# Video-surveillance methods and solutions

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## Outline

- Introductory concepts and definitions
- Motion analysis
- Video surveillance
- Building blocks:
  - Background construction
  - Change detection
  - Blob tracking
- Applications
- Discussion







## Definitions

• Image sequences:

a series of N images (frames) acquired at discrete time instants  $t_k = t_0 + kT$ , where T is a fixed time interval and k = 1, ..., N

• Acquisition rate:

it measures the acquisition speed. A typical rate is the *frame rate*, 24 fps (frames per second)





## Definitions

 It is important that T is small enough so that the image sequence is a "good" approximation of a continuously evolving scene.

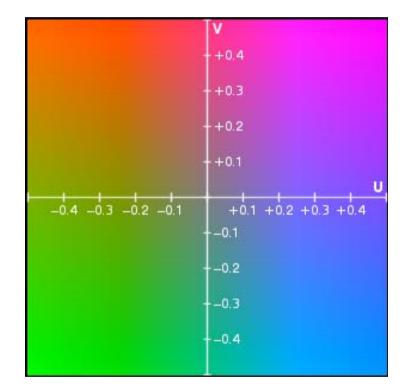






## Video color space

- The color space more common in videos is
  YUV
  - Y (*luminance component*) carries information on the pixel brightness
  - U and V (chrominance components) carry color information



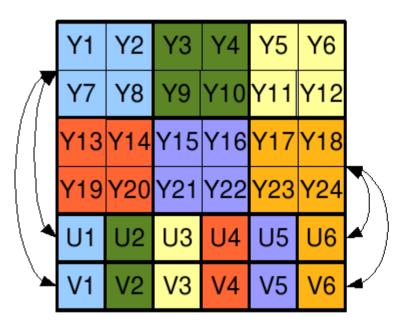






## Video color space

Single Frame YUV420:



Position in byte stream:

Y1 Y2 Y3 Y4 Y5 Y6 Y7 Y8 Y9 Y10 Y11 Y12 Y13 Y14 Y15 Y16 Y17 Y18 Y19 Y20 Y21 Y22 Y23 Y24 U1 U2 U3 U4 U5 U6 V1 V2 V3 V4 V5 V6





## Video formats

- Typical digital video formats:
  - PAL: 720x576 pixel, 25 fps
  - NTSC: 720x480 pixel, 30 fps
- Video compression algorithms:
  - Mpeg2: standard in DVDs
  - Mpeg4: when a more compact representation is required (Internet, portable readers - DivX, Xvid, QuickTime, iPod Video...)





## Video vs image sequence













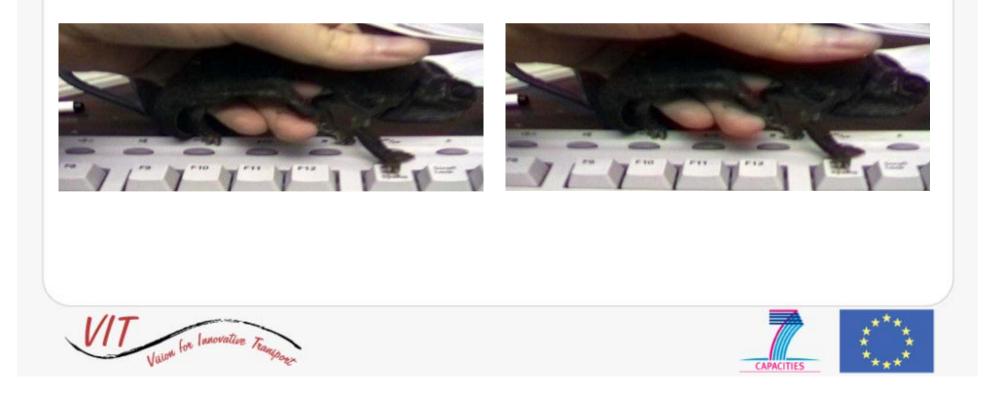






## Interlaced video

- An interlaced video is composed of *fields* with a smaller vertical resolution than the original video
  - The PAL format, for instance, is 720x288px



## Interlaced videos

- The two fields are shown in a sequence and they exploit the image persistence on the display (and on the retina)
- At a reasonable speed the observer does not perceive that part of the observed visual information is static
- They allow to reache the same frame rate at a smaller transmission cost







## Interlaced videos

• A single frame of an interlaced video









## Deinterlacing

#### Methods

- Waving (temporal resolution loss)
- Line doubling (spatial resolution loss)
- Blending (spatio-temporal resolution loss)
- Motion compensation







## Motion analysis is useful for..

- Inferring information
  - Changes in the scene
  - Objects evolving in time (matching along the temporal component)
  - Object tracking (and prediction)
- Applications
  - Video-surveillance and monitoring
  - Structure from motion
  - Video annotation







## Video-surveillance

- Video-surveillance refers to techniques and methods for inferring information on a scene under observation
  - Observation -> CCTV cameras
  - Information -> object localization and classification, object tracking, behaviour analysis...
- It is a rather general problem!





### In the context of video-surveillance...

- More focused applications:
  - Access control
  - Abandoned objects detection
  - Anomaly detection
  - Traffic monitoring







## Building blocks: change detection

- Motion segmentation: localize image regions with a common motion pattern
- If the camera is still motion segmentation is usually referred to as change detection
- Change detection is commonly addressed comparing each frame of the sequence with a reference model of the empty scene (the so-called **background**)
- Changes with respect to the background are usually caused by moving objects (foreground)





## Building blocks: change detection

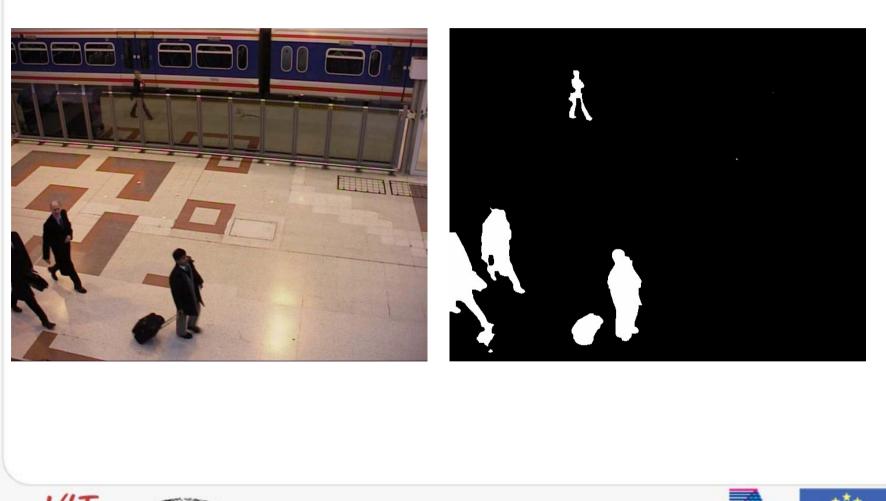
 Assuming that we can rely on a reference image I<sub>REF</sub>, change detection produces a binary map of the scene regions that changes w.r.t. the reference:

$$BM_{t}(x, y) = \begin{cases} 1 & \text{if } |I_{t}(x, y) - I_{REF}(x, y)| > s \\ 0 & \text{otherwise} \end{cases}$$





## Building blocks: change detection









## Building blocks: background construction

#### METHOD 1: frames average:

• The simplest model is an average of N video frames:

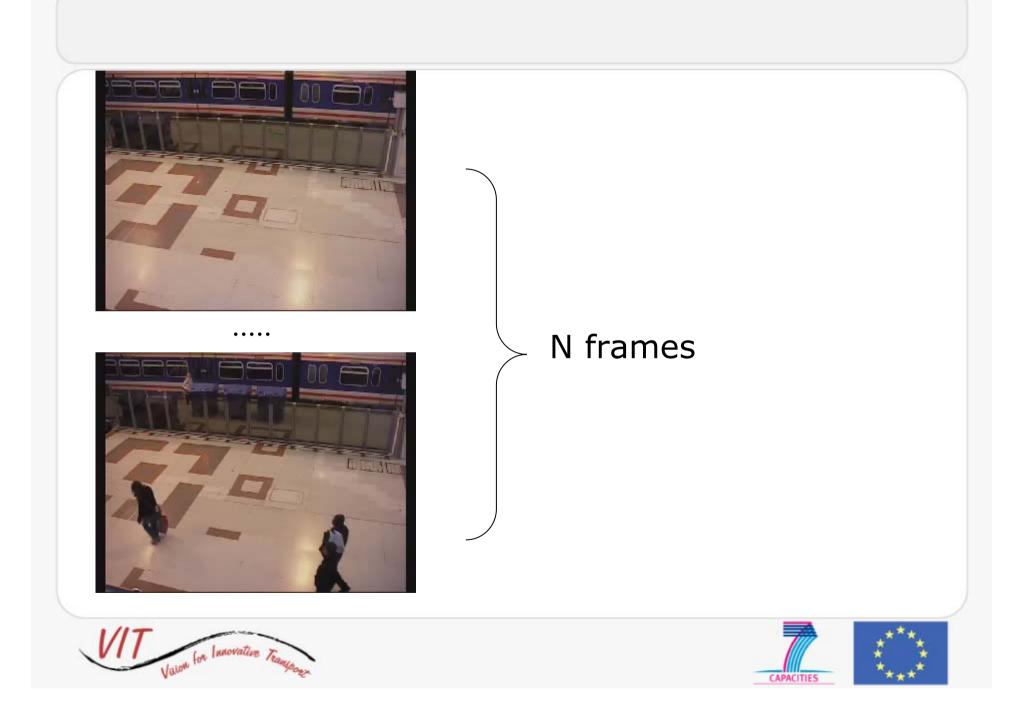
$$I_{REF} = B = \frac{1}{N} \sum_{t=1}^{N} I_t$$

• This is not always possible. WHY?









Building blocks: background construction

## METHOD 2: Running average

$$B_{t}(i,j) = \begin{cases} B_{t-1}(i,j) & \text{if } |I_{t}(i,j) - B_{t-1}(i,j)| \ge s \\ (1-\alpha)B_{t-1}(i,j) + \alpha I_{t}(i,j) & \text{otherwise} \end{cases}$$

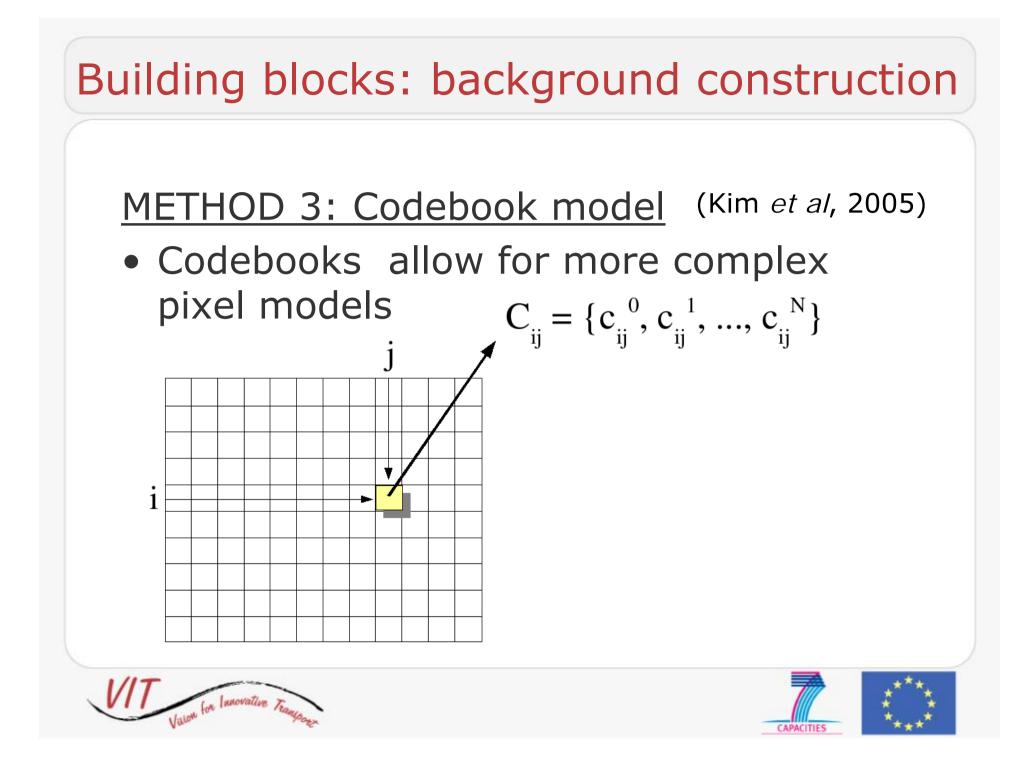
## Limits of simple algorithms



- In the previous methods each pixel of the background is described by a single value, therefore it is not possible to model evolving (e.g., periodic) patterns
- Examples: waving leaves, trembling objects..







## The codebook approach

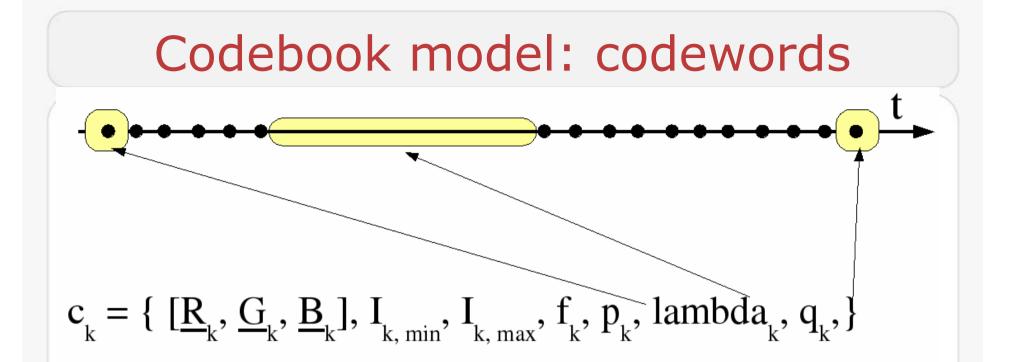
- Each pixel is associated a codebook
- Each codebook is formed by a set of codewords
- A codeword encodes information on the appearance and the dynamics of a pixel
- Abbiamo bisogno di una fase di allenamento (training) perché il sistema costruisca il codebook che modella la scena





## Codebook model





- Appearance is described by information on color and intensity values
- **Dynamics** is described by information on the codeword *life* (when it was first observed, how frequent is it observed, etc)





## Codebook construction

- A training set of N frames is used to initialize the model
- We associate a codebook to each position p=(i,j)
- For each p=(i,j) we have N observations:  $\{x_{p,t}=(R_{p,t},G_{p,t},B_{p,t})\}_{t=1,\dots,N}$





## **Codebook construction**

- For each  $x_{p,t} = (R_{p,t}, G_{p,t}, B_{p,t})$  in O (t=1,...N):
  - Look for a codeword  $c_i$  appropriate for  $x_{p,t}$
  - If it does not exist create a new codeword  $\rightarrow$  [I, I, 1, t, t-1, t]

$$\rightarrow [R_{p,t}, G_{p,t}, B_{p,t}]$$

$$\rightarrow [\min(\mathbf{I}, \mathbf{I}_{i}), \max(\mathbf{I}, \mathbf{I}_{i}), f_{i}+1, p_{i}, \max(\lambda_{i}, t-q_{i}), t]$$
  
 
$$\rightarrow [\frac{f_{i}R_{i}+R_{p,t}}{f_{i}+1}, \frac{f_{i}G_{i}+G_{p,t}}{f_{i}+1}, \frac{f_{i}B_{i}+B_{p,t}}{f_{i}+1}]$$





#### Codebook model: similarity decision boundary (codeword) 250 200 x, (input pixel) had 150 12 250 100 200 . R 50 BA 100 ΞĒ. 0.5 250 200 150 100 50 ÷6 Ġ. unovative Transp CAPACITIES

# Codebook model: example video



for Innovative Transp.





## Building blocks: blob tracking

- The binary map obtained from change detection can be described as a set of *connected components* (blobs)
- Each blob corresponds to an object moving in the scene







## Building blocks: blob tracking

- In order to analyse the dynamics of the moving object it is useful to match blob elements at time t+1 with blob elements observed at time t
- The sequence of matches over the video sequence is usually referred to as blob tracking
- Dynamic filters (e.g., Kalman filter) may be applied to smooth the observations and perform predictions





## Blob tracking: example video

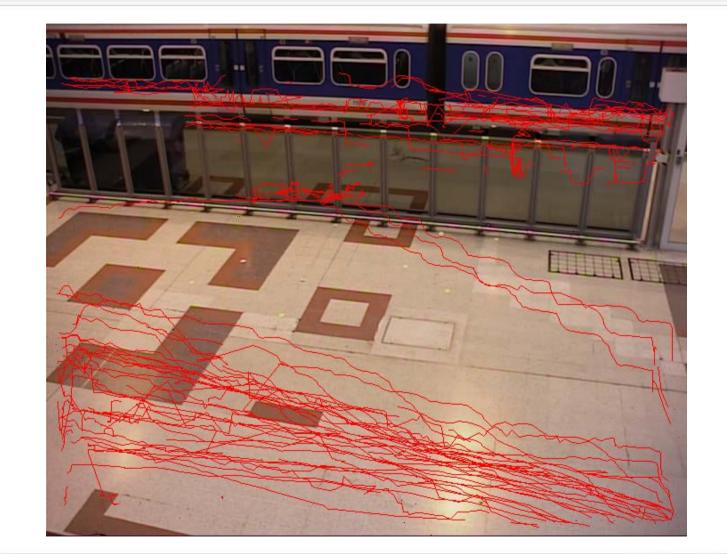


unovative Transp





## Blob tracking results

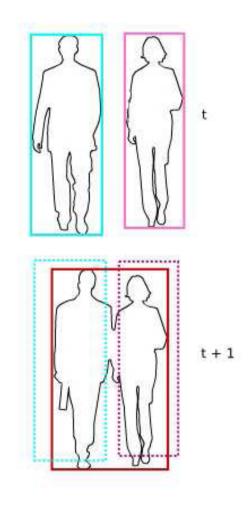






## Dealing with occlusions

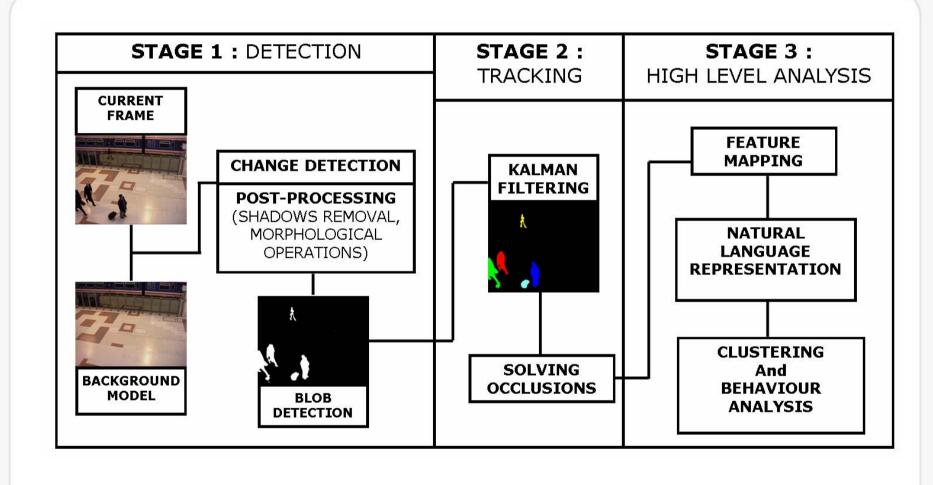
- If the scene is moderately crowded blob elements may merge
- How to deal with such a problem (data association)?







#### Current research: unsupervised behaviour analysis









#### Current research: video-based face detection e recognition



unovative Tra





# A straightforward application: people counting



