

TSBB15

Computer Vision

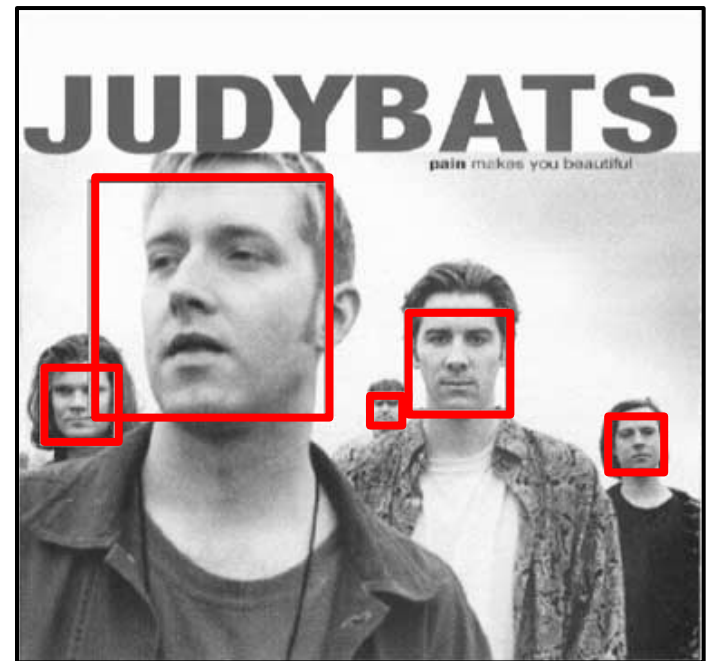
Lecture 2
Image Representations

Today's topics

- Scale spaces
- Pyramids
- Hierarchical representations
- Representation of uncertainty/ambiguity
 - case study: local orientation representation

Scale spaces: motivation 1

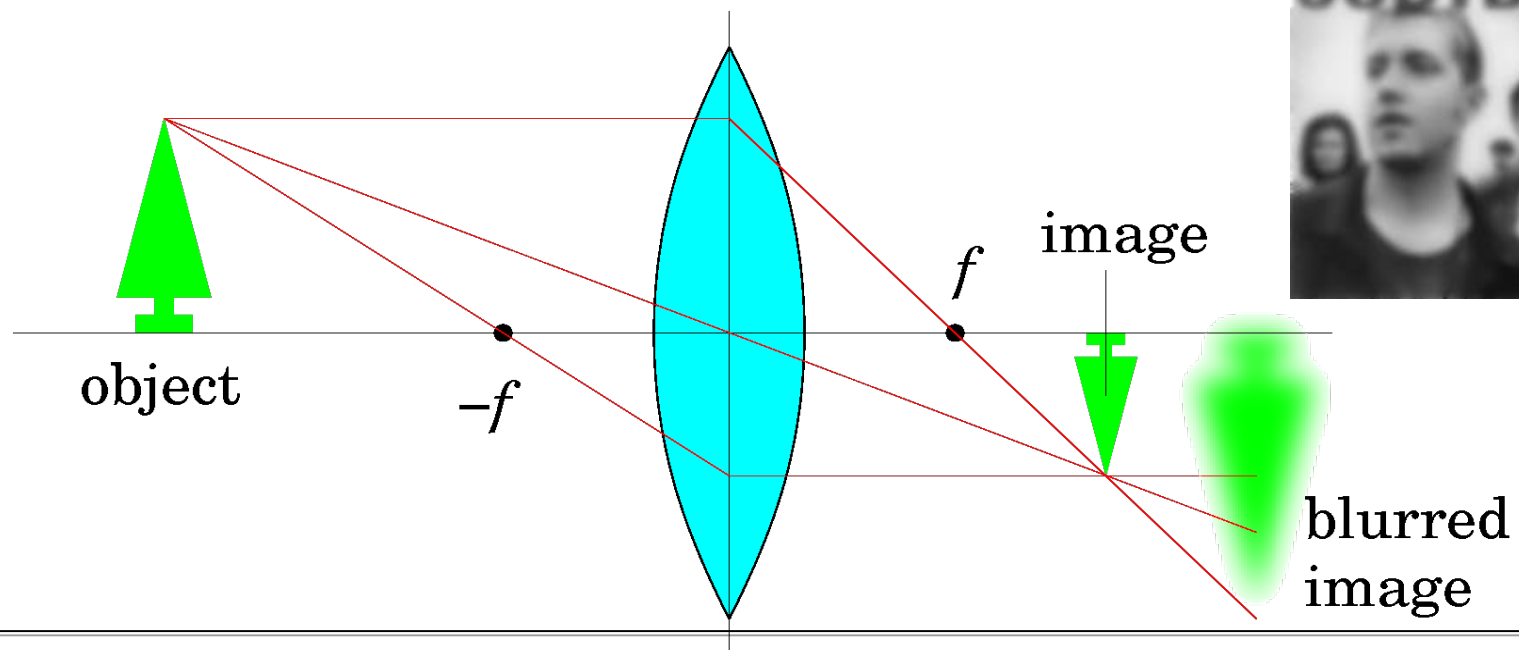
- Objects at different distances have different sizes in the image plane
- In object detection:
 - We want to detect them all
- How?



Example: face
detection

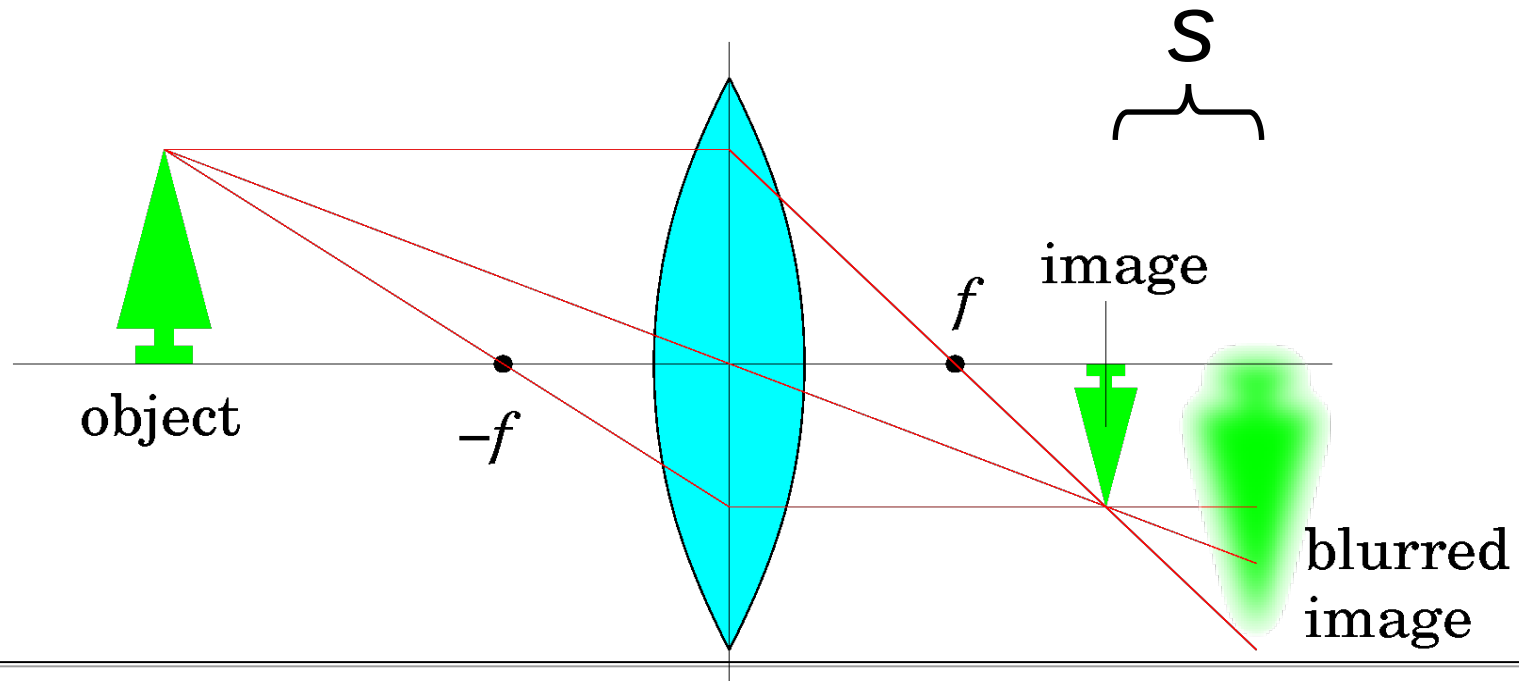
Scale spaces: motivation 2

- Cameras have limited depth-of-field
- We want our algorithms to robustly deal with out-of-focus blur

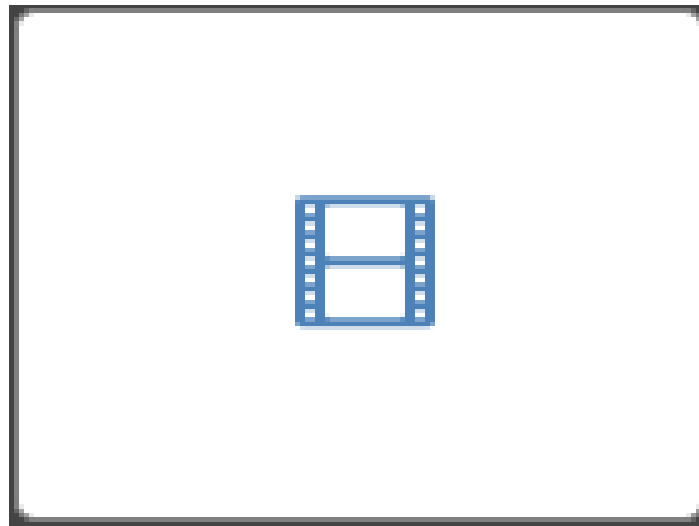


Scale spaces: motivation 2

- Image blur function: $\text{image}(s)$

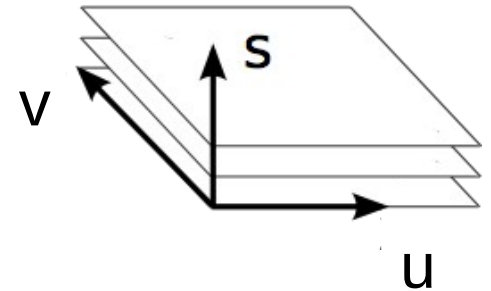


Image(s)



Representation: Scale Space

- Basic idea
 - Stack images in a 3D space
 - The third axis, s , is called *scale*
 - $s = 0$ corresponds to the original image
 - As s grows, the image becomes more blurred
- Intuitively: s can be thought of as a *defocus* or *blurring parameter*

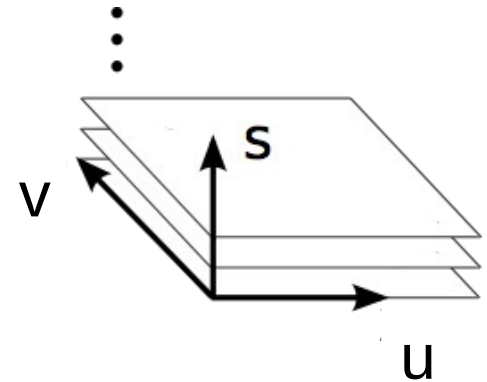


Scale Space

- Notation:
 - original image $I_0(u,v)$
 - blurred image $I_s(u,v)$

- $I_s = T_s \{ I_0 \}$

- T_s : transformation that produces I_s from I_0



Scale Space Axioms

[Iijima, 1959] specifies properties of T_s :

1. Linear
2. Shift-invariant
3. Semi-group property
4. Scale- and rotation-invariant
5. Maintain positivity
6. Separability (by later authors)

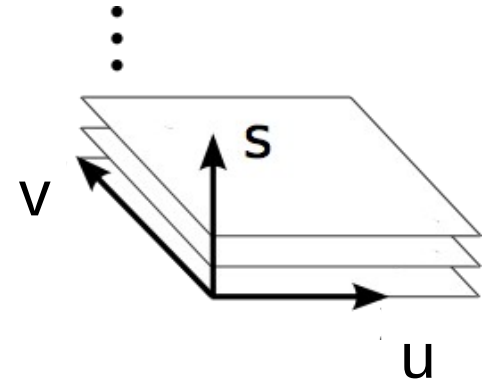
See video
on
ScaleSpace

Scale Space

- A1+A2: T_s is a convolution
 - original image $I_o(u,v)$
 - blur kernel $g_s(u,v)$
 - The scale space of I_o is given as the convolution:

$$I_s(u, v) = (g_s * I_o)(u, v)$$

In the Fourier domain: $F\{I_s\} = G_s \cdot F\{I_o\}$



Gaussian Scale Space

- The remaining axioms lead to a unique formulation of G_s as a Gaussian function:

$$G_s(\omega_u, \omega_v) = e^{-s \frac{\omega_u^2 + \omega_v^2}{2}} \quad g_s(u, v) = \frac{1}{2\pi s} e^{-\frac{u^2 + v^2}{2s}}$$

- Separability:

$$g_s(u, v) = \frac{1}{\sqrt{2\pi s}} e^{-\frac{u^2}{2s}} \frac{1}{\sqrt{2\pi s}} e^{-\frac{v^2}{2s}}$$

PDE formulation

- The Gaussian scale space can also be derived as the solution to the PDE:

$$\frac{\partial}{\partial s} I_s(u, v) = \frac{1}{2} \nabla^2 I_s(u, v)$$

boundary condition: $I_0(u, v) = I(u, v)$

- A.k.a. the **diffusion equation**
 - Compare to the *heat equation*, where $I_s(u, v)$ is the temperature at time s in point (u, v) , given initial temperature $I_0(u, v)$

PDE formulation

$$\frac{\partial}{\partial s} I_s(u, v) = \frac{1}{2} \left(\frac{\partial^2 I_s}{\partial u^2} + \frac{\partial^2 I_s}{\partial v^2} \right) (u, v)$$

- The change in $I_s(u, v)$ when we move only along the scale parameter s equals a local second order derivative of I_s at (u, v)

We will return to the PDE formulation of scale spaces in a later lecture

Implementation of the Gaussian Scale-Space

Different alternatives:

1. In the Fourier domain:
 1. 2D Fourier transform
 2. Multiplication with Gaussian function
 3. Inverse FT

2. Convolution:
$$I_s(u, v) = (g_s * I_0)(u, v)$$

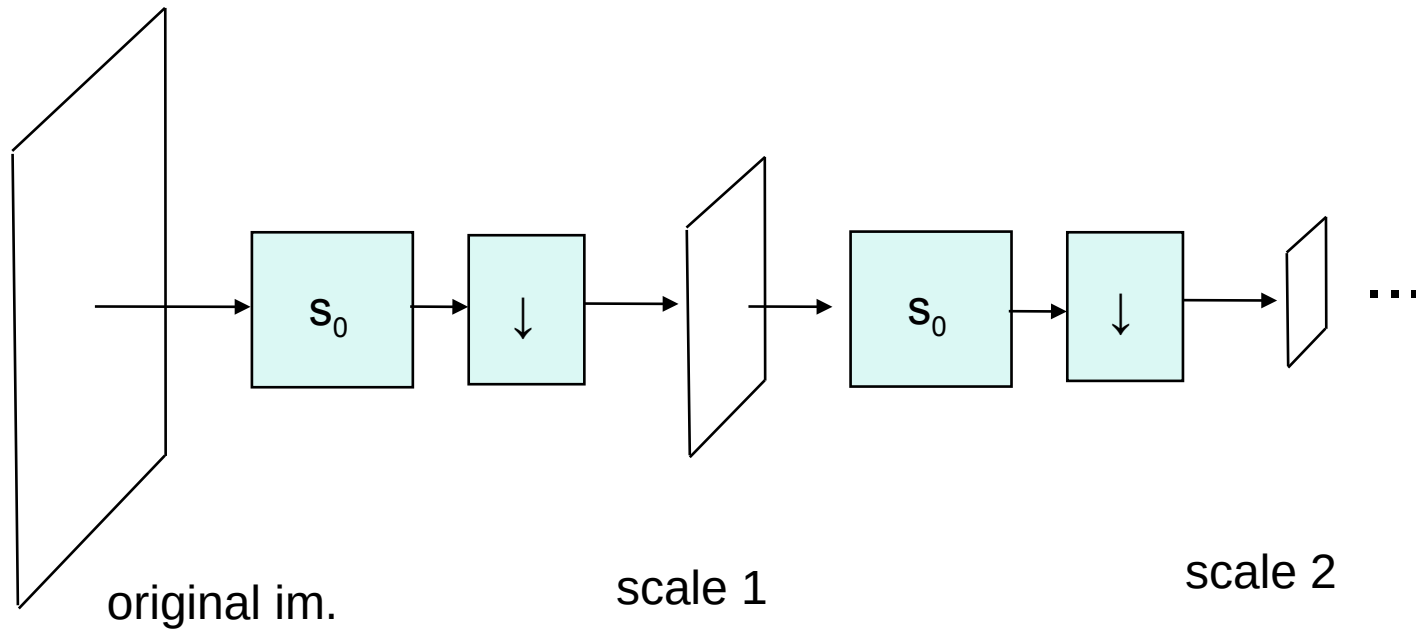
3. Integrating I_s as a solution of the PDE:

$$I_{s+\Delta s} = I_s + \Delta s \cdot \frac{\partial I_s}{\partial s} = I_s + \Delta s \cdot \frac{1}{2} \nabla^2 I_s$$

Representation: Scale Pyramid

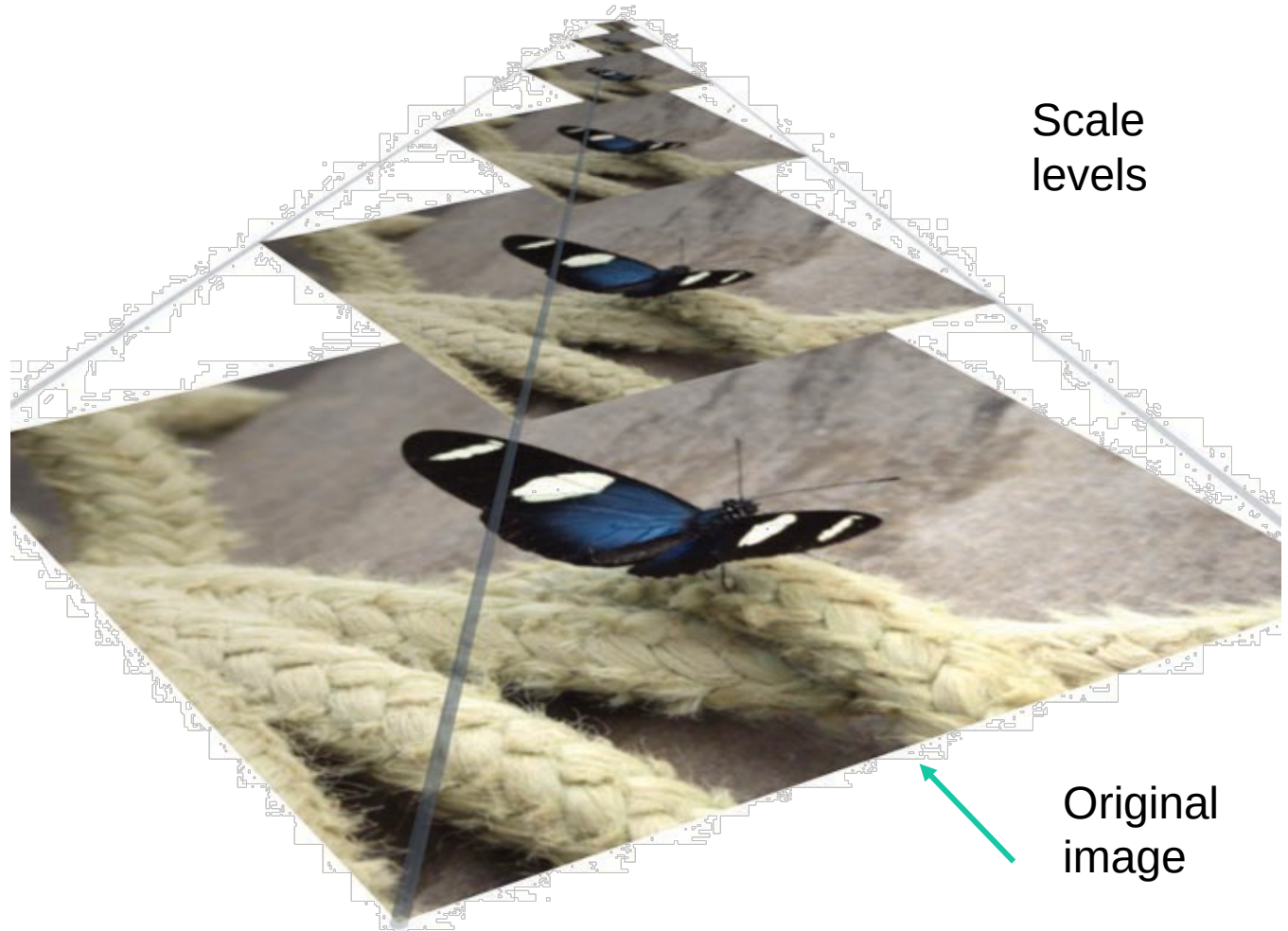
- Blurring (LP-filtering) reduces high frequencies
- At some scale s_o : frequencies over $\pi/2$ are sufficiently attenuated to allow down-sampling with a factor 2 without much aliasing
- At scale $2s_o$ we can down-sample the image with a factor 4, etc.

Gaussian Pyramid



Example

Coarser
scale



Scale
levels

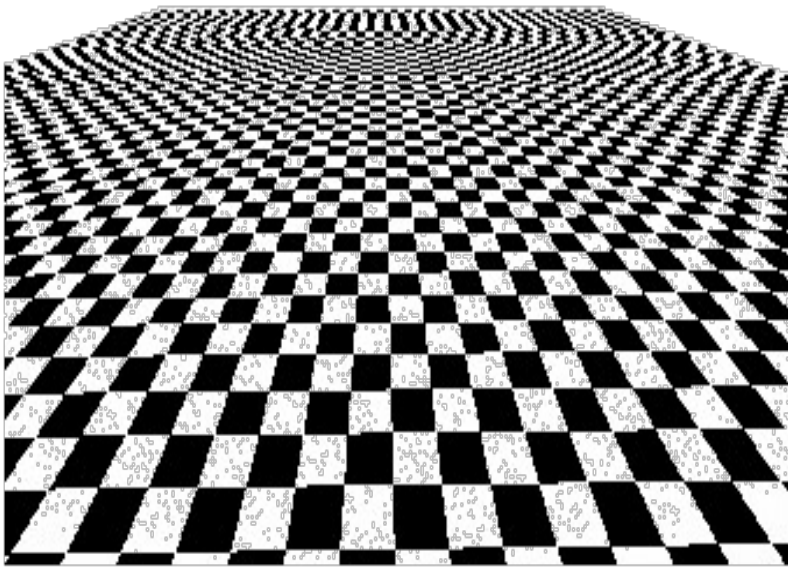
Finer
scale

Original
image

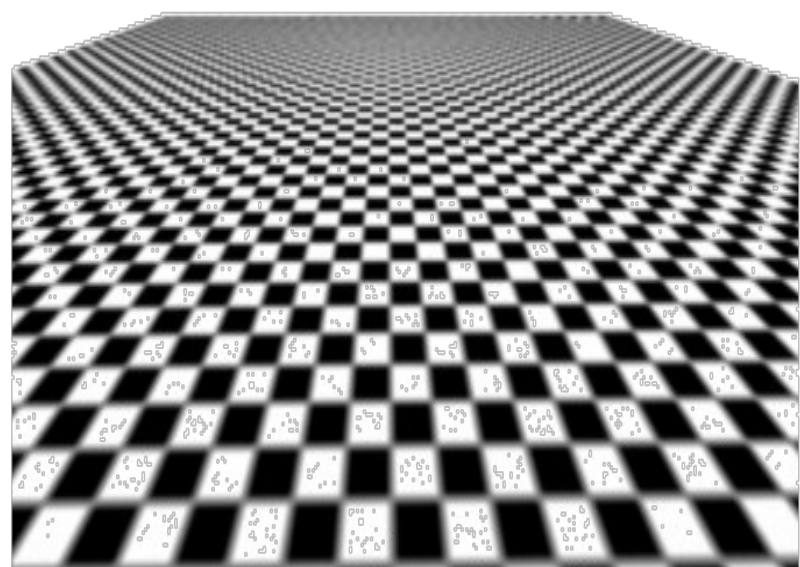
Scale Pyramid: Applications

- Used widely in Computer Graphics for texture resampling (called MIP maps)

Texture without MIP map



Texture with MIP map



Scale Pyramid: Applications

- Also very common in motion analysis

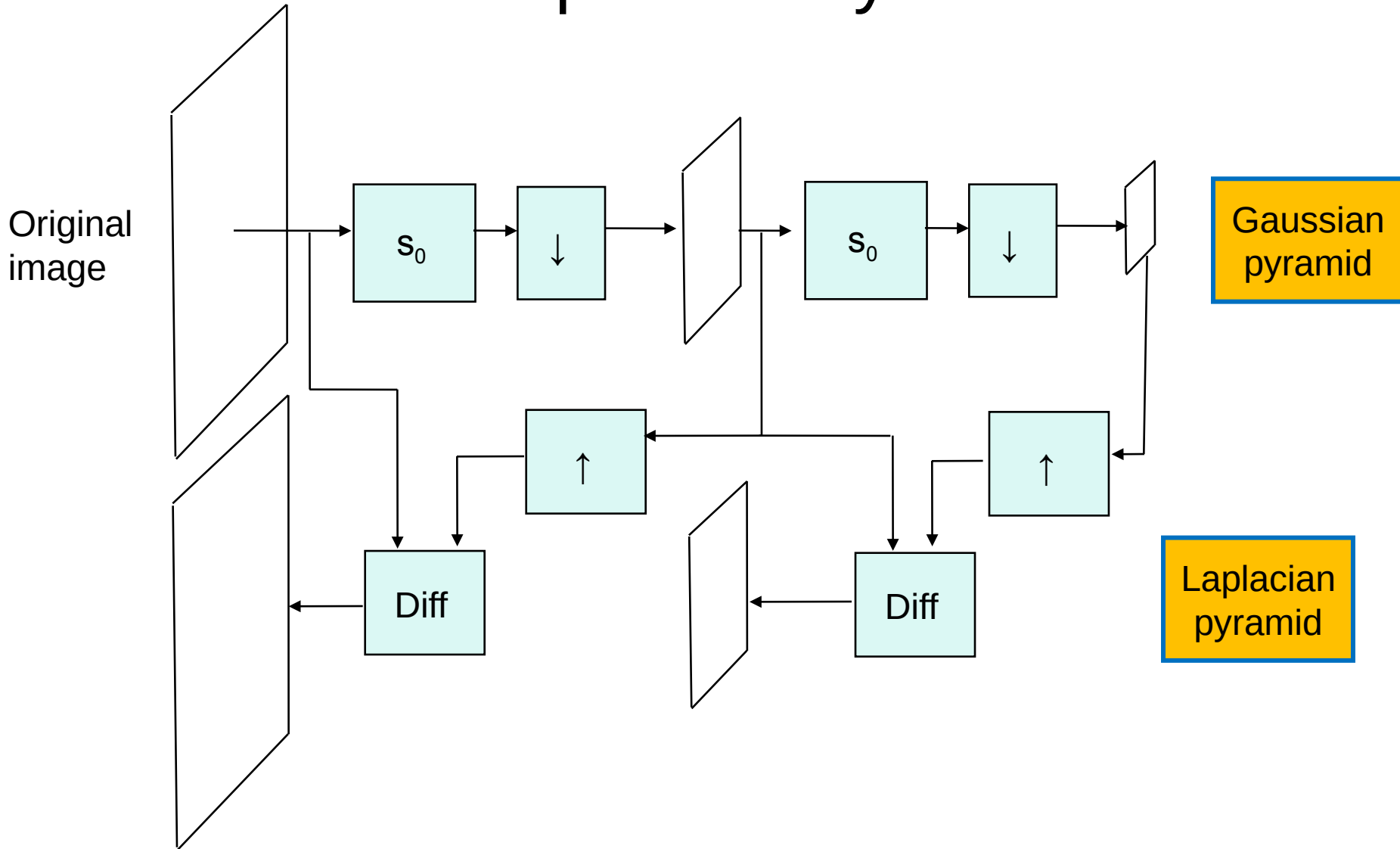
We will return to scale pyramids in later Lectures on motion analysis

- Multi-resolution processing
 - Face detection!

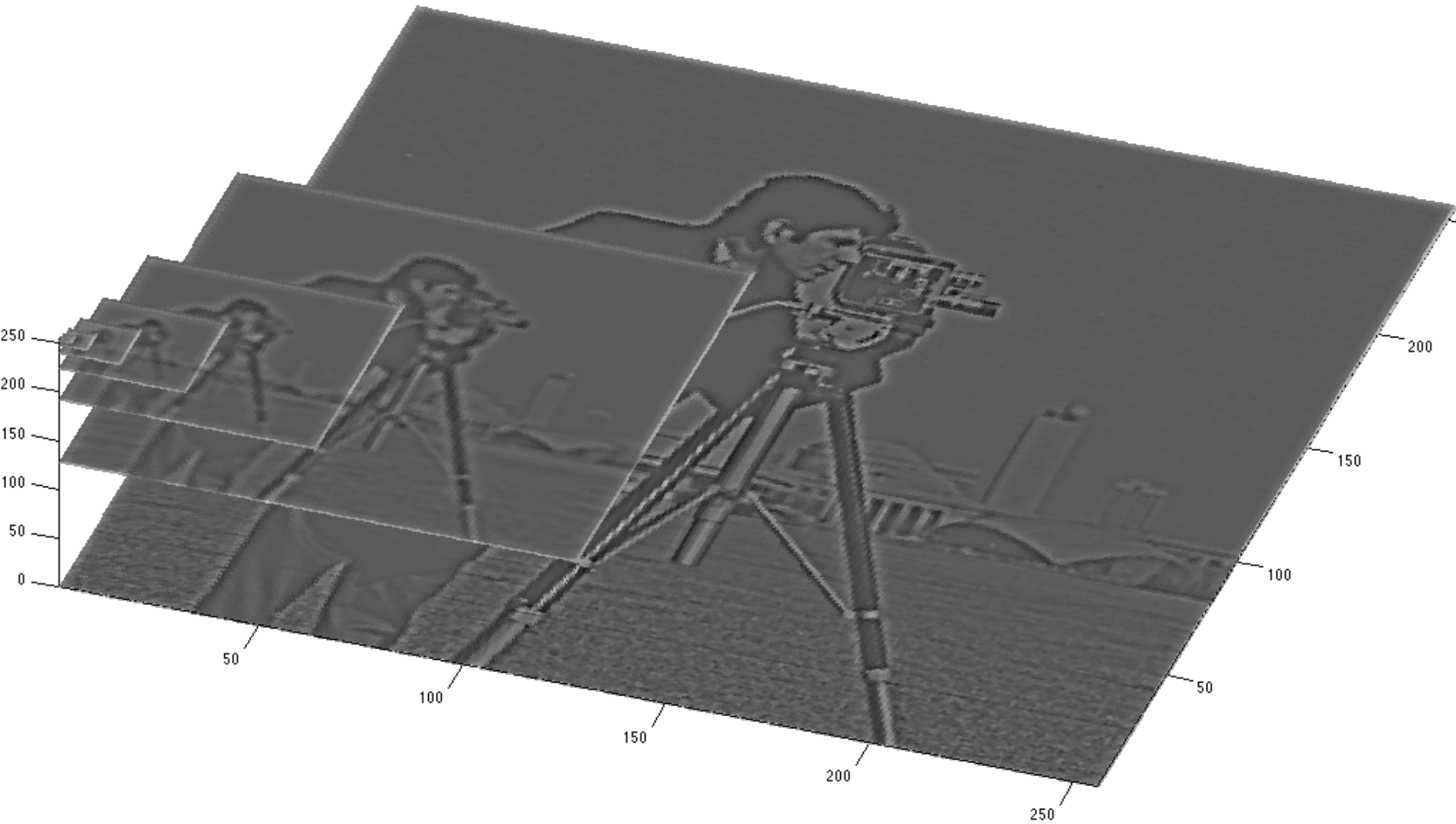
Laplacian Pyramid

- From a Gaussian pyramid, we can compute a *Laplacian pyramid*.
- Each level (scale) in a Laplacian pyramid is given as the **difference** between two levels of a Gaussian pyramid **at the same grid size**.
 - The coarser level needs to be up-sampled!
 - Or use the LP-filtered version of the finer scale!
- The Laplacian pyramid contains no information about the DC-component of the image

Estimation: Laplacian Pyramid



Example

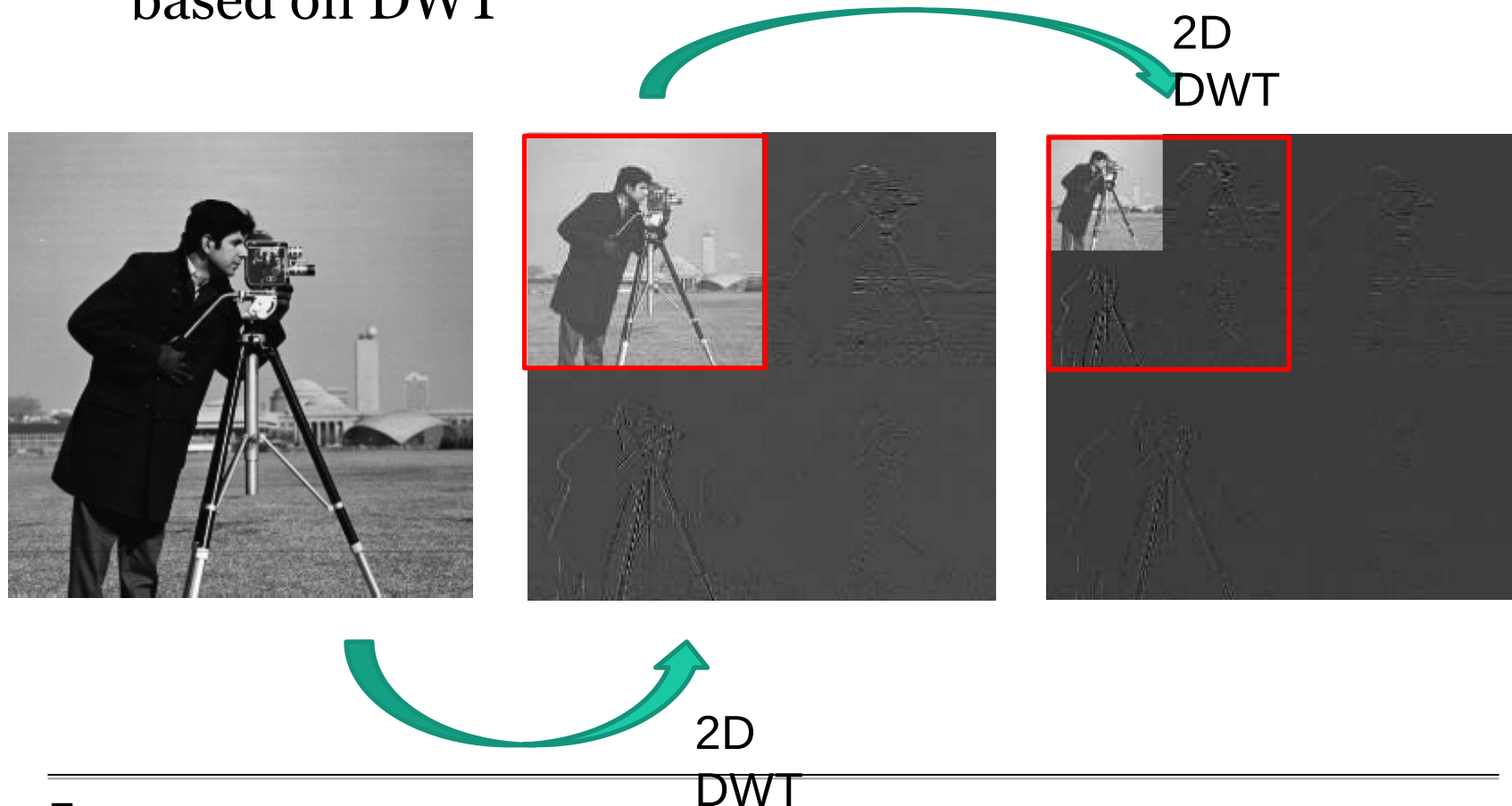


Completeness: Laplacian Pyramid

- The original image can be reconstructed from its Laplacian pyramid together with the coarsest level of its Gaussian pyramid
- How?

2D DWT, Example

- Another similar approach to scale spaces can be based on DWT

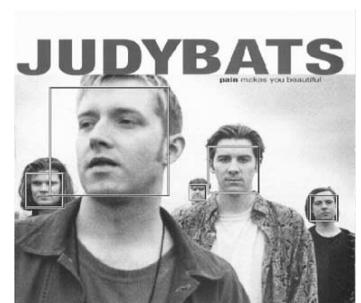
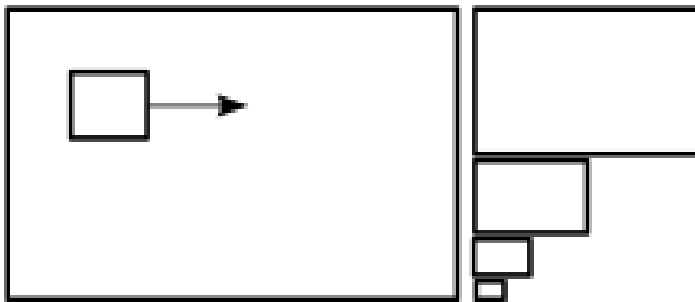


Analysis using scale hierarchies

- Scale-spaces, G/L-pyramids and DWT are examples of *scale hierarchies*
- Enables analysis of image features at different resolutions
 - Example: translations over different distances.
- Same or different analysis can be applied on each scale level
- Scaling of pixel coordinates between different levels!

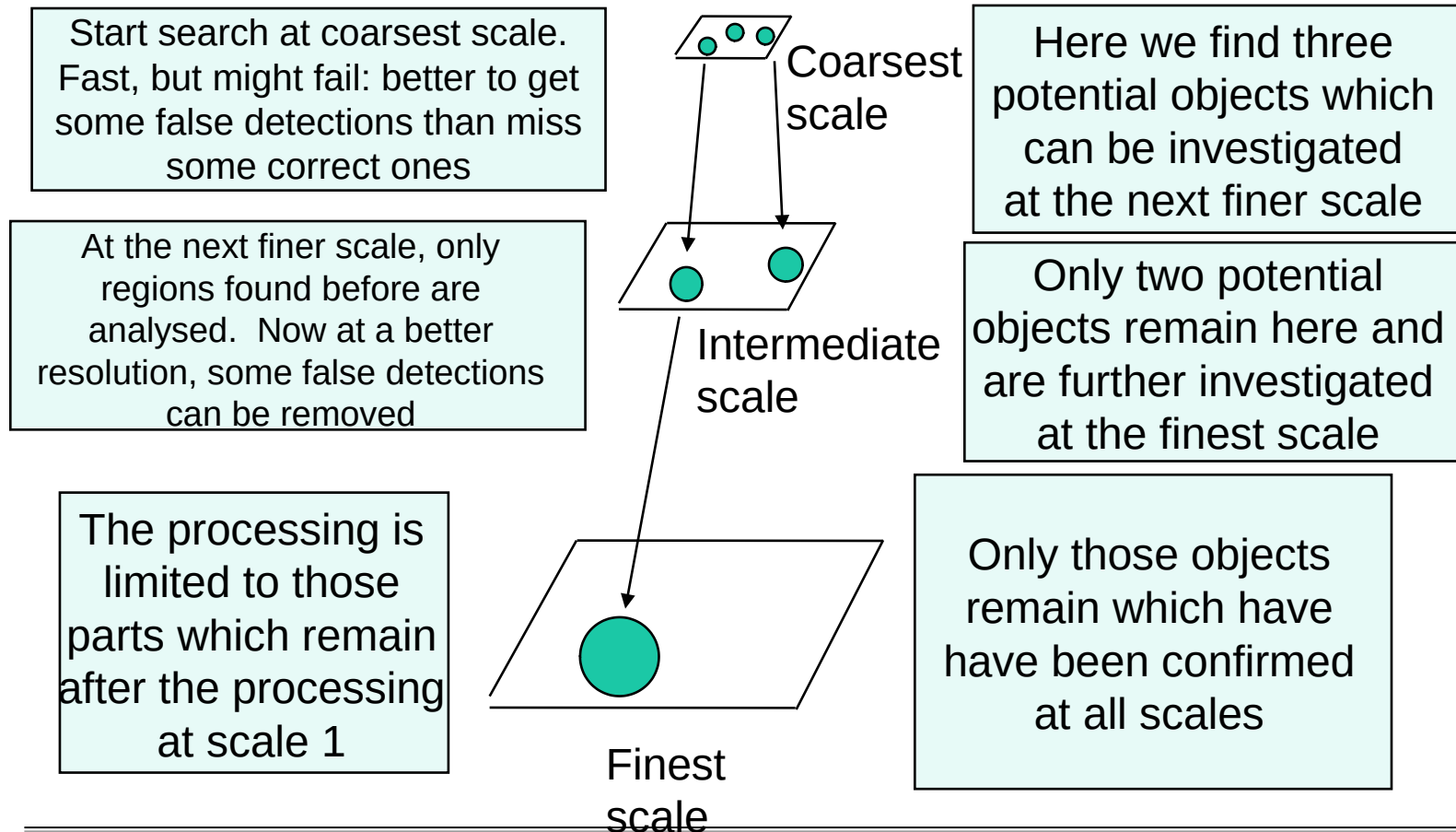
Multi-resolution processing

- Apply the same operation, e.g., for object detection, on all levels of a scale pyramid
 - Can be done in parallel
 - Collect all detections from all levels as distinct objects
 - The level where a detection was made indicates the “size” of the object
- If each level is down-sampled a factor 2:
 - Time for searching over scale is bounded by a factor $(1 + 1/4 + (1/4)^2 + \dots) = 4/3$



Example: face detection

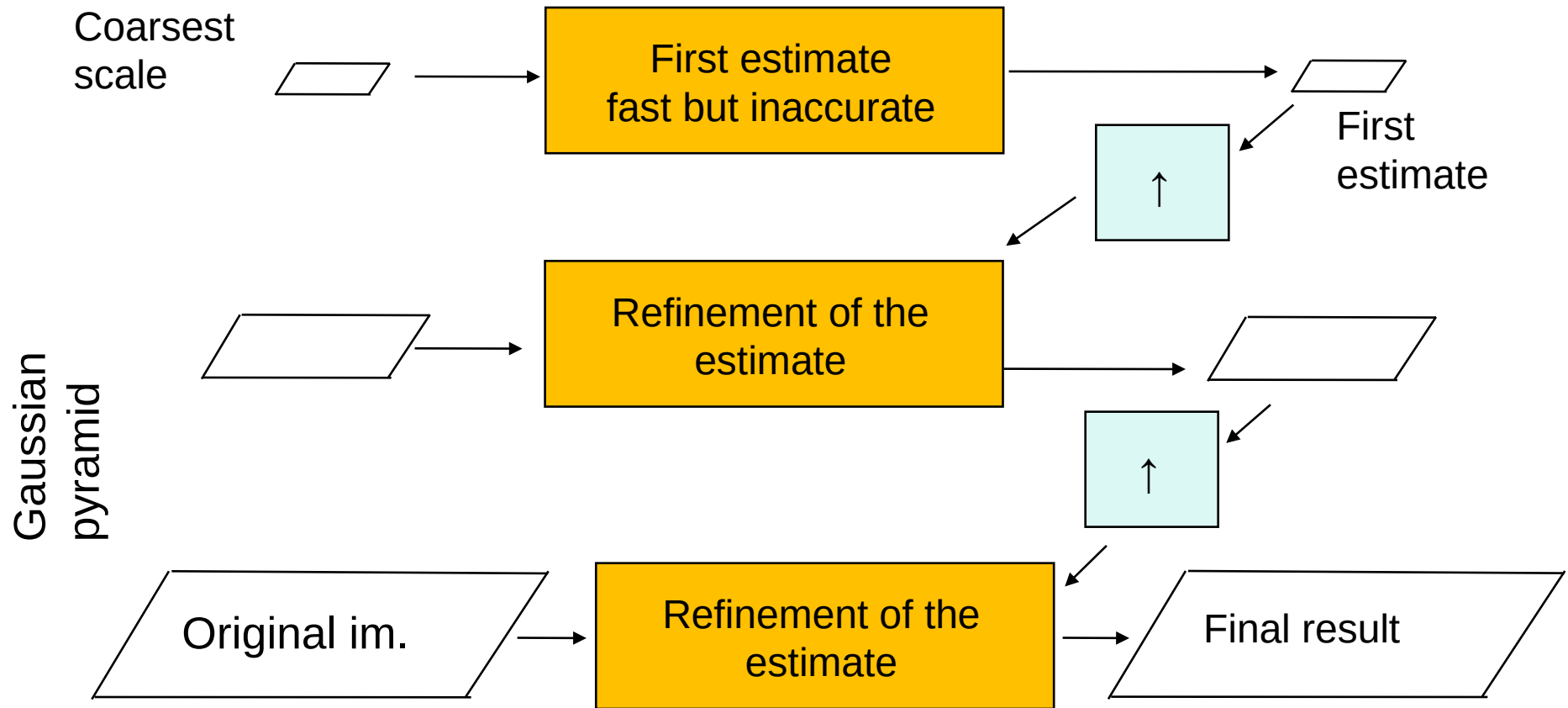
Coarse-to-fine search/detection



Coarse-to-fine refinement

- A similar, processing scheme is the following:
 - Estimate a local feature at the coarsest scale first
 - Little data – fast processing
 - Coarse scale – inaccurate
 - The coarse estimate of the feature is then up-sampled to the size of the second coarsest scale, where the estimate is refined
 - The refinement is based on estimating the refinement of the coarsest estimate by analyzing the image at the second coarsest scale.
 - The refinement estimate is then up-sampled and refined again.
 - By repeating this procedure, we obtain a very accurate estimate of the feature at the finest scale.
 - Example: estimation of local velocity or disparity
-

Coarse-to-fine refinement



Example: Depth from stereo



Images from Wallenberg & Forssén:
*Teaching Stereo Perception
to YOUR Robot*, BMVC 2012

Compute a scale hierarchy. Start estimating *disparity* at the coarsest level, and refine

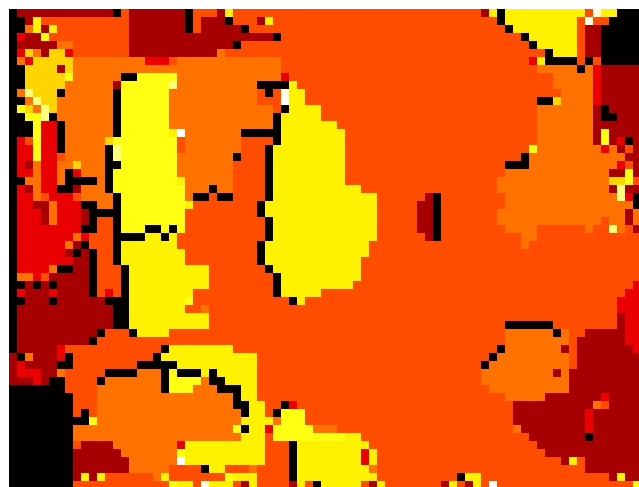
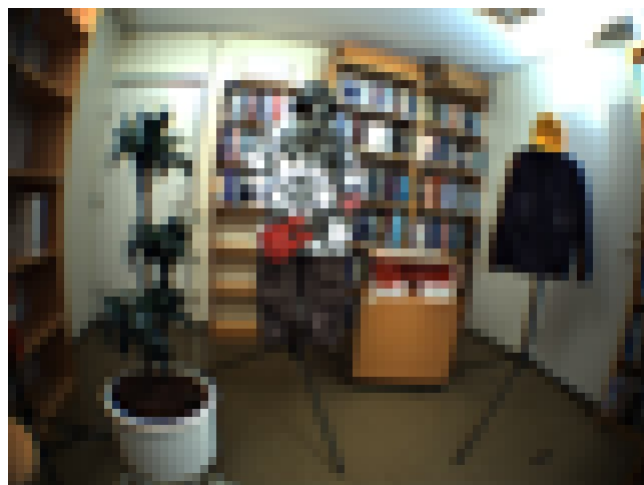
Example: C2F Stereo disparity



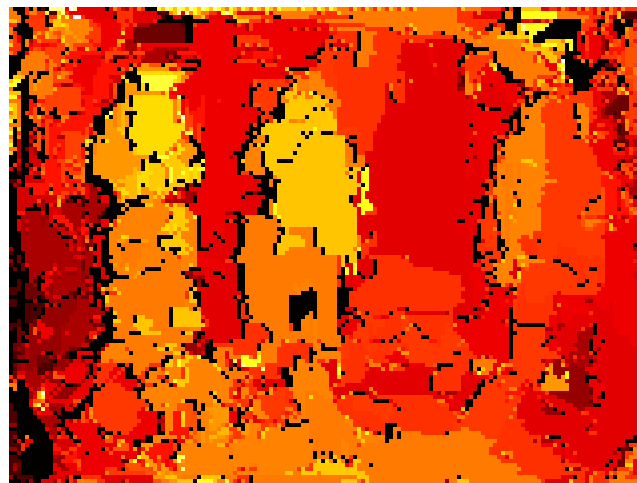
Example: C2F Stereo disparity



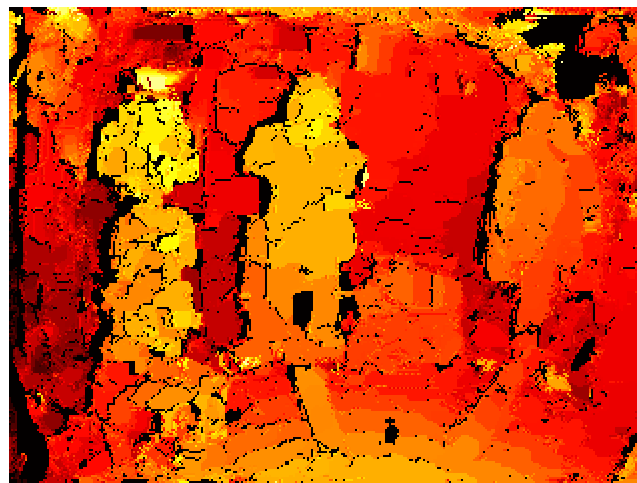
Example: C2F Stereo disparity



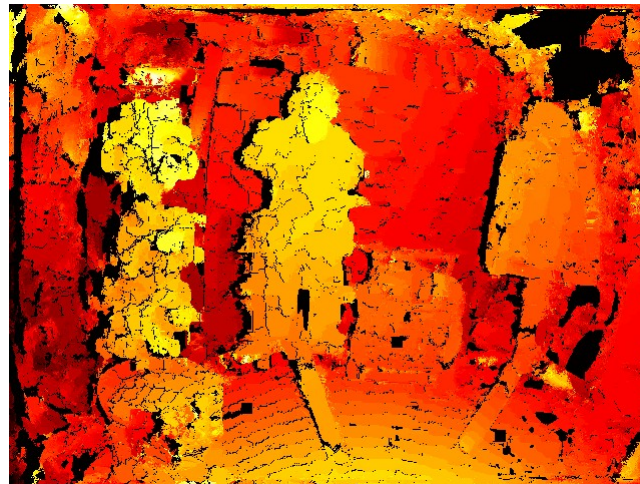
Example: C2F Stereo disparity



Example: C2F Stereo disparity



Example: C2F Stereo disparity



Images

- An image typically represents, at each position $\mathbf{p}=(u,v)$ a measurement of
 - Light intensity
 - Color
 - Absorption (X-ray)
 - Reflection (Ultrasonic)
 - Hydrogen content (MRI)
- All these represent physical phenomena
- All these can be input to a scale hierarchy

Feature image

- The value at position $\mathbf{p}=(u,v)$ can also be used to represent a *local image feature*
- May not have a direct physical interpretation
 - Local mean or variance (scalars)
 - Local edge presence (binary)
 - Local gradient (a vector)
 - Local orientation (to be discussed)
 - Local curvature (to be discussed)
 - Interest points (to be discussed)

Edge representation



Canny

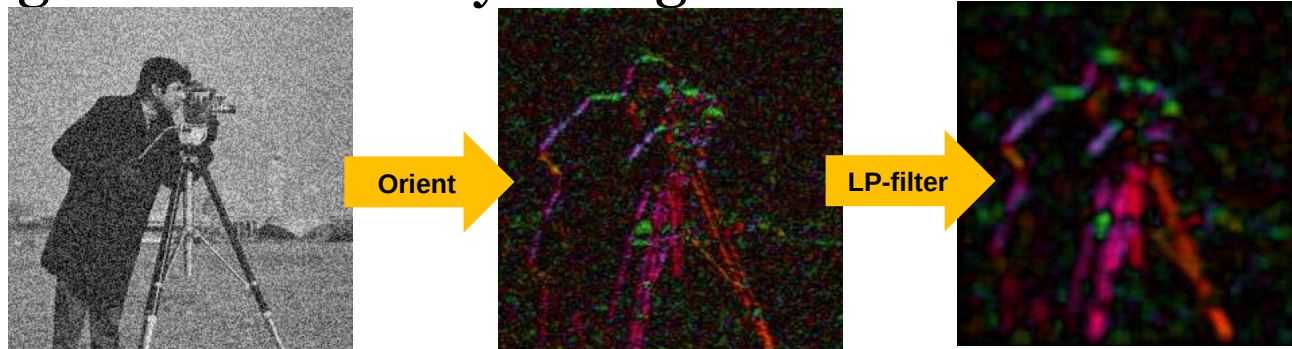


Orient



Notes on Representations

- If a local feature can be assumed to be constant in a neighborhood, it is desirable that its representation can be *locally averaged*
 - The averaged representation = the feature mean
 - Noise in the signal results in noise in the estimate of the feature representation
 - By low-pass filtering the representation (local mean value), the noise is reduced
 - In general: intensity changes faster than orientation

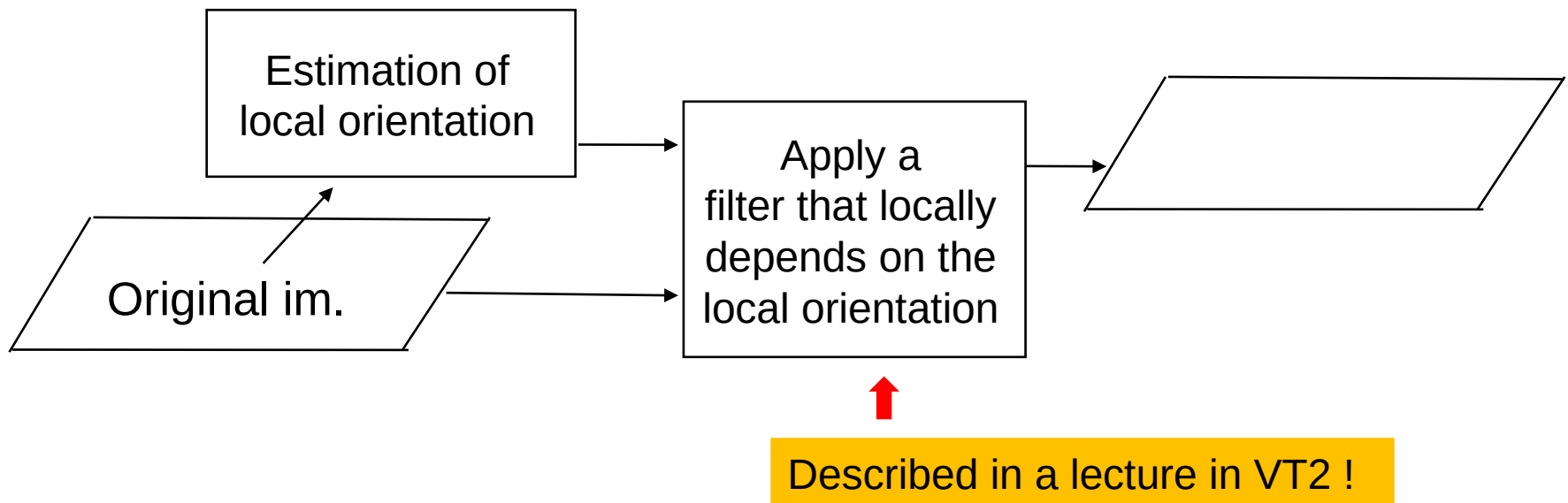


Confidence measure

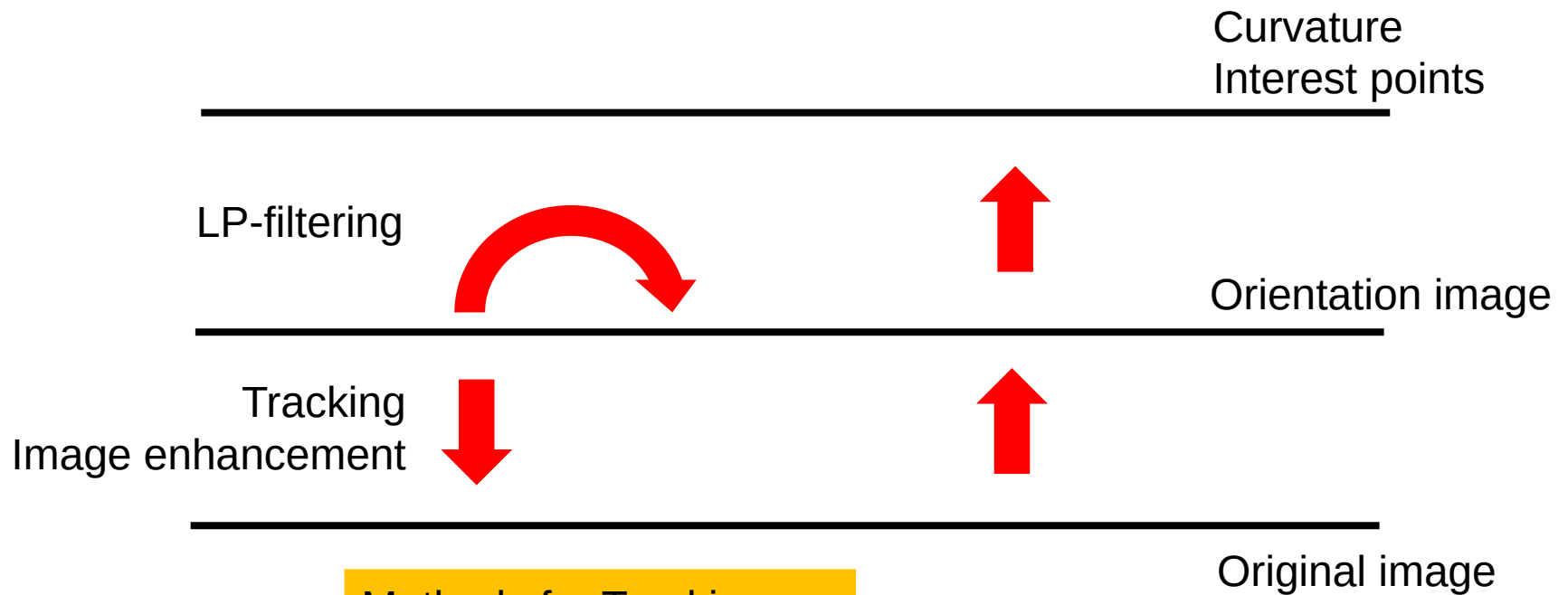
- Feature representations should contain a confidence measure (or variance estimate), separated from the feature estimate itself
 - Measures how confidence of the feature estimate
 - For example: in the range $[0, 1]$
 - Value 0: no confidence, value 1: max confidence
- The confidence can be used to weight the feature representation when estimating the mean value
 - Normalized convolution!

Model-Based Processing

- Orientation images can be used to control the processing of an image
- Example: adaptive image enhancement



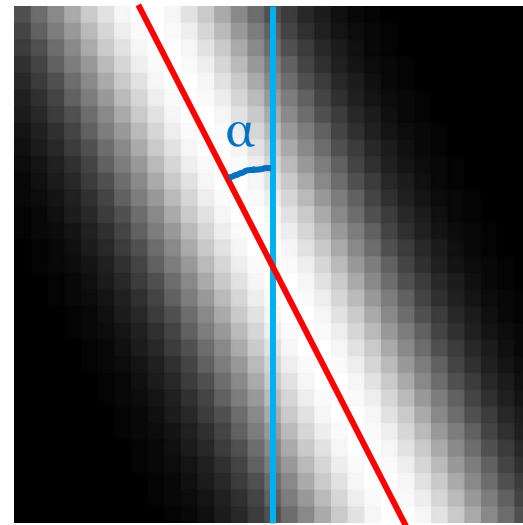
Orientation images Applications



Methods for Tracking and Image enhancement are described in later lectures

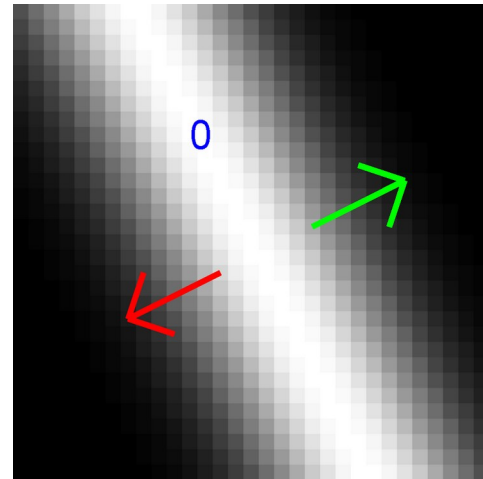
Representation of Local Orientation: Angle

- Signal model: simple signal (i1D, lecture 1)
- In a local region of each image point:
 - measure an angle α , e.g. between the vertical axis and the lines of constant signal intensity, e.g. in the interval 0 to 180°
- Average-able?
 - No! (**why?**)
- Confidence measure?
- How to extend to 3D?



Estimation of Local Orientation: Gradient

- In each point we measure the local gradient of the signal (e.g. using a Sobel-operator)
- Issues:
 - For an 1D signal, the sign of the gradient depends on where we do the measurement
 - The gradient might be $= 0$ at certain lines of the 1D signal
 - Confidence measure?

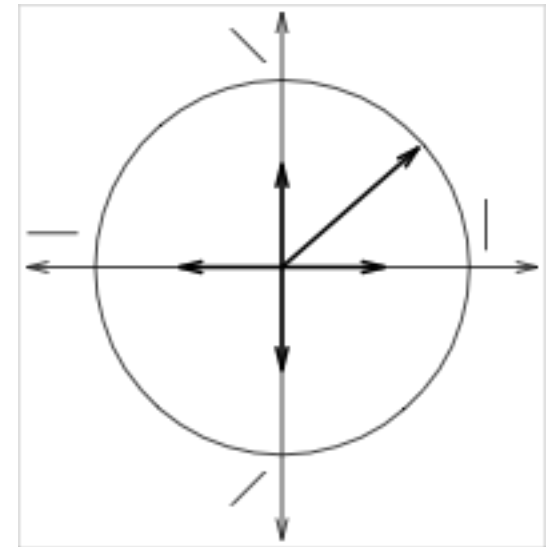


Representation of Local Orientation: Double angle vector

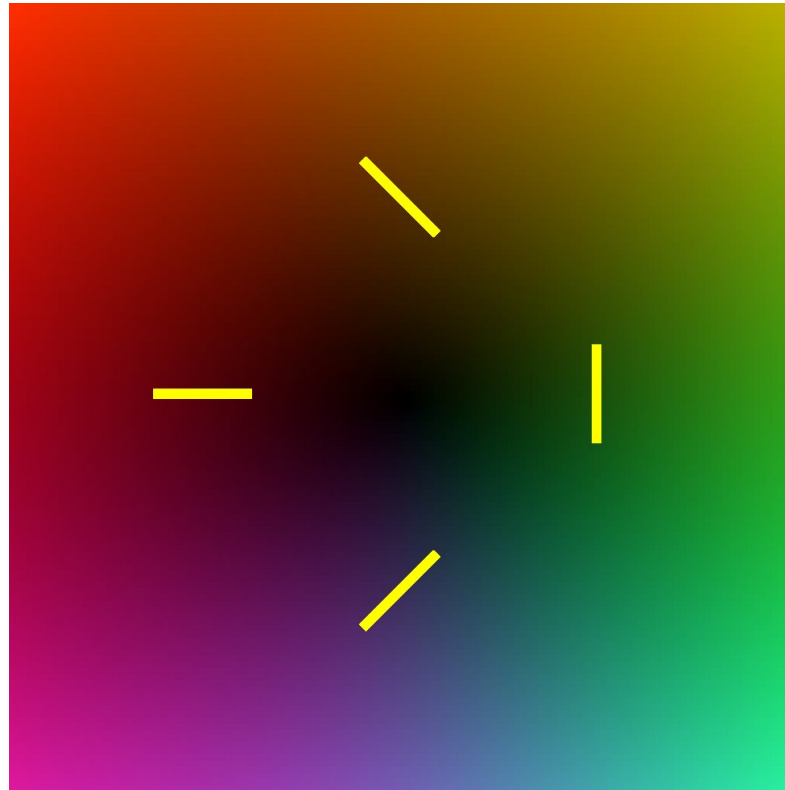
- Alternative: double the angle to 2α , which lies in the interval 0 to 360°
- Form a 2D vector \mathbf{v} which points with the angle 2α
- Let the norm of \mathbf{v} represent the confidence measure
- Called: *double-angle representation* of local 2D orientation

Representation of Local Orientation

- The double-angle representations of two similar orientations are always similar (*continuity* results in *compatibility*)
- Two orientations which differ most (90°) are always represented by vectors that point in opposite directions (*complementarity*)



Colour coding of the double angle representation



Representation of Local Orientation

- Double-angle representations of local 2D orientations can be averaged
 - The averaged representation = the feature mean
- Averaging of vectors is automatically weighted with the confidences

In later lectures:

- How to estimate the double-angle representation from image data?
- What to do in 3D?

Representation of Local Orientation

- Signal model for simple (i1D) signal at point \mathbf{p}
$$I(\mathbf{p} + \mathbf{x}) = g(\mathbf{x} \cdot \hat{\mathbf{n}}), \quad \hat{\mathbf{n}} = (\cos \alpha, \sin \alpha)^\top$$
- I is the local signal (2 or more dimensions)
- g is the 1D function that defines the variations of the i1D signal
- \mathbf{x} is a deviation from position \mathbf{p}
- \mathbf{n} is a vector that defines the orientation
- BUT: the direction (sign) of \mathbf{n} is not unique

Representation of Local Orientation: Tensor

- The double-angle vector \mathbf{v} becomes

$$\mathbf{v} = \lambda (\cos 2\alpha, \sin 2\alpha)^T$$

- λ is a scalar which gives the confidence
- Alternative: form a 2 x 2 symmetric matrix

$$\mathbf{T} = \lambda \hat{\mathbf{n}} \hat{\mathbf{n}}^T = \lambda \begin{pmatrix} \cos \alpha \\ \sin \alpha \end{pmatrix} (\cos \alpha \quad \sin \alpha)$$

- *Tensor representation of local orientation*

Representation of Local Orientation

- Tensor components

$$\mathbf{T} = \begin{pmatrix} T_{11} & T_{12} \\ T_{12} & T_{22} \end{pmatrix} = \begin{pmatrix} \cos^2 \alpha & \cos \alpha \sin \alpha \\ \cos \alpha \sin \alpha & \sin^2 \alpha \end{pmatrix}$$

- Vector components

$$\mathbf{v} = \begin{pmatrix} \cos 2\alpha \\ \sin 2\alpha \end{pmatrix} = \begin{pmatrix} \cos^2 \alpha - \sin^2 \alpha \\ 2 \cos \alpha \sin \alpha \end{pmatrix} = \begin{pmatrix} T_{11} - T_{22} \\ 2 T_{12} \end{pmatrix}$$

- The tensor contains one more element than \mathbf{v}

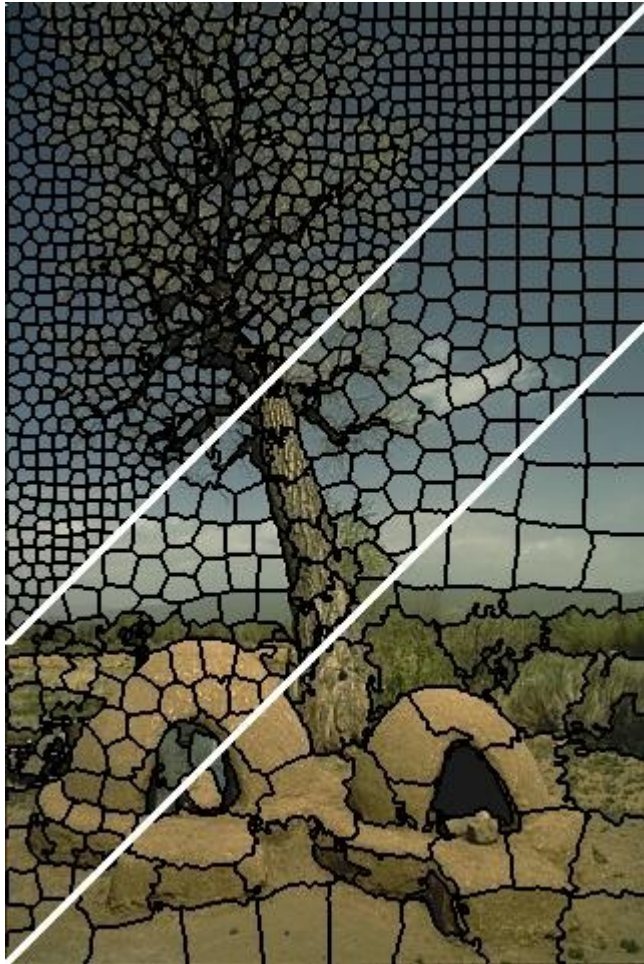
Representation of Local Orientation

- \mathbf{n} is an eigenvector of \mathbf{T} with eigenvalue λ
- \mathbf{T} (but not \mathbf{v}) can be defined for any dimension of signals (3D, 4D, ...)
- How to estimate \mathbf{v} and \mathbf{T} from signals?

Tensor or Matrix?

- In this course, the term *tensor* is used as synonym for *symmetric matrix*.
- Why tensor and not matrix?
 - A matrix is just a representation, consisting of a container with numbers in a table.
 - A tensor can be represented as a matrix but it must furthermore obey certain laws under transformations of the coordinate system.
 - Note the different use in Deep Learning

Super-pixels



Examples from
Achanta et al,
(SLIC)

Showing different
sizes of the
clusters

Also known as:
Over-
segmentation

Super-pixels

- The array/matrix representation of an image implies that, in principle, each pixel must be examined in order to extract information about the image
- An alternative to the array/matrix representation is to **cluster** neighboring pixels with similar values to *super-pixels*
 - Often with restrictions on the cluster: size, shape
- Each super-pixel is represented as the common value and a cluster of pixels
- The image is represented as the set of its super-pixels
- Normal image: approx. 1 M pixels
- Super-pixels image: approx. 1 k super-pixels

Super-pixels

Typical approach:

- Initialize a regular grid of “square” super-pixels
- Iteratively modify each super-pixel to increase homogeneity regarding its corresponding pixel values
 - Split super-pixels into smaller ones if necessary
 - Merge similar super-pixels if possible
 - Move pixels from one super-pixel to a neighboring one to improve super-pixel shape