Dynamics for Robust Computer Vision

Octavia Camps and Mario Sznaier

Robust Systems Lab
Dept. of Electrical and Computer Engineering
Northeastern University
CV Enabling Technology for

- Surveillance
  - Security
  - Safety
  - Assisted Living
  - Traffic monitoring

- HCI: Assisting individuals with disabilities

- Image guided therapies
  - radiation oncology
  - precision surgery

- Recycling
Cameras Everywhere...
Why aren’t CV systems more widespread?
Challenges:

Persistent Tracking
• Similar targets
• Dynamic targets
• Occlusion

Event Detection
• What is an event?
• Highlight only relevant data

In both cases, comparatively rare, relevant events are encoded in $10^{-2}$ to less than $10^{-6}$ of the data.
Challenge:

Need Robust Vision Systems Capable of

• Processing massive amounts of high dimensional data quickly
• Discovering a very small fraction of relevant data
• Achieving near optimal performance under a wide range of conditions

Certified Robustness by Design
Outline

• Capturing Dynamics from Video Data
• Tracking
• Dynamic Appearance
• Completing Missing Data
• Dynamic Data Association
• Structure from Dynamics
• Summary
Looking for the Hidden Dynamics

We will model temporally evolving data as the output of unknown dynamic systems.

- Data prediction
- Recovery of missing data
- Event detection
- Temporal correlations
- Often, no need to identify the systems!
Capturing Dynamics from Experimental Data: The Hankel Matrix

Given a sequence of measurements: $y_1, y_2, y_3 \ldots$

Its Hankel matrix is defined as:

$$H_y = \begin{bmatrix}
y_1 & y_2 & \cdots & y_{n-1} & y_n \\
y_2 & y_3 & \cdots & y_n & y_{n+1} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
y_m & y_{m+1} & \cdots & y_{m+n-2} & y_{m+n-1}
\end{bmatrix}$$

$\text{Rank}(H_y)$ measures the complexity of the underlying dynamics.
Data Prediction: Receding Horizon Tracking

Hankel approach:

- Assemble Hankel matrix with noise

\[
H = \begin{bmatrix}
  y_1 + \eta_1 & y_2 + \eta_2 & y_3 + \eta_3 & \cdots & y_n + \eta_n \\
  y_2 + \eta_2 & y_3 + \eta_3 & y_4 + \eta_4 & \cdots & y_{n+1} + \eta_{n+1} \\
  y_3 + \eta_3 & y_4 + \eta_4 & y_5 + \eta_5 & \cdots & y_{n+2} + \eta_{n+2} \\
  \vdots & \vdots & \vdots & \ddots & \vdots \\
  y_n + \eta_n & y_{n+1} + \eta_{n+1} & y_{n+2} + \eta_{n+2} & \cdots & y_{2n-1} + \eta_{2n-1}
\end{bmatrix}
\]

- Minimize \( \text{rank}(H) \) wrt noise
- Predict next measurement/update
Modeling Appearance of Complex Targets

Too many signals!

Non-linear mapping

LLE
Locally Linear Embedding

u

y

S

S'
Feedback: Adaptive Appearance Modeling
Correct description: minimizes the rank($H$)
Maintaining Identity

- Automatically stitch tracklets:
- guarantee persistent surveillance
- assist other sensors in establishing target identity
Event Detection

Key observation: Mode switches increase overall model complexity.

Mode switches increase rank of the overall Hankel matrix.

(no need to explicitly find the model!)
Fast Event Detection

QuickTime™ and a decompressor are needed to see this picture.
Dynamic Data Association

Look for simplest joint model -- i.e. low Hankel rank
Projecting 3D into 2D images loses depth information. Points that move rigidly have simpler dynamics.

\[ u_{ki} = f \frac{X_{ki}}{Z_{ki}} \]
\[ v_{ki} = \alpha \frac{Y_{ki}}{Z_{ki}} \]
3D Reconstruction from Video

QuickTime™ and a decompressor are needed to see this picture.

QuickTime™ and a YUV420 codec decompressor are needed to see this picture.
Summary

Dynamic models as the key to encapsulate and analyze (extremely) high dimensional data:

• Data as manifestation of “hidden” dynamic structures
• Exploiting information: finding dynamic patterns in high volume data streams
• Interesting connections with other communities: controls, compressive sensing, machine learning
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More information at: http://robustsystems.ece.neu.edu