introduction to Computer Vision

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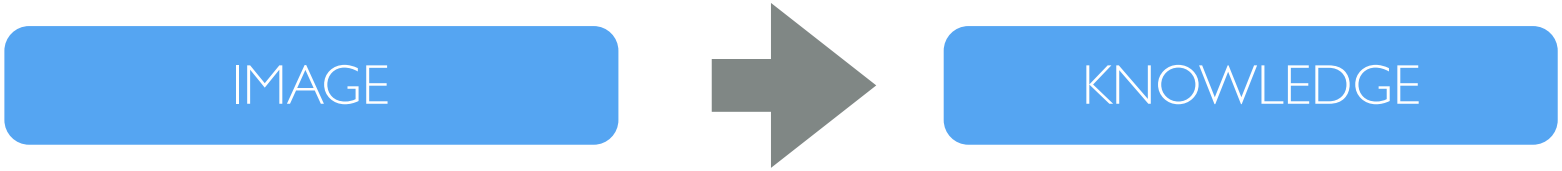
What is Computer Vision about?



- **extracting descriptions of the world from images**
- descriptions of what kind?
  - *qualitative* or *quantitative*
  - *geometric:* shape and position of object or relative distances in the real 3D world
  - *semantic:* what objects do I see?
  - *dynamic:* scene changes, objects velocities, actions, …

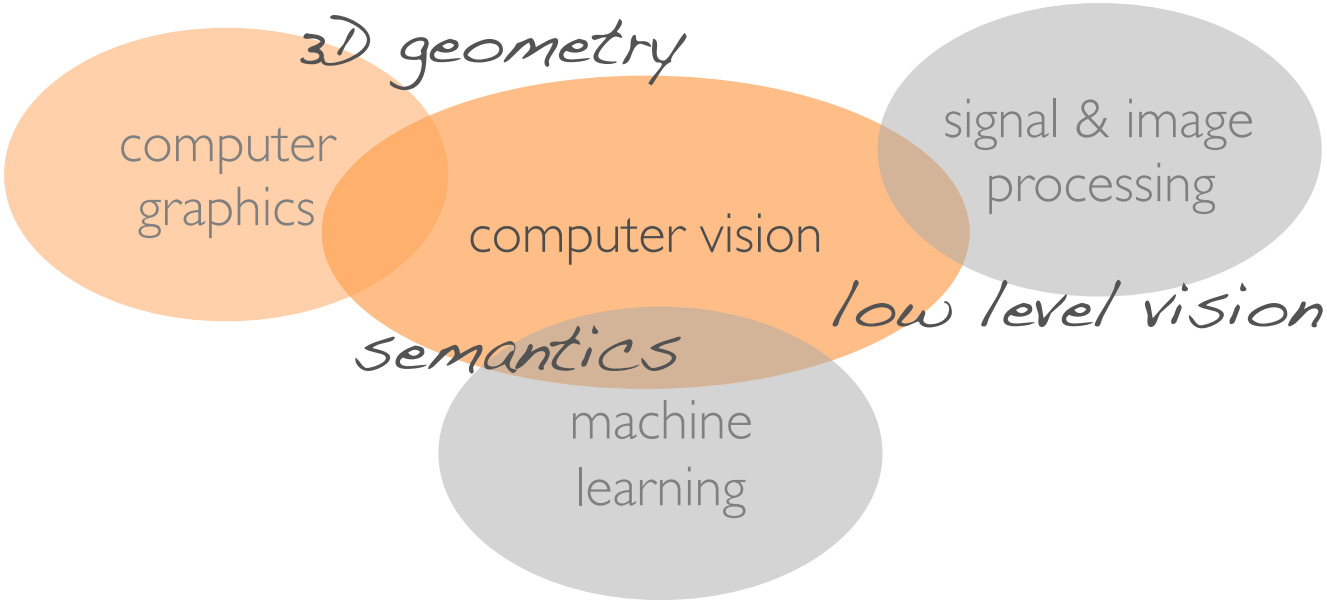
Computer Vision - A brief history

- 1960s - started as a student summer project at MIT
  - the goal of the project was to link a camera to a computer, getting the computer to describe what it saw
- 1970s mainly seen as a part of **artificial intelligence** (emulating **human visual perception**)
  - simplification of the world ("lego-like")
  - pioneering work of David Marr (mainly on) **low level vision**
- 1980s more **sophisticated mathematics**

Computer Vision - A brief history

- 1990s computer vision reaches its maturity
  - **geometric approaches** - optical flow
- 2000s: **machine learning** paves the way to scene understanding
- Today: we are dealing with very large data and **very large datasets** (deep architectures)

Computer Vision - An incomplete view of related disciplines



Outline

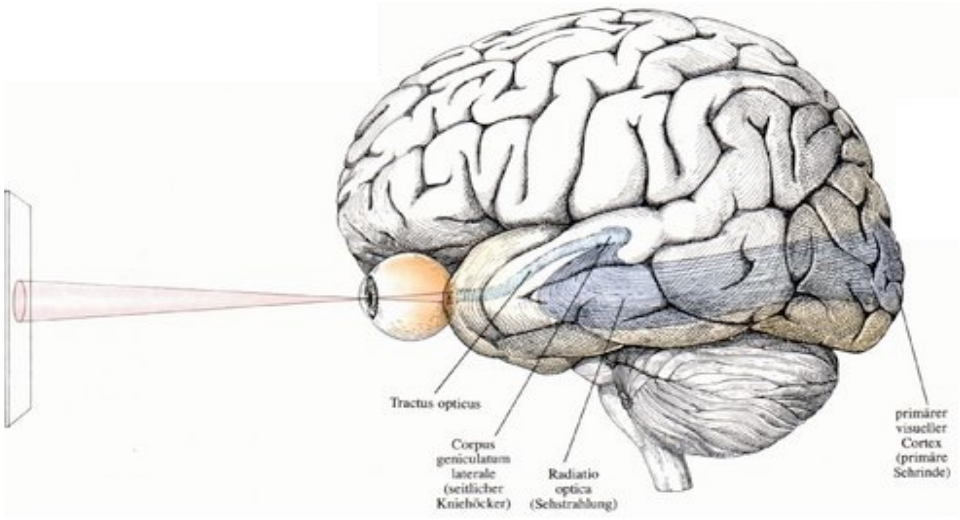
- A few words on human vision
- Digital images and low level elements

- Building blocks: image correlation

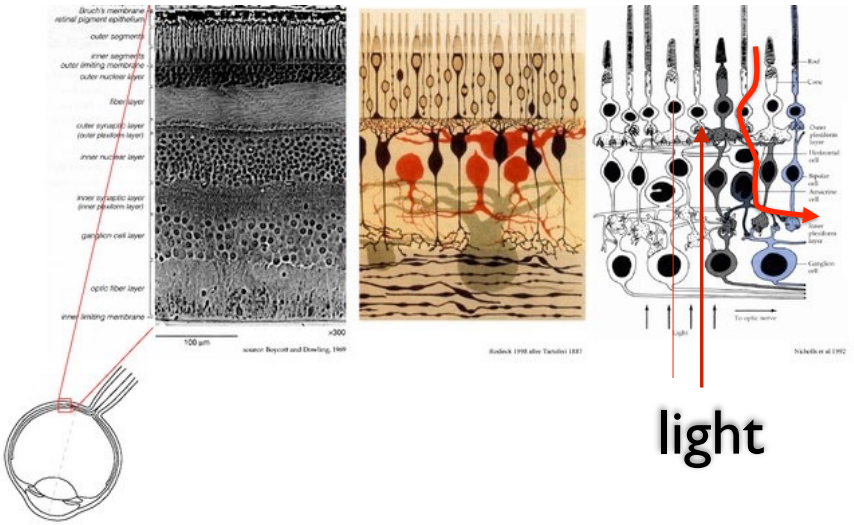
- Depth: computing disparity maps
- Motion: estimating optic flow

- Other ways of analysing motion: motion segmentation (in brief)

The human visual system



Hubel 1985

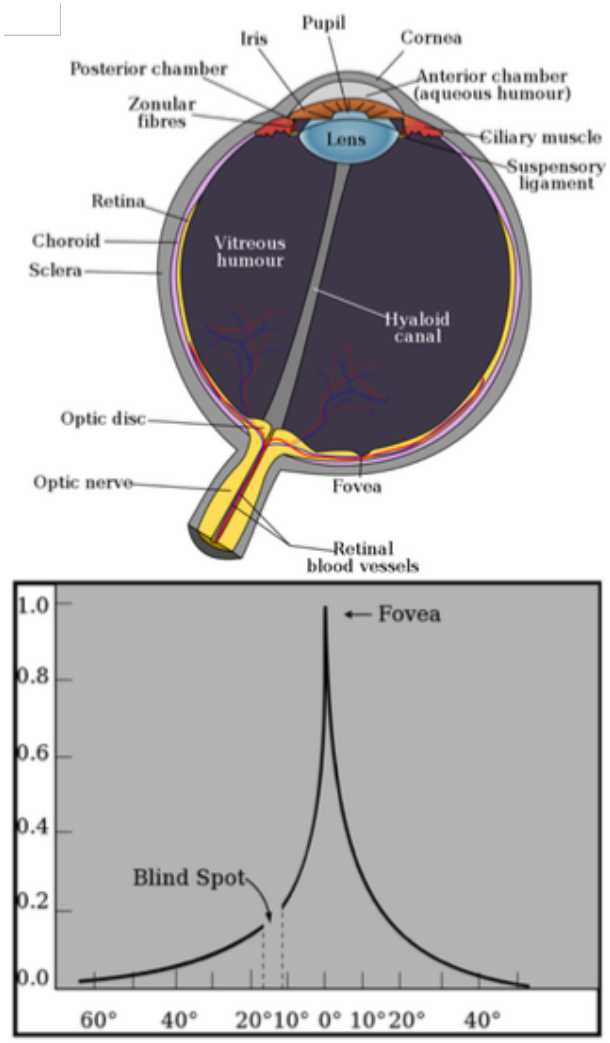


neural signal

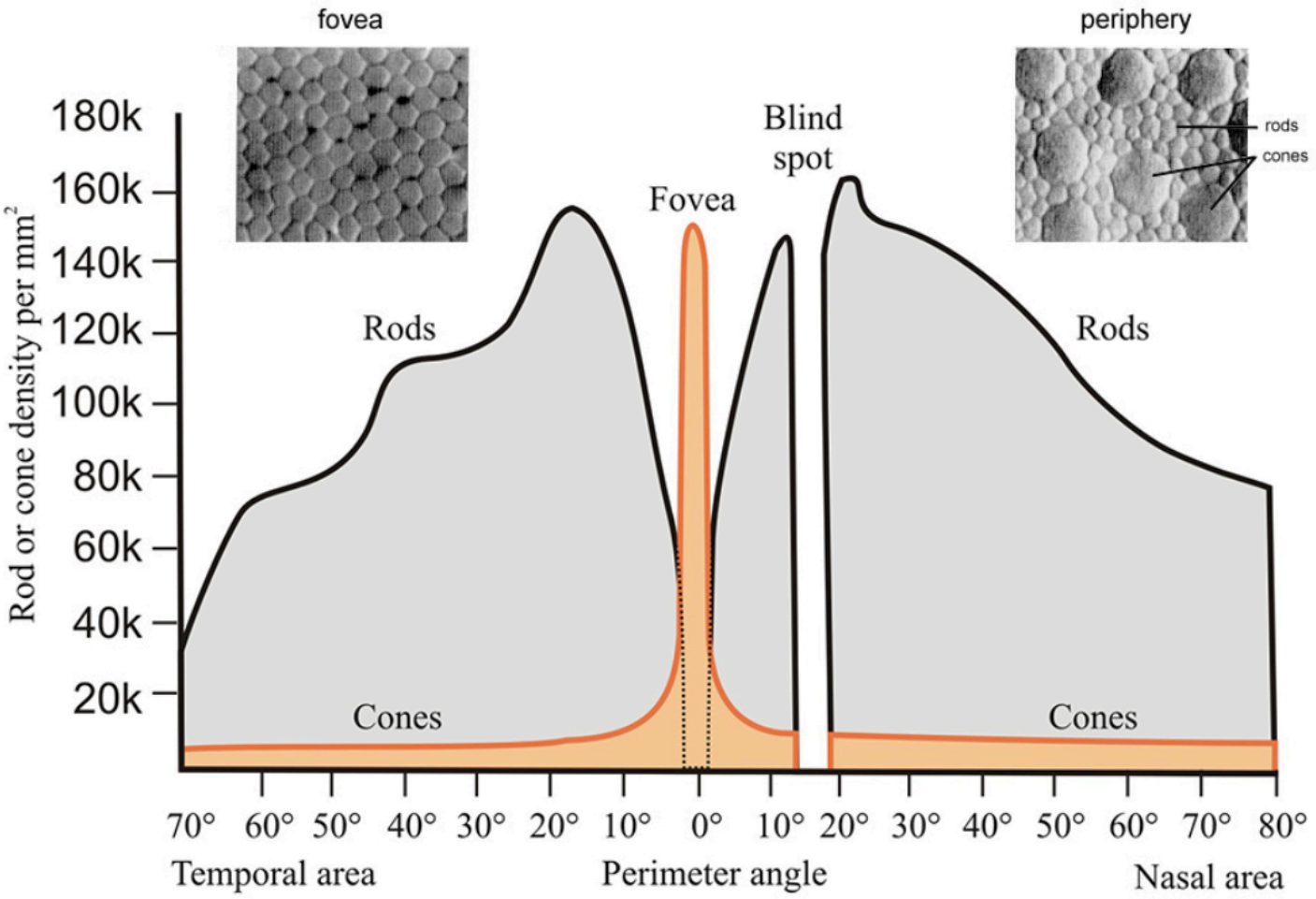
light

The human visual system

- Cones:
  - color vision
  - dense in the center
  - 5-6 millions
- Fovea:
  - central zone of retina
  - only cones, 27 times the density
  - responsible for central vision
- Rods:
  - b/w vision
  - peripheral vision
  - 120 millions

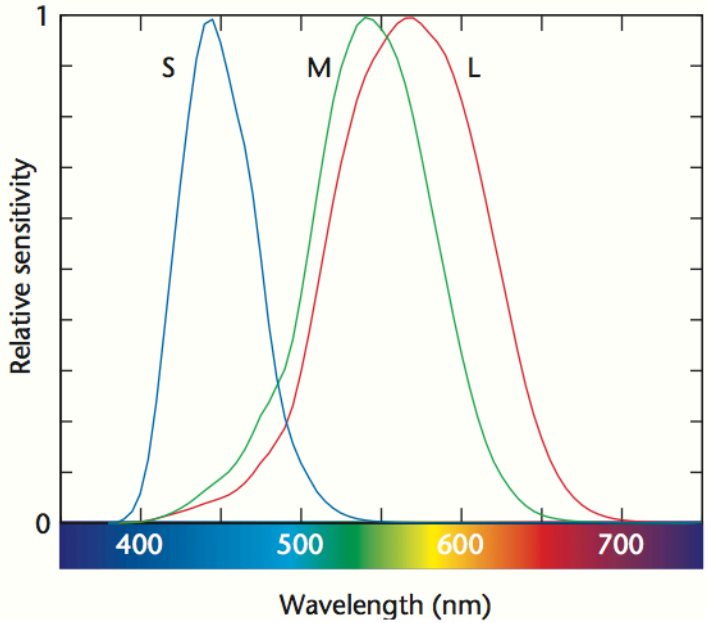


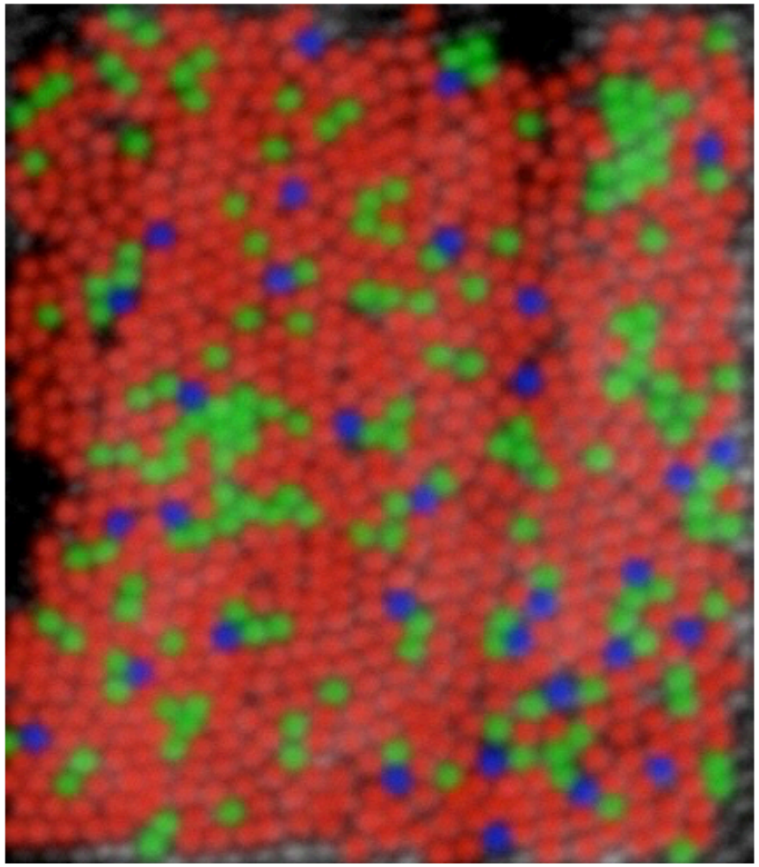
The human visual system



Color vision

- Three different types of cones:
  - present with different densities
  - each type sensitive to a different range of frequencies in the visible spectrum
  - called L, M, S from the zones of spectrum at which they have highest response

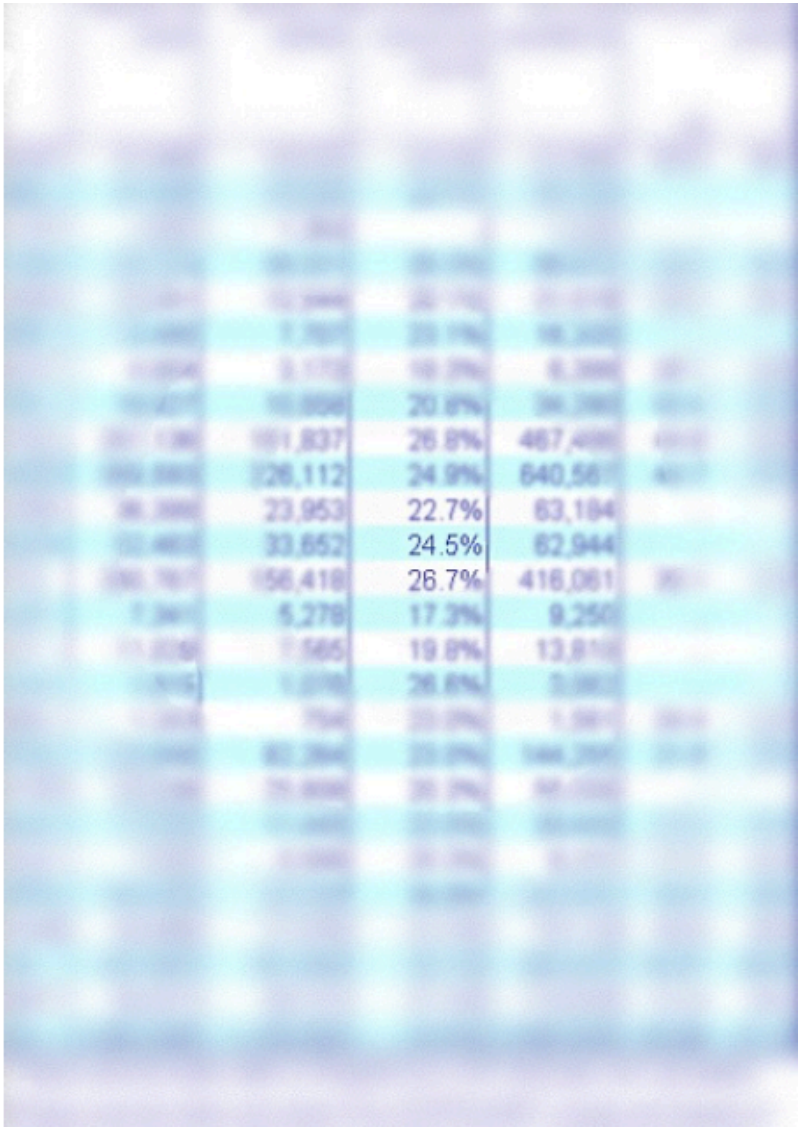




R 63% - G 31% - B 6%

The human visual system

- The eye is not like a camera
- At each instant in time, our vision is sharp only in a very small area around the fovea
- All the rest is badly blurred and vaguely coloured
- Areas outside the fovea provide just contextual information

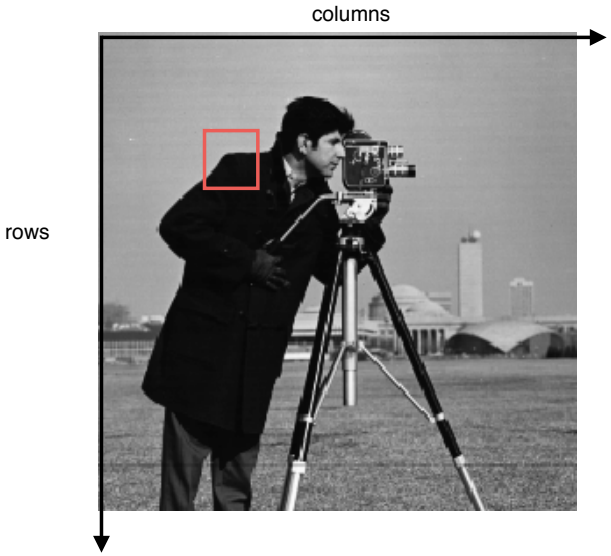


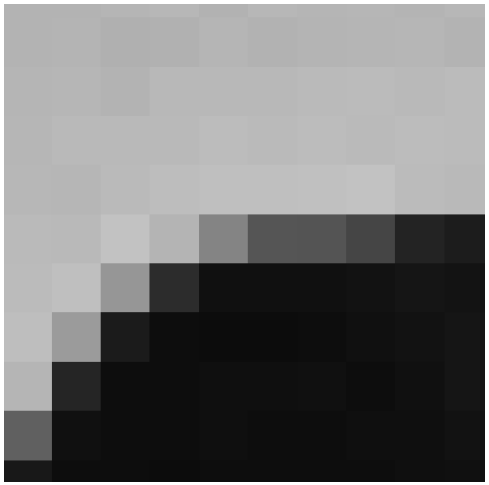
The human visual system

- Vision works as a sequence of *fixations* and *saccades*:
  - Fixation: maintaining gaze on a single location (200-600 ms)
  - Saccade: moving between different locations (20-100 ms)
- Our mental images are a form of integration of several snapshots focused at different spots, as obtained with fixation
- Where do we fixate our gaze?
  - where there's something attractive
  - where we know there's something we want to look at

http://www.cs.ubc.ca/~mikewu/cs547/

A digital image





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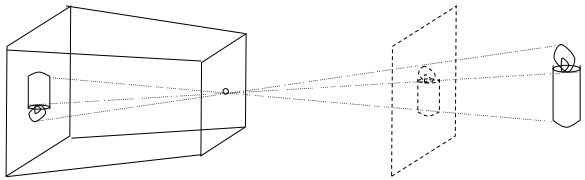
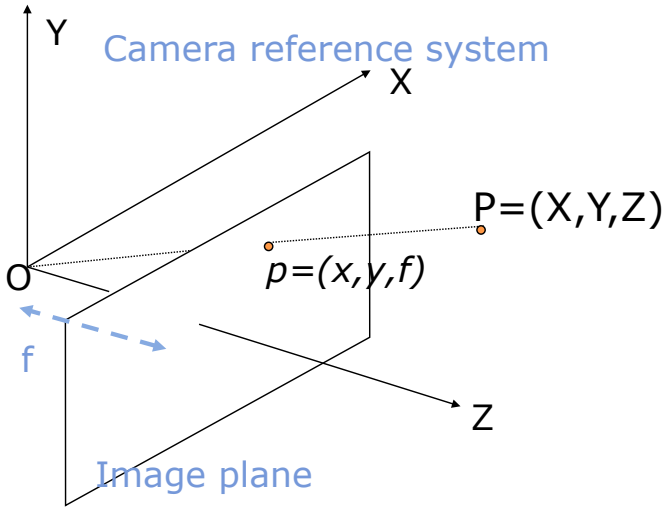
The geometry of image acquisition

At the basis of image acquisition there is a projection from the 3D world to the 2D image





- The pin-hole camera model is a perspective projection
- it is the simplest model of camera and well describes the **geometry** of image formation of a camera system:
  - human vision
  - photo/video cameras

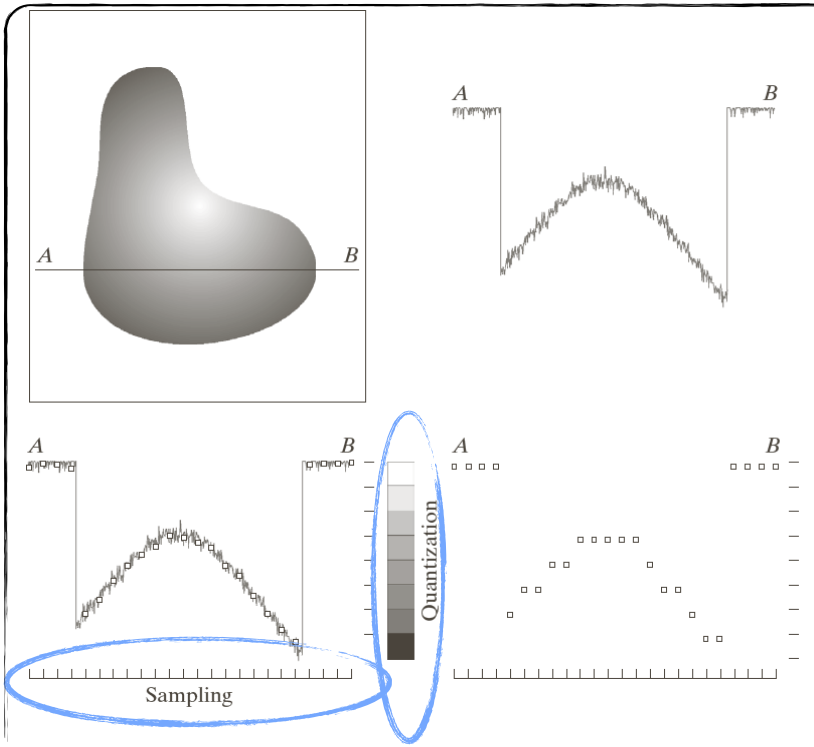
f focal length

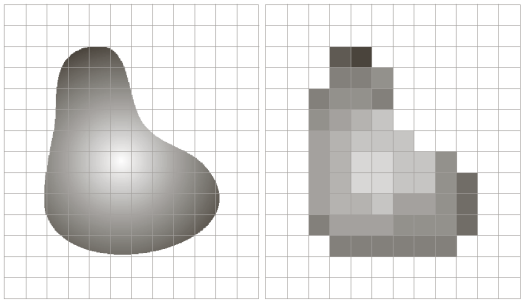
$$x = f\frac{X}{Z}$$

$$y = f\frac{Y}{Z}$$

Sampling and digitalization

during the acquisition process the continuum observations of the world are acquired and stored in digital media



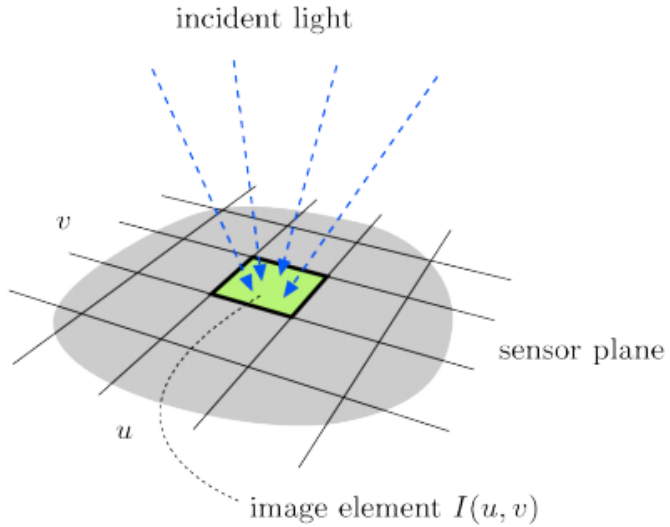


a b

FIGURE 2.17 (a) Continuous image projected onto a sensor array. (b) Result of image sampling and quantization.

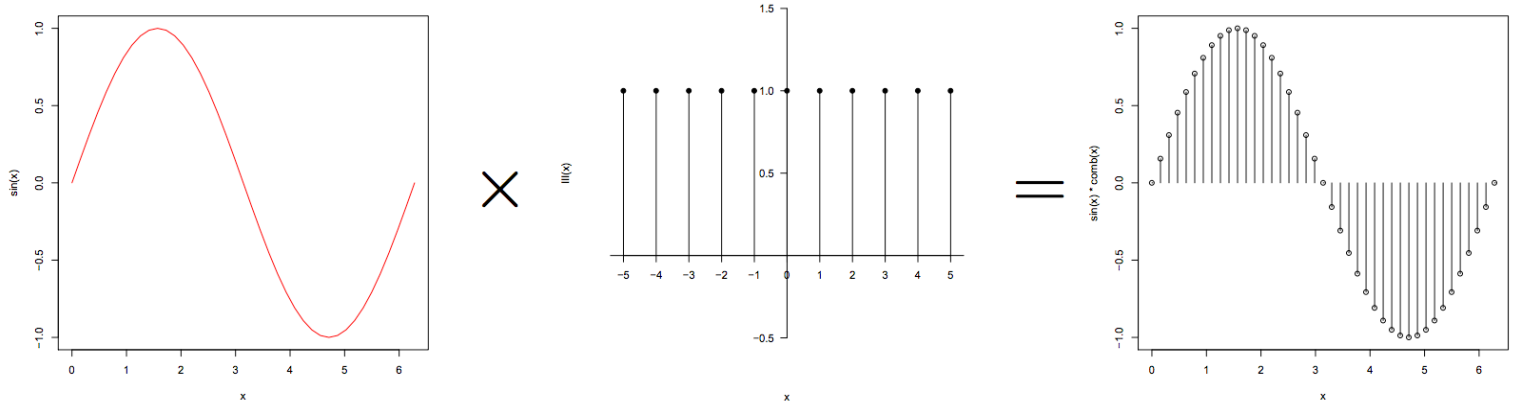
Spatial sampling

- Let us imagine an image to be digitalized is overlaid with a regular grid.
- This grid is referred to as **sampling grid.**
- Each element of the grid will contain a portion (region) of the image. The whole portion will be approximated by a unique (average) value.
- A coarse sampling grid produces an image with fewer details



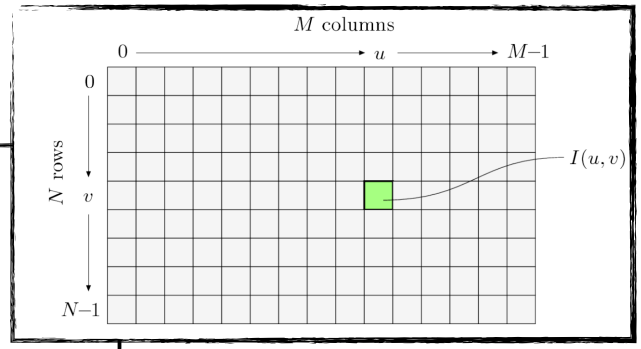
Spatial sampling

- we can think of spatial sampling as a multiplication of a continuous signal with a comb function



the SIZE ...

- The size of the image is given by the number of pixels composing it.
- The size is conventionally expressed by the number of rows times the number of columns of the image matrix, eg 640 x 480.



.... and the RESOLUTION

- An image with a fixed size (in *pixels*) can be visualized at different sizes (in *mm*) on a **support** (paper, monitor, …)
- The *visualization size* is controlled by the **resolution.**
- The resolution depends on the size of the image *and* the size of the support
- It is measured in dots/cm or, more frequently, dots/inches (dpi).

The resolution describes how *dense* are the elements on the support.

Pixels content - information

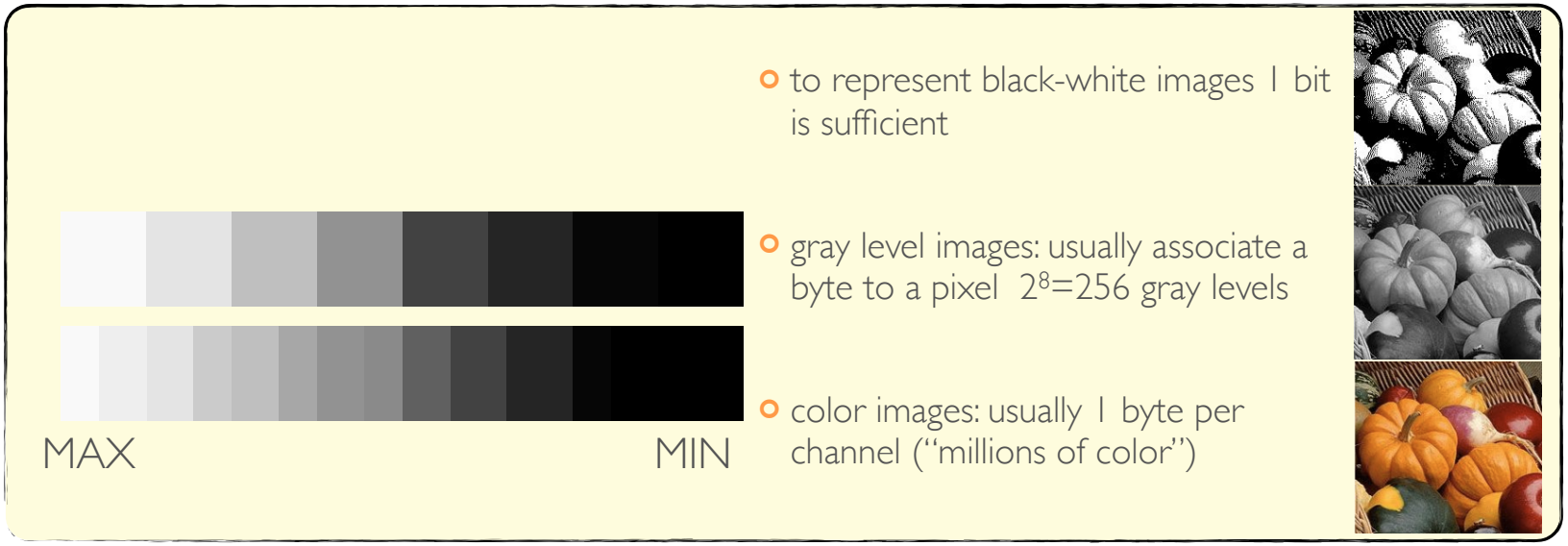
- Pixels contents depend on the image type
  - Gray level pictorial digital images ("black and white photos"): *intensity*
  - Color pictorial digital images: *color* (modeled as triplets, eg RGB)
  - Range images: *depth information*
  - Medical images: *radiations absorbance level*
  - Termal images: *heat*
  - ....

Pixels Content - Dynamic Range

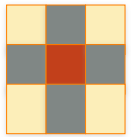
- Total number of distinctive values occurring in the image

this is related to the quantization process...

- it is limited by the number of bit per pixel we may want to use
- it is also limited by the physical dynamic range of the sensor



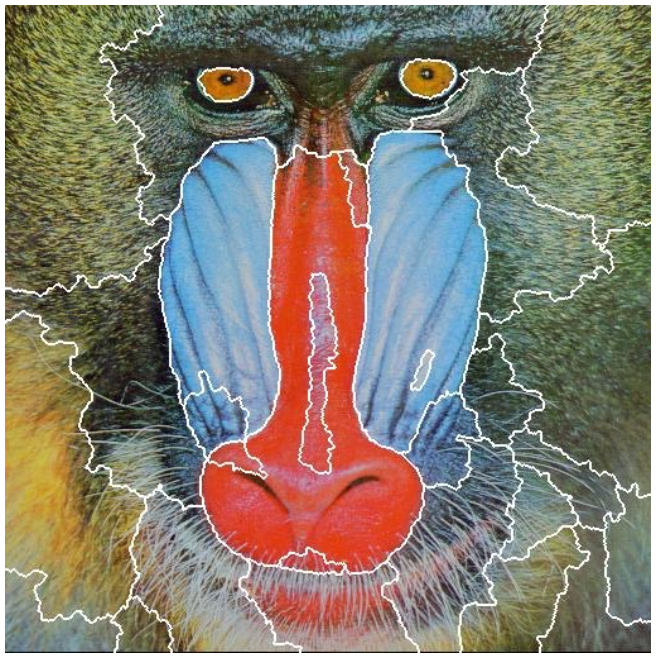
Spatial correlation - pixel neighbourhoods



- A pixel *p* at coordinates *(i,j)* has four horizontal and vertical **neighbors** at coordinates *(*i-1,j) (i+1,j) (i,j-1) (i,j+1)
  - This set is called **4-neighborhood** $N_4(p)$
- The pixel also has four diagonal neighbors:
  (i-1,j-1) (i+1,j-1) (i+1,j-1) (i+1,j+1)
  - The 8 points together form a **8-neighborhood** $N_8(p)$

Connected components

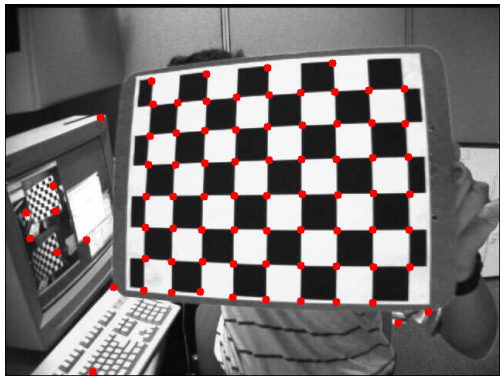
- groups of connected (aggregated) pixels with common properties
- the properties could be a similar color, texture, or motion pattern, …



Keypoints

- "Special" pixels in the image associated with some important properties

EDGES - sharp signal variations



CORNERS - points where the signal varies in at least two directions

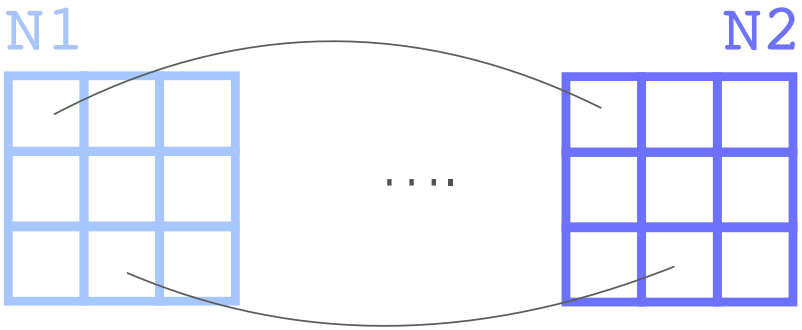
- We have *feature detection algorithms* to find them automatically

From parts to objects

Similarity between image patches

- Let N1 and N2 be two square image patches (or neighbourhoods) of size WxW
  - Goal: to measure how similar they are by means of an appropriate function
  - How: we introduce the so-called correlation methods

$$\phi(N1, N2)$$



Here W = 3

Similarity between image patches

– SSD: Sum of Squared Differences

$$\phi_{SSD}(N1, N2) = - \sum_{k,l=-\frac{W}{2}}^{\frac{W}{2}} (N1(k,l) - N2(k,l))^2$$

– NCC: Normalized Cross Correlation

$$\phi_{NCC}(N1, N2) = - \sum_{k,l=-\frac{W}{2}}^{\frac{W}{2}} \frac{(N1(k,l) - \mu_1)(N2(k,l) - \mu_2)}{W^2 \sigma_1 \sigma_2}$$

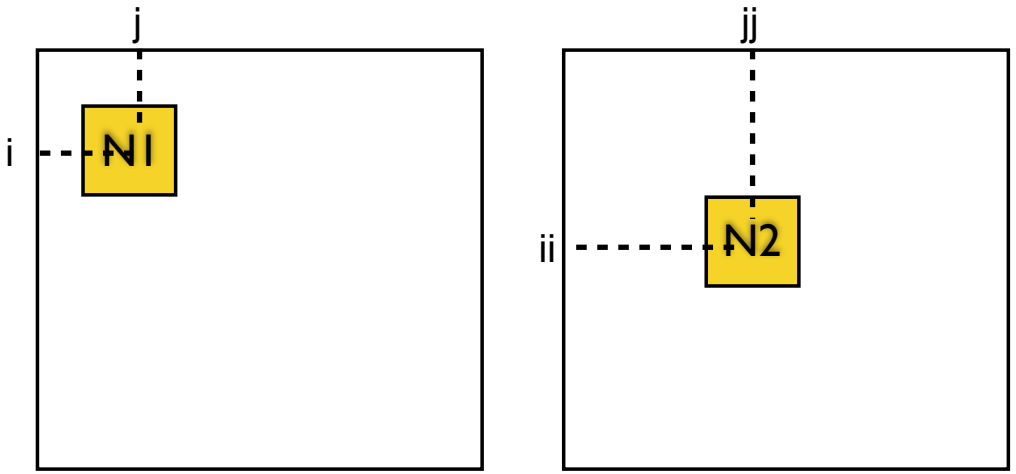
$$\mu_i = \frac{1}{W} \sum_{k,l=1}^{W} Ni(k,l)$$

$$\sigma_i = \sqrt{\frac{1}{W} \sum_{k,l=1}^{W} (Ni(k,l) - \mu_i)^2} \quad \text{with } i = 1, 2$$

NCC: values in the range [-1, 1]

Relative position w.r.t the image

- usually patch N1 belongs to an image I_1, that is, it is a neighbour of a pixel at position (i,j)
- similarly N2 will belongs to an image I_2 as a neighbourhood of a pixel (ii,jj)
- therefore we need to translate the patches to their appropriate position



$$\phi_{NCC}(N1_{i,j}, N2_{ii,jj}) = -\sum_{k,l=-\frac{W}{2}}^{\frac{W}{2}} \frac{(N1(i+k, J+l) - \mu_1)(N2(ii+k, jj+l) - \mu_2)}{W^2 \sigma_1 \sigma_2}$$

The correspondence problem

correlation methods

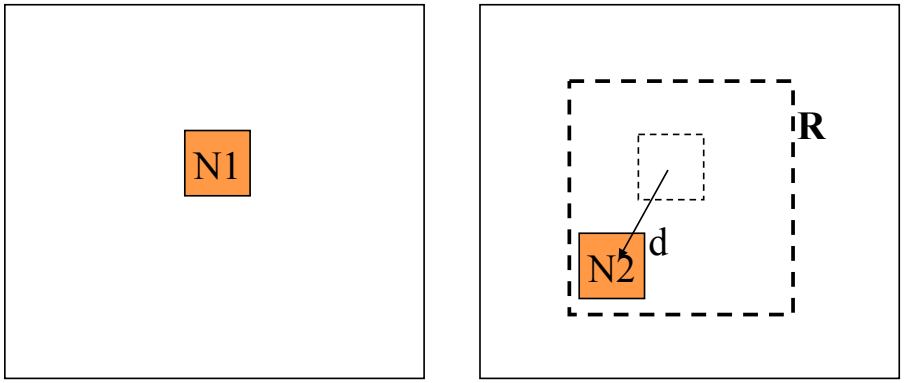
- Now we have all the ingredients to address (in a simple way) an important problem in computer vision: finding correspondences

- Correspondence problem: given **two images**, estimate which parts of the first image correspond to which parts of the second image
  - that is, which parts are projection of the same scene element

- The problem can be addressed as a *dense* or a *sparse* estimation
  - dense correspondence: *for each image pixel*
  - sparse correspondence: *for a set of well defined points*

Where to look for the corresponding feature

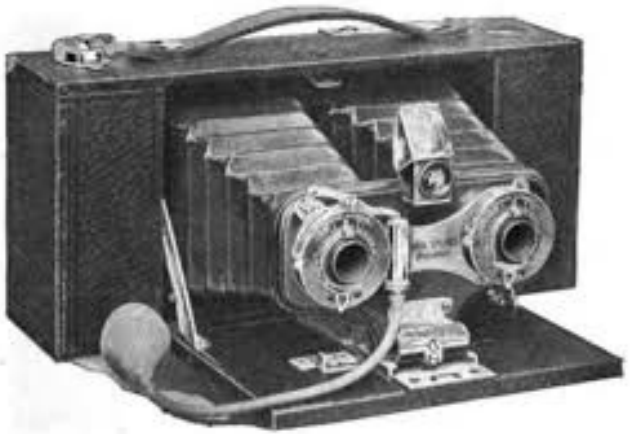
if we have a prior on the corresponding feature position (region **R**)

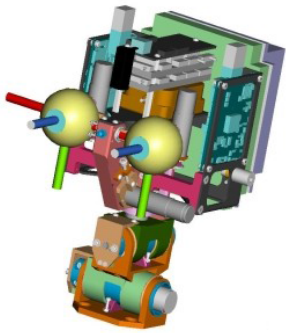


if we don't have a prior on a possible search region we should try all possibilities and this becomes unfeasible as the number of elements grow

Stereopsis

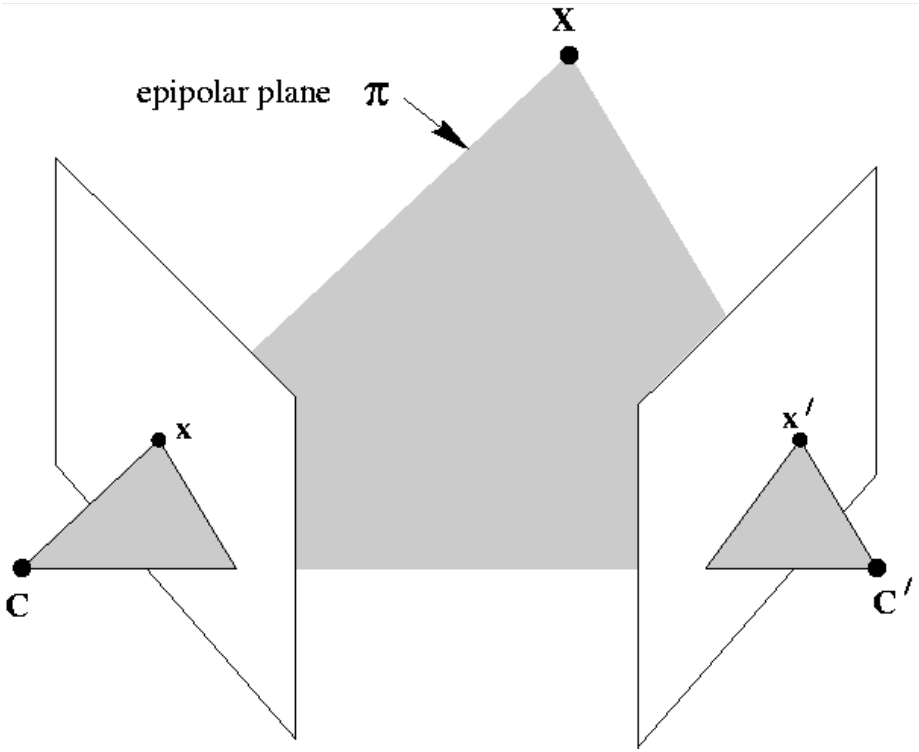
- we refer to stereo vision as the problem of inferring 3D information (structure and distances) from two or more images taken from different viewpoints





Epipolar geometry

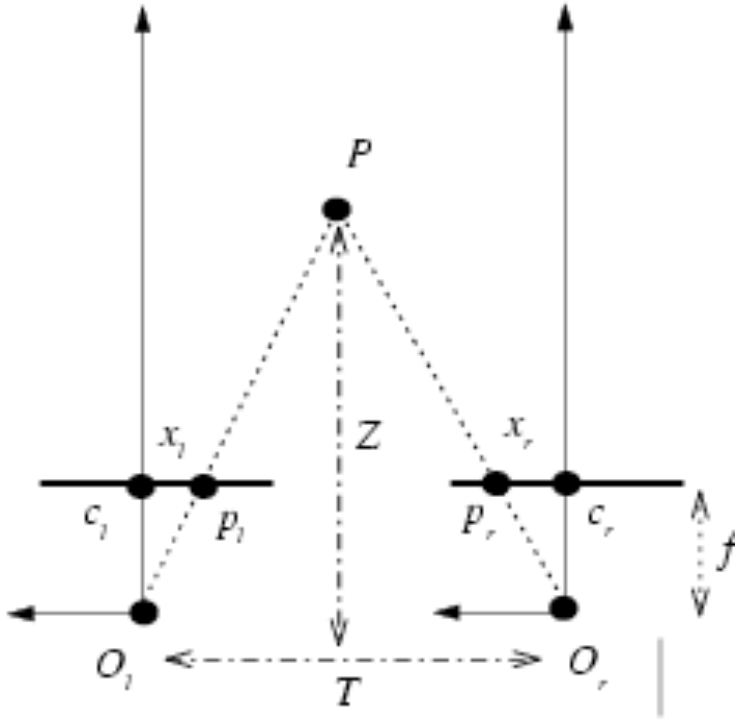
- the geometry of a stereo-system is called epipolar geometry
- it provides a geometrical prior to the algorithms



corresponding points lie on lines (called the epipolar lines)

Stereopsis: depth and disparity

- *Disparity d* is the relative distance between corresponding points (on the image plane)
- *Depth Z* is the distance from a 3D point to the viewing system
- Depth is inversely proportional to disparity



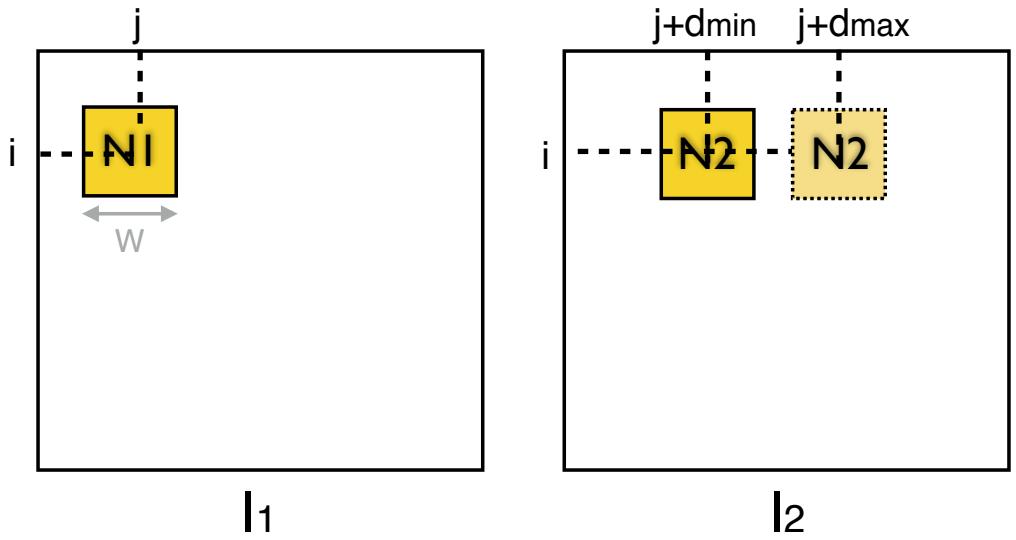
$$Z = \frac{fT}{x_r - x_l} = \frac{fT}{d}$$

Dense stereo correspondences

- we assume we have two *rectified images*, where conjugate points lie on corresponding scanlines of the image ("rows")
- our goal is to obtain a **disparity map** giving the relative displacement for each pixel

- assuming a fixation point at infinity disparity is proportional to the inverse of the distance
- in a standard color coding bright areas correspond to high disparities (closer objects)

Dense correspondences: algorithm sketch



- input:
  - a stereo pair of **rectified** images I_l and I_r
  - size of a correlation window W
  - a search range [d_{min}, d_{max}]

- for each pixel *(i,j)* in I_l
  - for each disparity d in the search range
    - estimate the similarity

$$c(d) = \phi(N1(i,j), N2(i,j+d))$$

    - the disparity of the pixel is

$$\overline{d} = \text{argmax}_{d \in [d_{min}, d_{max}]}\{c(d)\}$$

Dense correspondences: left-right consistency

- correspondences are made more difficult by occlusions (points with no counterpart on the other image)
- let us compute
  - D_{lr}: disparity map from I_l to I_r
  - D_{rl}: disparity map from I_r to I_l
- then $D(i,j)=d$ iff $D_{lr}(i,j)= -D_{rl}(i,j+d)= d$

dense correspondences

Motion perception

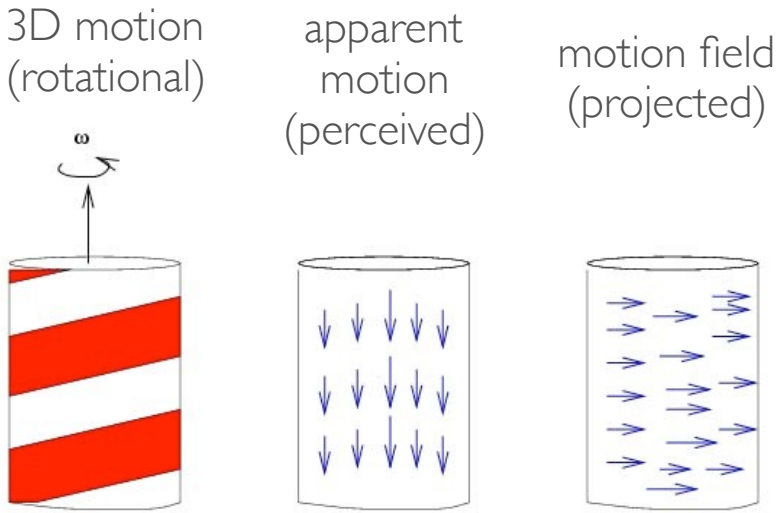
- We are observing a scene with **one** camera acquiring a set of images "close in time"
- **image sequence:** series of N images, or *frames*, acquired at discrete time instants

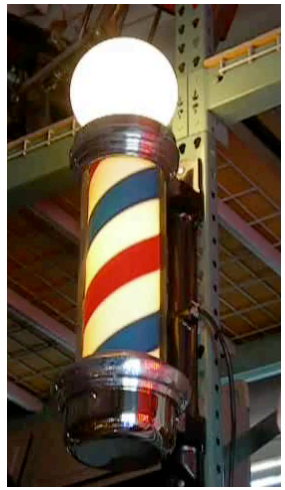
fixed time interval (small)

$$t_k = t_0 + k\Delta t$$

motion field and its estimate

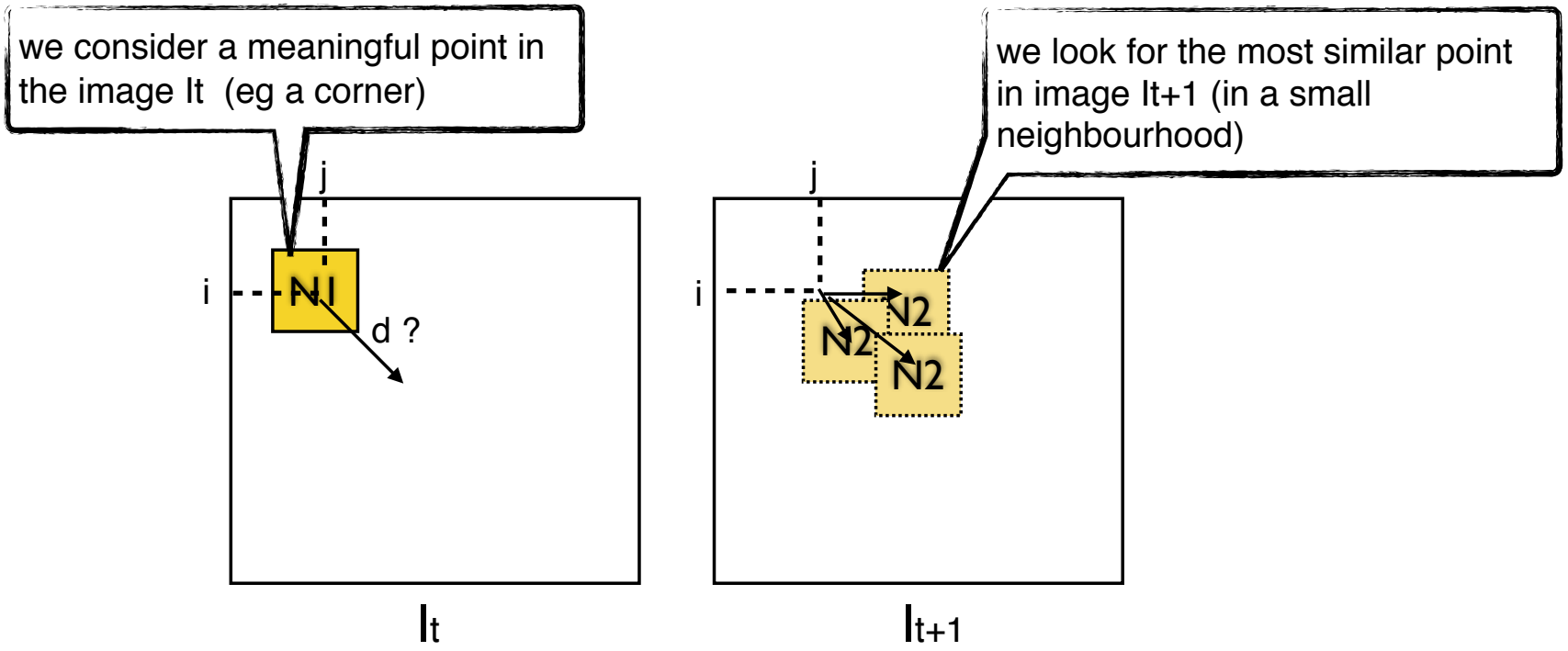
- we may estimate the motion field from images, but what we estimate will be related to the *apparent* motion
- what is the motion field of an object moving in a dark room? or of a uniform object on a similar background?





Correlation-based motion estimation

- Two different images of the same scene, this time acquired by the same camera at adjacent temporal instants
- Prior: in this case we may assume the displacement *d* to be very small



A classical derivative-based algorithm - Lucas Kanade

- We start from an assumption on the *image brightness constancy*

$$\frac{dI}{dt} = 0$$

$$\frac{d(I(x,y,t))}{dt} = \frac{\partial I}{\partial x}\frac{dx}{dt} + \frac{\partial I}{\partial y}\frac{dy}{dt} + \frac{\partial I}{\partial t} = 0$$

$$(\nabla I)^\top \mathbf{u} + I_t = 0$$

image brightness constancy equation

A classical derivative-based algorithm - Lucas Kanade

- The optical flow is a vector field subject to the constraint

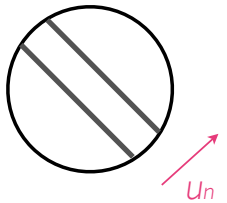
$$(\nabla I)^\top \mathbf{u} + I_t = 0$$

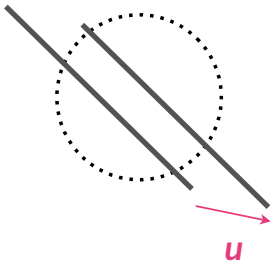
- Notice that **one** constraint is not enough to compute the optical flow (**2** unknowns)

The aperture problem

- the image brightness constancy equation allows us to determine the optical flow component parallel to the spatial image gradient
- Analytically

$$u_n = \frac{(\nabla I)^\top \mathbf{u}}{||\nabla I||} = \frac{-I_t}{||\nabla I||}$$





A classical derivative-based algorithm - Lucas Kanade

- many algorithms start from the idea of adding constraints to the underdetermined system obtained by the brightness constancy equation
- we will see a simple way of doing so: the Lucas-Kanade algorithm
  - assumption: **u** is constant in a small neighbourhood of a point

A classical derivative-based algorithm - Lucas Kanade

- the assumption allows us to obtain a system of equations with one equation for each point in the neighbourhood

$$(\nabla I(\mathbf{x}_i, t))^\top \mathbf{u} + I_t(\mathbf{x}_i, t) = 0 \quad \mathbf{x}_i \in N$$

- we then obtain a linear system **Au=b** with

$$A = \begin{bmatrix} \nabla I(\mathbf{x}_1, t)^\top \\ \nabla I(\mathbf{x}_2, t)^\top \\ \cdot \\ \cdot \\ \cdot \\ \nabla I(\mathbf{x}_m, t)^\top \end{bmatrix} \qquad \mathbf{b} = \begin{bmatrix} -I_t(\mathbf{x}_1, t) \\ -I_t(\mathbf{x}_2, t) \\ \cdot \\ \cdot \\ \cdot \\ -I_t(\mathbf{x}_m, t) \end{bmatrix}$$

m elements in the *N* neighbour.

A classical derivative-based algorithm - Lucas Kanade

- The linear system may be solved with the pseudo-inverse

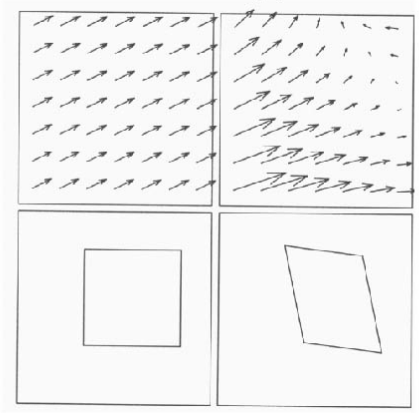
$$\mathbf{u} = A^{\dagger}\mathbf{b} \quad \text{with} \quad A^{\dagger} = (A^{\top}A)^{-1}A^{\top}$$

- notice that the inversion of the matrix will be ill-posed if the matrix is not full rank
- the matrix is full rank in the proximity of corners (points who do not suffer from the aperture problem)
  this is why often times Lucas Kanade is implemented as a *sparse* algorithm (after a corner detection stage)

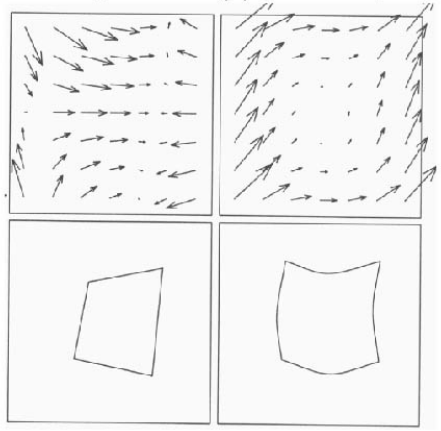
other parametric models

- the hypothesis of a locally constant (translational) optical flow can be extended with more complex models (affine, projective, quadratic, ...)

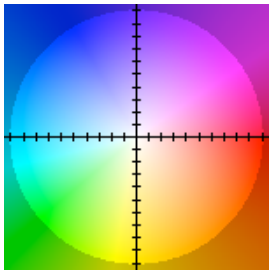
(a) Modello traslazionale (b) modello affine



(c) modello proiettivo (d) modello quadratico



Optic flow - example

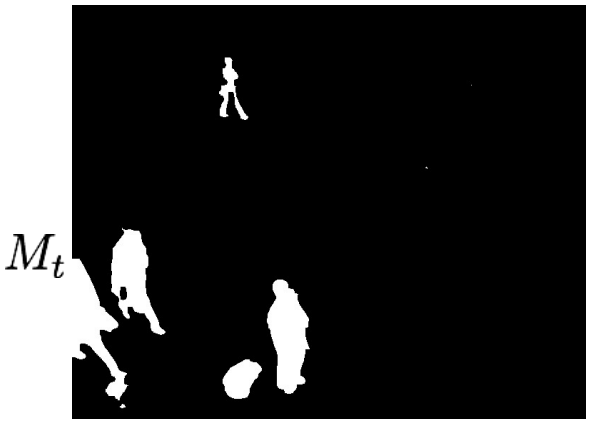


MAIN DIRECTIONS
color coding

motion segmentation

- A different problem of motion analysis is motion segmentation
- **motion segmentation:** what regions of the image plane correspond to different moving objects?
- in the case the camera is still, motion segmentation is called **change detection**

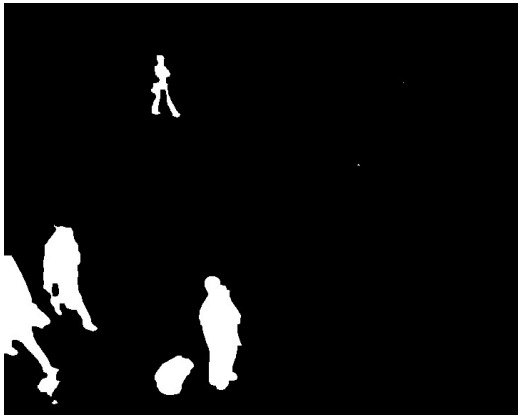
motion segmentation: change detection



- Motion segmentation aims at identifying image regions undergoing a uniform 2D motion field
- Change detection: given a sequence of images taken by a fixed camera, find the regions of the image, if any, corresponding to the different moving objects
- Pixel classification: still or moving?

motion segmentation: change detection

I_t



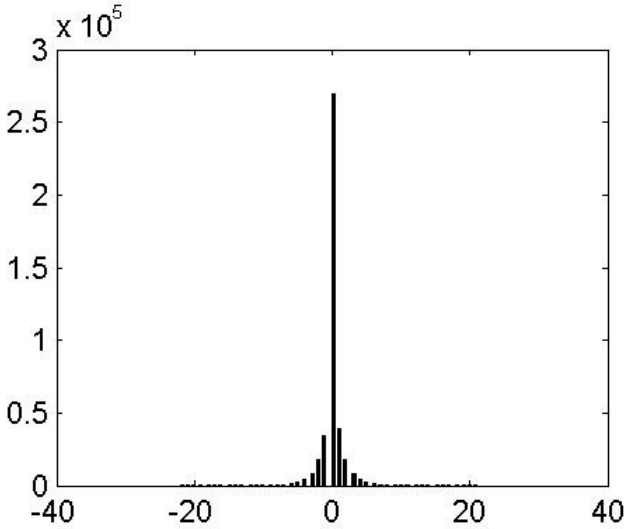
M_t

- in the case the camera is still motion segmentation can be implemented as a difference operation
- assuming we have a reference image

$$M_t(x,y) = \begin{cases} 1 & \text{if } |I_t(x,y) - I_{ref}(x,y)| > \tau \\ 0 & \text{otherwise} \end{cases}$$

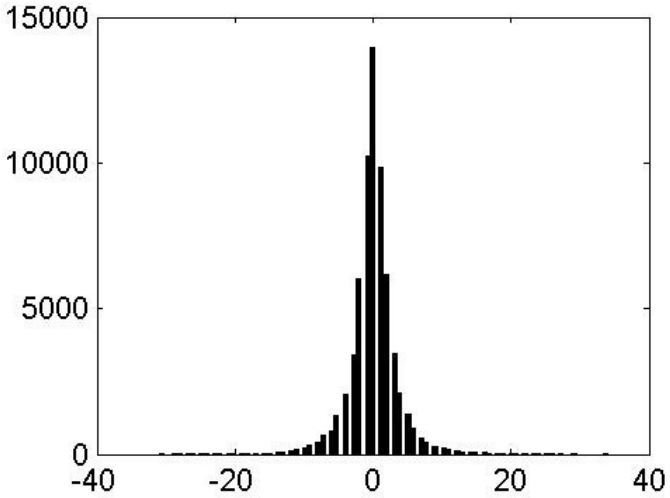
- the thresold must be chosen considering a trade-off between false positives and false negatives

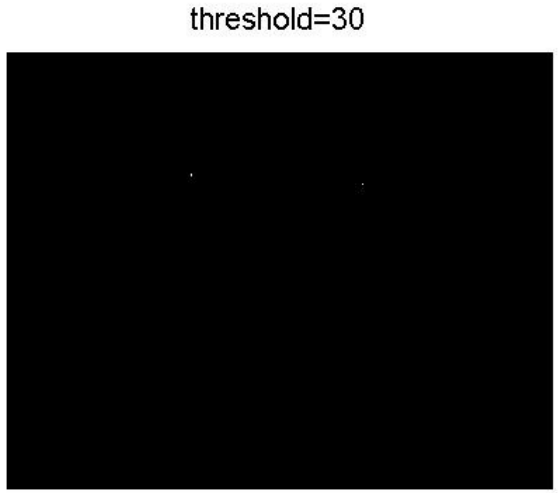
change detection



threshold=10

change detection





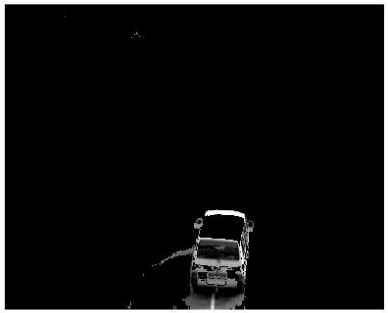
change detection: what is a reference image?

- the simplest way of detecting moving objects is to compare consecutive (or close) frames

frame 1

frame 2

|I1-I2|>th



Artifacts
Difficult to detect slow motion
Noisy localization

change detection: what is a reference image?

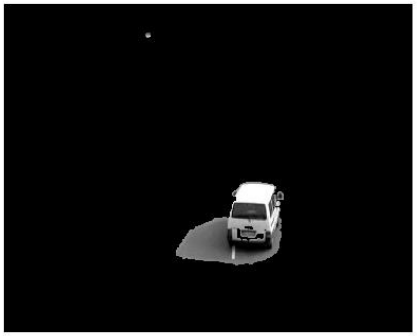
- the reference image or, more in general the *background model*, is a "picture" of the empty scene, containing all the parts which are not moving

sfondo

frame

|I-B|>th

after a cleaning procedure



change detection: what is a reference image?

- the reference image or, more in general the *background model*, is a "picture" of the empty scene, containing all the parts which are not moving
- the simplest way of computing it is to average the first N frames (assuming that at the beginning the scene is stationary)

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

Background modeling: a running average

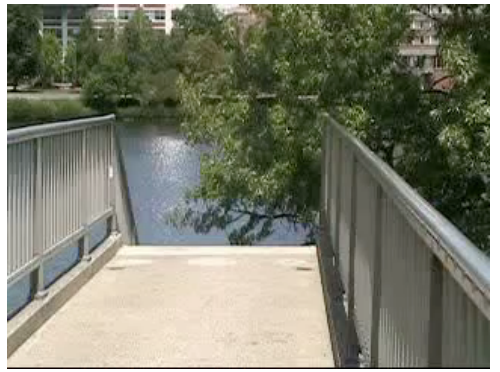
$$B_t(i,j) = \begin{cases} \alpha B_{t-1}(i,j) + (1-\alpha) I_t & \text{if } (i,j) \text{ is classified as static} \\ B_{t-1}(i,j) & \text{otherwise} \end{cases}$$

notice: the background model is updated at each frame

- it is quite robust to moving objects in the scene
- it incorporates stable changes (at a speed which is proportional to α)
- it is simple and computationally efficient

CONS

- it does not deal with repetitive (and uninteresting) motion



motion segmentation: moving cameras

- We need to consider the presence of a dominant motion (the ego motion)
- A possible approach is to first obtain a rough estimate of the ego motion and then compensate it to generate a synthetic datum *as if* the camera were still
- Much harder and computationally intensive (as an alternative we often look for semantic info: people detection, car detection, …)

- change detection may be applied during fixation periods (eye/camera is still) but in this case we cannot use a reference background
- for small eye movements we can eliminate ego motion by thresholding and then cluster optical flow values

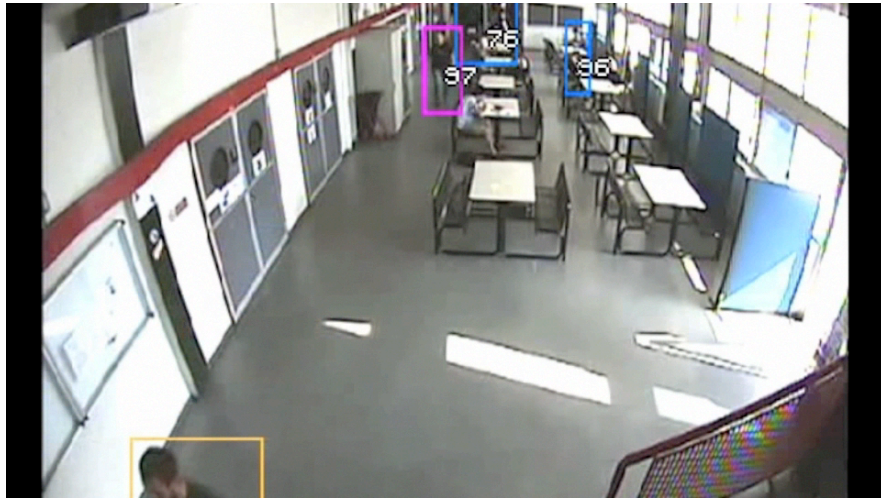
blob detection & object tracking

- After a segmentation procedure we obtain larger portions of coherent pixels

  pixel ⟶ blob (connected component of moving pixels)

- Blob: a region of the image associated with a coherent information, it can be described through its size, shape, color, texture, …

- After motion segmentation, we can perform blob similarity between blobs detected at time *t* and *t+1*



Wrapping up

- We have introduced a selection of *basic* computer vision algorithms

- They can be seen as building blocks for
  - human-robot interation: locating interacting agents
  - understanding the surrounding environment
  - locating interesting (closest disparity) points to control fixation
  - …

- To bridge a semantic gap between pixels and semantic meaning we need to know more (see next classes on machine learning)