Multi-camera networks

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Multi-camera networks
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Multi-camera networks
Context

EU FP7 project APIDIS
Autonomous production of images via distributed and intelligent sensing
www.apidis.org

UK EPSRC project MOTINAS
Multi-modal object tracking in networks of audiovisual sensors
www.spevi.org

EU Erasmus Mundus Joint Doctorate ICE
Interactive and Cognitive Environments
www.icephd.org

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Motivation

Traditional & desired solutions
Deployment examples
Scale
Traditional solution

- Traditional multi-camera systems
  - stream images to a powerful centralised (processing) facility
  - need accurate calibration
  - need precise synchronisation
  - have limited scalability
Desired solution

- Current trend
  - from centralised to distributed
  - processing at the nodes
  - exchange of metadata
  - scalability
  - multimodal sensors
Deployment example 1

www.apidis.org
Deployment example 2
What for?

multi-camera processing
Multi-camera networks: scale

- In-body health
  - Personal video conferencing
    - Home energy efficiency
      - Building service optimisation
        - Facility goods tracking
          - City traffic control
            - Inter-city traffic monitoring
              - In the wild fauna monitoring
Multi-camera networks

Processing pipeline
States and observations
Bayesian approaches
Context: on-line learning
User feedback
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Information flow

Feature extraction

Observation $z_k$

Input (image frame) $I_k$

Output (target state) $X_k$

Estimation

$E_I$, $E_o$, $E_s$
Target state

• The state \( x_k \) is a vector of parameters
  – Shape and position
  – Appearance
  – Higher order moments (e.g. speed, acceleration)
Observation

- The observation vector $Z_k$ represents object information extracted from the image
  - Low-level information
    - e.g. pixel colour, gradient
  - Mid-level features
    - e.g. location of edges
  - High-level features
    - e.g. object detection
  - Combinations of the above
Object detection strategies

BACKGROUND MODEL

BACKGROUND detector

OBJECT MODEL

OBJECT detector

fusion

observation (measurements)
Multi-target observation and state: example

- **Observations**
  \[ Z_k = \{ z_{k,1}, \ldots, z_{k,N(k)} \} \]
  \[ z = [y_1, y_2, w, h] \]

- **State**
  \[ X_k = \{ x_{k,1}, \ldots, x_{k,M(k)} \} \]
  \[ x = [y_1, y_2, \dot{y}_1, \dot{y}_2, w, h] \]
Some basics first…
Single-target Particle Filter

- **State**
  \[ x_k = f_k(x_{k-1}, u_k) \]

- **Observation**
  \[ z_k = h_k(x_k, n_k) \]

- **Objective**
  - to estimate unknown state \( x_k \)
  - based on a sequence of observations \( z_k, k = 0,1, \ldots \)
  - to approx. the posterior distribution

- **Solution (Bayesian)**
  - **Prediction** step
    - Based on state equation
  - **Update** step
    - Based on likelihood function

\[ p(x_k | z_{1:k}) \approx \sum_{i=1}^{L} w_k^i \delta(x_k - x_k^i) \]
Sequential Monte Carlo (Particle Filter)

- Monte Carlo approximation of the Bayes recursion
  - Approximate the posterior pdf
    \[ p(x_k \mid z_{1:k}) \approx \sum_{i=1}^{L} \omega_{k}^{(i)} \delta(x_k - x_k^{(i)}) \]
  - Samples propagated using state and observation equations
    \[ \omega_{k}^{(i)} \propto \omega_{k-1}^{(i)} \frac{g(z_k \mid x_k^{(i)}) f(x_k^{(i)} \mid x_{k-1}^{(i)})}{q(x_k^{(i)} \mid x_{k-1}^{(i)}, z_k)} \]

- Sequential Importance Sampling (SIS)
  - Sample according to dynamics
    \[ q(x_k \mid x_{k-1}, z_k) = f(x_k \mid x_{k-1}) \]
Resampling

• **SIS problem**
  – The sampling *does not depend on the measurement*
  – After some steps particles have *small weights*

• **Solution**
  – To eliminate particles with **small weight**
  – To propagate multiple times particles with **large weight**

• **Sequential Importance Resampling (SIR)**
  – Sample proportionally to \( \omega_{k-1}^{(i)} \)
  – New weight \( \omega_k^{(i)} \propto g(z_k \mid x_k^{(i)}) \) likelihood
CONDENSATION

\[ f(x_{k+1}^{i} \mid x_{k}^{i}) \]

resampling

\[ g(z_{k} \mid x_{k}^{i}) \]

\[ f(x_{k}^{i} \mid x_{k-1}^{i}) \]

\[ p(x_{k-1} \mid z_{1:k-1}) \]
Back to the multi-object case…
Multi-target observation and state

• Observations

\[ Z_k = \{z_{k,1}, \ldots, z_{k,N(k)} \} \]

\[ z = [y_1, y_2, w, h] \]

• State

\[ X_k = \{x_{k,1}, \ldots, x_{k,M(k)} \} \]

\[ x = [y_1, y_2, \dot{y}_1, \dot{y}_2, w, h] \]
Data association filters

- **Objective**
  - to associate detections

- **Approaches**
  - **Nearest Neighbour (NN) filter**
    - one hypothesis per trajectory
  - **Joint Probabilistic Data Association Filter (JPDAF)**
    - evaluate all associations between two frames
    - handles clutter
  - **Multiple Hypotheses Tracker (MHT)**
    - evaluates hypotheses over multiple frames
  - *gating* to reduce computational cost
  - *extending the Bayes recursion* to multiple targets (using Random Finite Sets)
Filtering in the multi-target space
Multi-target Bayes filter

**Single target**

Random vectors

\[
\begin{align*}
    \mathbf{x}_k &= f(\mathbf{x}_{k-1}, \mathbf{u}_k) \\
    \mathbf{z}_k &= g(\mathbf{x}_k, \mathbf{n}_k)
\end{align*}
\]

**Multiple targets**

Random Finite Sets (RFS)

\[
\begin{align*}
    \Xi_k &= S_k(X_{k-1}) \cup \Gamma_k \\
    \Omega_k &= \Theta_k(X_k) \cup K_k
\end{align*}
\]

- Recursively propagates the multi-target state
  - **Prediction**
    \[
    p(X_k | Z_{1:k-1}) = \int f(\mathbf{x}_k | X_{k-1}) p(X_{k-1} | Z_{1:k-1}) \mu_s(dX_{k-1})
    \]
  - **Update**
    \[
    p(X_k | Z_{1:k}) = \frac{g(Z_k | X_k) p(X | Z_{1:k-1})}{\int p(Z_k | X_k) p(X_k | Z_{1:k-1}) \mu_s(dX_k)}
    \]
Multi-target Bayes filter

- Model target *birth, death, clutter* and *missing detections*

- Monte Carlo approximation
  - Dimensionality of the state grows with the number of targets
  - Number of particles is exponential with the number of targets
  - Not feasible in real-world applications!

- Solution
  - to propagate the *first order moment of the RFS only* [Mahler]

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Probability Hypothesis Density (PHD)

- The first order moment of a RFS $\rightarrow$ PHD
  - The integral on any $R$ gives the expected number of targets in $R$

$$\int_R D_{\Xi}(x)dx = E[|\Xi \cap R|]$$

The expected number of targets in $R$ is 3.

Multiple-target Bayes filter

PHD Filter

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Recursive PHD filter

- **Prediction**
  \[ D_{k|k-1}(x_k) = \gamma(x) + \int \phi(x_k, x_{k-1}) D_{k-1|k-1}(x_{k-1}) dx_{k-1} \]
  - PHD state transition

- **Update**
  \[ D_{k|k}(x_k) = \begin{bmatrix} p_M(x_k) + \sum_{z \in Z_k} \kappa(z) + <\psi_z, D_{k|k-1}(x_k)> \end{bmatrix} D_{k|k-1}(x_k) \]
  - Survival probability
  - Single target transition
  - Birth intensity
  - Clutter intensity
  - Normalization
  - Missing likelihood
  - Single target likelihood

\[ \psi_z(x) = (1 - p_M(x))g(z \mid x) \]
Example: PHD propagation

- **Input**: Face detector
- **Output**: Monte Carlo approximation of the PHD

When a new target appears the mass of the corresponding peak converges to 1

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Tracking with the PHD filter

- **Advantage**: Linear complexity with the target number
- **Drawback**: Data association is not integrated in the Bayesian recursion
Results – CLEAR/i-LIDS dataset

Detections

PHD output

Efficient multi-target visual tracking using Random Finite Sets
E. Maggio, M. Taj, A. Cavallaro
Tracking with context modelling
Using scene context in the PHD recursion

- **Goal:** context adaptive filtering
  - Birth intensity -- **to model** entry areas
  - Clutter intensity -- **to model** detection errors
- **Data collection**
  - Birth events from the output of the tracker
  - Clutter events via user feedback
- **Density estimation**
Example: learning birth intensity
Birth and clutter intensities

\[ \gamma(x) \]

\[ \kappa(z) \]
Comparison: w. and w.o. context learning

- Performance improvement on CLEAR dataset
- Reference: PHD tracker with uniform birth and clutter intensities

Learning scene context for multiple object tracking
E. Maggio and A. Cavallaro
Multi-camera networks

Layout
Approaches
Multiple cameras

- Layout
  - Partially overlapping
  - Non-overlapping
Approaches

Data fusion

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Approach 1: track and then fuse
Approach 2: fuse and then track
A simple example: 2 cameras
Global trajectory reconstruction

- Detection & tracking
- Ground-plane projection
- Feature extraction

Ground-plane matching
- Image-plane verification
- Association
- Fusion
- Linkage

Detection & tracking
- Candidates
- Ground-plane projection
- Feature extraction

Trajectory association and fusion across multiple partially overlapping cameras
N. Anjum, A. Cavallaro
IEEE AVSS 2009 [best paper award]
Global trajectory reconstruction
Approach 1: track and then fuse
Approach 2: fuse and then track
Track before detect

Multi-camera track-before-detect
M. Taj, A. Cavallaro
Proc. of ACM / IEEE ICDSC 2009
Multi-camera tracking
Applications

Behaviour analysis
Camera scheduling
Behaviour analysis

Trajectories  Common patterns  Outliers

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Trajectory clustering

Multi-feature object trajectory clustering for video analysis
N. Anjum, A. Cavallaro
*IEEE Trans. on Circuits and Systems for Video Tech.* 18(11), 2008
Content production (camera scheduling)

- **Example**

- **Example with audio**

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**Multi-camera scheduling for video production**
F. Daniyal, A. Cavallaro

**Content and task-based view selection from multiple video streams**
F. Daniyal, M. Taj, A. Cavallaro
Multi-camera networks

Distributed calibration
Topology
Distributed tracking
Calibration methods

- Small scale *(overlapping fields of view)*
  - multi-view geometry
  - epipolar geometry
  - projective transformations
  - feature detection and matching

- Large scale *(partially/non overlapping fields of view)*
  - observations of an object
  - simultaneous calibration and tracking
  - simultaneous calibration and synchronization
Non-overlapping cameras

- How to localize randomly placed cameras?
  - non-overlapping field of view
  - top-down view
    - optical axis is perpendicular to the ground plane, or
    - removed perspective deformation

- Approach
  - Learn regression parameters from available trajectories
  - Extrapolate trajectory data to unobserved regions
  - Kalman filtering on available and estimated trajectory
Example: estimation result

Automated localization of a camera network
N. Anjum, A. Cavallaro
IEEE Intelligent Systems, to appear 2011
Topology

Distributed and decentralized multi-camera tracking
M. Taj, A. Cavallaro
Distributed Particle Filters (DPFs)

• Approach 1
  – each node executes a local Particle Filter (PF)
  – agreement on particle set reached by nodes at each time step
    – expensive!

• Approach 2
  – common posterior distribution
    – expensive!

• Solution: independence from the number of particles
  – approximating the posterior with a Gaussian Mixture Model

WiSE-MNet: an experimental environment for Wireless Multimedia Sensor Networks
C. Nastasi, A. Cavallaro

Simulator: www.eecs.qmul.ac.uk/~andrea/wise-mnet.html
Convergence of multiple disciplines

Multi-camera networks

- Computer vision
  - Object tracking
  - Scene understanding
- Sensors design
  - Vectorial data
  - Low power, low cost
- Signal processing
  - Embedded computing
  - Collaborative methods
- Sensor networks
  - Wireless communication
  - Networking
- Privacy & ethics
  - Acceptability
  - Societal constraints
- Bio-inspired algorithms
  - Attention
  - Observe and detect

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To conclude …
Exciting open challenges:

- **Signal processing**
  - multi-layered/hybrid data exchange among cameras
  - collaborative deduction about events
  - exploitation of spatio-temporal redundancies

- **Sensor networks / embedded computing**
  - large amounts of data produced by imagers (bandwidth, latency)
  - network scalability issues
  - joint estimation and decision: tradeoffs

- **Computer vision design**
  - multi-view methods with partial processing of video locally
  - system-level constraints \(\rightarrow\) influence algorithm design
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References and contact information

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youtube.com/smartcameras