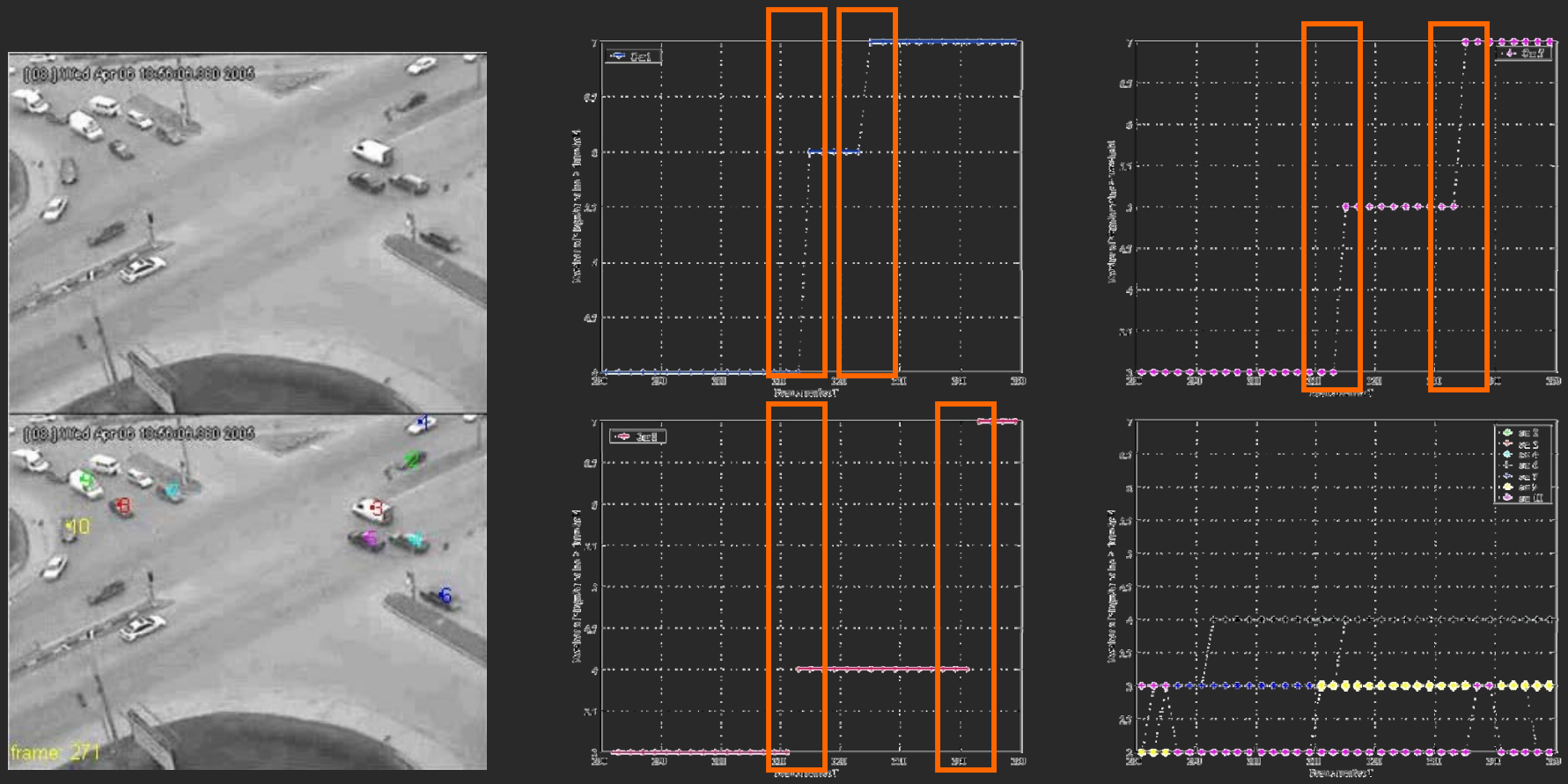
two parameters: v_1, v_2

one parameter: velocity v_1

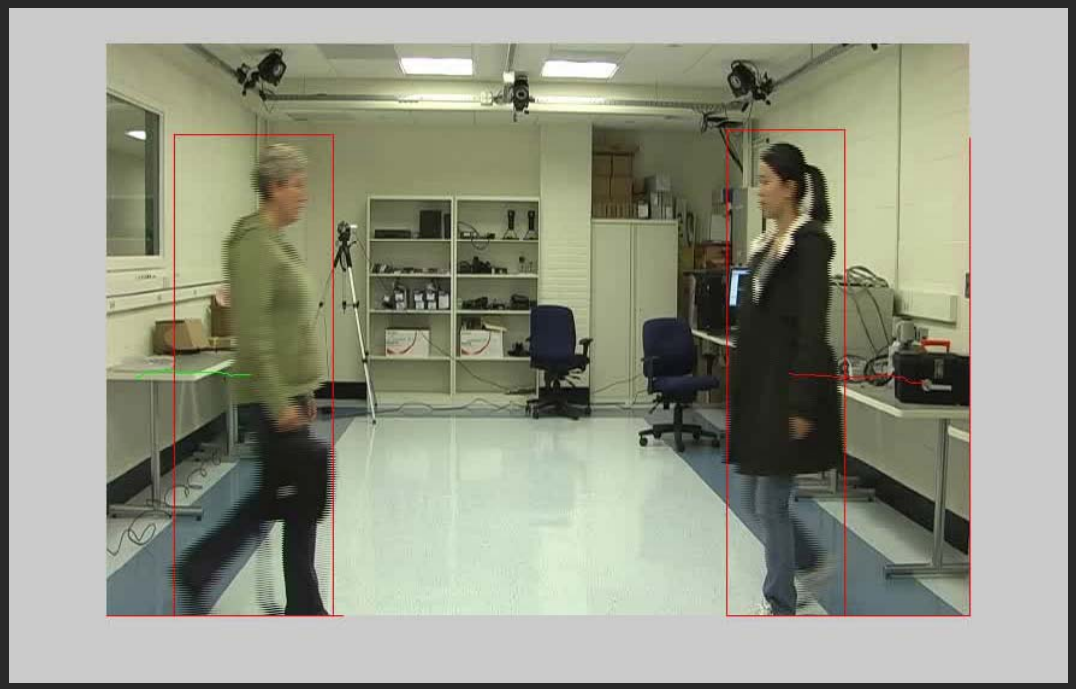
one parameter: velocity v_2

Look for changes in the rank of the Hankel matrix

Hankel Rank Based Fast Event Detection



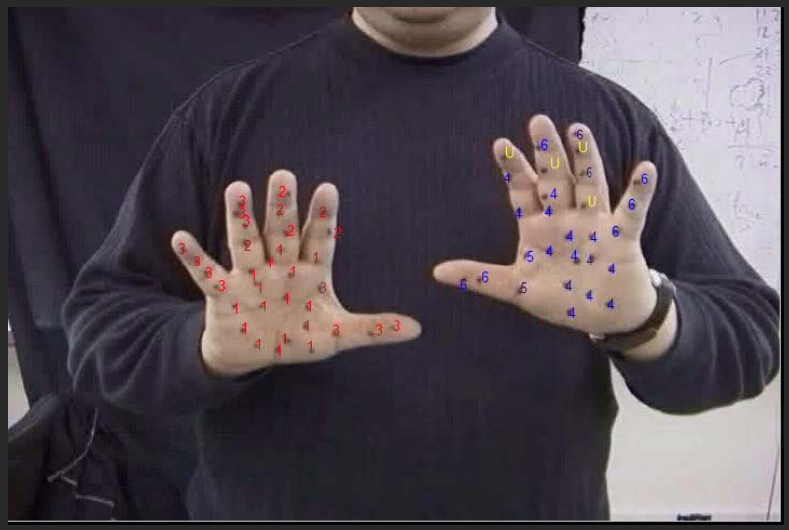
Hankel Rank Based Fast Event Detection



Contextually abnormal activity

Contextually normal activity

Dynamics Based Segmentation



Look for simplest joint models (e.g. low Hankel rank)

Summary

- Dynamic vision complements traditional sensing modalities:
  - Pervasive, passive sensors, millions already deployed
  - Potential to detect suspicious events at a distance
  - Wide area coverage: can correlate spatio-temporally distributed events.
  - Can assist other sensors by identifying “targets of interest”
- Challenges:
  - Robust tracking of large number of targets
  - Avoiding data deluge
  - Use of the information to uncover threats

We can overcome these challenges through a combination of computer vision, machine learning and dynamical systems tools

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More information as http://robustsystems.ece.neu.edu