AUTOMATIC SCENE ACTIVITY MODELLING AND ANOMALY DETECTION IN VIDEO FOOTAGE
OUTLINES

- Goal of this task
- Dataset used
- Particles tracking
- Cascade HMM/HDP-HMM
- Experiments
- Perspectives
AUTOMATIC SCENE ACTIVITY MODELLING

**Goal:** Construct a model which:
- automatically discover normal activities
- avoid manual labelling data
- recognize normal activities and consequently abnormal activities *on-the-fly*
- is based on **low level features**

**Dataset used:**

![Dataset Example 1](image1)

![Dataset Example 2](image2)
CASCADE OF HMM/HDP-HMM: MAIN STEPS

1. Video
2. Particle tracking
3. HMM
4. Trajectory classes
5. HDP-HMM
6. Activities & Temporal relations
**Particle tracking:**

- **Random** initialization of inactive particles
- Activation with a **frame-differencing** threshold
- Tracking active particle with **bloc-matching**.
- **Filtering** of the trajectories (linearity, length, orientation...)

![Image of particle tracking](image-url)
HMM:

HMM with gaussian mixture:

- Input features: position of the point \((x,y)\) and mean direction (angle)
- Observation sequence = trajectory
- Output: trajectory classes
HDP-HMM:

- Infinite Hidden Markov Model: Generalization of HMM
- Use DP to model the lines of the transition/emission matrix

\[ v_t : \text{state at time } t \]
\[ y_t : \text{observations at time } t \]
\[ \phi_k : \text{probability distribution over the possible observations} \]
\[ \pi_k : \text{transition probability} \]
\[ \gamma, \alpha, H : \text{parameters} \]
HDP-HMM:

- Inputs: trajectory classes appearing during a fix duration (clip) using the Viterbi path
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- Inputs: trajectory classes appearing during a fix duration (clip) using the Viterbi path
- Output: Activities & Temporal relation between them
**ABNORMALITY MEASURES:**

- **Measure on trajectories:**
  - Abnormal value for trajectory \( m \) at time \( t \) given a neighborhood \( (N) \) and the HMM parameter \( (\lambda) \):

  \[
  AV^m_t = \sum_{n\in N_m} (1 - 2 \times H(LL_t(n) - Thresh))
  \]

  where: \( LL_t(n) = \frac{1}{t} \times \log(P(O_{1:t}(n) / \lambda)) \)

  \( H \): Heaviside step function

- **Measure on clip content:**

  \[
  LL^d_t = \frac{1}{n_d} \times \sum_{y \in d} \left( \log\left( \sum_k \left( P(y / \pi_k) \times P(\pi_k / d) \right) \right) \right)
  \]
EXPERIMENTS:

- Number of trajectory classes: 20
- Clip length: 2s
- Resolution: 320x288
- Frame rate: 30 fps
- Training/Testing: 5min / 1H
ACTIVITIES DISCOVERED BY THE FRAMEWORK:

Sample image with trajectories of each activity:

Activity patterns:
TRANSITION MATRIX DISCOVERED AT THE SECOND LEVEL:

Possible cycles:
- (a)-(b)-(c)-(d)
- (b)-(c)

White = high probability
Black = low probability

Transition from activity (c) to activity (d)
TRANSITION MATRIX DISCOVERED AT THE SECOND LEVEL:

Cycle extracted (non significant probability and self-transition removed):

(a)  (b)

(c)  (d)
ONLINE ANOMALY DETECTION (FIRST LEVEL MEASURE):
ONLINE ANOMALY DETECTION (SECOND LEVEL MEASURE):
**ANOMALY DETECTION:**

<table>
<thead>
<tr>
<th></th>
<th>Ground truth</th>
<th>Detected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Illegal U-turn</td>
<td>11</td>
<td>3</td>
</tr>
<tr>
<td>Drive wrong way</td>
<td>16</td>
<td>9</td>
</tr>
<tr>
<td>Jaywalking</td>
<td>13</td>
<td>8</td>
</tr>
<tr>
<td>Uninteresting</td>
<td>-</td>
<td>13</td>
</tr>
</tbody>
</table>

![Precision-Recall Curve](image)
EXPERIMENTS ON METRO:

- Number of trajectory classes: 20
- Clip length: 3s
- Resolution: 704x288
- Frame rate: 5 fps
- Training/Testing: 2H / 1H
ACTIVITIES DISCOVERED BY THE FRAMEWORK:

Activity patterns:
TEMPORAL RELATIONS:

Cycle:
- (a)-(b)-(e)-(f)-(d)

White = high probability
Black = low probability

Transition from activity (c) to activity (d)
TRANSITION MATRIX DISCOVERED AT THE SECOND LEVEL:

Cycle extracted (non significant probability, self-transition and transition implying activity c removed):
ABNORMALITY DETECTION:

- Detect a high density of unseen or rarely seen trajectories.
ABNORMALITY DETECTION:

- Detect behaviors that do not appear alone during the training sequence.
CONCLUSIONS/PERSPECTIVES:

- Conclusions:
  - Encouraging results for activity recognition and abnormality detection tasks
  - Run faster than real-time (~65 fps)

- On-going works and perspectives:
  - Have a less noisy abnormality measure for the HDP-HMM
  - Define a new metric for recognition activity task
  - Add information for static objects
  - Use multi-view information

- Questions?