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CENTER FOR MACHINE PERCEPTION

Local Feature Extraction and Description for

Wide-Baseline Matching, Object Recognition and Image Retrieval Methods, Stitching and more ...

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The Correspondence Problem

Establishing correspondence is the key issue in many computer vision problems:

- Object recognition and Image retrieval
- Wide baseline matching
- Detection and localisation
- 3D Reconstruction
- Image Stitching
- Tracking

Local Features

- Methods based on “Local Features” are the state-of-the-art for number of computer vision problems (often those. that require local correspondences).

- E.g.: Wide-baseline stereo, object recognition and image retrieval.

- Terminology is a mess:
  Local Feature = Interest “Point” = The “Patch” =
  = Feature “Point”
  = Distinguished Region
  = (Transformation) Covariant Region

Image Stitching: Building a Panorama:
Example of a Method Based on Local Features

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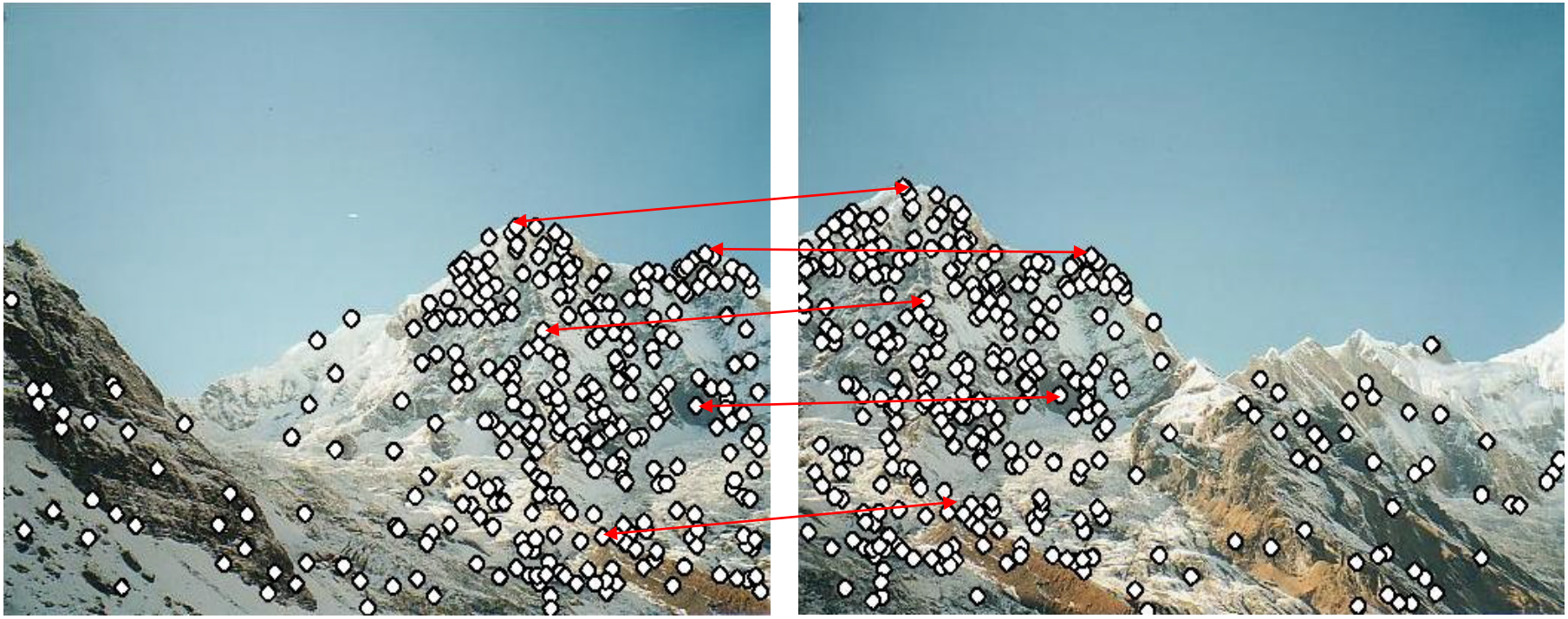
M. Brown and D. G. Lowe. Recognising Panoramas. ICCV 2003

How do we build a panorama?

- We need to match (align) images = find (dense) correspondence
- (technically, this can be done only if both images taken from the same viewpoint)

Possible Approach: Matching Features

1. Detect feature points in both images
2. Find corresponding pairs
3. Estimate transformations (Geometry and Photometry)
4. Put all images into one frame, blend.



Matching with Features

- Problem 1:
  - Detect the *same* point *independently* in both images*
  - Note that the set of "points" is rather sparse

no chance to match!

A repeatable detector needed.

* does it have to be independent

Matching with Features

- Problem 2:
  - how to correctly recognize the corresponding points?

Solution:

1. Find a discriminative and stable descriptor
2. Solve the matching problem

Matching with Features

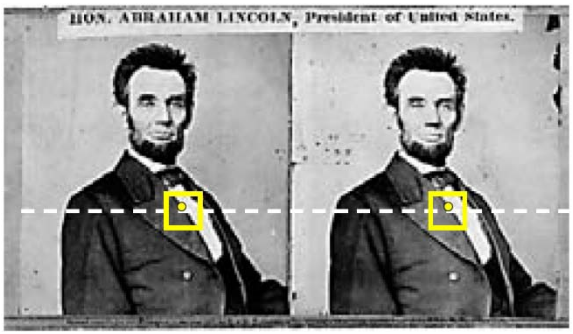
- Detect feature points in both images
- Find corresponding pairs
- Use these pairs to align images

Any alternatives?

Perhaps "Feature Points" not needed? Classical Stereo.

1. Local Feature (Region) = a rectangular "window"
   - robust to occlusion, translation invariant
   - windows matched by correlation, assuming small displacement
2. Local Feature (Region) = a circle around an "interest point"

- translation and rotation invariant, robust to occlusion
- matching based on correlation or rotation invariants *(note that the set of circles of a fixed radius is closed under translation and rotation).*
- successful in tracking and stereo matching



Hard Impossible for a Local feature based method?

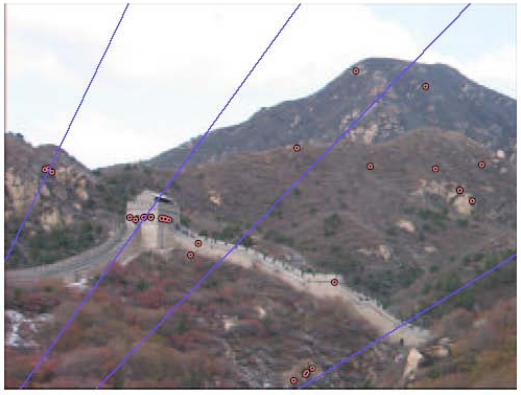
From Classical (= Narrow) to Wide Baseline Stereo

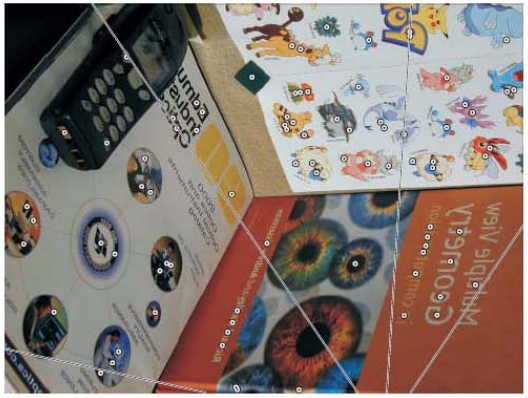
3. Widening of baseline or zooming in/out

• local deformation is well modelled by affine or similarity transformations

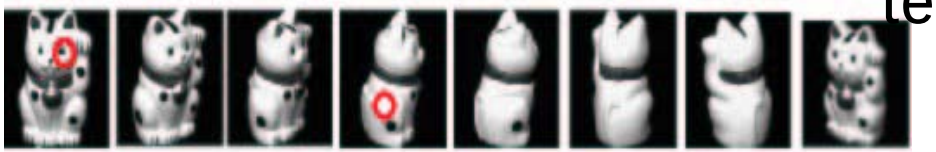
• How can the "interest point" concept be generalised? *The set of ellipses is closed under affine tr., but its too big to be tested* ..

•Window scanning approach becomes computationally difficult.





(Specific Object) Recognition:



Pose space search v. Correspondence (matching) problem?

The pose space is high dimensional, but translation, scale (in a pyramid), rotation (a discrete set of angles) can be handled already ...in combination with sequential techniques.

Local Invariant Features

Design of Local Features

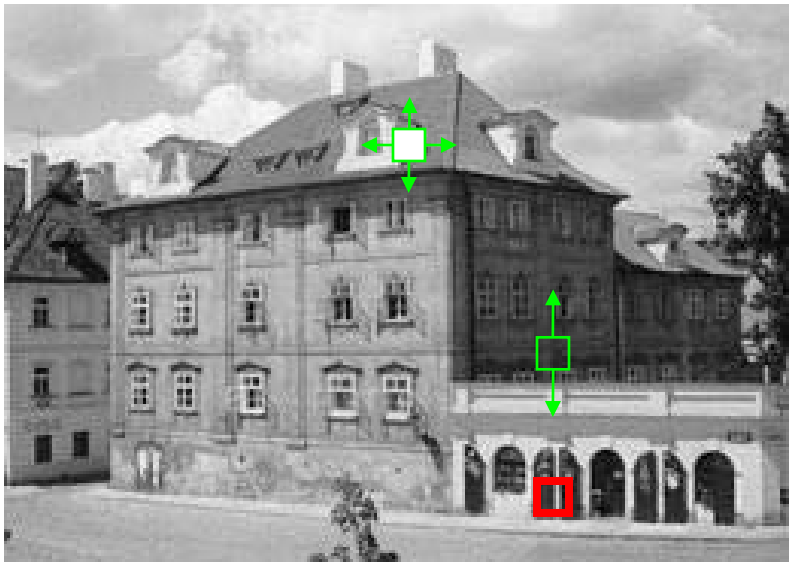
- "Local Features" are **regions,** i.e. in principle arbitrary sets of pixels (not necessarily contiguous) with
- High **repeatability,** (invariance in theory) under
  - Illumination changes
  - Changes of viewpoint $\Rightarrow$ geometric transformations

  i.e. are **distinguishable** in an image regardless of viewpoint/illumination $\Rightarrow$ are **distinguished regions**
- Are **robust to occlusion** $\Rightarrow$ must be **local**
- Must have discriminative neighborhood $\Rightarrow$ they are **"features"**

Methods based on local features/distinguished regions (DRs) formulate computer vision problems as matching of some representation derived from DR
(as opposed to matching of images)

Harris detector (1988)

3500 citations



undistinguished patches:

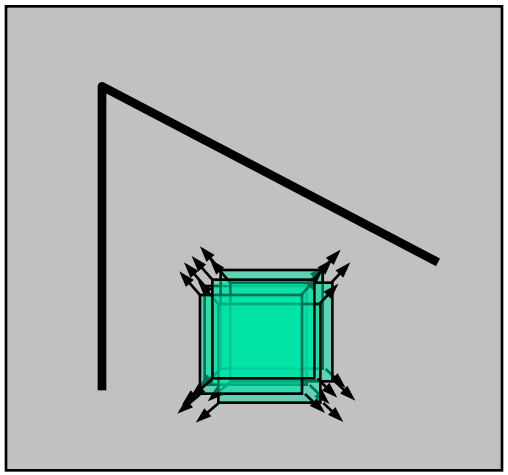
distinguished patches:

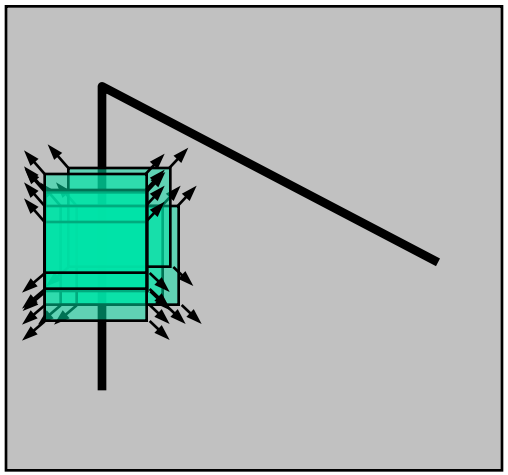
Two core ideas (in “modern terminology”):

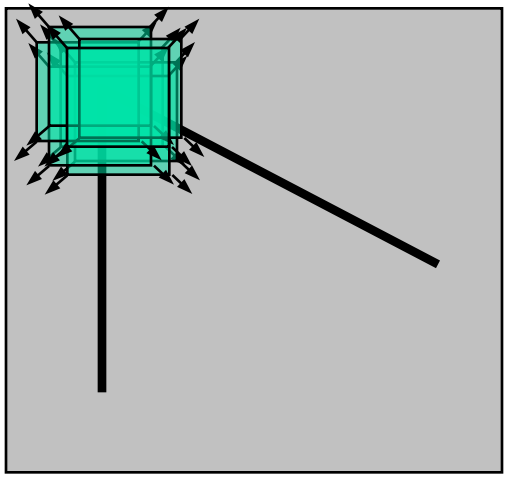
1. To be a distinguished region, a region must be *at least* distinguishable from *all* its neighbours.
2. Approximation of Property 1. can be tested very efficiently, without explicitly testing.

Note: both properties were proposed before Harris paper, (1) by Moravec, (1)+(2) by Foerstner.

Harris Detector: Basic Idea







"flat" region: no change in all directions

"edge": no change along the edge direction

"corner": significant change in all directions

- We should easily recognize the point by looking through a small window
- Shifting a window in *any direction* should give *a large change*

Harris Detector: Mathematics

Window-averaged change of intensity for the shift $[u,v]$:

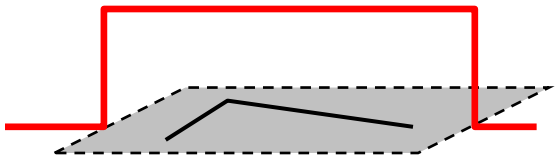
$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

Window function

Shifted intensity

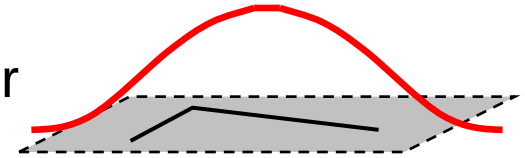
Intensity

Window function $w(x,y)$ =



1 in window, 0 outside

or



Gaussian

Harris Detector: Mathematics

Expanding E(u,v) in a 2nd order Taylor series expansion, we have,for small shifts $[u,v]$, a *bilinear* approximation:

$$E(u,v) \cong \begin{bmatrix} u,v \end{bmatrix} \quad M \quad \begin{bmatrix} u \\ v \end{bmatrix}$$

where M is a 2×2 matrix computed from image derivatives:

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

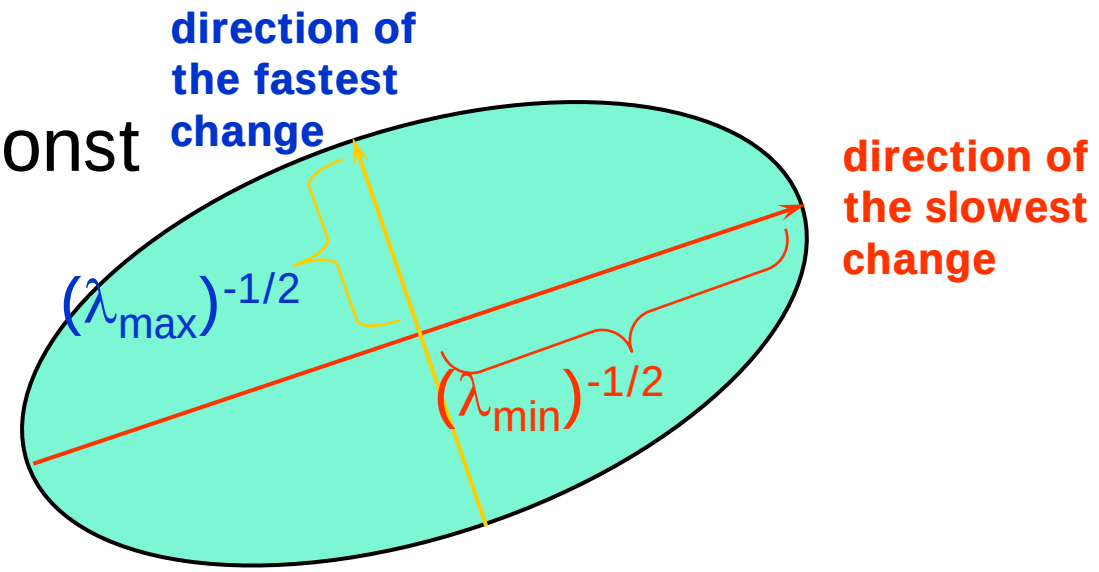
Harris Detector: Mathematics

Intensity change in shifting window: eigenvalue analysis

$$E(u,v) \cong \begin{bmatrix} u, v \end{bmatrix} \; M \; \begin{bmatrix} u \\ v \end{bmatrix}$$

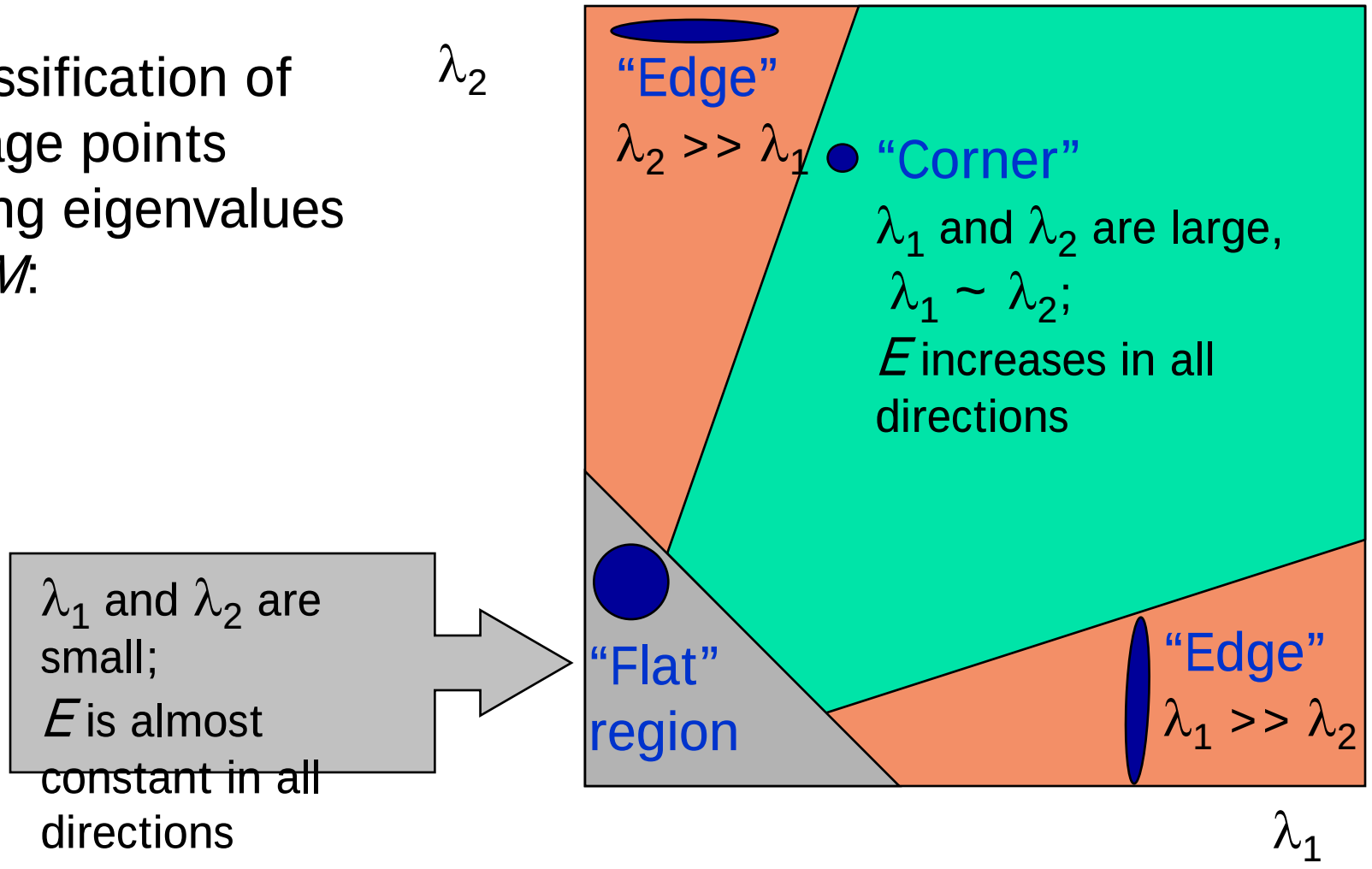
λ_1, λ_2 – eigenvalues of M

Ellipse $E(u,v)$ = const



Harris Detector: Mathematics

Classification of image points using eigenvalues of *M*:



Harris Detector: Mathematics

Measure of corner response:

$$R = \det M - k\left(\operatorname{trace} M\right)^2$$

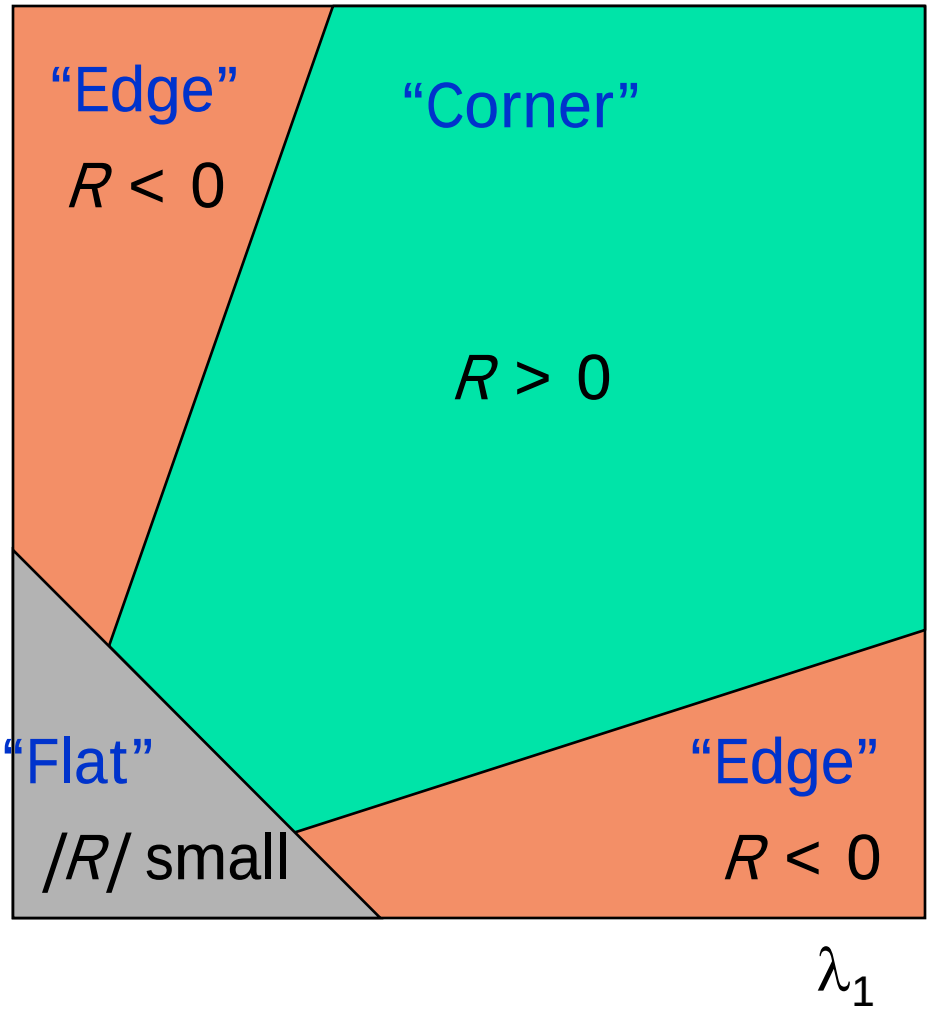
$$\det M = \lambda_1 \lambda_2$$

$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

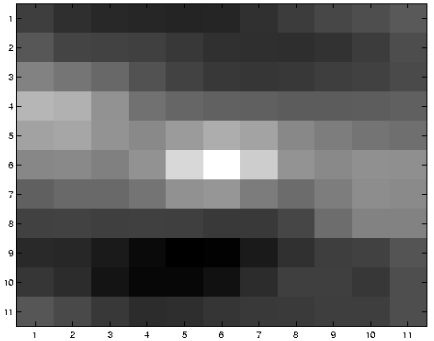
(k – empirical constant, k = 0.04-0.06)

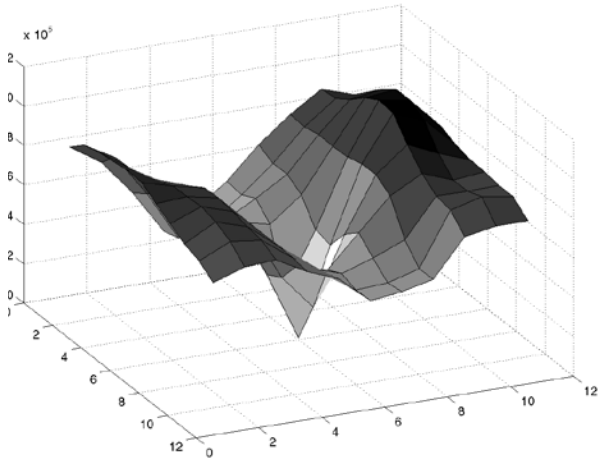
Harris Detector: Mathematics

- R depends only on eigenvalues of M
- R is large for a corner
- R is negative with large magnitude for an edge
- $|R|$ is small for a flat region



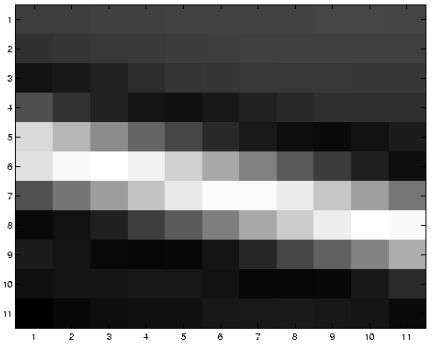
Selecting Good Features

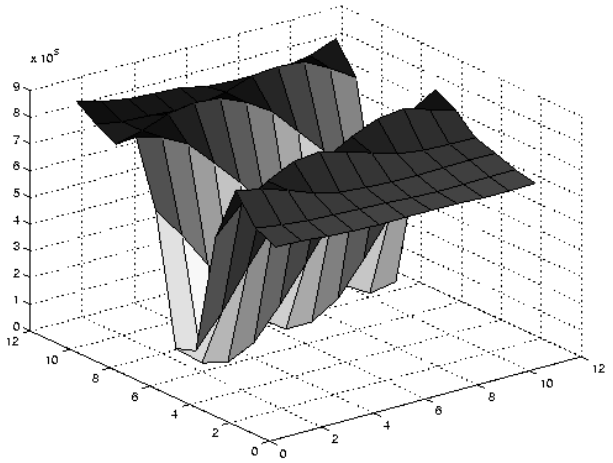




λ_1 and λ_2 are large

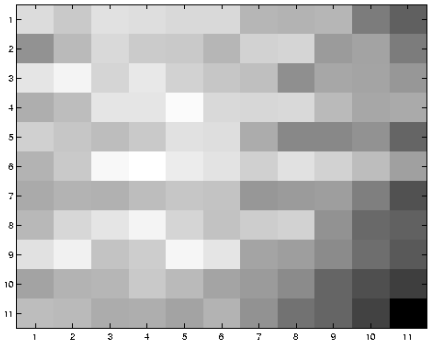
Selecting Good Features

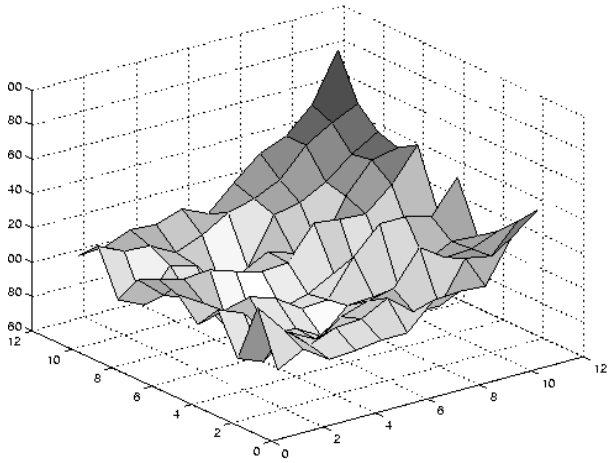




large λ_1, small λ_2

Selecting Good Features





small λ_1, small λ_2

Harris Detector

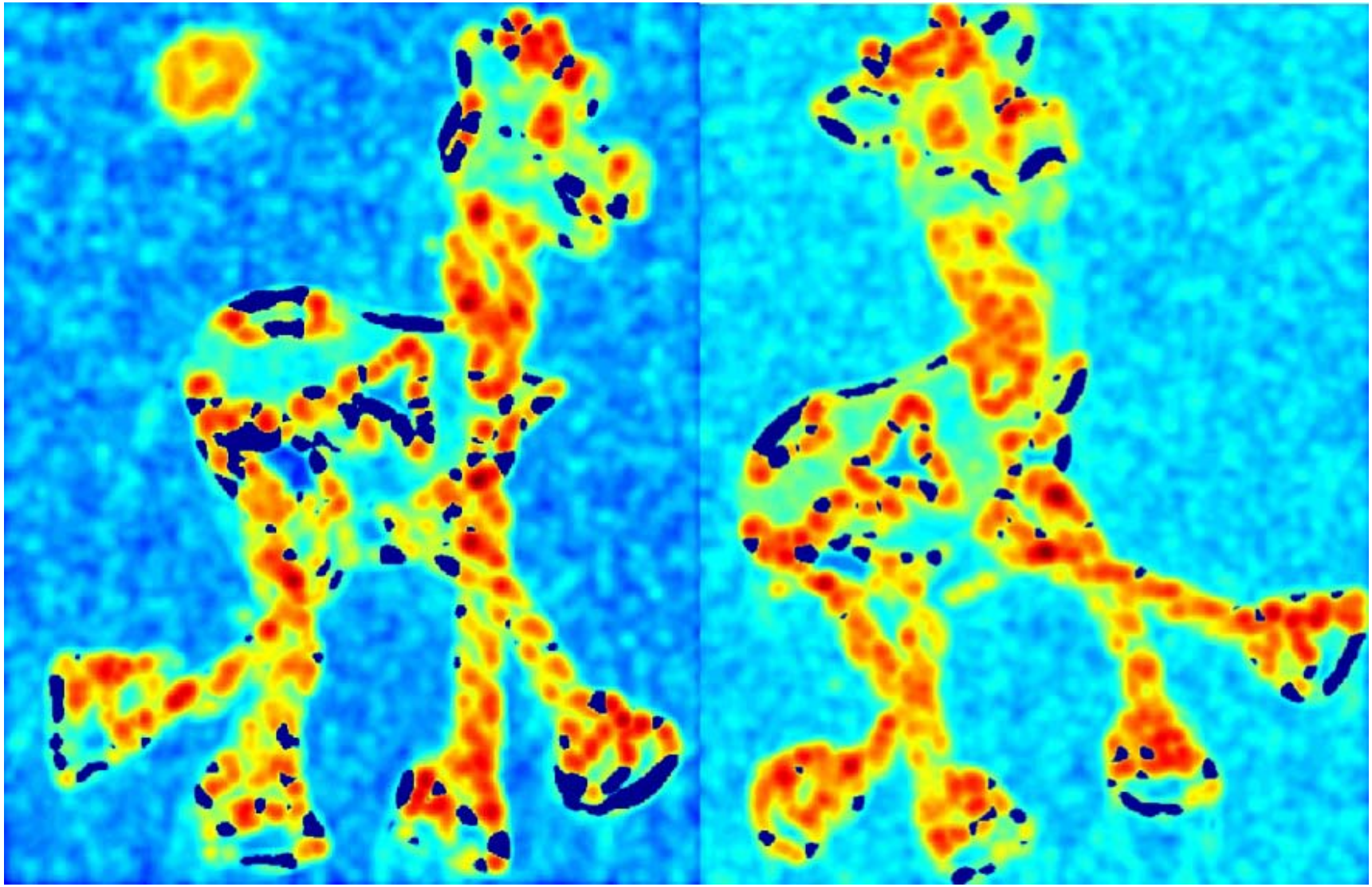
- The Algorithm:
  - Find points with large corner response function R ($R >$ threshold)
  - Take the points of local maxima of R

- Parameters:
  - Threshold on R
  - Scale of the derivative operator (standard setting: very small, just enough to filter anisotropy of the image grid)
  - Size of window W (“integration scale”)
  - Non-maximum suppression algorithm

Harris Detector: Workflow

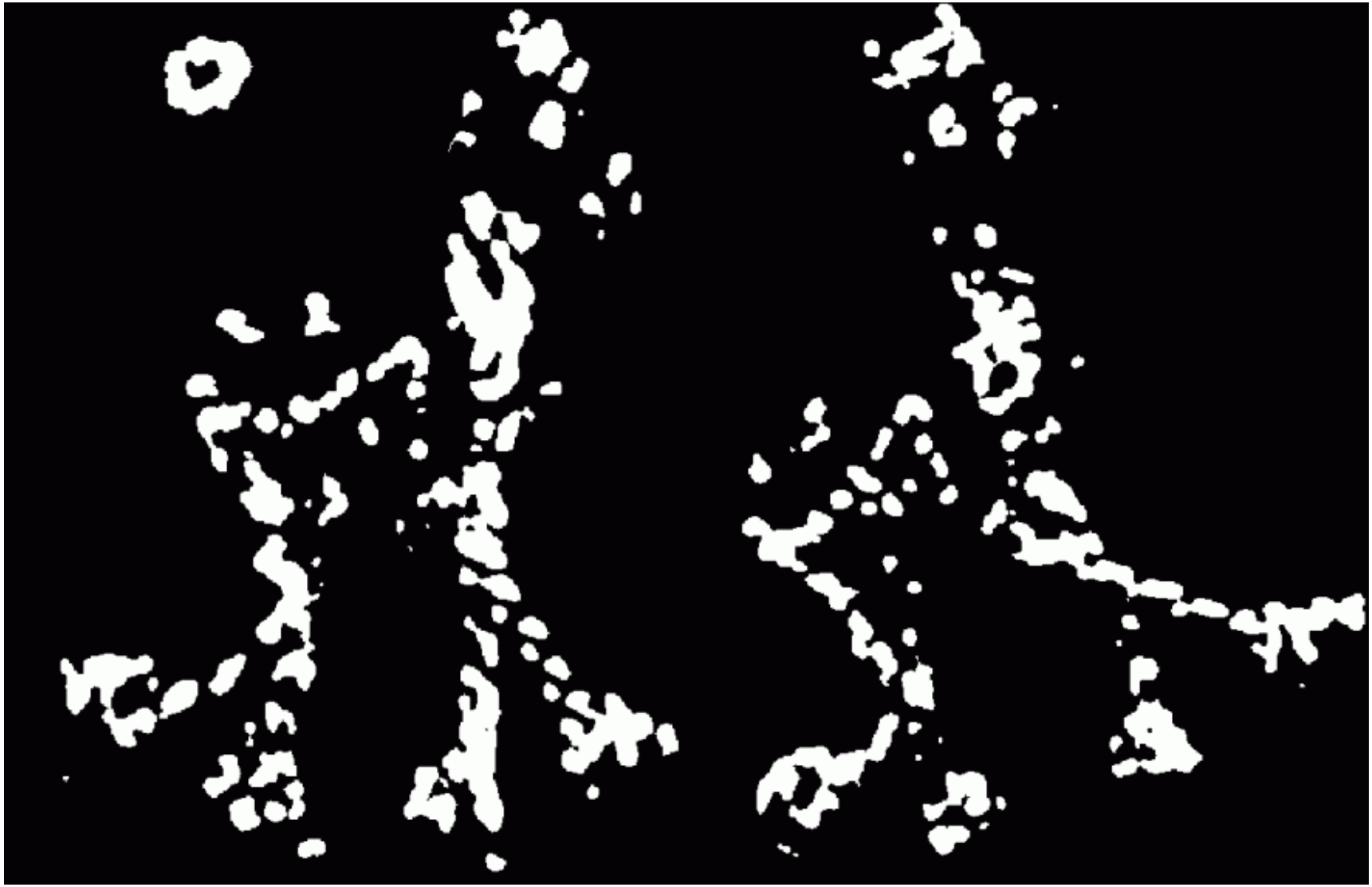
Harris Detector: Workflow

Compute corner response R



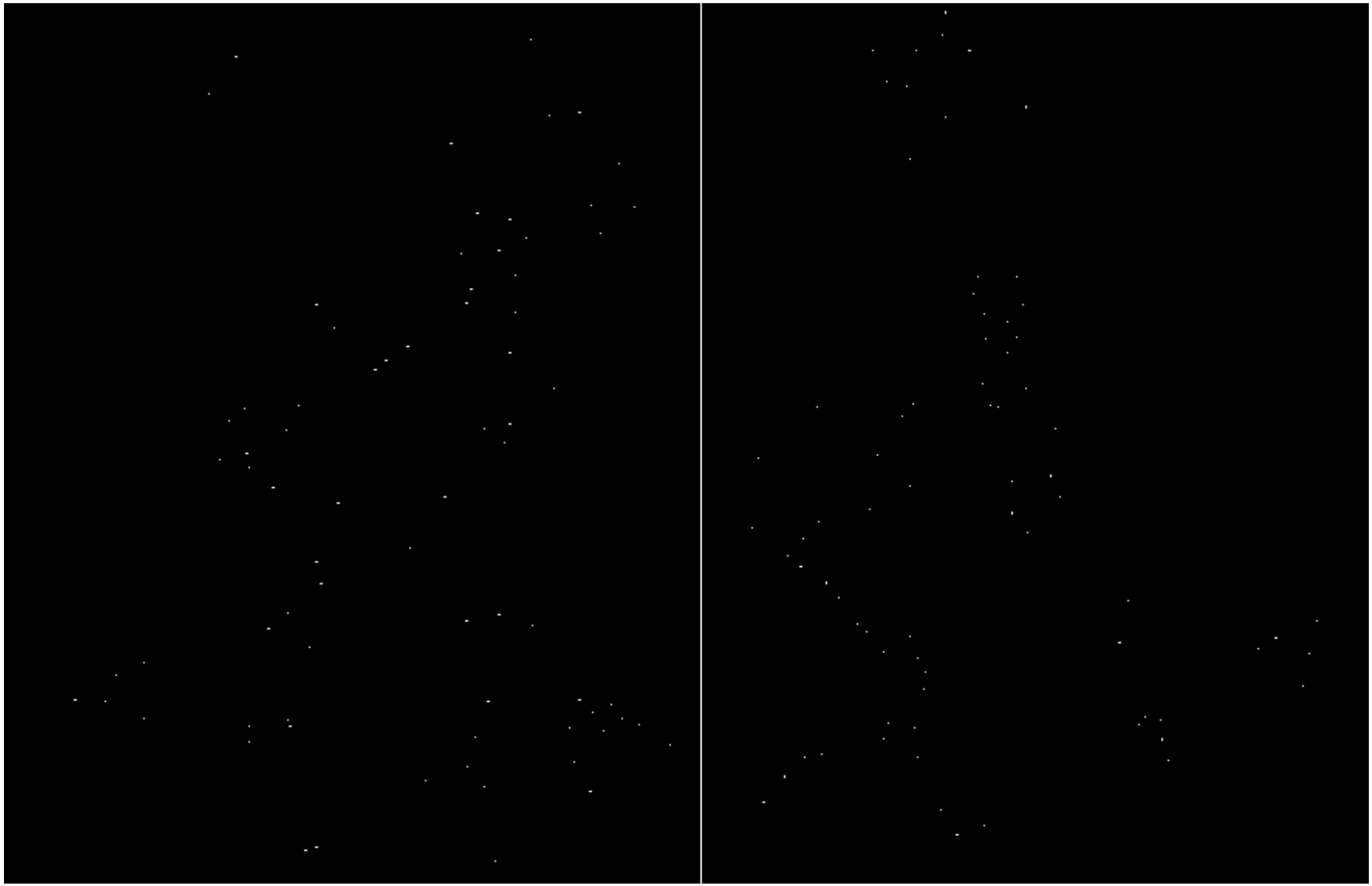
Harris Detector: Workflow

Find points with large corner response: R>threshold



Harris Detector: Workflow

Take only the points of local maxima of R



Harris Detector: Workflow

Harris Detector: Summary

- Average intensity change in direction $[u, v]$ can be expressed as a bilinear form:

$$E(u,v) \cong [u,v] \quad M \quad \begin{bmatrix} u \\ v \end{bmatrix}$$

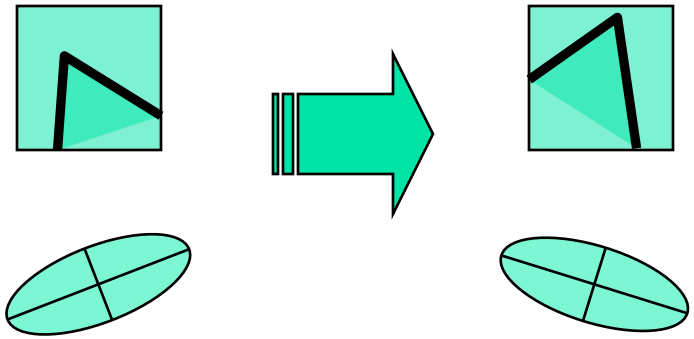
- Describe a point in terms of eigenvalues of M: *measure of corner response*

$$R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$

- A good (corner) point should have a *large intensity change* in *all directions*, i.e. R should be large positive

Harris Detector: Properties

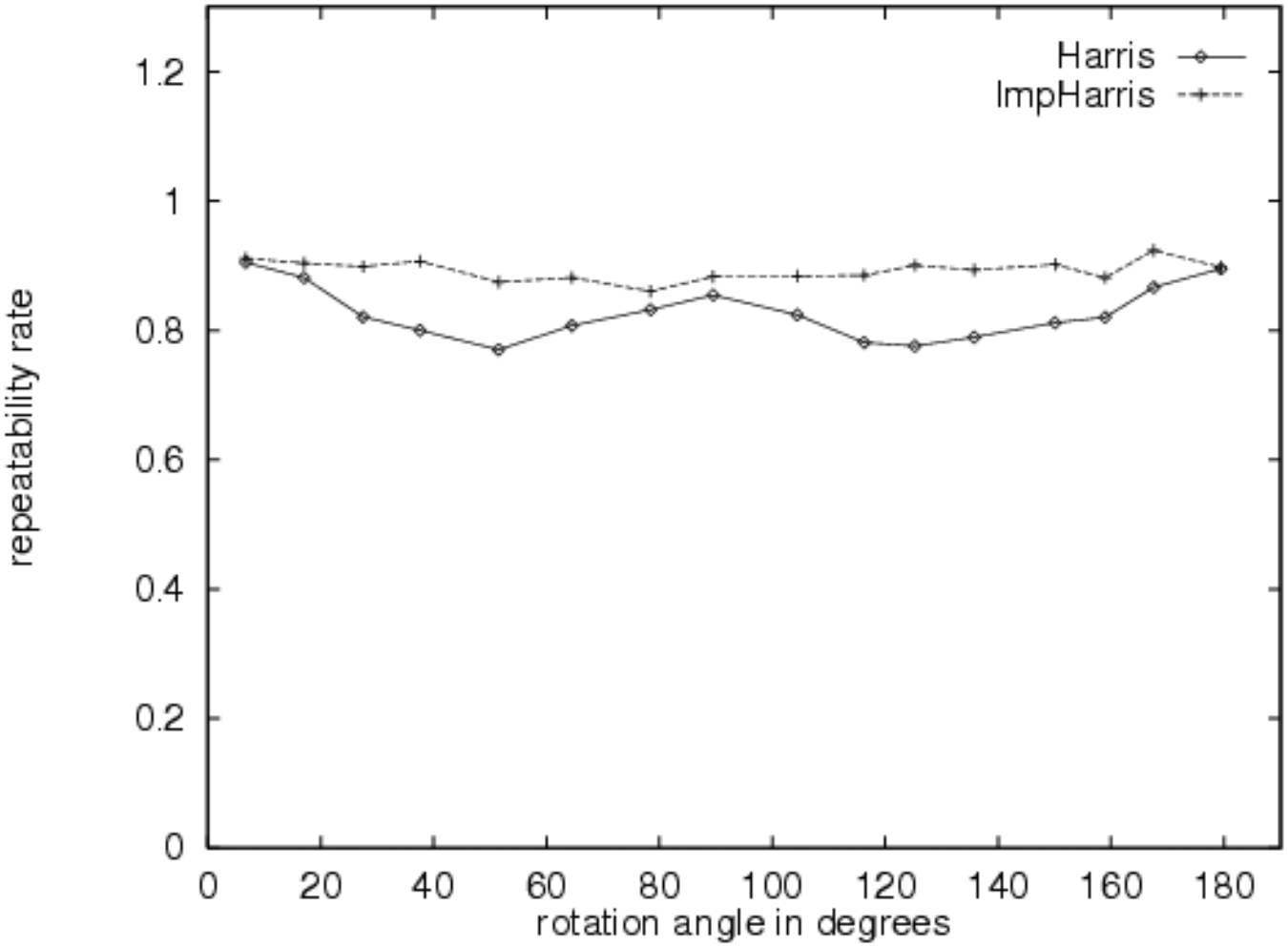
- Rotation invariance



Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response R is invariant to image rotation

Rotation Invariance of Harris Detector



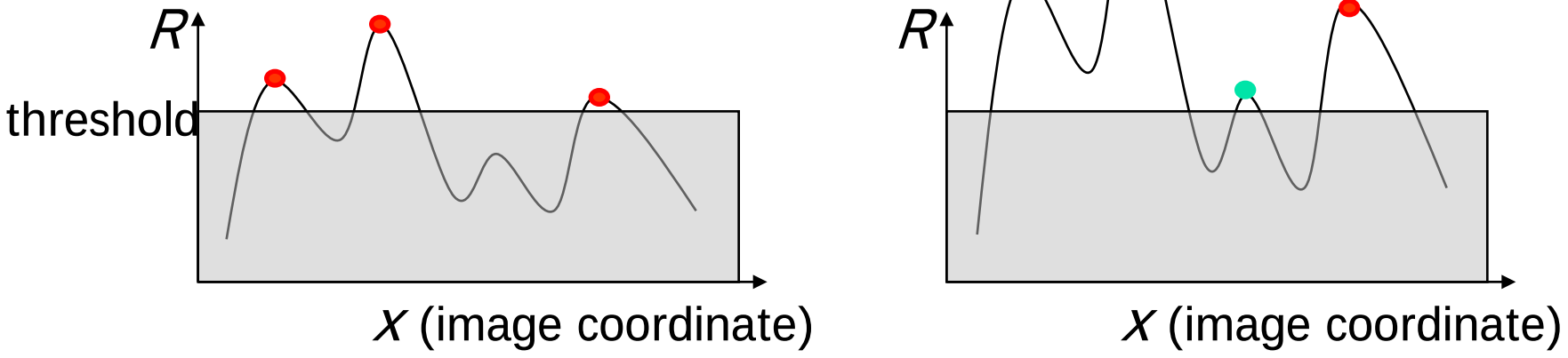
C.Schmid et.al. “Evaluation of Interest Point Detectors”. IJCV 2000

Harris Detector: Intensity change

- Partial invariance to additive and multiplicative intensity changes

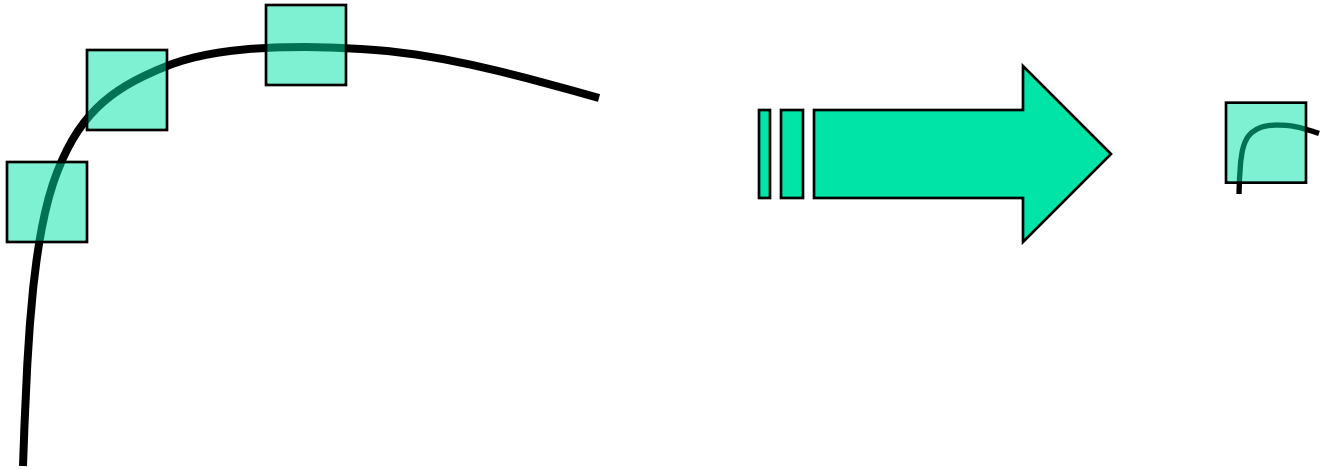
  ✓ Only derivatives are used =>
  invariance to intensity shift $I \rightarrow I + b$

  ? Intensity scale: $I \rightarrow a\,I$



Harris Detector: Scale Change

- Not invariant to *image scale*!



All points will be classified as edges

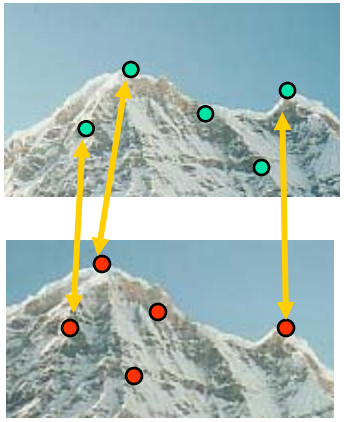
Corner !

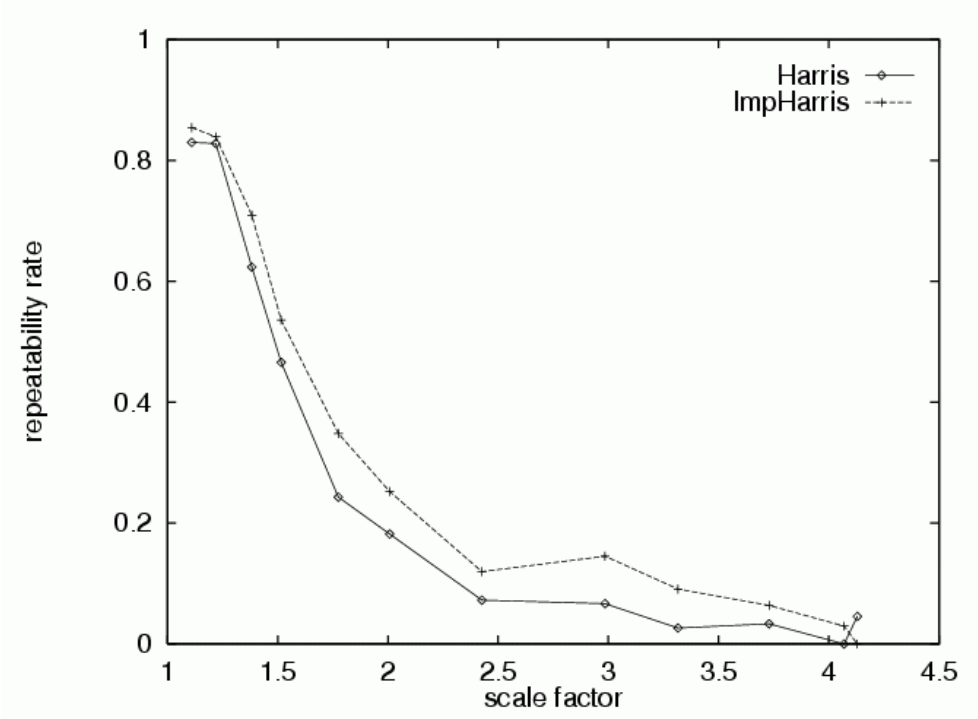
Harris Detector: Scale Change

- Quality of Harris detector for different scale changes

Repeatability rate:

$$\frac{\#\ \text{correspondences}}{\#\ \text{possible correspondences}}$$

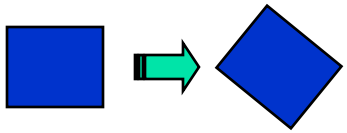


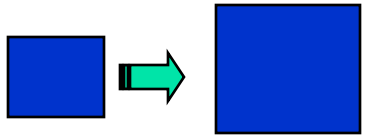


C.Schmid et.al. “Evaluation of Interest Point Detectors”. IJCV 2000

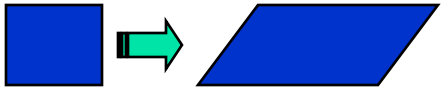
Models of Image Change

- Geometry
  - Rotation
  - Similarity (rotation + uniform scale)

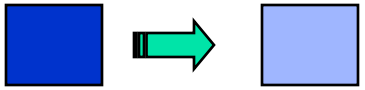




  - Affine (scale dependent on direction)
    valid for: orthographic camera, locally planar object

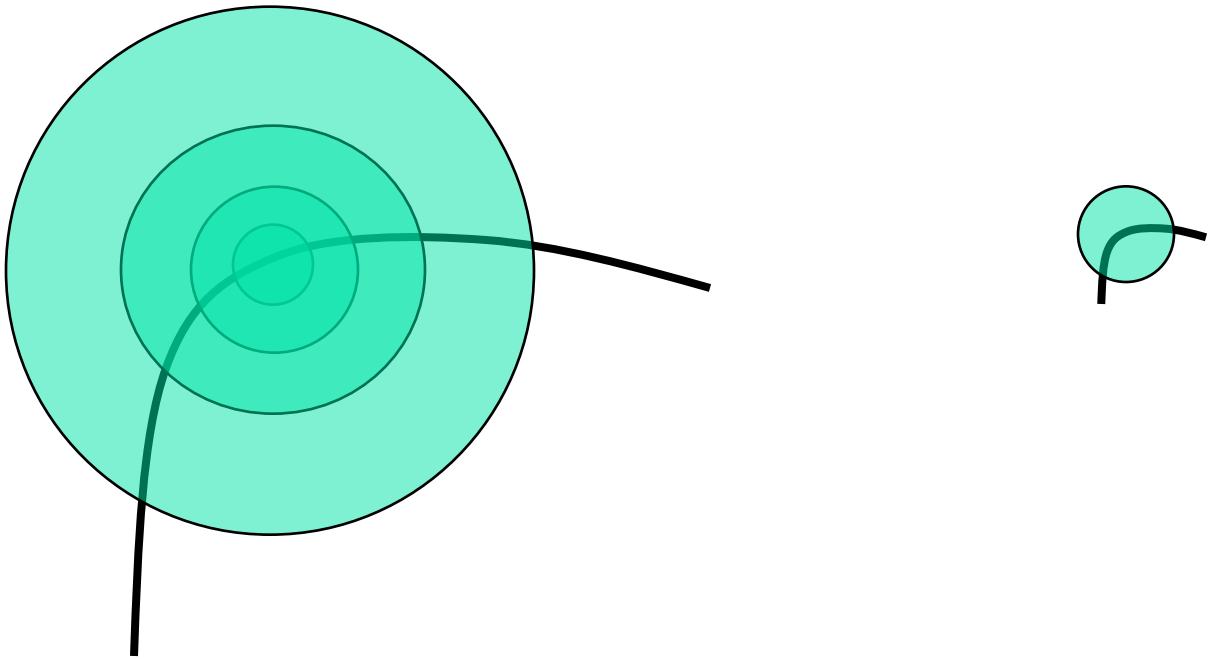


- Photometry
  - Affine intensity change ($I \rightarrow a\,I + b$)



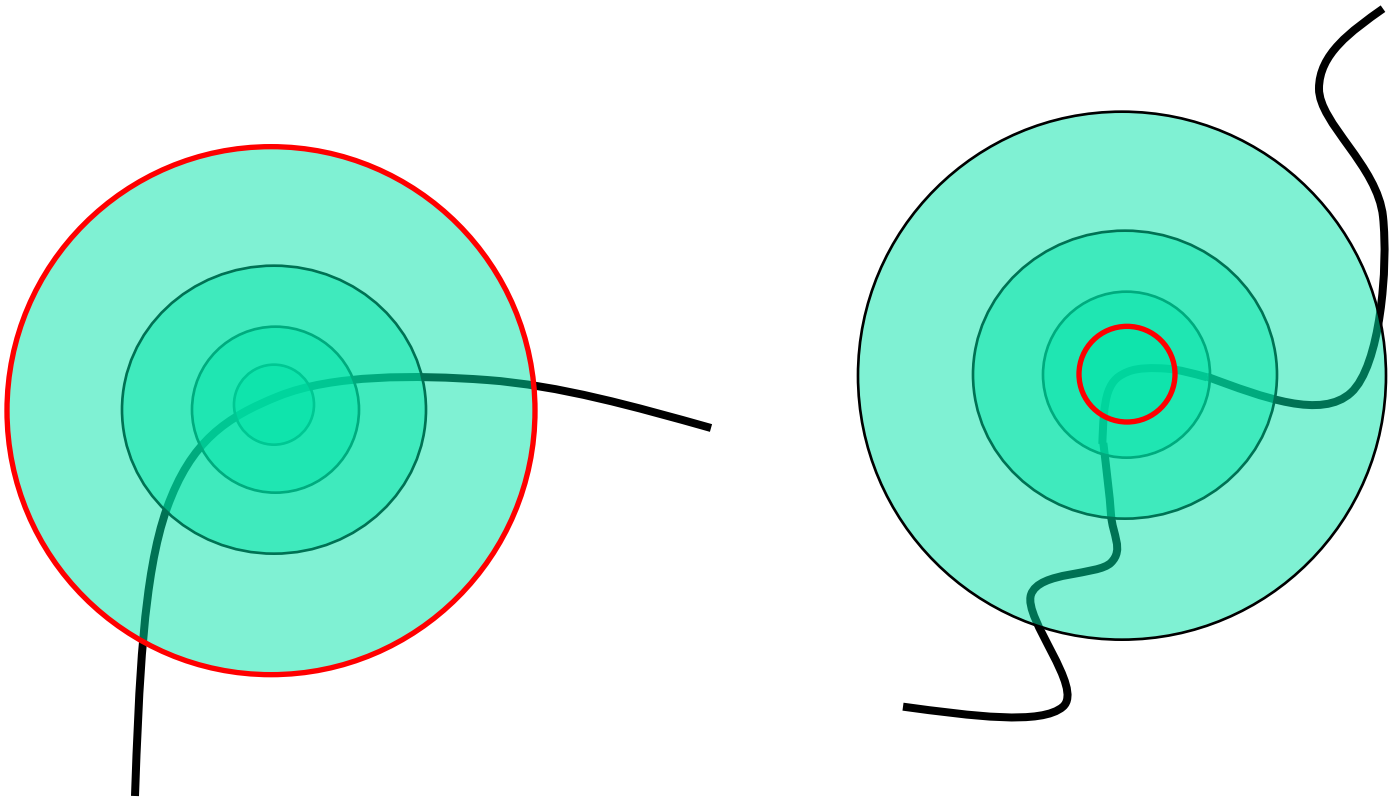
Scale Invariant Detection

- Consider regions (e.g. circles) of different sizes around a point
- Regions of corresponding sizes will look the same in both images



Scale Invariant Detection

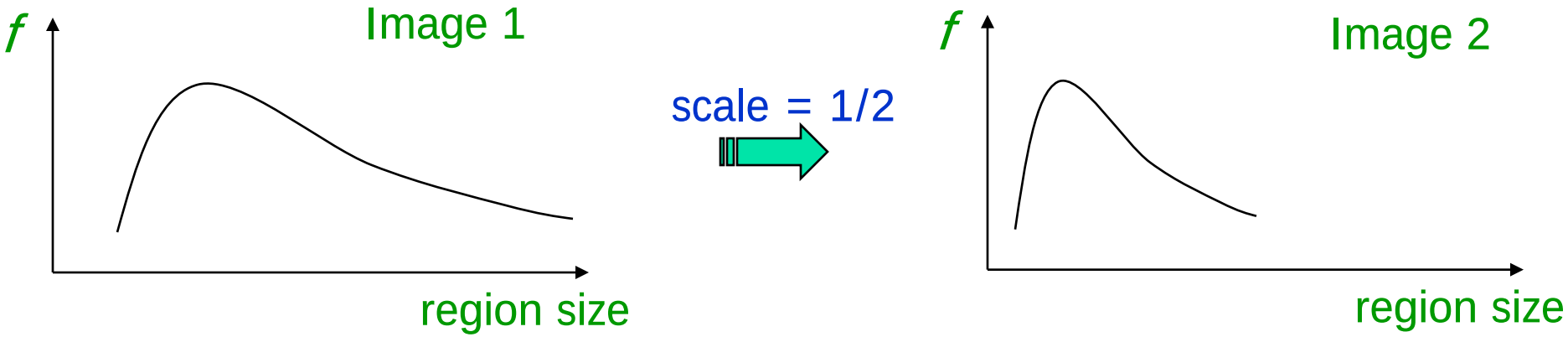
- The problem: how do we choose corresponding circles ***independently*** in each image?



Scale Invariant Detection

- Solution:
  - Design a function on the region (circle), which is "scale covariant" (the same for corresponding regions, even if they are at different scales)

  – For a point in one image, we can consider it as a function of region size (circle radius)



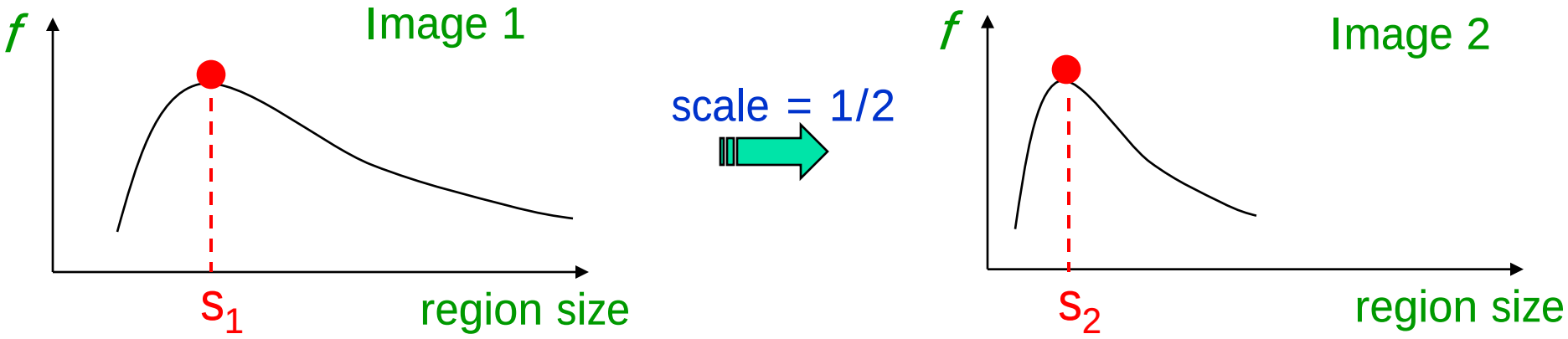
Scale Invariant Detection

- Common approach:

  Take a local maximum of some function

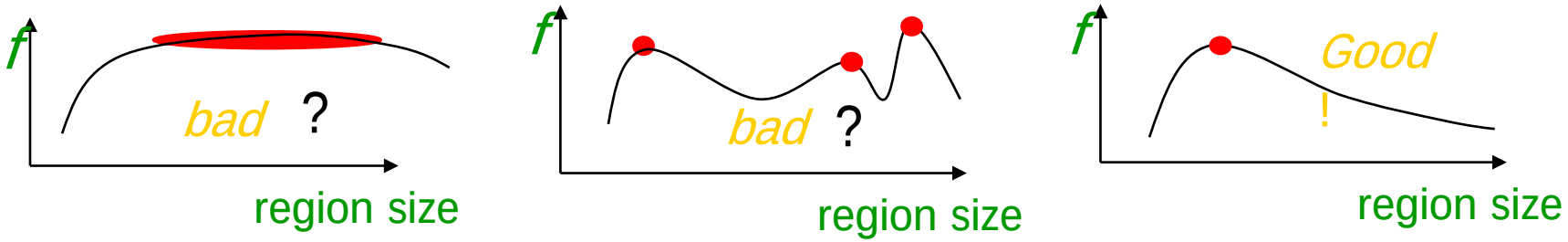
  Observation: region size, for which the maximum is achieved, should be *invariant* to image scale.

Important: this scale invariant region size is found in each image independently!
(*but think about verificaiton*)



Scale Invariant Detection

- A “good” function for scale detection:
  has one stable sharp peak



- For usual images: a good function would be a one which responds to contrast (sharp local intensity change)

Scale Invariant Detection

- Functions for determining scale $f = \text{Kernel} * \text{Image}$

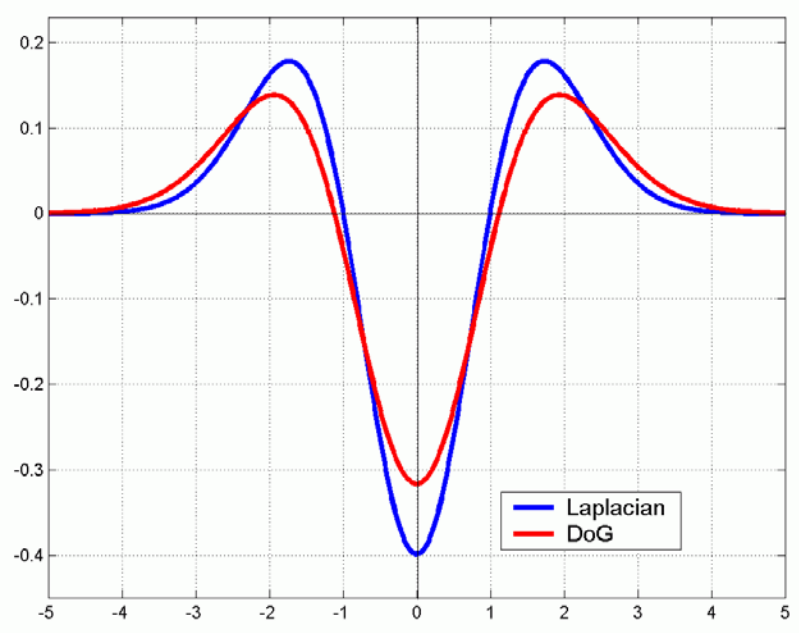
Kernels:

$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right)$$

(Laplacian)

$$Do\ \ G = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)



where Gaussian

$$G(x, y, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

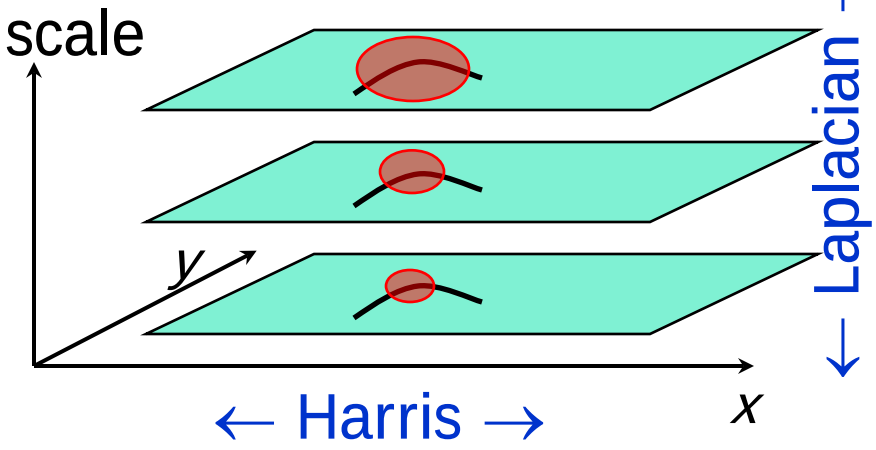
Note: both kernels are invariant to *scale* and *rotation*

Scale Invariant Detectors

Harris-Laplacian[1]

Find local maximum of:

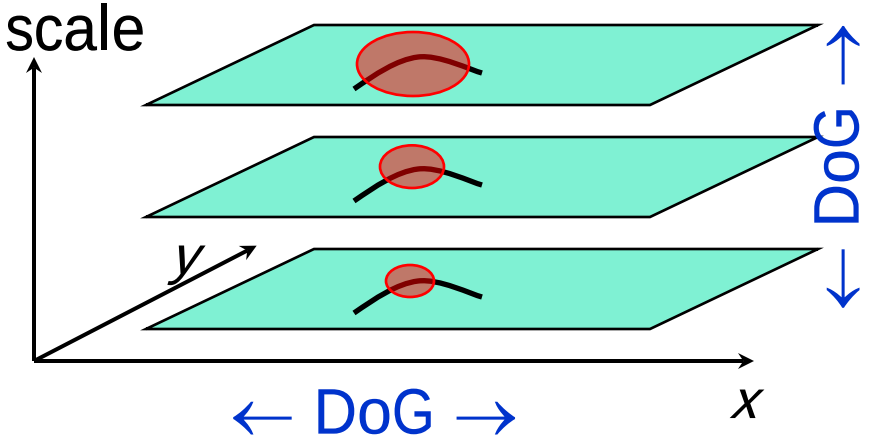
- Harris corner detector in space (image coordinates)
- Laplacian in scale



Laplacian-Laplacian = "SIFT" (Lowe)[2]

Find local maximum of:

– Difference of Gaussians in space and scale



Other options: Hessian, …

Harris does not work well for scale selection

[1] K.Mikolajczyk, C.Schmid. "Indexing Based on Scale Invariant Interest Points". ICCV 2001

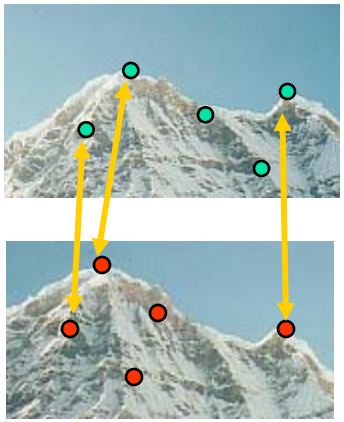
[2] D.Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". IJCV 2004

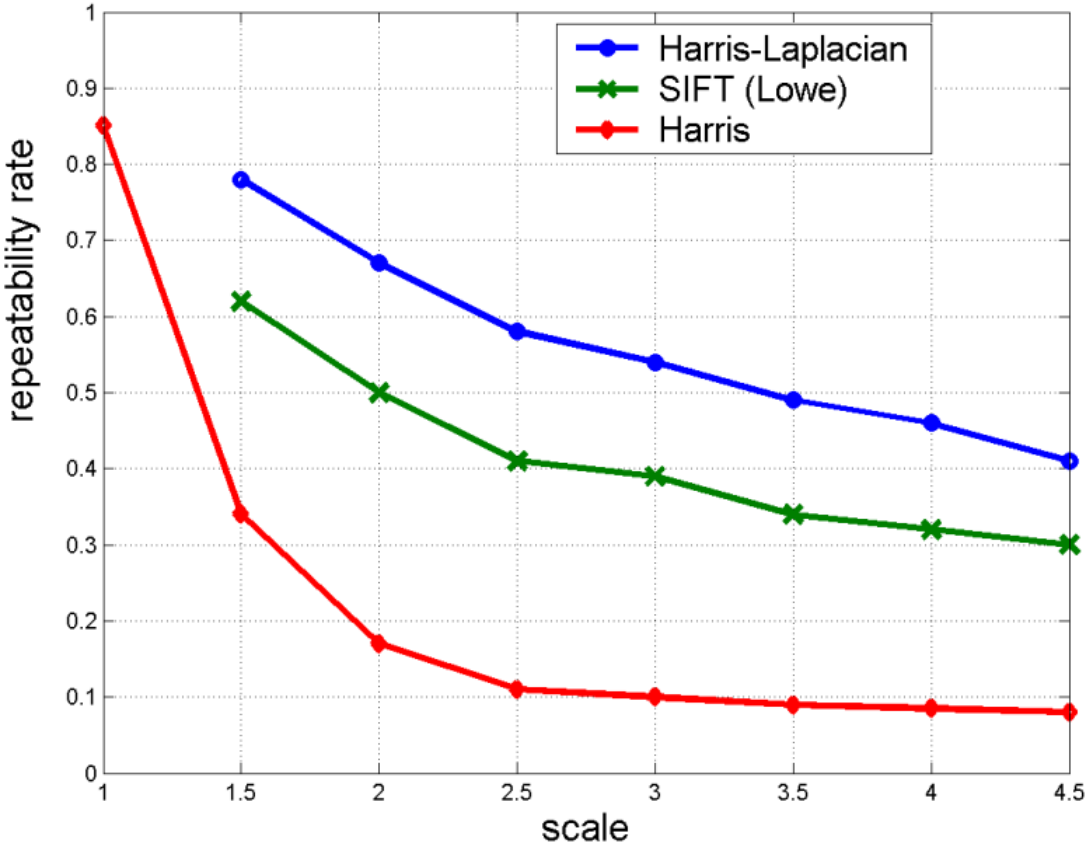
Scale Invariant Detectors

- Experimental evaluation of detectors w.r.t. scale change

Repeatability rate:

$$\frac{\#\ \text{correspondences}}{\#\ \text{possible correspondences}}$$

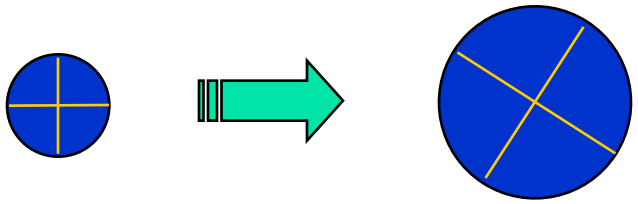




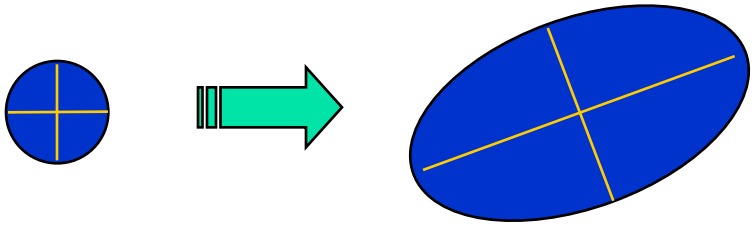
K.Mikolajczyk, C.Schmid. “Indexing Based on Scale Invariant Interest Points”. ICCV 2001

Affine Invariant Detection

- Above we considered:
  Similarity transform (rotation + uniform scale)

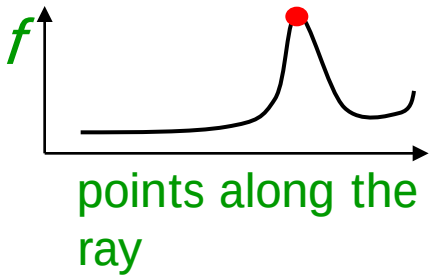


- Now we go on to:
  Affine transform (rotation + non-uniform scale)



Affine Invariant Detection

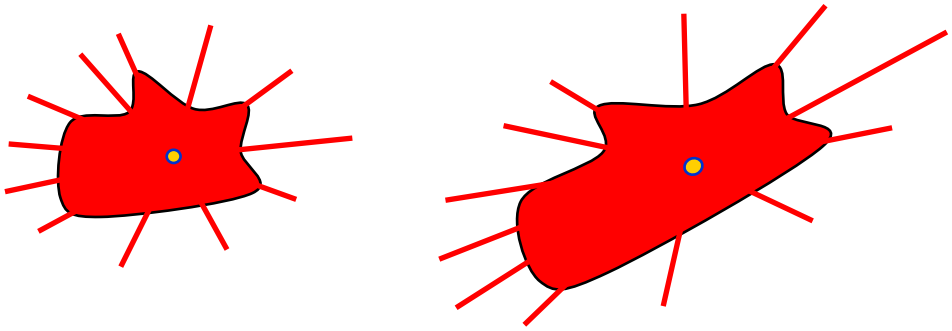
- Take a local intensity extremum as initial point
- Go along every ray starting from this point and stop when extremum of function f is reached



$$f(t) = \frac{\left|I(t) - I_0\right|}{\frac{1}{t}\int_o^t \left|I(t) - I_0\right| dt}$$

- We will obtain approximately corresponding regions

Remark: we search for scale in every direction



T.Tuytelaars, L.V.Gool. “Wide Baseline Stereo Matching Based on Local, Affinely Invariant Regions”. BMVC 2000.

Affine Invariant Detection

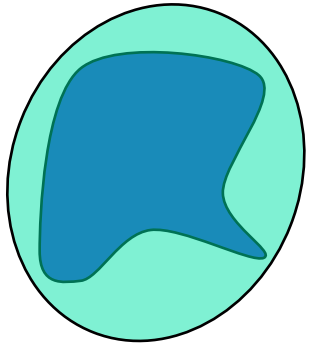
- The regions found may not exactly correspond, so we approximate them with ellipses

- Geometric Moments:

$$m_{pq} = \int_{\mathbb{R}^2} x^p y^q f(x,y)\,dxdy$$

Fact: moments m_{pq} uniquely determine the function f

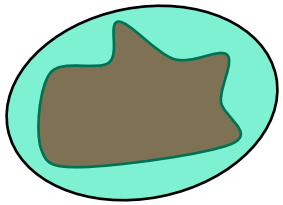
Taking f to be the characteristic function of a region (1 inside, 0 outside), moments of orders up to 2 allow to approximate the region by an ellipse



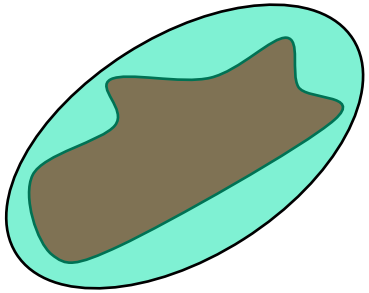
This ellipse will have the same moments of orders up to 2 as the original region

Affine Invariant Detection

- Covariance matrix of region points defines an ellipse:



$$q = Ap$$



$$p^T \Sigma_1^{-1} p = 1$$

$$q^T \Sigma_2^{-1} q = 1$$

$$\Sigma_1 = \left\langle pp^T \right\rangle_{\text{region 1}}$$

$$\Sigma_2 = \left\langle qq^T \right\rangle_{\text{region 2}}$$

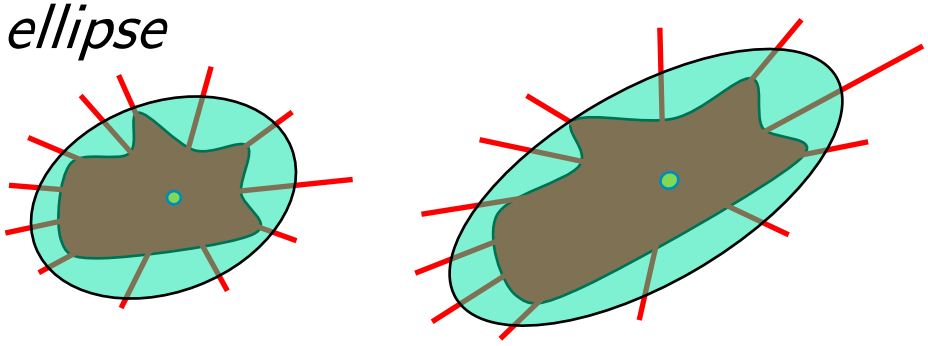
($p = [x, y]^T$ is relative to the center of mass)

$$\Sigma_2 = A \Sigma_1 A^T$$

Ellipses, computed for corresponding regions, also correspond!

Affine Invariant Detection

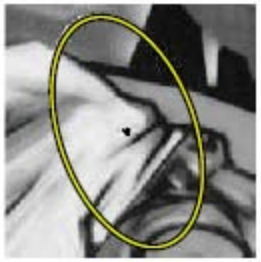
- Algorithm summary (detection of affine invariant region):
  - Start from a *local intensity extremum* point
  - Go in *every direction* until the point of extremum of some function f
  - Curve connecting the points is the region boundary
  - Compute *geometric moments* of orders up to 2 for this region
  - Replace the region with *ellipse*



T.Tuytelaars, L.V.Gool. “Wide Baseline Stereo Matching Based on Local, Affinely Invariant Regions”. BMVC 2000.

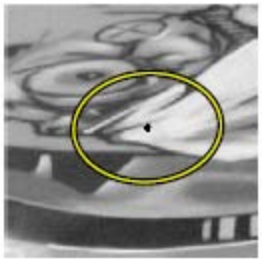
Harris/Hessian Affine Detector

1. Detect initial region with Harris or Hessian detector and select the scale.
2. Estimate the shape with the second moment matrix
3. Normalize the affine region to the circular one
4. Go to step 2 if the eigenvalues of the second moment matrix for new point are not equal.

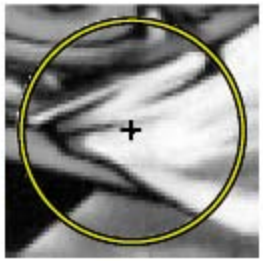


$$\mathbf{x}_L \longrightarrow M_L^{-1/2}\mathbf{x}'_L$$

$$\mathbf{x}'_L \longrightarrow R\mathbf{x}'_R$$



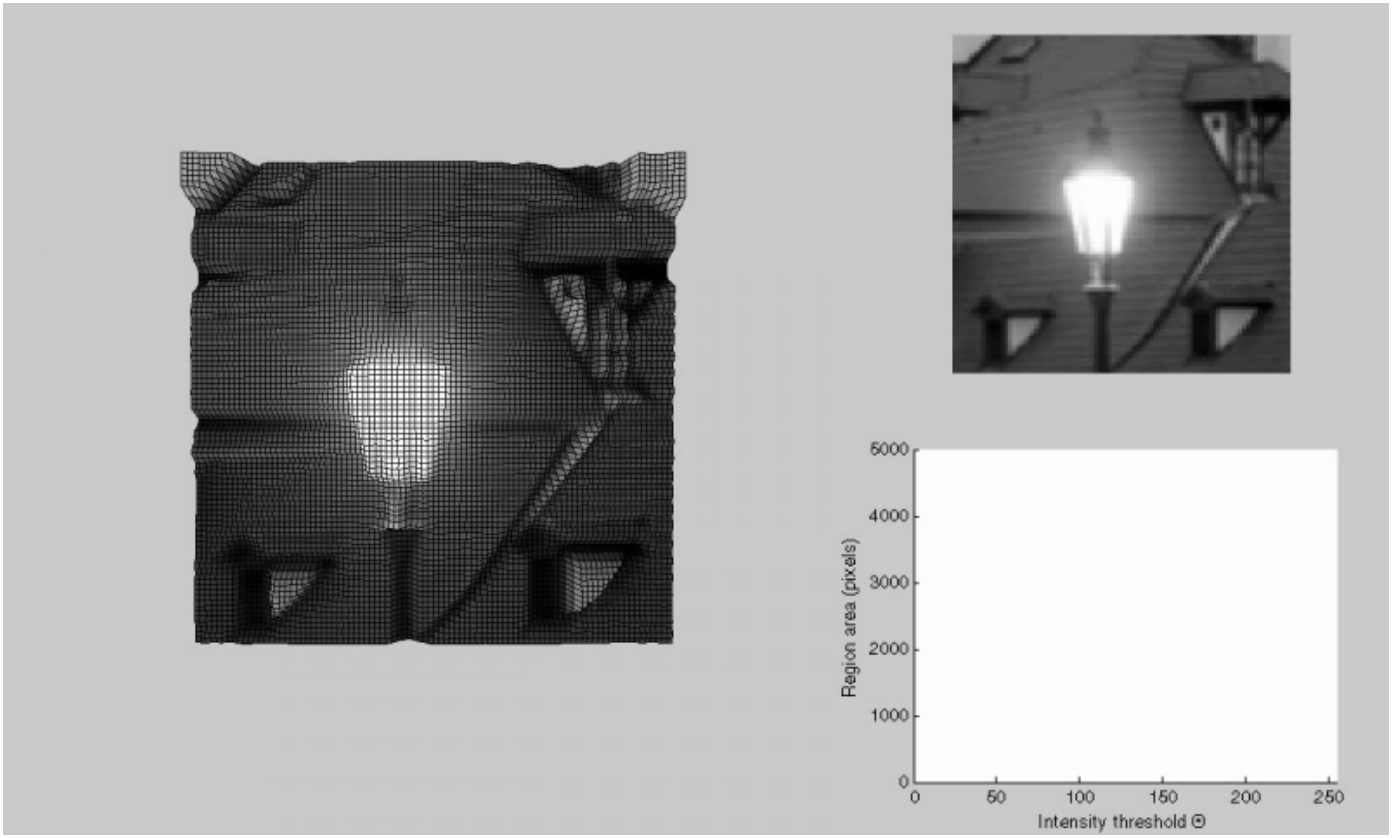
$$\mathbf{x}_R \longrightarrow M_R^{-1/2}\mathbf{x}'_R$$



The Maximally Stable Extremal Regions

- Consecutive image thresholding by all thresholds
- Maintain list of Connected Components
- Regions = Connected Components with stable area (or some other property) over multiple thresholds selected

video



J.Matas et.al. “Distinguished Regions for Wide-baseline Stereo”. Research Report of CMP, 2001.

The Maximally Stable Extremal Regions

video

MSER Stability

CENTER FOR MACHINE PERCEPTION

Step 1: Detect MSERs

Properties:

- Covariant with continuous deformations of images
- Invariant to affine transformation of pixel intensities
- Enumerated in O(n log log n), real-time computation

MSER regions (in green). The regions 'follow' the object (video1, video2).

Matas, Chum, Urban, Pajdla: "Robust wide baseline stereo from maximally stable extremal regions". BMVC2002

Descriptors of Local Invariant Features

Descriptors Invariant to Rotation

- Image moments in polar coordinates

$$m_{kl} = \iint r^k e^{-i\theta l} I(r,\theta) dr d\theta$$

Rotation in polar coordinates is translation of the angle:

$$\theta \rightarrow \theta + \theta_0$$

This transformation changes only the phase of the moments, but not its magnitude

Rotation invariant descriptor consists of magnitudes of moments:

$$|m_{kl}|$$

Matching is done by comparing vectors $[|m_{kl}|]_{k,l}$

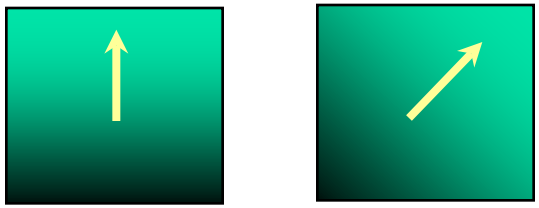
J.Matas et.al. “Rotational Invariants for Wide-baseline Stereo”. Res. Report of CMP, 2003

Descriptors Invariant to Rotation

CENTER FOR MACHINE PERCEPTION

- Find local orientation

  Dominant direction of gradient



- Compute image derivatives relative to this orientation

[1] K.Mikolajczyk, C.Schmid. “Indexing Based on Scale Invariant Interest Points”. ICCV 2001

[2] D.Lowe. “Distinctive Image Features from Scale-Invariant Keypoints”. IJCV 2004

Descriptors Invariant to Scale

- Use the scale determined by detector to compute descriptor in a normalized frame

For example:

- moments integrated over an adapted window
- derivatives adapted to scale: sI_x

Affine Invariant Descriptors

- Affine invariant color moments

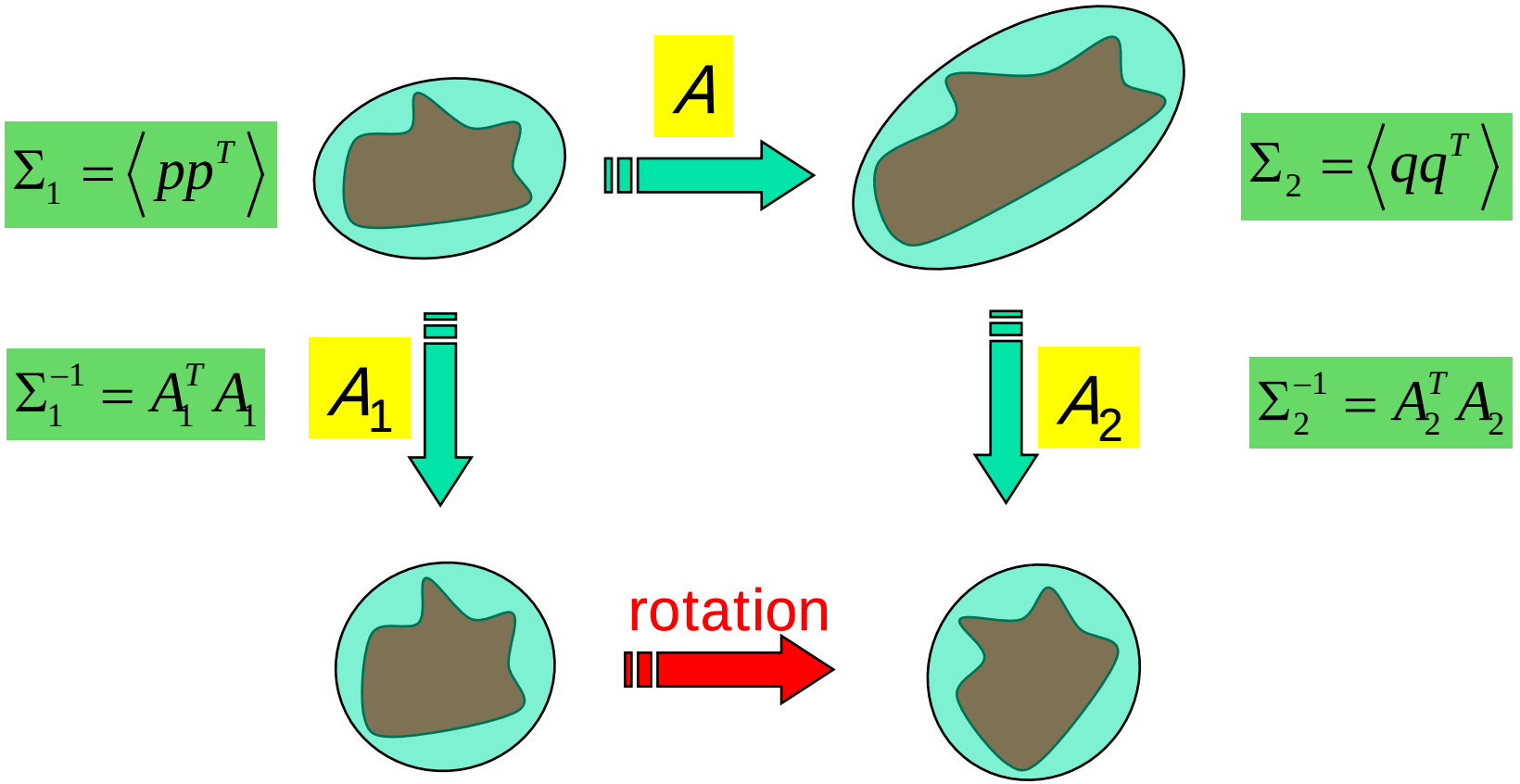
$$m_{pq}^{abc} = \int_{region} x^p y^q R^a(x,y) G^b(x,y) B^c(x,y) dx dy$$

Different combinations of these moments are fully affine invariant

Also invariant to affine transformation of intensity $I \rightarrow a\,I + b$

Affine Invariant Descriptors

- Find affine normalized frame



- Compute rotational invariant descriptor in this normalized frame

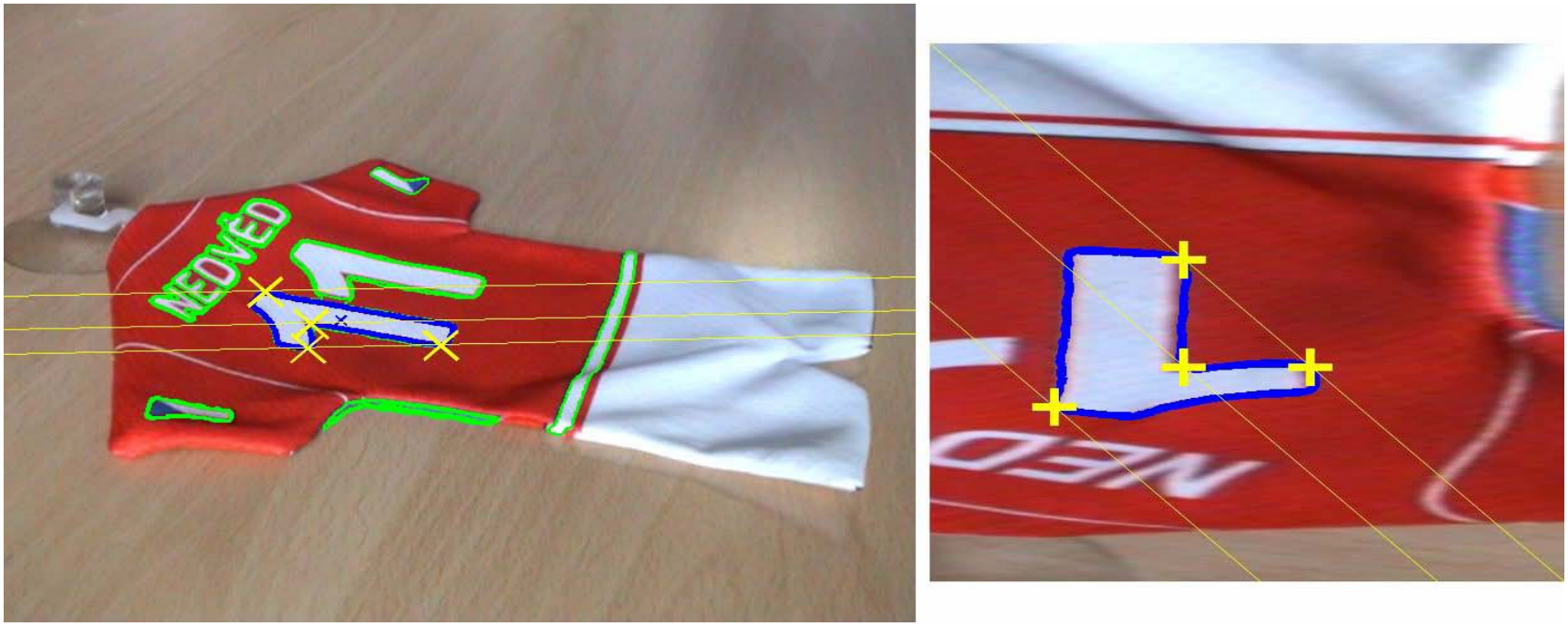
J.Matas et.al. “Rotational Invariants for Wide-baseline Stereo”. Res. Report of CMP, 2003

Local Affine Frames

Step 2: Construct **Local Affine Frames (LAFs)** (local coordinate frames)

Step 3**: Geometrically normalize** some measurement region (MR) expressed in LAF coordinates

All measurements in the nomalised frame are Invariants!



Stability of LAFs: concavity, curvature max 1, curvature max 2

Obdržálek and Matas: "Object recognition using local affine frames on distinguished regions". BMVC02
Obdržálek and Matas: "Sub-linear Indexing for Large Scale Object Recognition", BMVC 2005

Affine-Covariant Constructions: Taxonomy

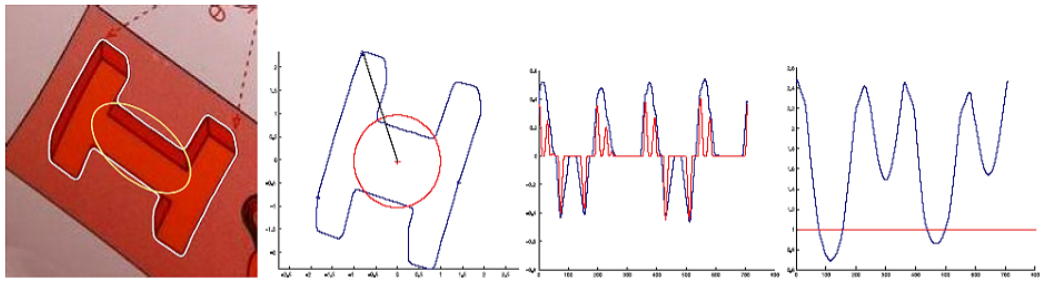
- Derived from ***region outer boundary***
  - Region area (1 constraint)
  - Center of gravity (2 constraints)
  - Matrix of second moments (symmetric 2x2 matrix: 3 const

$$|\Omega| = \int_\Omega \mathbf{1} d\Omega$$

$$\mu = \frac{1}{|\Omega|} \int_\Omega \mathbf{x} d\Omega$$

    - Points of extremal distance to the center of gravity (2 constraints)
    - Points of extremal curvature (2 constraints)

$$\Sigma = \frac{1}{|\Omega|} \int_\Omega (\mathbf{x} - \mu)(\mathbf{x} - \mu)^T d\Omega$$

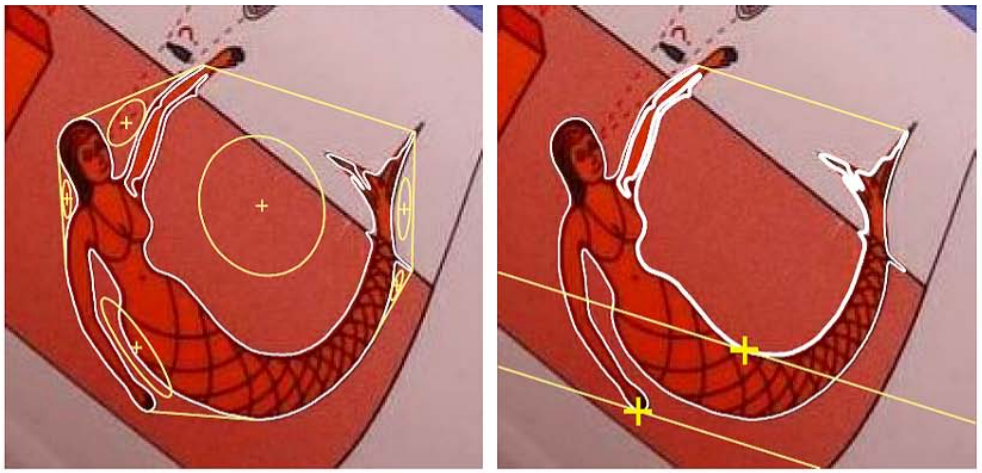


(a) (b) (c) (d)

Shape normalisation by the covariance matrix. (a) a detected region, (b) the region shape-normalised to have unit covariance matrix, (c) local curvatures of the normalised shape, (d) distances to the center of gravity.

Affine-Covariant Constructions: Taxonomy

- Derived from ***region outer boundary*** (continued)
  - Concavities (4 constraints for 2 tangent points)
    - Farthest point on region contour/concavity (2 constraints)



(a) (b)

Example region concavities. (a) A detected non-convex region with indicated concavities and their covariance matrices (b) One of the concavities - the bitangent line and region and concavity farthest points.

Affine-Covariant Constructions: Taxonomy

- Derived from ***image intensities*** in a region (or its neigbourhood)
  - From orientation of gradients
    - peaks of gradient orientation histograms [Low04] (1 constraint)
  - Direction of dominant texture periodicity (1 constraint)
  - Extrema or centers of gravity of R, G, B components, or of any scalar function of the RGB values (2 constraints)
  - many other

[Low04] D. G. Lowe. Distinctive image features from scale-invariant keypoints. *International Journal on Computer Vision*, 2004.

Affine-Covariant Constructions: Taxonomy

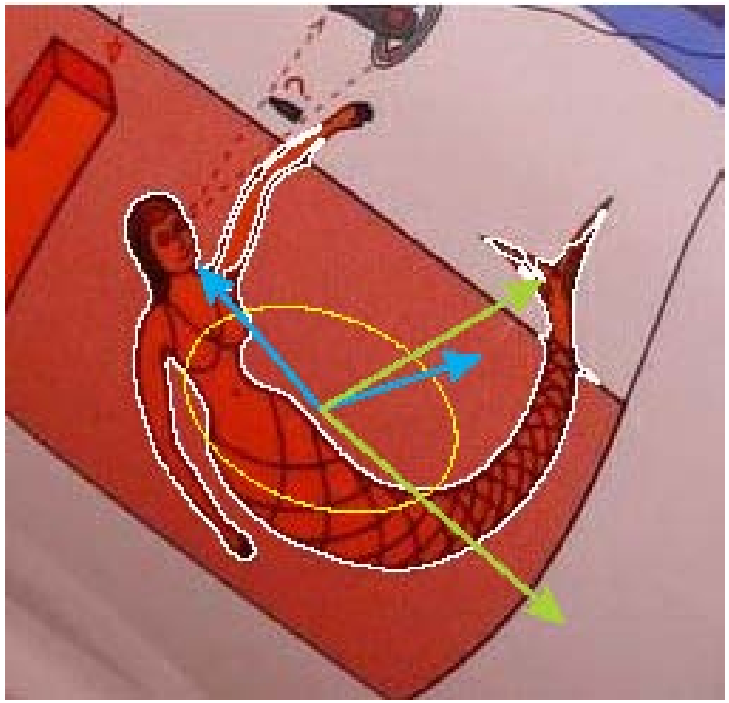
- Derived from *topology* of regions
  - mutual configuration of regions (combined constraints)
    - nested regions
    - incident regions
    - neighbouring regions

- Region holes and concavities can be considered as regions of their own
  - all aforementioned constructions recursively applicable

- Convex hull of a region without loosing affine invariance

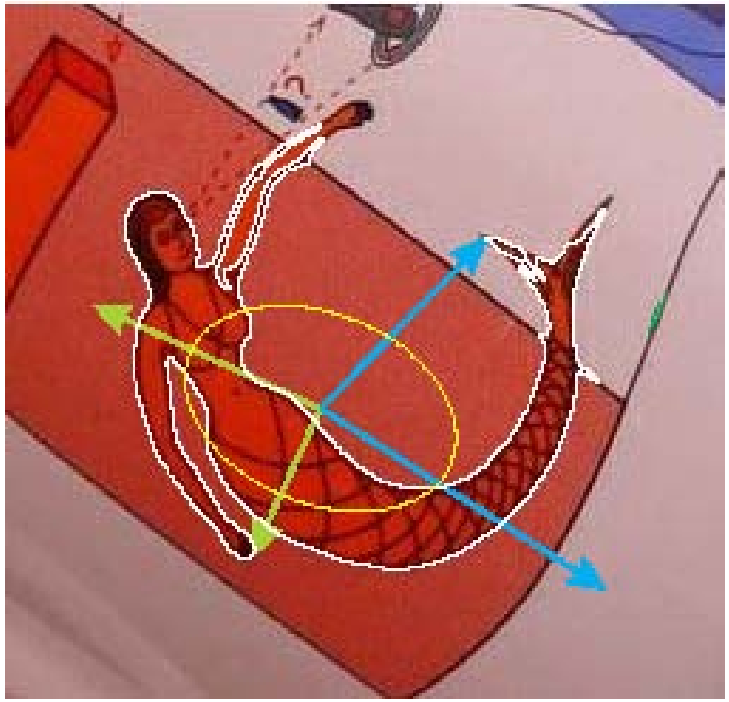
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + covariance matrix + curvature minima



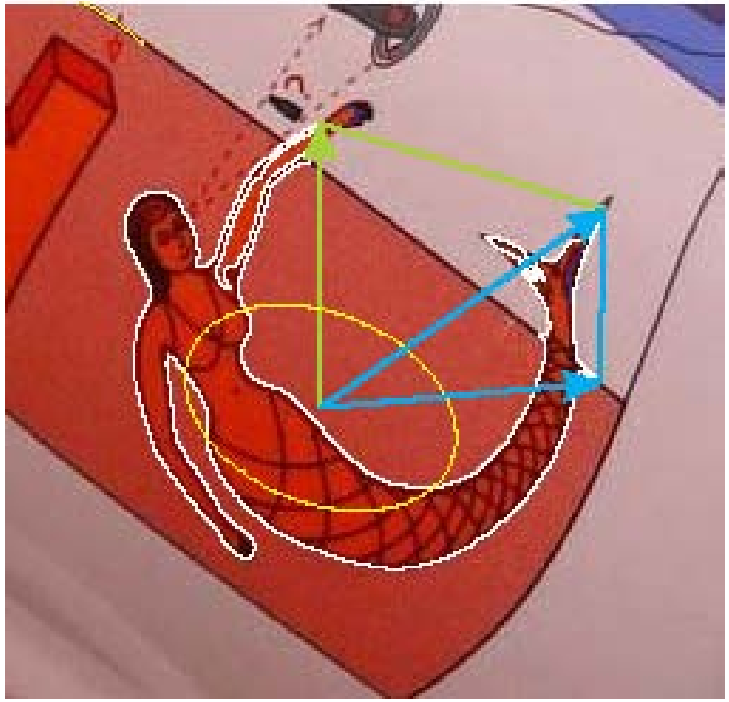
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + covariance matrix + curvature maxima



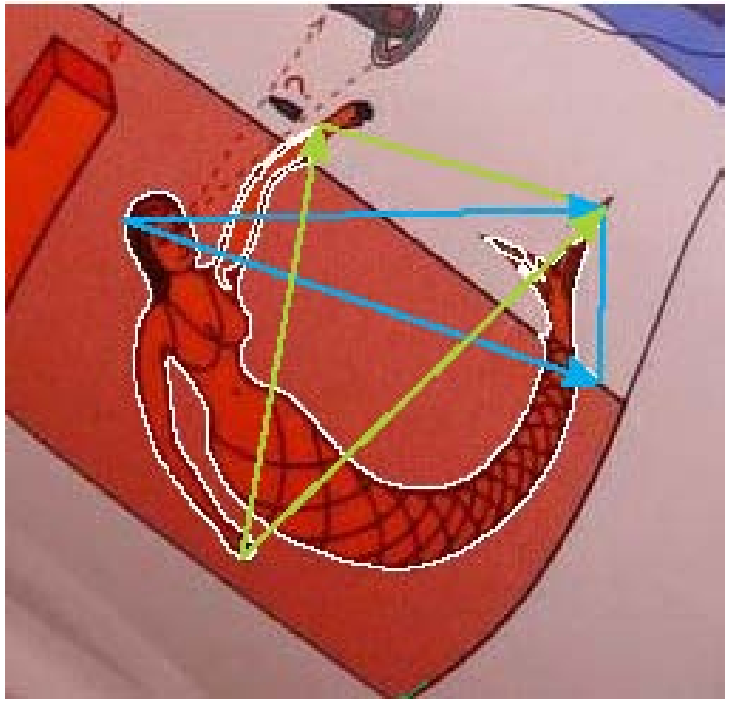
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + tangent points of a concavity



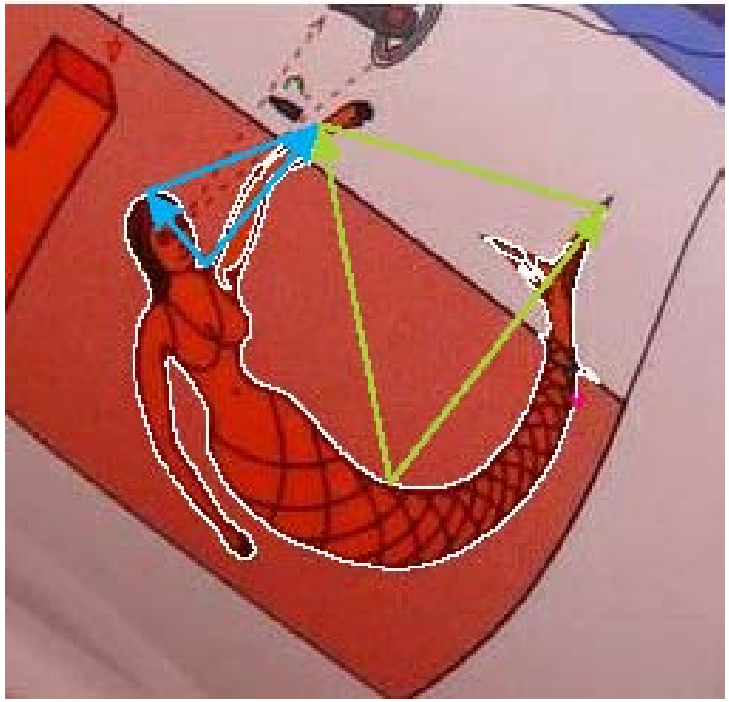
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - tangent points + farthest point of the region



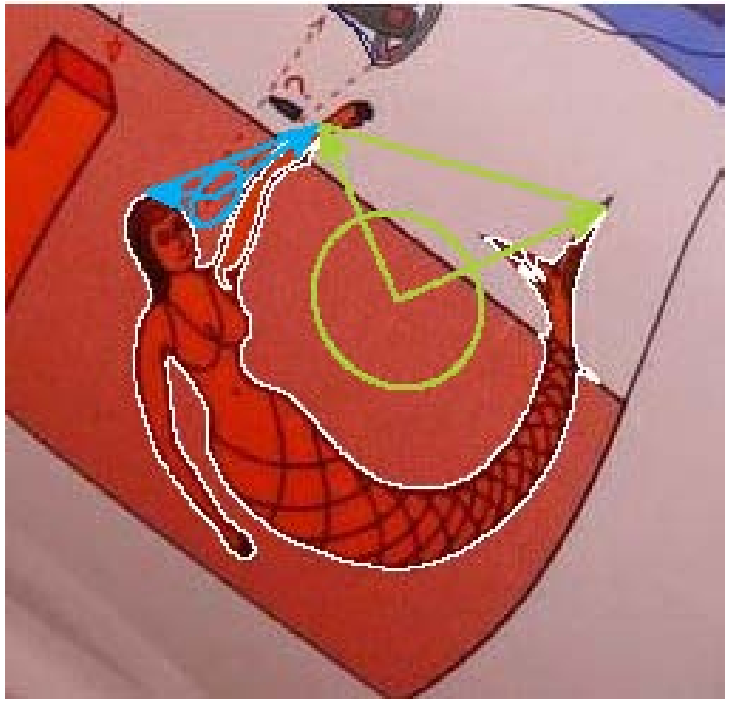
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - tangent points + farthest point of the concavity



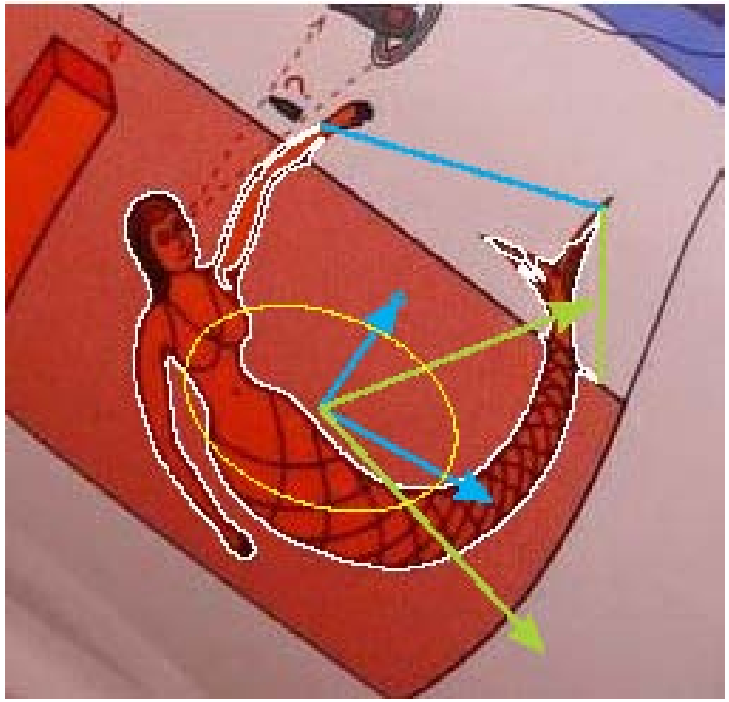
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - tangent points + center of gravity of the concavity



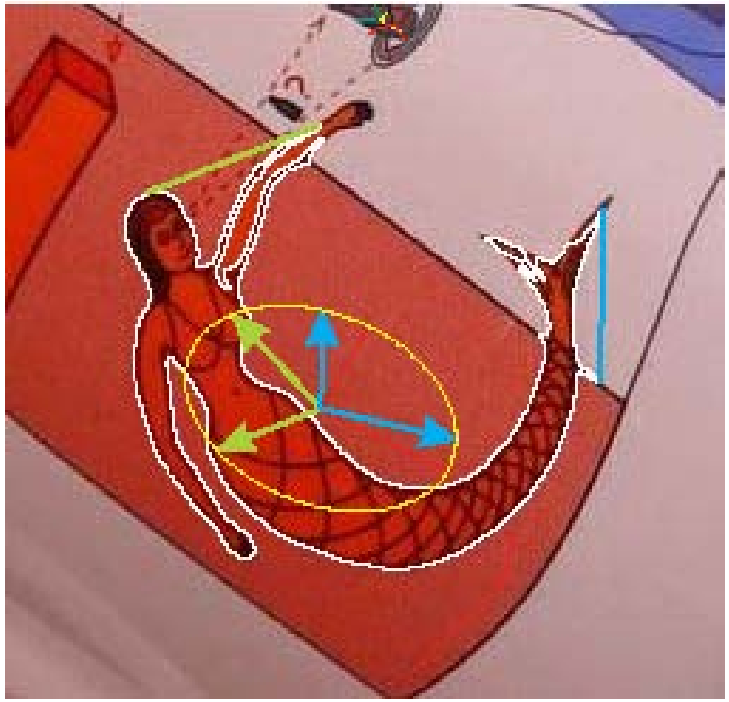
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + covariance matrix + center of gravity of a concavity



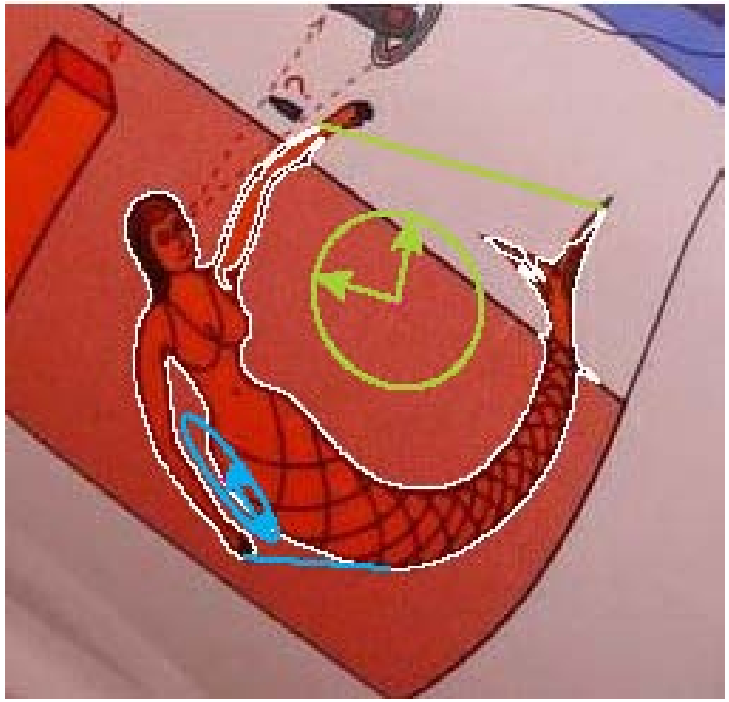
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + covariance matrix + direction of a bitangent



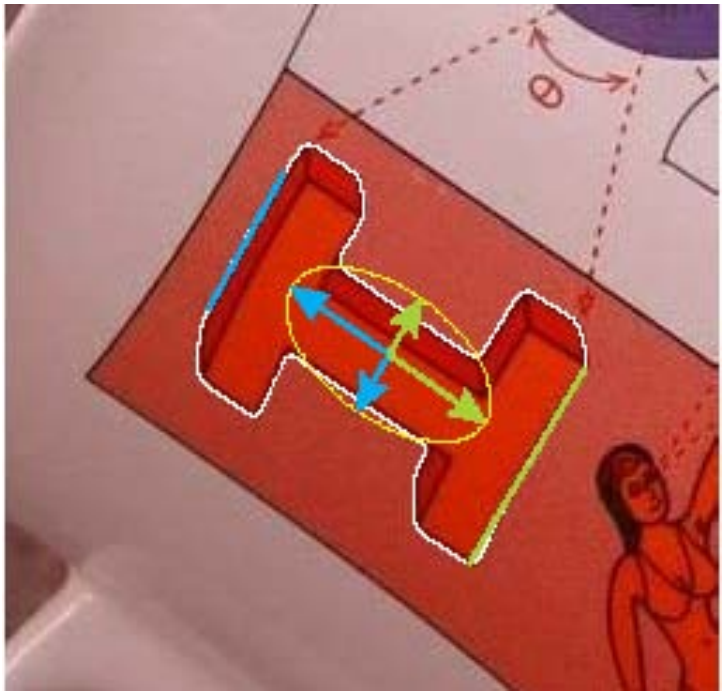
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity of a concavity + covariance matrix of the concavity + the direction of the bitangent



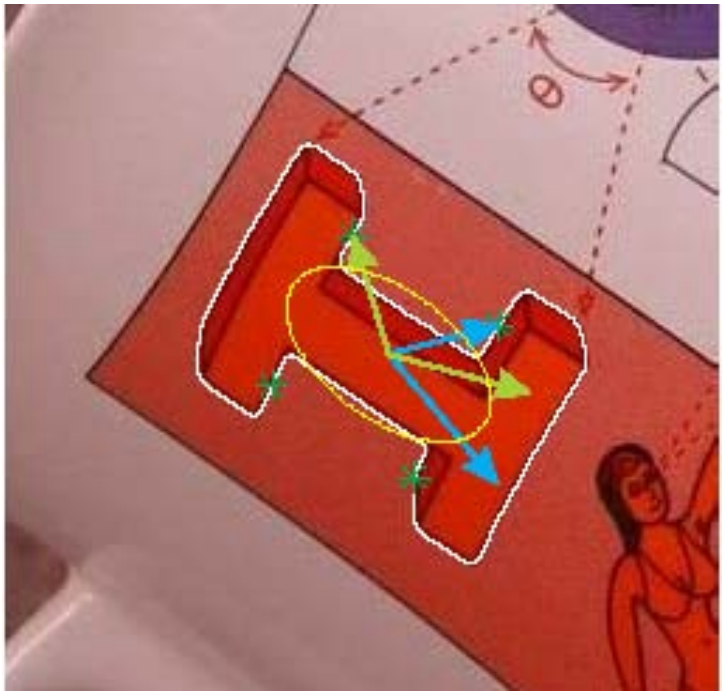
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + covariance matrix + the direction of a linear segment of the contour



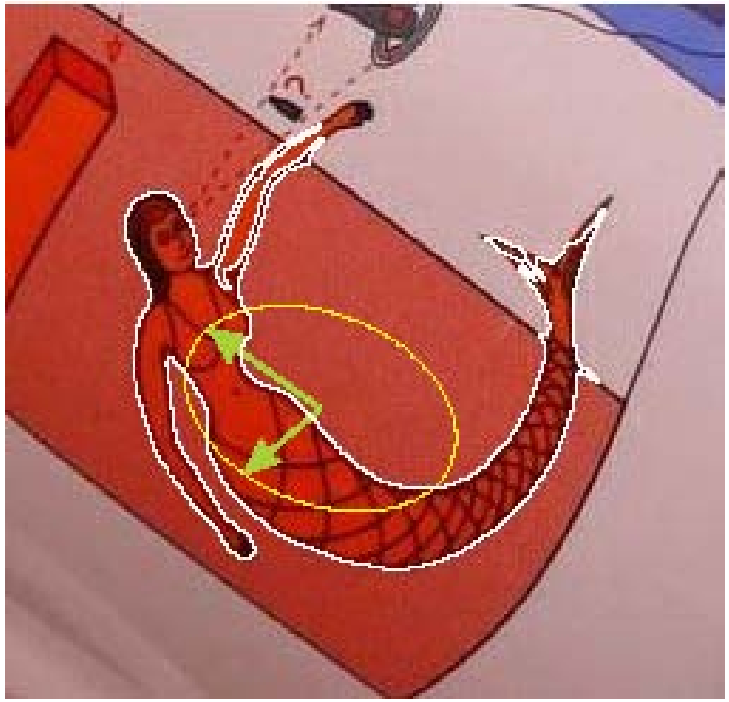
Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + covariance matrix + the direction to an inflection point



Constructions of Local Affine Frames

- Combinations of constructions used to form the local affine frames
  - center of gravity + covariance matrix + the direction given by the third-order moments of the region



Affine-Covariant Constructions: Taxonomy

CENTER FOR MACHINE PERCEPTION

- Derived from ***region outer boundary*** (continued)
  - Points of curvature inflection (2 constraints)
    - curvature changes from convex to concave or vice-versa
  - Straight line segments (1 stable constraint for direction, or 4 for the end-points)
  - Higher than 2nd order moments

    a complex number formed from 3rd order moments

    whose phase angle

$$c = \mu_{x^3} + \mu_{xy^2} + i(\mu_{x^2y} + \mu_{y^3})$$

    changes covariantly with the region's rotation [Hei04] (1 constraint)

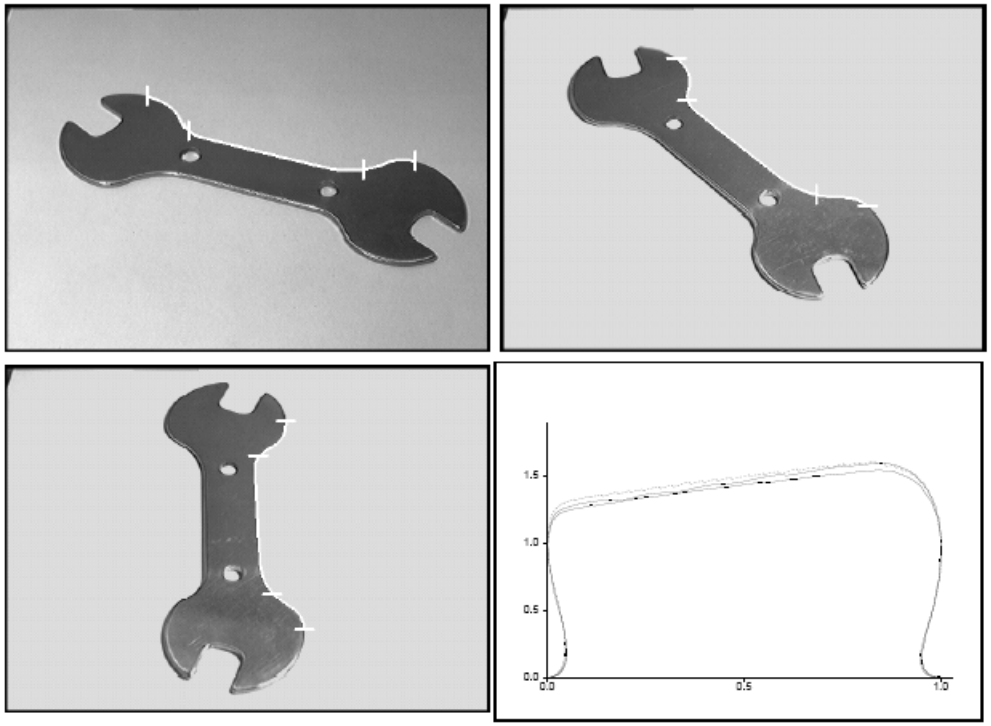
$$\alpha = \tan^{-1}\left(\frac{\mu_{x^2y} + \mu_{y^3}}{\mu_{x^3} + \mu_{xy^2}}\right)$$

[Hei04] Janne Heikkilä. Pattern matching with affine moment descriptors. *Pattern Recognition*, 37(9):1825–1834, 2004.

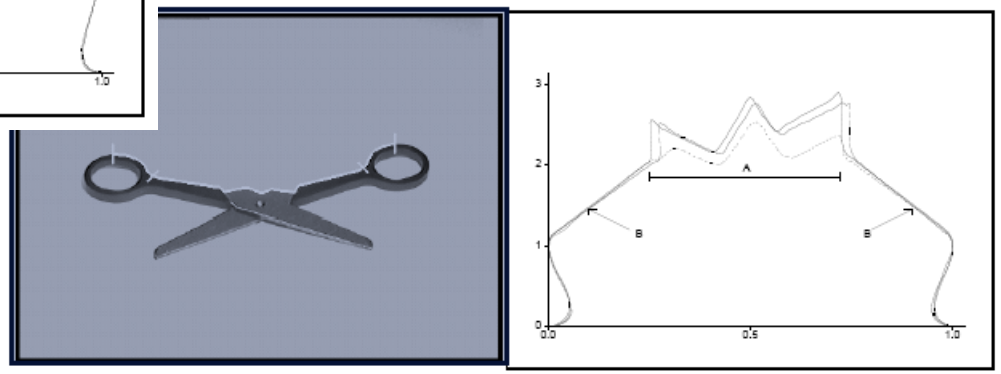
Canonical Frames are an old idea …

CENTER FOR MACHINE PERCEPTION

Rothwell, Zisserman, Forsyth, Mundy:
Canonical Frames for Planar Object Recognition, 1992



- Multiple reference frames
- Grouping of distinguished points is based on ordering on the segment



Construction of a projective frame

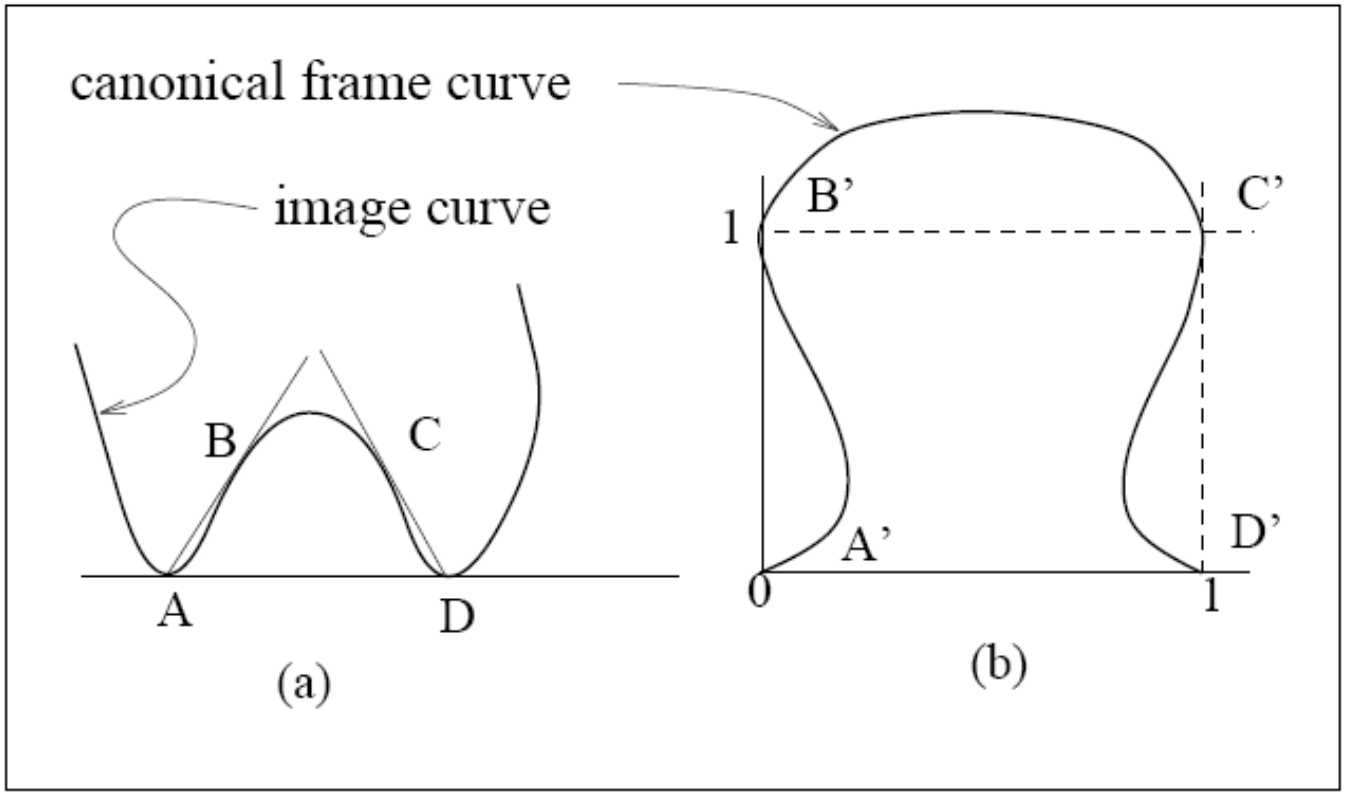


Fig. 1. (a) Construction of the four points necessary to define the canonical frame for a concavity. The first two points $(A\ D)$ are points of bitangency that mark the entrance to the concavity. Two further distinguished points, $(B\ C)$, are obtained from rays cast from the bitangent contact points and tangent to the curve segment within the concavity. These four points are used to map the curve to the canonical frame. (b) Curve in canonical frame. A projection is constructed that transforms the four points in (a) to the corner of the unit square. The same projection transforms the curve into this frame.

occlusion, clutter, multiple objects

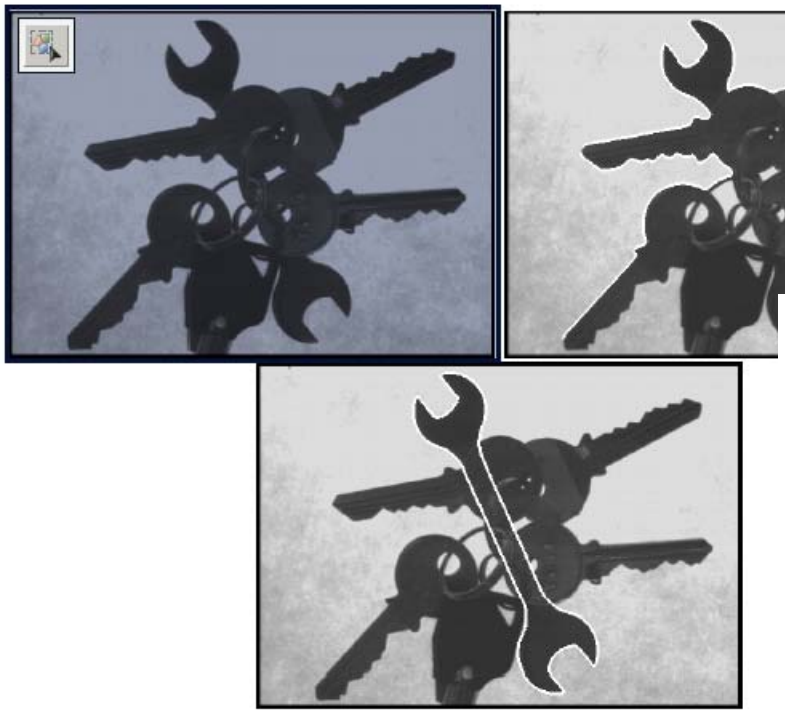


Fig. 6. (a) Spanner almost entirely occluded by keys. The keys are not the li
in this scene. (b) Detected concavities, highlighted in white, which are used
(c) The spanner which is the only model in the scene contained in the libra
the end slot concavity. The projected outline used for verification is highli

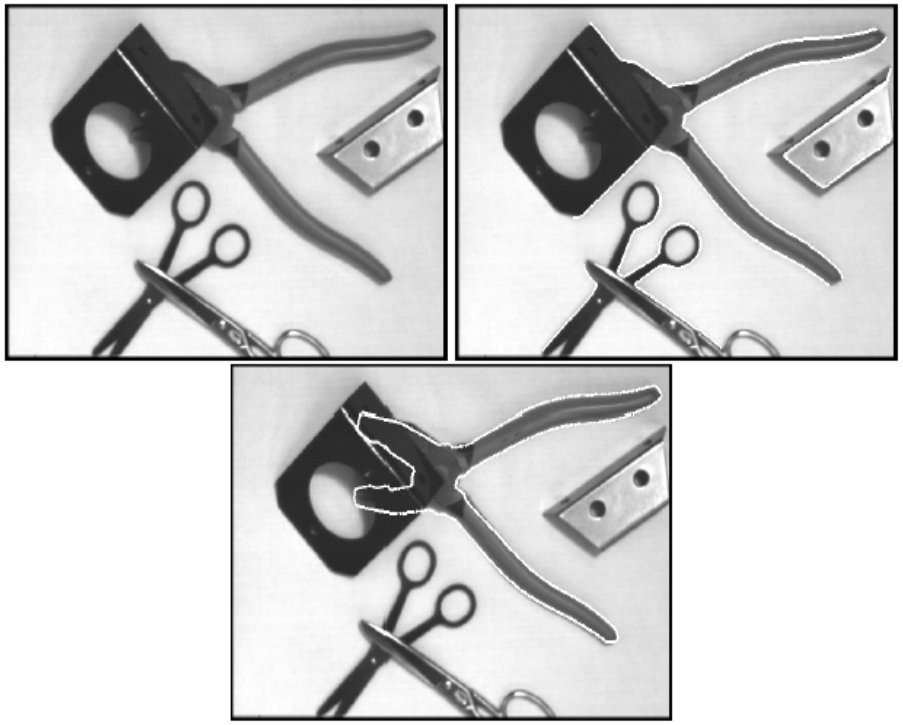


Fig. 7. (a) Image of various planar objects. (b) Concavities, highlighted in white, which are used to compute indexes (c) The pliers which are the only model in the scene contained in the library, is recognised and verified by projecting the edgels from an acquisition image, and checking overlap with edgels in this image.

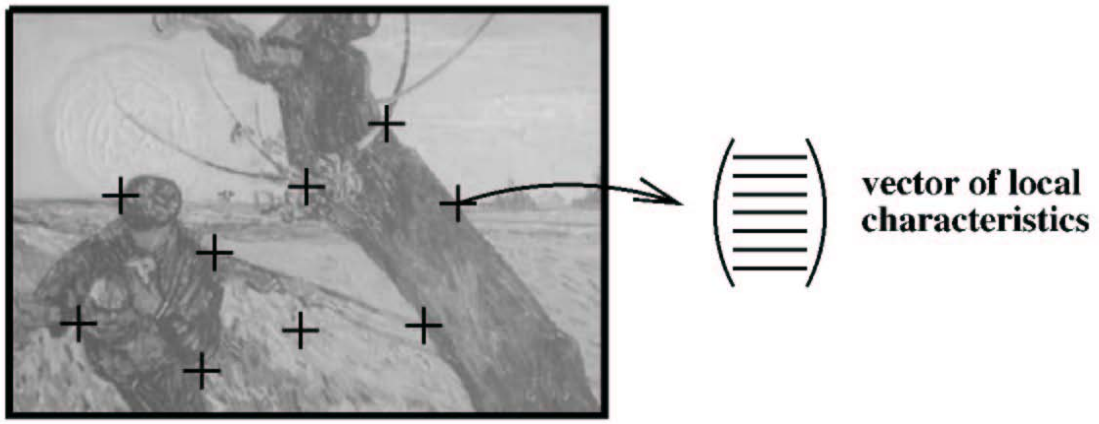
Common Structure of "Local Feature" Algorithms

1. **Detect affine- (or similarity-) covariant regions (=distinguished regions) = local features**
   Yields regions (connected set of pixels) that are detectable with high repeatability over a large range of conditions.
2. **Description: Invariants or Representation in Canonical Frames**
   Representation of local appearance in a Measurement Region (MR). Size of MR has to be chosen as a compromise between discriminability vs. robustness to detector imprecision and image noise.
3. **Indexing**
   For fast (sub-linear) retrieval of potential matches
4. **Verification of local matches**

5. **Verification of global geometric arrangement**
   Confirms or rejects a candidate match

Local features meet Invariants: Schmid and Mohr, 1997. 700 citations

- Multi-scale differential gray value invariants computed at Harris points
- Scale and rotation invariant
- Feature vectors compared by Mahalanobis distance
- Similarity-based geometric constraint to reject mismatches
- *Canonical Frame not used* .



C. Schmid, R. Mohr, "Local Gray-Value Invariants for Image Retrieval", IEEE Trans. PAMI, vol. 19 (5), 1997, pp. 530--535.

D. Lowe, *Object recognition from local scale-invariant features*, ICCV, 1999 2000 citations

Detector:

- Scale-space peaks of Difference-of-Gaussians filter response (Lindeberg 1995)
- **Similarity frame** from modes of gradient histogram

SIFT Descriptor:

- Local histograms of gradient orientation
- Allows for small misalignments
  => robust to non-similarity transforms

Indexing :

- kD-tree structure

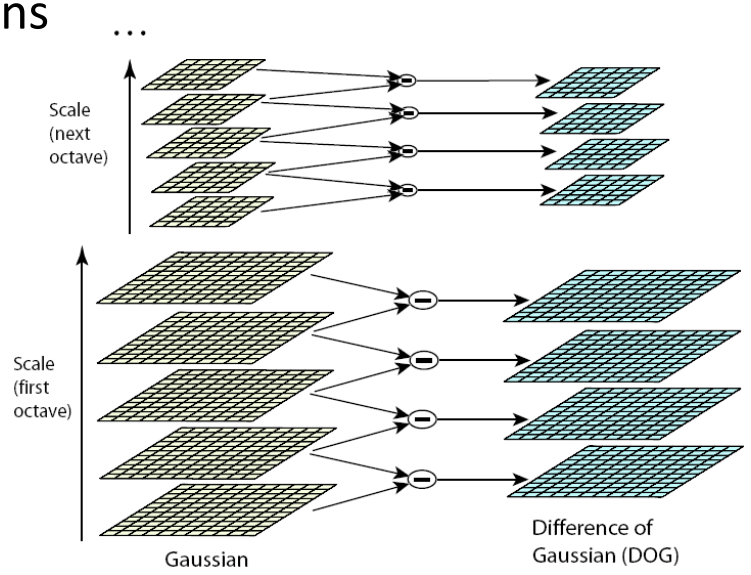
Matching:

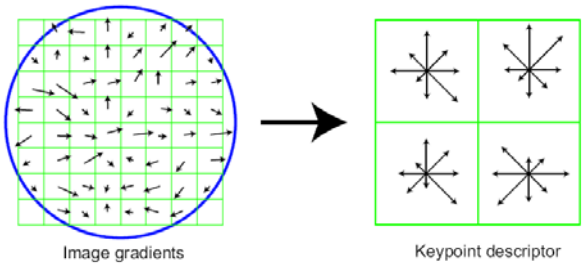
- test on euclidean distance of 1st and 2nd match

Verification:

- Hough transform based clustering of correspondences with similar transformations

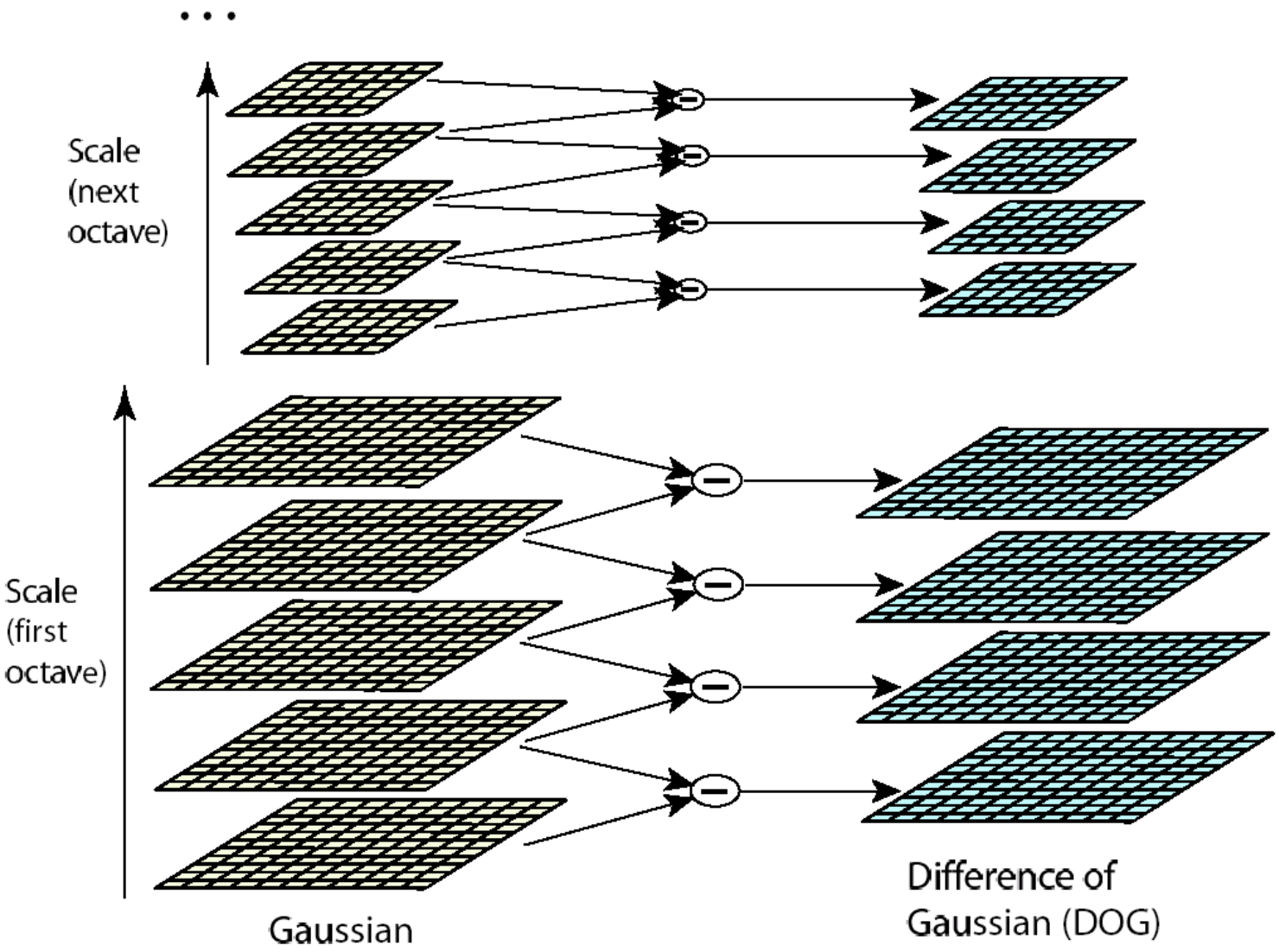
Fast, efficient implementation**, real-time recognition**





D. G. Lowe: "Distinctive image features from scale-invariant keypoints". IJCV, 2004.

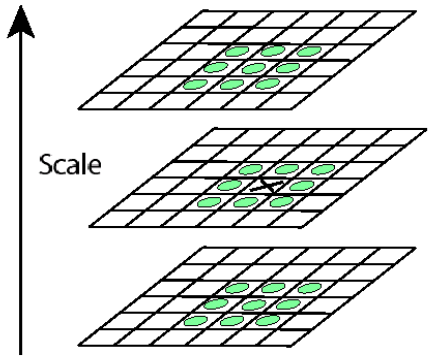
Scale space processed one octave at a time



Sub-pixel/ Sub-level Keypoint Localization

- Detect maxima and minima of difference-of-Gaussian in scale space
- Fit a quadratic to surrounding values for sub-pixel and sub-scale interpolation (Brown & Lowe, 2002)
- Taylor expansion around point:

$$D(\mathbf{x}) = D + \frac{\partial D}{\partial \mathbf{x}}^T \mathbf{x} + \frac{1}{2}\mathbf{x}^\mathbf{T}\frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x}$$



- Offset of extremum (use finite differences for derivatives):

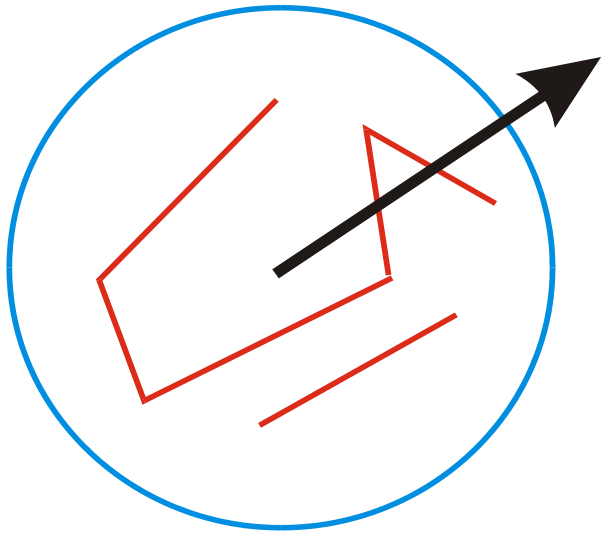
$$\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1}\frac{\partial D}{\partial \mathbf{x}}$$

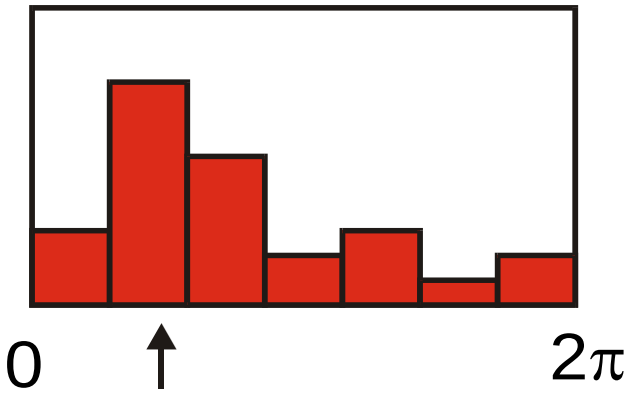
Building a Similarity Frame (s) (my terminology)

Select canonical orientation (s)

- Compute a histogram of local gradient directions computed at the selected scale
- Assign canonical orientation(s) at peak(s) of smoothed histogram
- (x, y, scale) + orientation defines a local *similarity frame;* equivalent to detecting 2 distinguished points

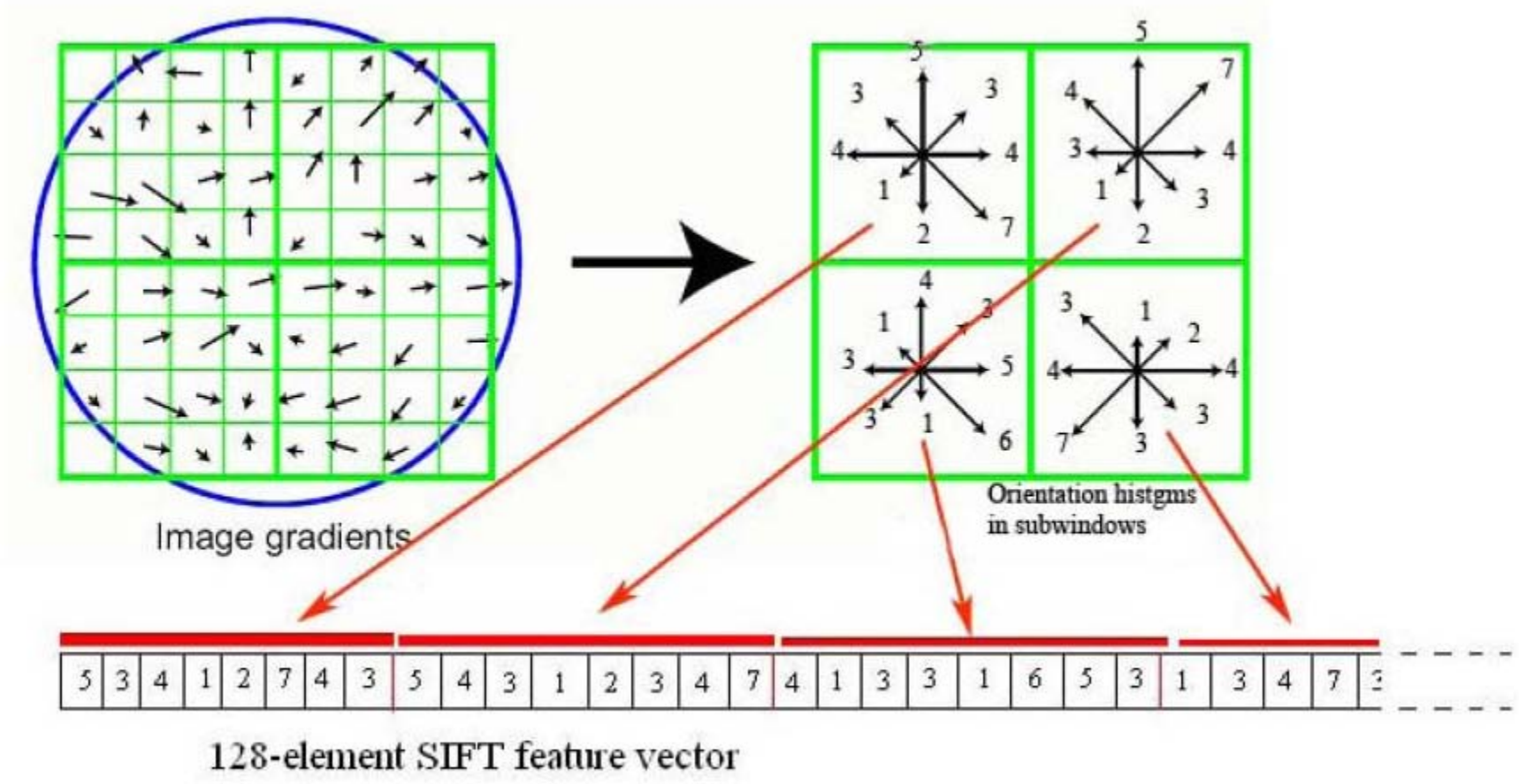
Note: if orientation of the object (image) is known, it may replace this construction





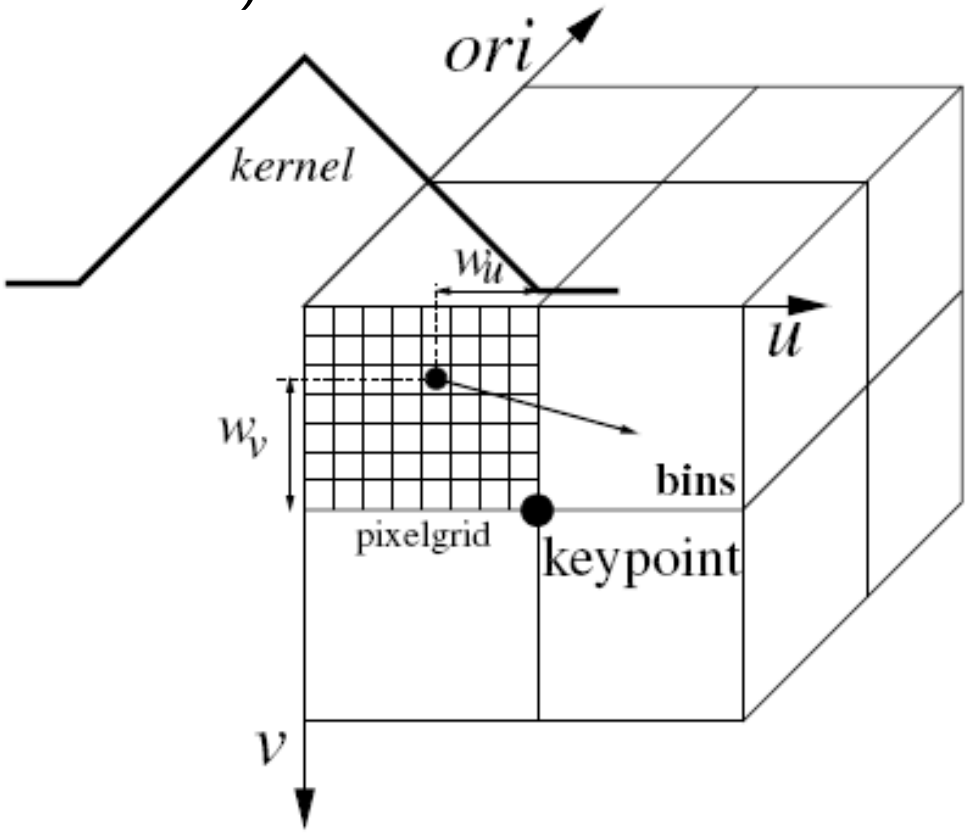
SIFT Descriptor

- A 4x4 histogram lattice of orientation histograms
- Orientations quantized (with interpolation) into 8 bins
- Each bin contains a weighted sum of the norms of the image gradients around its center, with complex normalization



SIFT Descriptor

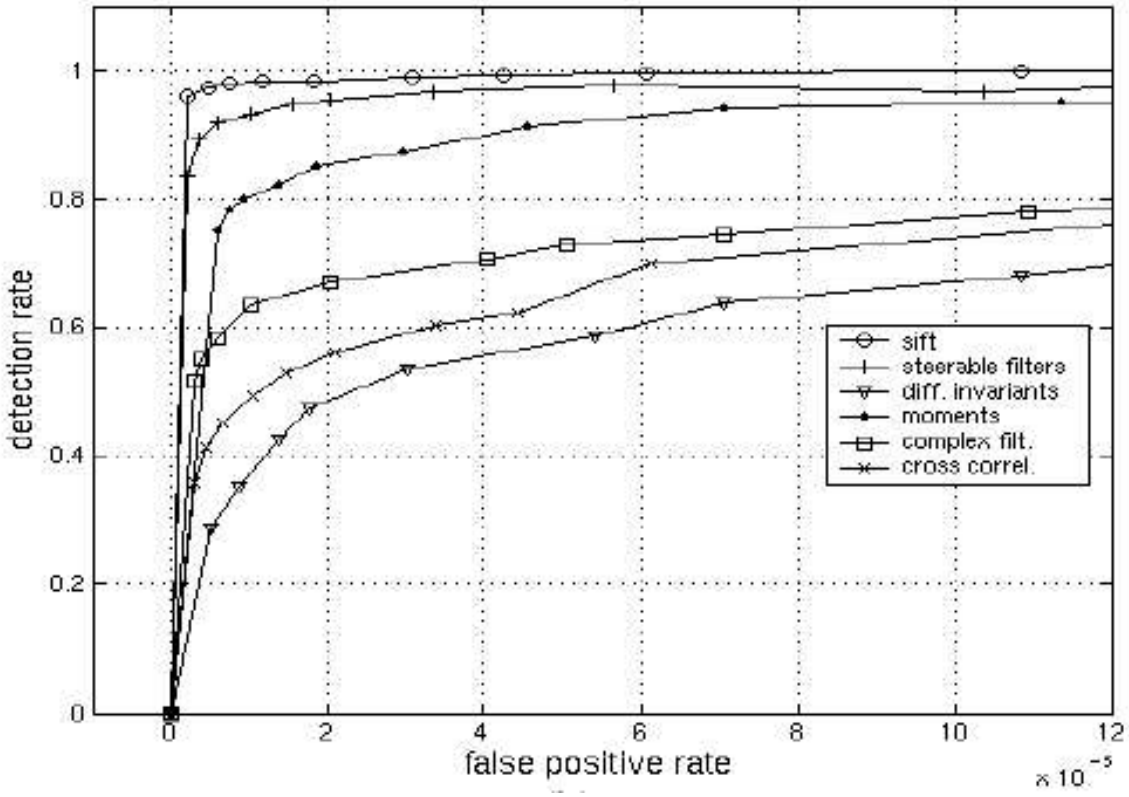
- SIFT descriptor can be viewed as a 3–D histogram in which two dimensions correspond to image spatial dimensions and the additional dimension to the image gradient direction (normally discretised into 8 bins)



SIFT – Scale Invariant Feature Transform[1]

- Empirically found[2] to show very good performance, invariant to *image rotation*, *scale*, *intensity change*, and to moderate *affine* transformations

Scale = 2.5
Rotation = 45^0



[1] D.Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". IJCV 2004
[2] K.Mikolajczyk, C.Schmid. "A Performance Evaluation of Local Descriptors". CVPR 2003

SIFT invariances

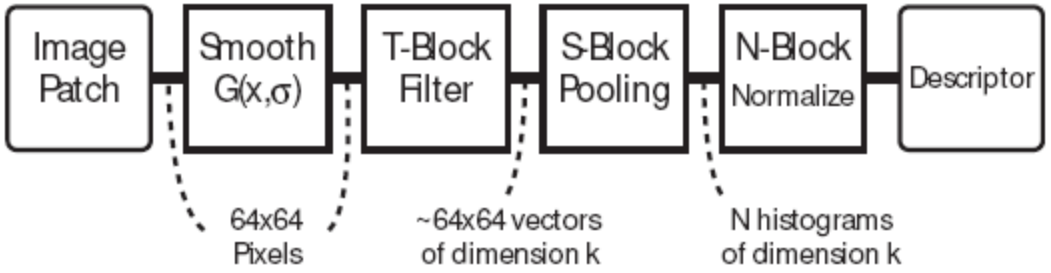
- Based on gradient orientations, which are robust to illumination changes
- Spatial binning gives tolerance to small shifts in location and scale, affine change.
- Explicit orientation normalization
- Photometric normalization by making all vectors unit norm
- Orientation histogram gives robustness to small local deformations

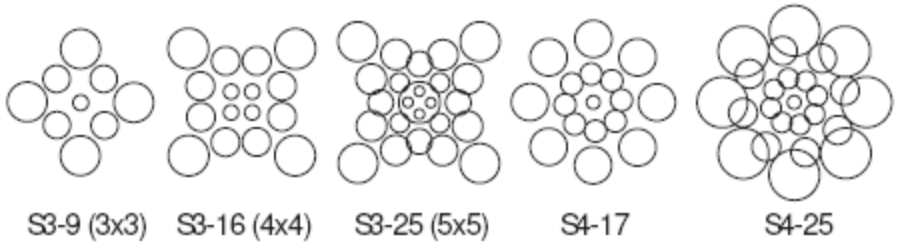
SIFT Descriptor

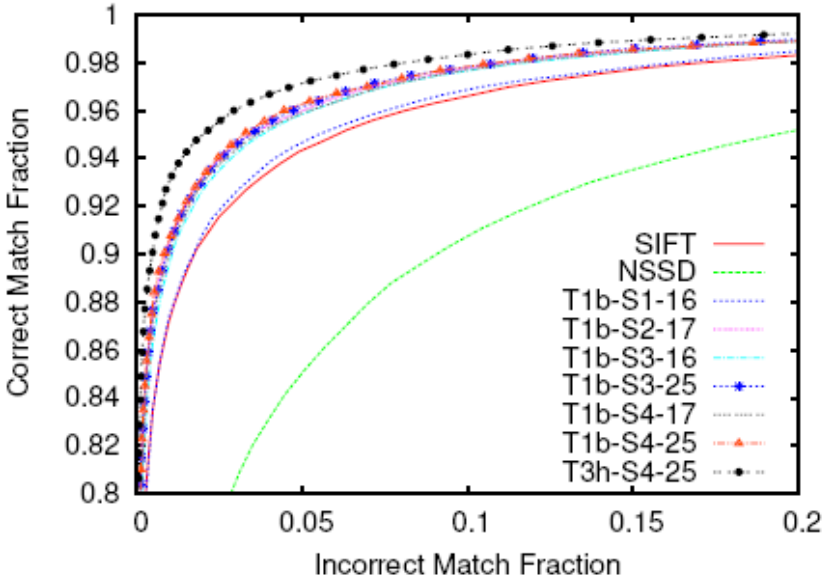
- By far the most commonly used distinguished region descriptor:
  - fast
  - compact
  - **works for a broad class of scenes**
  - source code available
- large number of ad hoc parameters $\Rightarrow$ Enormous follow up literature on both "improvements" and improvements [HoG, Daisy, Cogain]
  - GLOH, HoG: different grid, not 4x4, not necessarily a square
  - Daisy: many parameters optimized

Learning Local Image Descriptors

Simon A. J. Winder Matthew Brown
Microsoft Research
1 Microsoft Way, Redmond, WA 98052, USA







The best result of all was obtained by combining steerable filters with the polar plan of S4 to give T3h-S4-25. At just under a 2% error rate, this is one third of the error rate produced by SIFT at 95% correct matches. The ROC curve for this descriptor is plotted on Figure 11. However the dimensionality is quite high at 400.

DAISY local image descriptor

CENTER FOR MACHINE PERCEPTION

I. Histograms at every pixel location are computed

$$\mathbf{h}_\Sigma(u,v) = \left[\mathbf{G}_1^\Sigma(u,v), \ldots, \mathbf{G}_8^\Sigma(u,v)\right]^\top ,$$

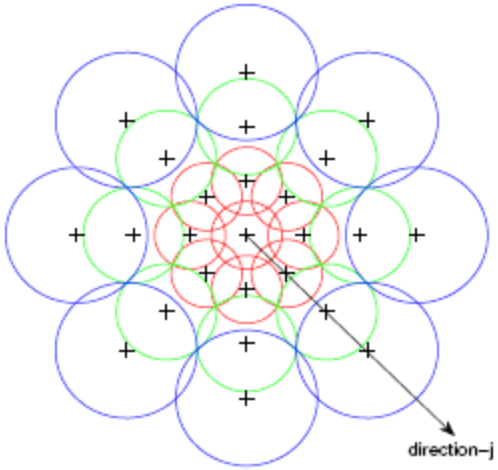
$\mathbf{h}_\Sigma(u,v)$: histogram at location (u, v)

$\mathbf{G}_1^\Sigma$: Gaussian convolved orientation maps

II. Histograms are normalized to unit norr

III. l as

$$\mathcal{D}(u_0,v_0) = \Big[\widetilde{\mathbf{h}}_{\Sigma_1}^\top(u_0,v_0), \widetilde{\mathbf{h}}_{\Sigma_1}^\top(\mathbf{l}_1(u_0,v_0,R_1)), \cdots, \widetilde{\mathbf{h}}_{\Sigma_1}^\top(\mathbf{l}_N(u_0,v_0,R_1)), \widetilde{\mathbf{h}}_{\Sigma_2}^\top(\mathbf{l}_1(u_0,v_0,R_2)), \cdots, \widetilde{\mathbf{h}}_{\Sigma_2}^\top(\mathbf{l}_N(u_0,v_0,R_2)), \widetilde{\mathbf{h}}_{\Sigma_3}^\top(\mathbf{l}_1(u_0,v_0,R_3)), \cdots, \widetilde{\mathbf{h}}_{\Sigma_3}^\top(\mathbf{l}_N(u_0,v_0,R_3)) \Big]^\top$$



DAISY v. SIFT: computational complexity

- Convolution is time-efficient for separable kernels like Gaussian

- Convolution maps with larger Gaussian kernel can be built upon convolution maps with smaller Gaussian kernel:

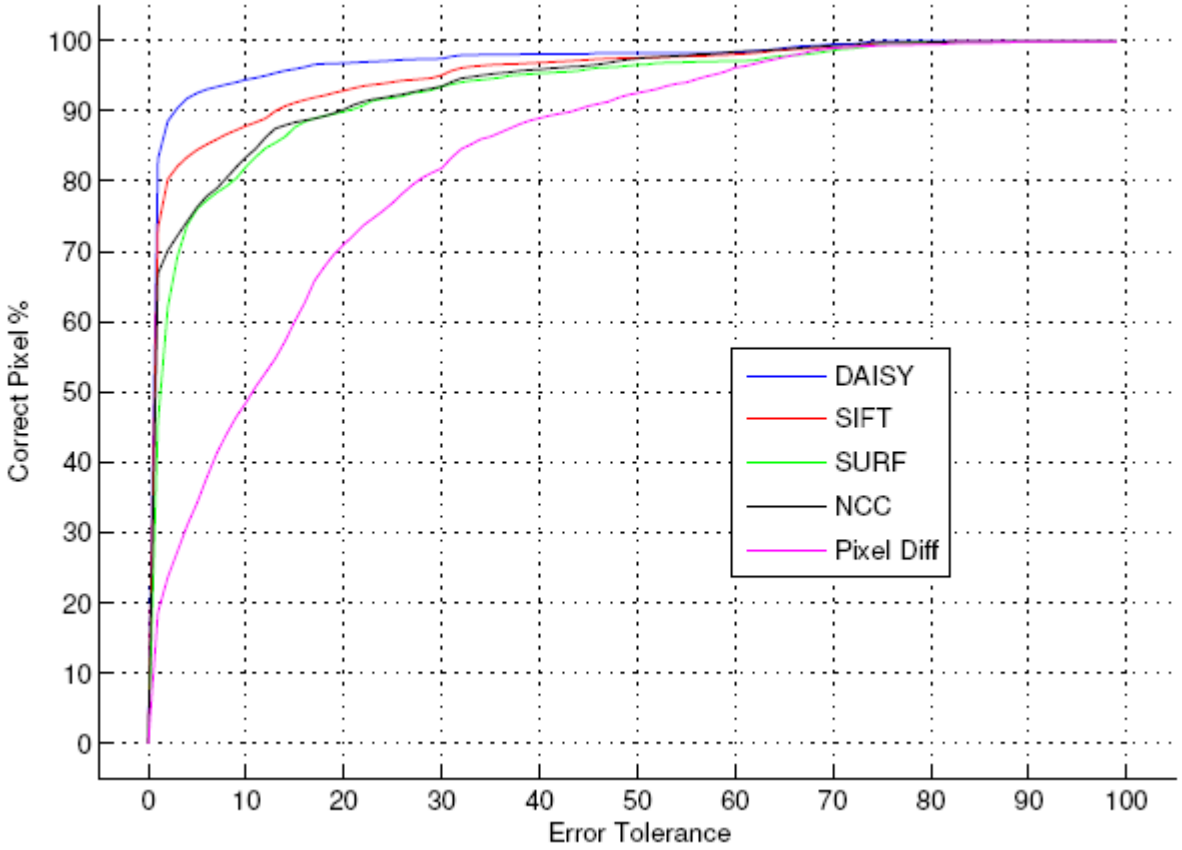
$$\mathbf{G}_o^{\Sigma_2} = G_{\Sigma_2} * \left(\frac{\partial \mathbf{I}}{\partial o}\right)^+ = G_{\Sigma} * G_{\Sigma_1} * \left(\frac{\partial \mathbf{I}}{\partial o}\right)^+ = G_{\Sigma} * \mathbf{G}_o^{\Sigma_1},$$

with $\Sigma = \sqrt{\Sigma_2^2 - \Sigma_1^2}$.

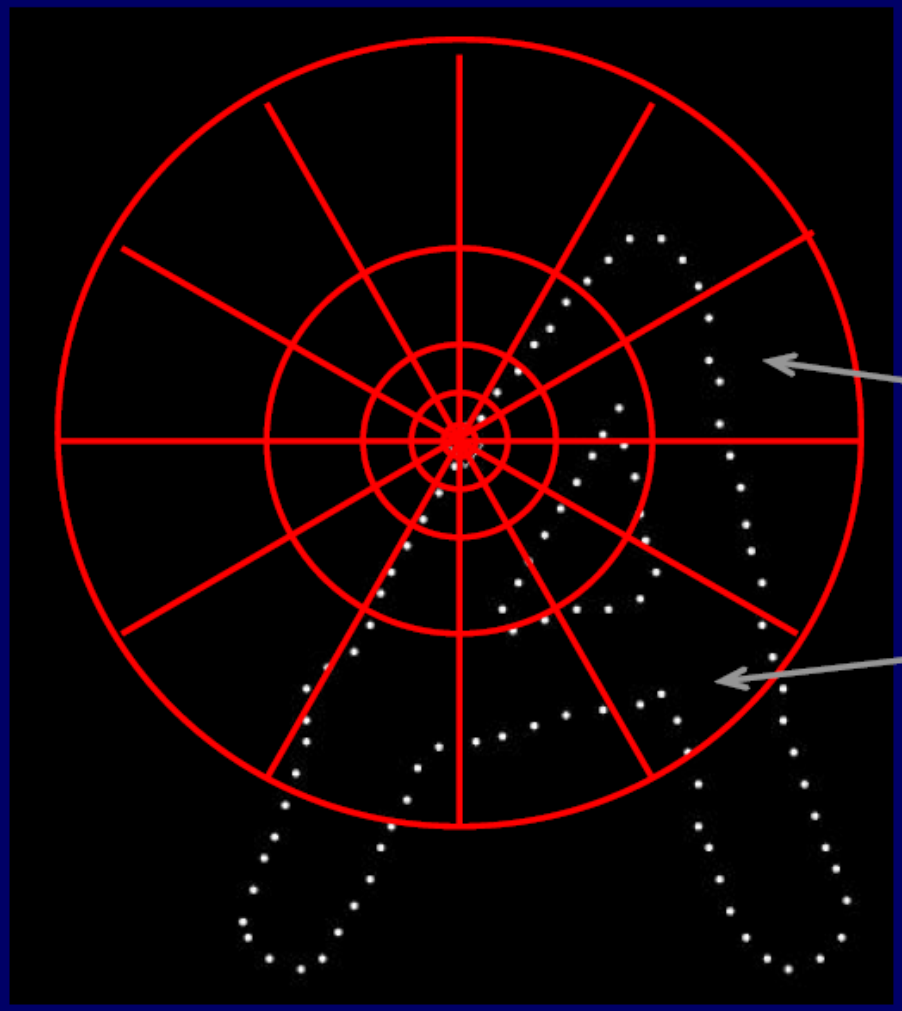
Image Size	DAISY	SIFT
800x600	5	252
1024x768	10	432
1290x960	13	651

Table 1. Computation Time Comparison (in seconds)

Results


Correct Pixel %
Error Tolerance
0
10
20
30
40
50
60
70
80
90
100
DAISY
SIFT
SURF
NCC
Pixel Diff

Shape Context



Count the number of points inside each bin, e.g.:

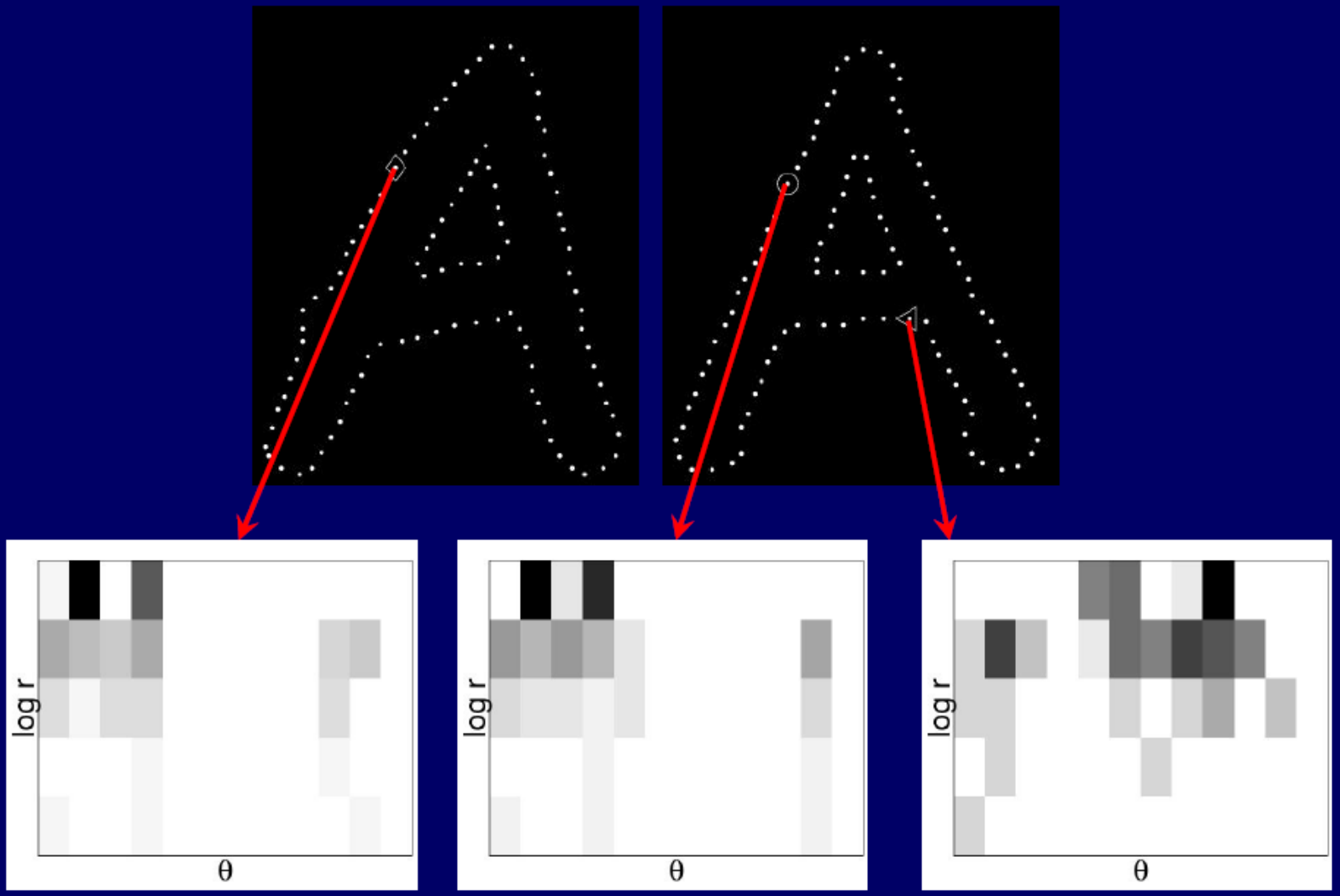
Count = 4

⋮

Count = 10

☞ Compact representation of distribution of points relative to each point

Shape Context

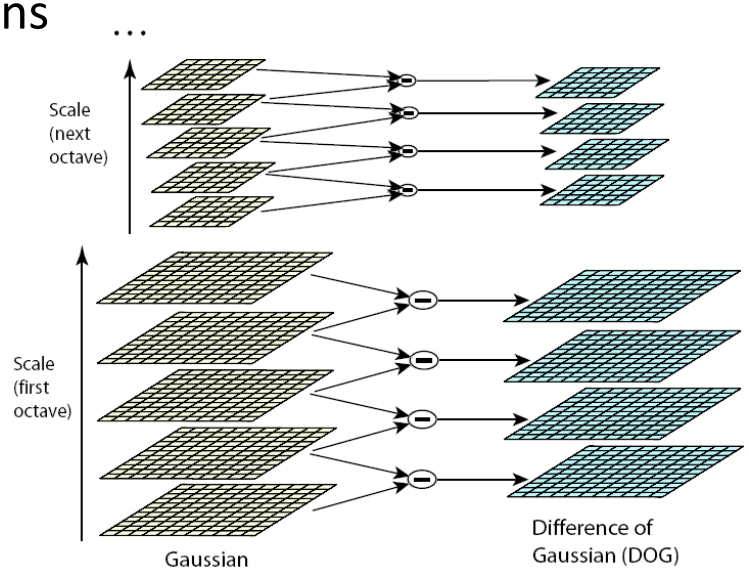


D. Lowe, *Object recognition from local scale-invariant features*, ICCV, 1999 2000 citations

CENTER FOR MACHINE PERCEPTION

Detector:

- Scale-space peaks of Difference-of-Gaussians filter response (Lindeberg 1995)
- **Similarity frame** from modes of gradient histogram



SIFT Descriptor:

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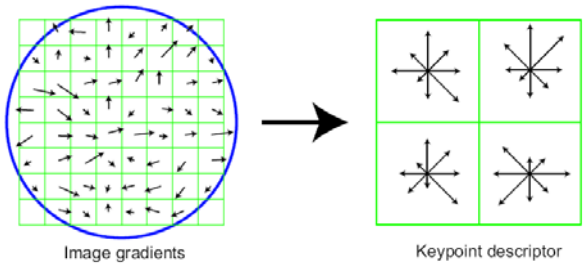
Indexing:

- Modified kD-tree structure

Verification:

- Hough transform based clustering of correspondences with similar transformations



Fast, efficient implementation**, real-time recognition**

D. G. Lowe: "Distinctive image features from scale-invariant keypoints". IJCV, 2004.

Nearest-neighbor matching

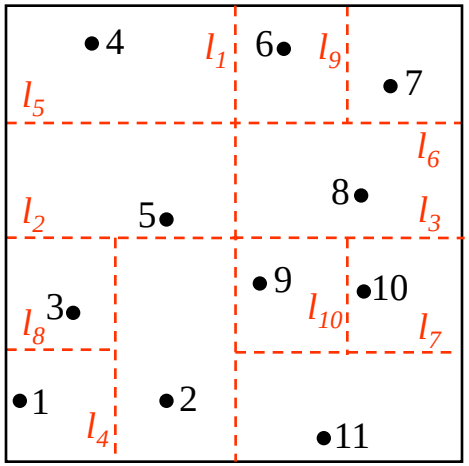
- Solve following problem for all feature vectors, $\mathbf{x}$:

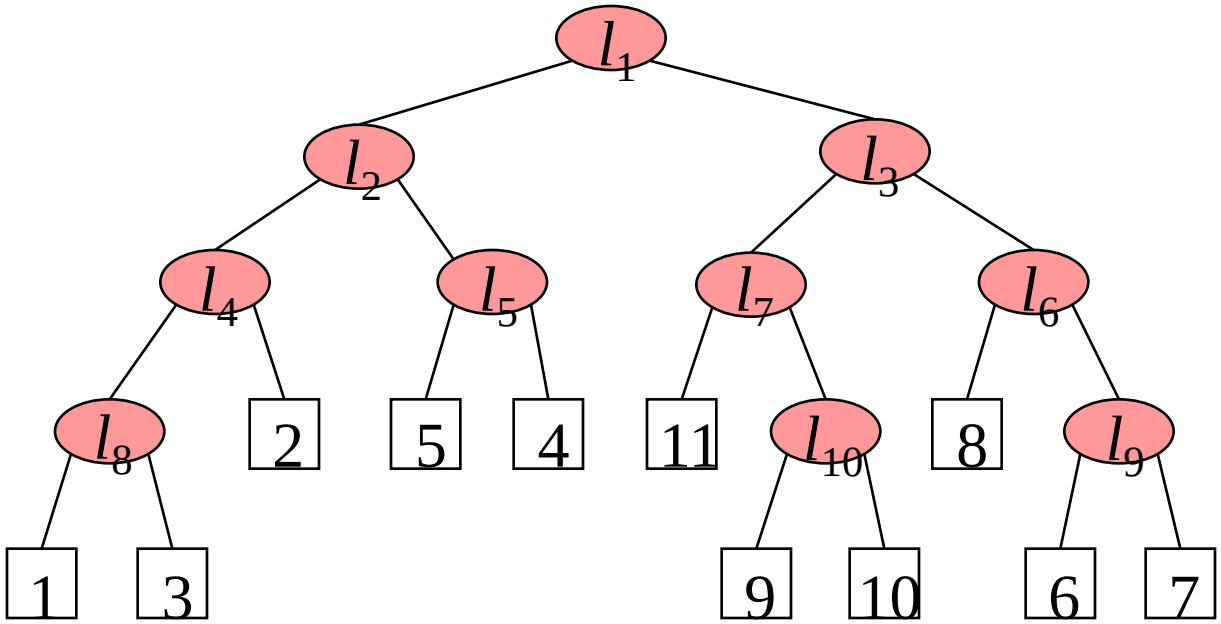
$$\forall j \; NN(j) = \arg\min_{i} ||\mathbf{x}_i - \mathbf{x}_j||, \; i \neq j$$

- Nearest-neighbor matching is the major computational bottleneck
  - Linear search performs dn^2 operations for n features and d dimensions
  - No exact methods are faster than linear search for d>10 (?)
  - Approximate methods can be much faster, but at the cost of missing some correct matches. Failure rate gets worse for large datasets.

K-d tree construction

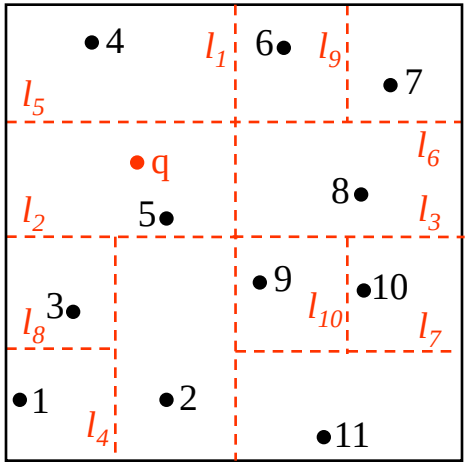
Simple 2D example

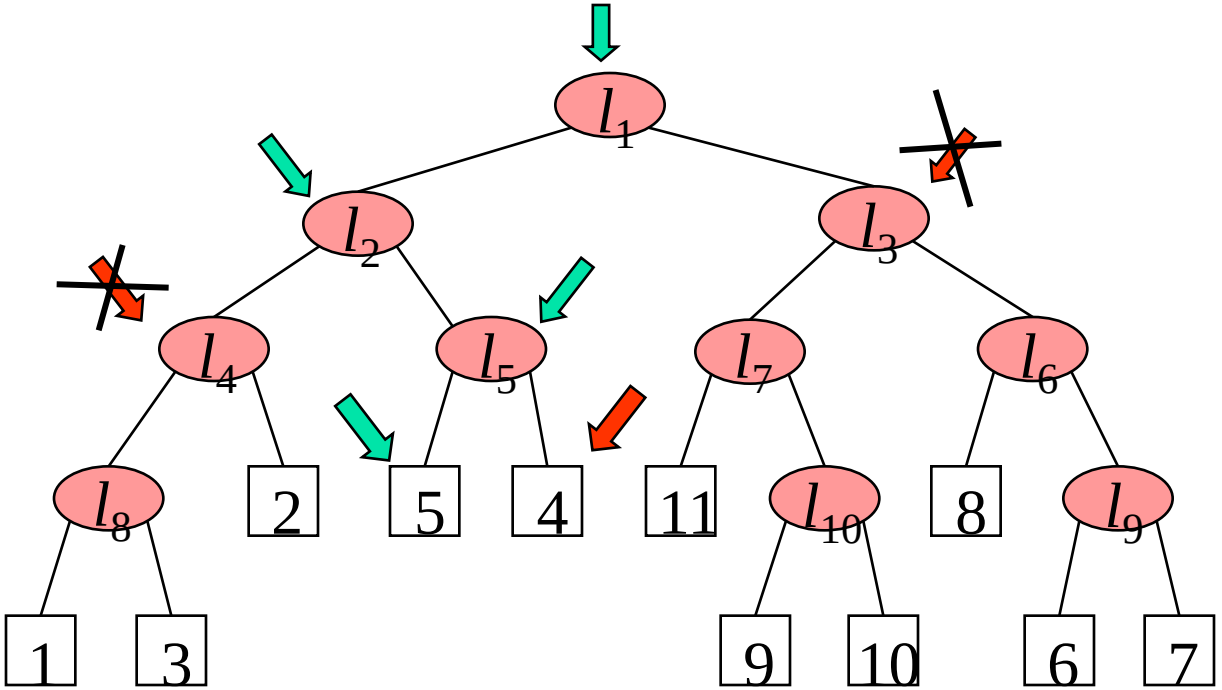




Slide credit: Anna Atramentov

K-d tree query

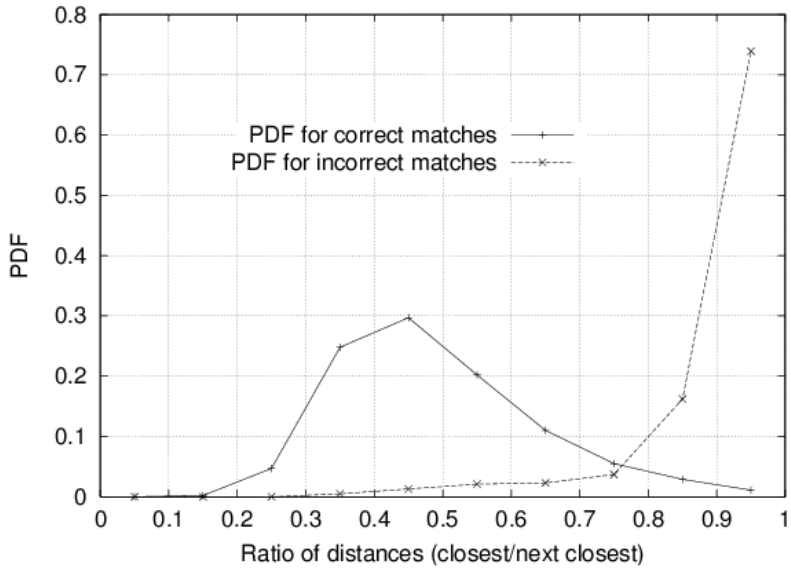




Slide credit: Anna Atramentov

Feature space outlier rejection

- How can we tell which putative matches are more reliable?
- Heuristic: compare distance of **nearest** neighbor to that of **second** nearest neighbor
  - Ratio will be high for features that are not distinctive
  - Threshold of 0.8 provides good separation

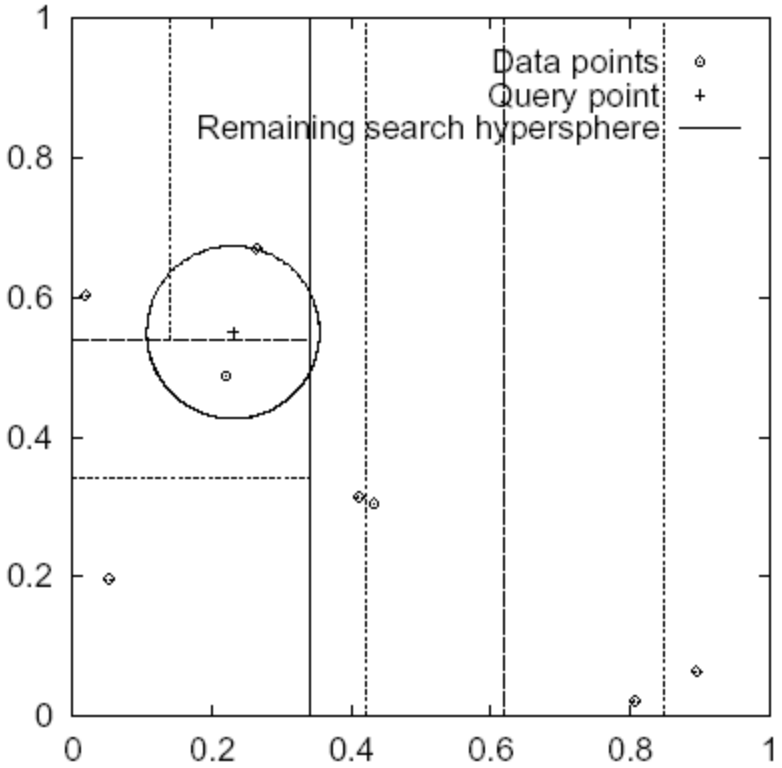


David G. Lowe. "Distinctive image features from scale-invariant keypoints." *IJCV* 60 (2), pp. 91-110, 2004.

Approximate k-d tree matching

Key idea:

- Search k-d tree bins in order of distance from query
- Requires use of a priority queue
- Copes better with high dimensionality
- Many different varieties
  - Ball tree, Spill tree etc.



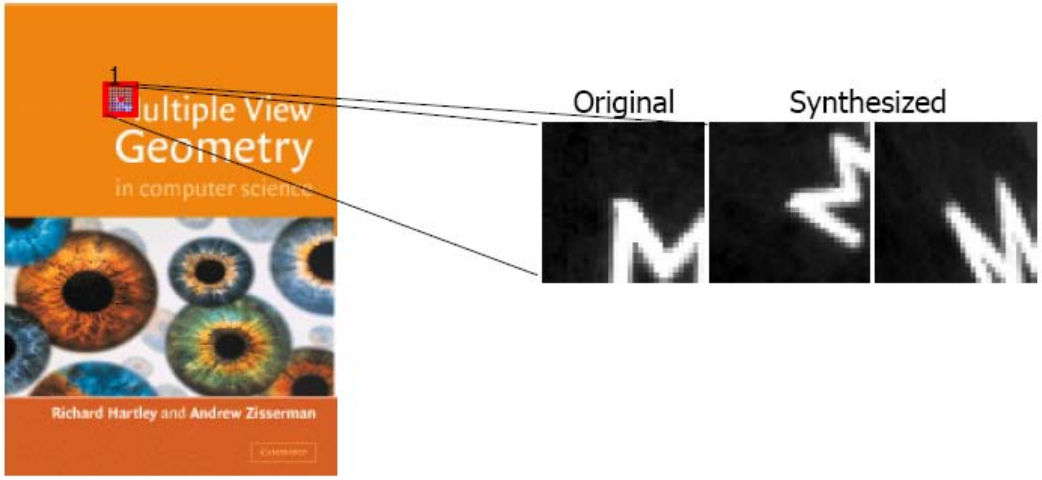
Randomized Forests

- Feature matching as a classification problem

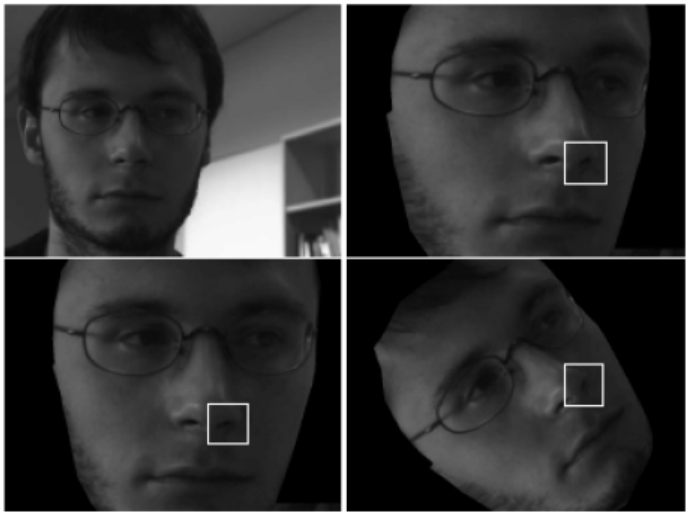
Lepetit, Lagger and Fua. Randomized Trees for Real-Time Keypoint Matching, CVPR 2005

Synthesize training examples

- Planar object



3-D object



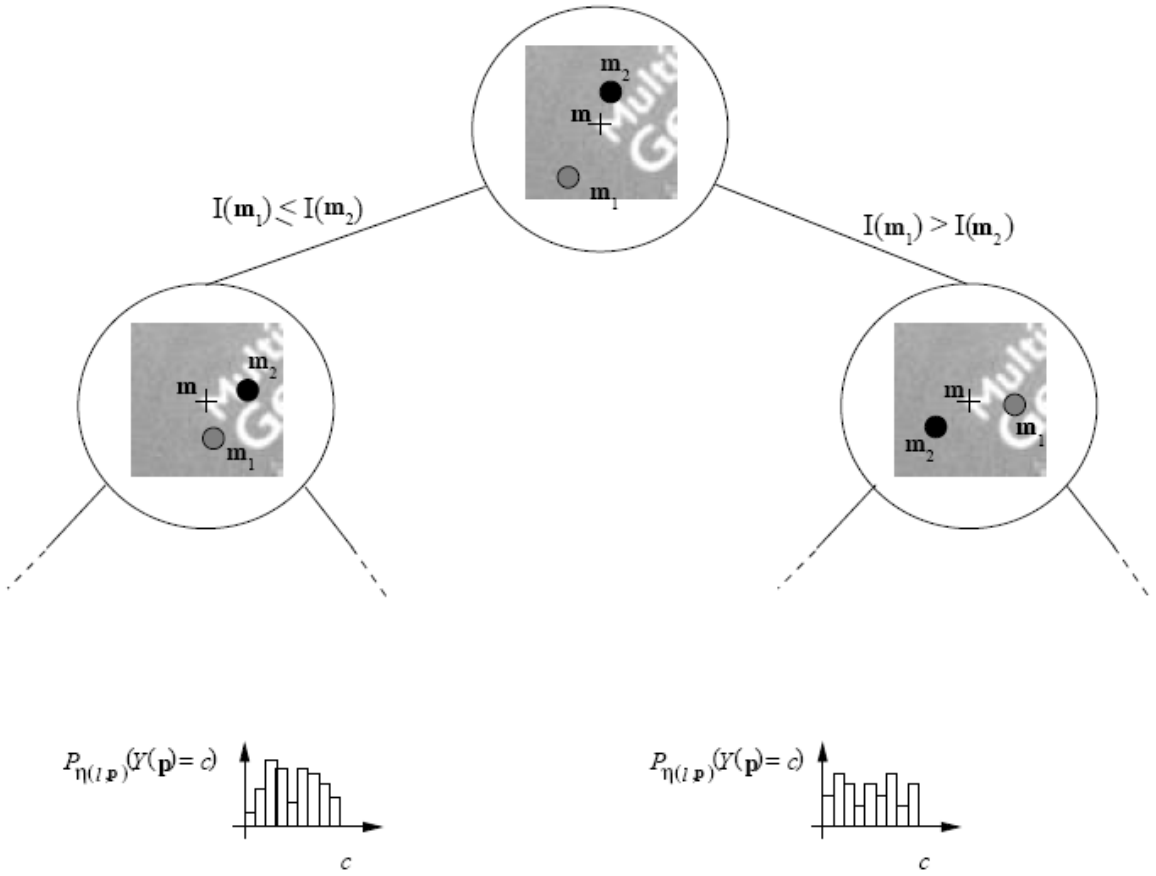
Lepetit, Lagger and Fua. Randomized Trees for Real-Time Keypoint Matching, CVPR 2005

Randomized Decision Tree

- Compare intensity of pairs of pixels
- In construction, pick pairs randomly

• Insert all training examples into tree

• Distribution at leaves is descriptor for the particular feature



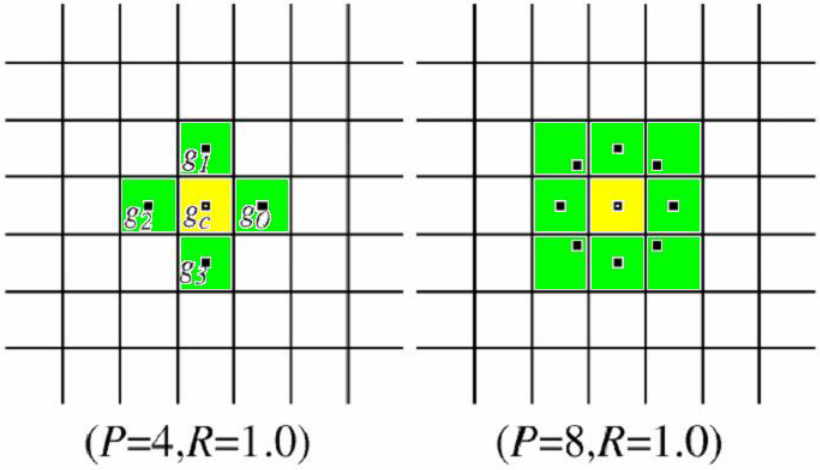
Randomized Forests

- Use multiple trees (i.e. forest) to improve performance
- Very quick to compute in testing
  - Just comparison of pairs of pixels
  - Real-time performance
- ~10x faster than SIFT, but slightly inferior performance

Local Binary Pattern (LBP) Descriptor

The primitive LBP (P,R) number that characterizes the spatial structure of the local image texture is defined as:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(x)2^p \;,\; x = g_p - g_c \qquad \text{where ,} \qquad s(x) = \begin{cases} 1 \; if \;\; x \geq 0 \\ 0 \; if \;\; x < 0 \end{cases}$$



Circularly symmetric neighbor sets (P: angular resolution, R: spatial resolution)

2^7	2^0	2^1
2^6	g_c	2^2
2^5	2^4	2^3

LBP values in a 3 x 3 block

The LBP descriptor is invariant to any monotonic transformation of image

slide credit: Sara Arasteh et al.

Rotation Invariant LBP …

- In order to remove the effect of rotation and assign a unique identifier to each, Rotation Invariant Local Binary Pattern is defined as:

$$LBP_{P,R}^{ri} = \min\left\{ ROR(LBP_{P,R}, i) \;\middle|\; i = 0,1,\ldots, P-1 \right\}$$

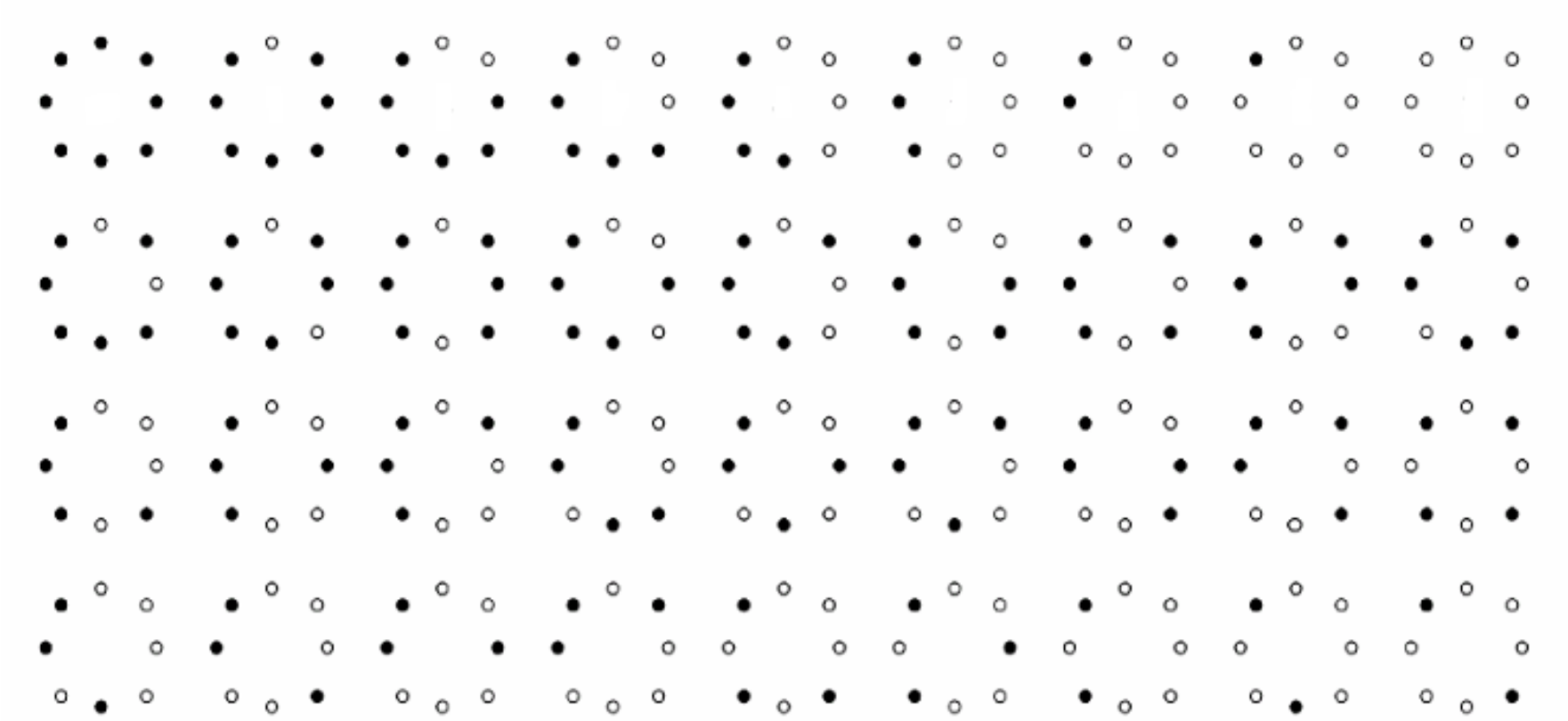
where *ROR(x,i)* performs a circular bit-wise right shift on P-bit number x , i time.

- 36 unique rotation invariant binary patterns can occur in the circularly symmetric neighbor set of $LBP_{8,1}$.

slide credit: Sara Arasteh et al.

Rotation Invariant LBP ...

- This figure shows 36 unique rotation invariant binary patterns.

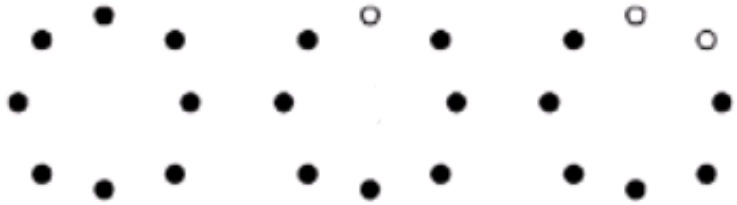


slide credit: Sara Arasteh et al.

Rotation Invariant LBP ...

- Rotation Invariant LBP patterns include:
  - Uniform patterns
    - At most two transitions from 0 to 1
  - Non-uniform patterns
    - More than two transitions from 0 to 1

Samples of non-uniform patterns



Samples of uniform patterns

slide credit: Sara Arasteh et al.

Uniform LBP (ULBP)

- It is observed that the uniform patterns are the majority, sometimes over 90 percent, of all 3 x 3 neighborhood pixels present in the observed textures.
- They function as templates for microstructures such as :
  - Bright spot (0)
  - Flat area or dark spot (8)
  - Edges of varying positive and negative curvature (1-7)

Uniform Local Binary Patterns

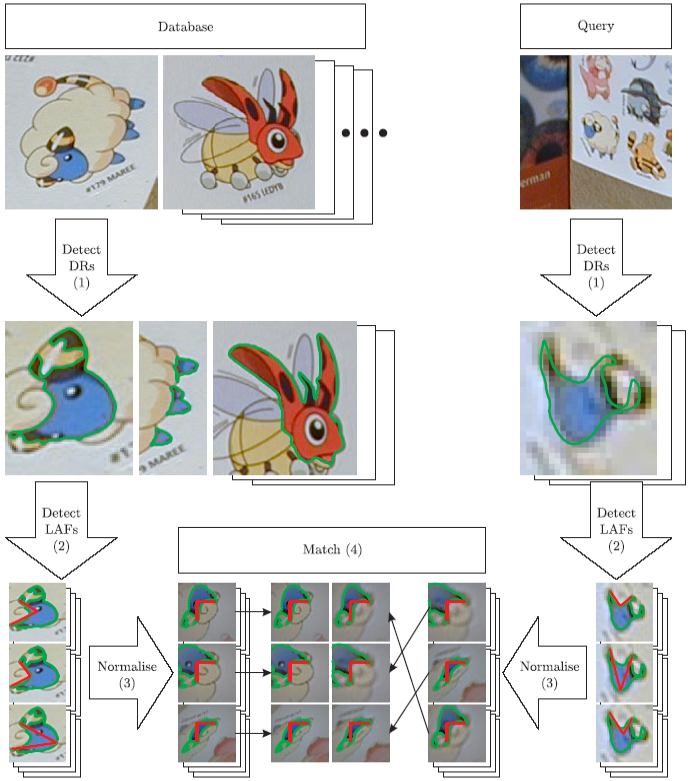
LBPs are popular, numerous modifications exist

slide credit: Sara Arasteh et al.

MSER-LAF-Tree, Obdrzalek and Matas, 2005 180 citations

CENTER FOR MACHINE PERCEPTION

1. **Detect Distinguished Regions** Maximally Stable Extremal Regions (MSERs)
2. Construct **Local Affine Frames (LAFs)** (local coordinate frames)
3. **Geometrically normalize** some measurement region (MR) expressed in LAF coordinates
4. **Photometrically normalize** measurements inside MR, compute some derived description
5. Establish local (tentative) correspondences by the **decision-measurement tree method**
6. Verify global geometry (e.g. by RANSAC, geometric hashing, Hough transform.)



Matas, Chum, Urban, Pajdla: "Robust wide baseline stereo from maximally stable extremal regions". BMVC2002

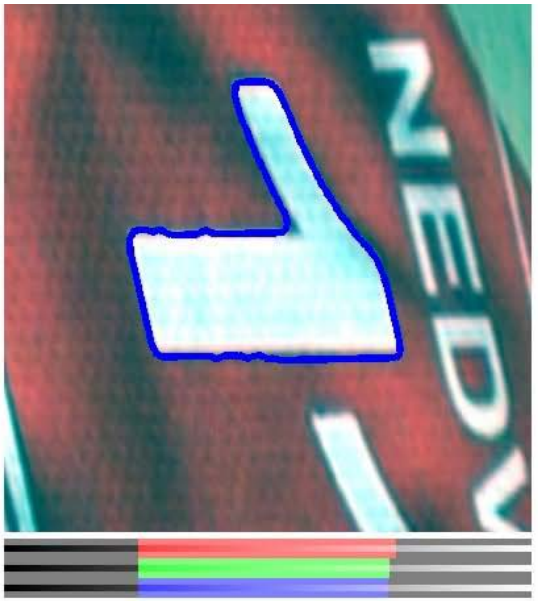
Obdržálek and Matas: "Object recognition using local affine frames on distinguished regions". BMVC02

Obdržálek and Matas: "Sub-linear Indexing for Large Scale Object Recognition", BMVC 2005

MSER-LAF-Tree, Obdrzalek and Matas, 2005

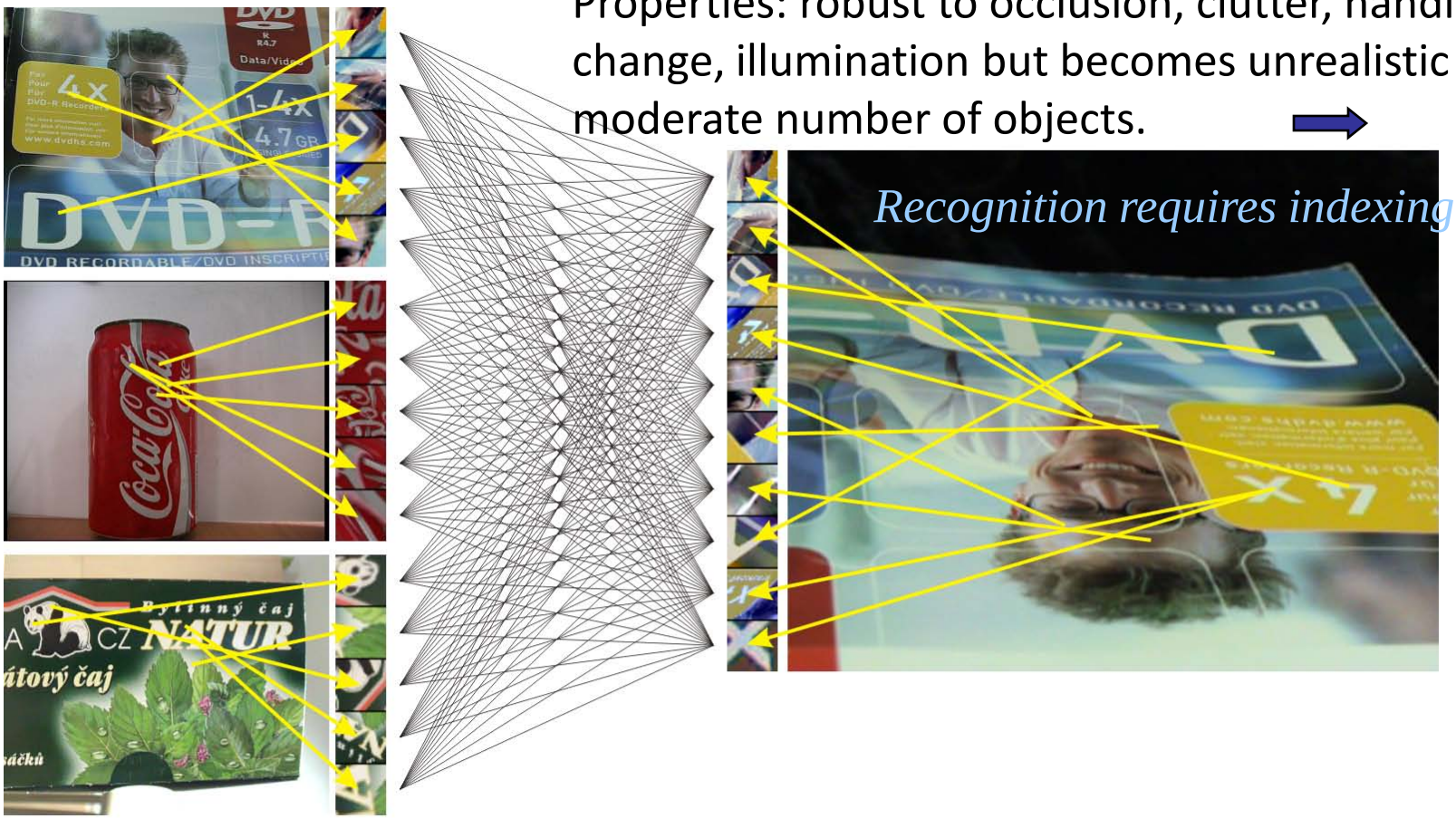
4. Photometrically normalize measurements inside MR, compute some derived description

video1, video2

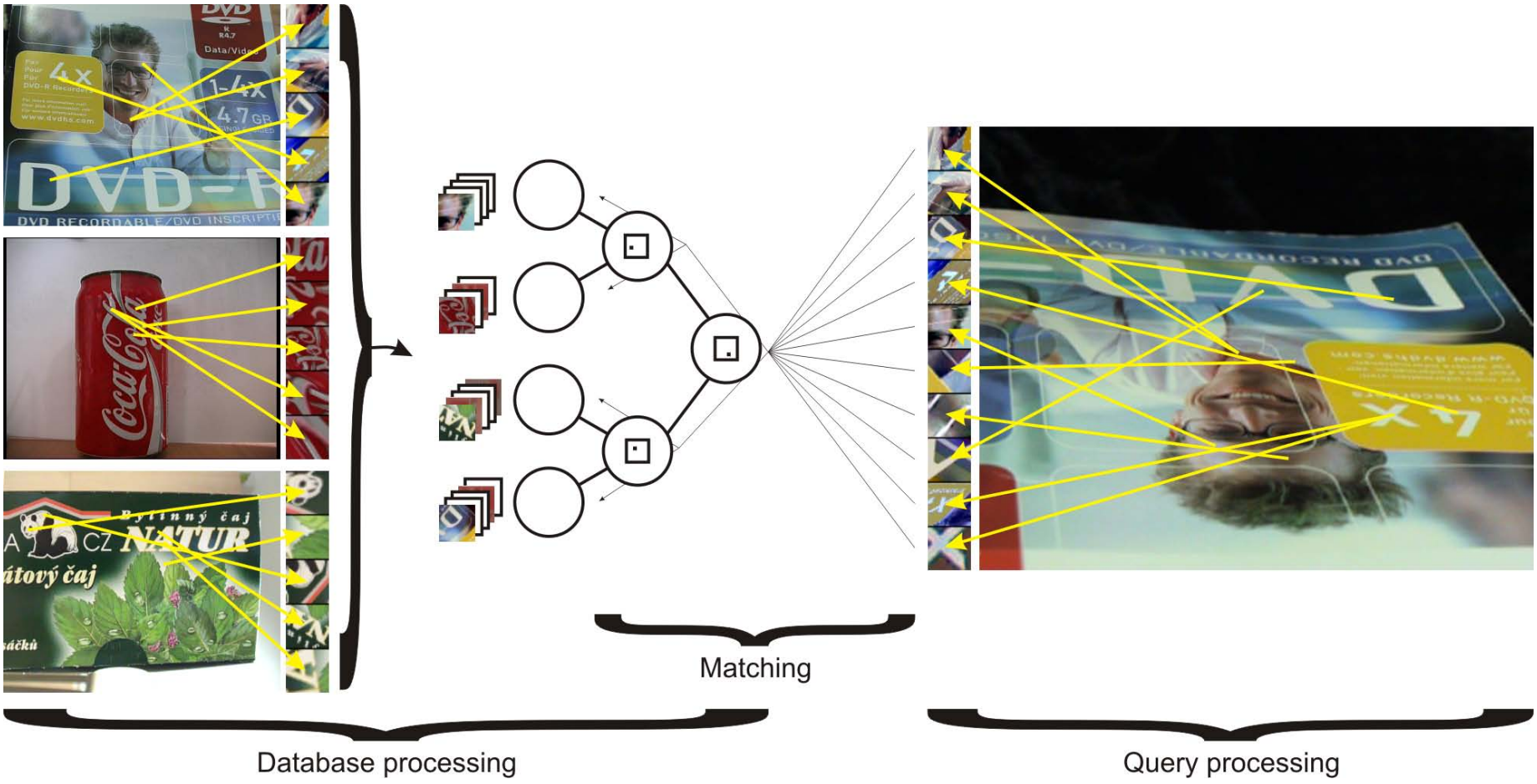


"Recognition" as a Sequence of Wide-Baseline Matching Problems ??

Properties: robust to occlusion, clutter, handles pose change, illumination but becomes unrealistic even for moderate number of objects.



Simultaneous Recognition of Multiple Objects Using the Decision-Measurement Tree



Performance Evaluation 1.:Image Retrieval from ZuBuD[1]

- Publicly available dataset ZuBuD
- Database: 201 buildings, each represented by 5 images, more than 1000 images in the DB
- Queries: 115 new images
- Forced match

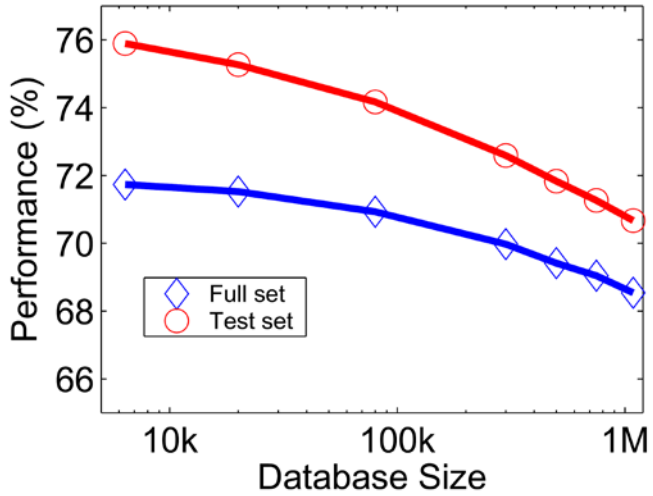
Recognition rates (rank 1 correct):

- Repeated LAF-MSER matching:
  100% @ 27 seconds /retrieval
- Tree matching:
  93% @ 0.014 seconds
  99% @ 0.510 seconds

[1] Shao, Svoboda, Tuytelaars, Gool: “HPAT indexing for fast object/scene retrieval”, CIVR2004

Example 2: D. Nistér, H. Stewénius. *Scalable Recognition with a Vocabulary Tree*, CVPR 2006

- MSER detector, SIFT descriptor, K-means tree
- Very carefully implemented
- Evaluated on large databases
  - Indexing with up to 1M images
- Online recognition for database of **50,000 CD covers**
  - **Retrieval in ~1s**



D. Nistér, H. Stewénius. *Scalable Recognition with a Vocabulary Tree, CVPR 2006* 300 citations

However:

- Recognition of images, not objects
- Some of the object have no chance of being recognized via MSER+SIFT on different background

ImageSearch at the VizCentre

New query: Browse... Send File

File is 500x320

Top n results of your query.

bourne/im1000043322.pgm bourne/im1000043323.pgm bourne/im1000043326.pgm bourne/im1000043327.pgm

Local Features : Application Examples

- Detection of goods in tray at supermarket checkout
- Database: 500 objects, 6 images each

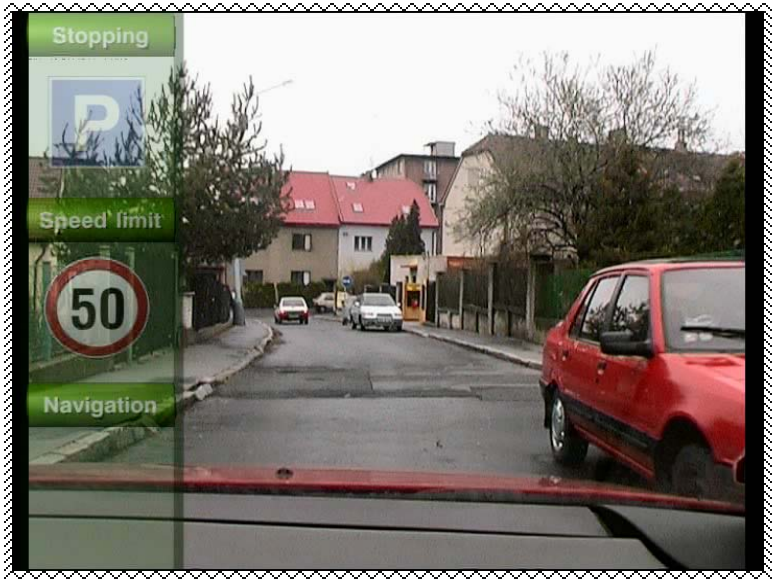
- Queries: images captured from a camera at the checkout

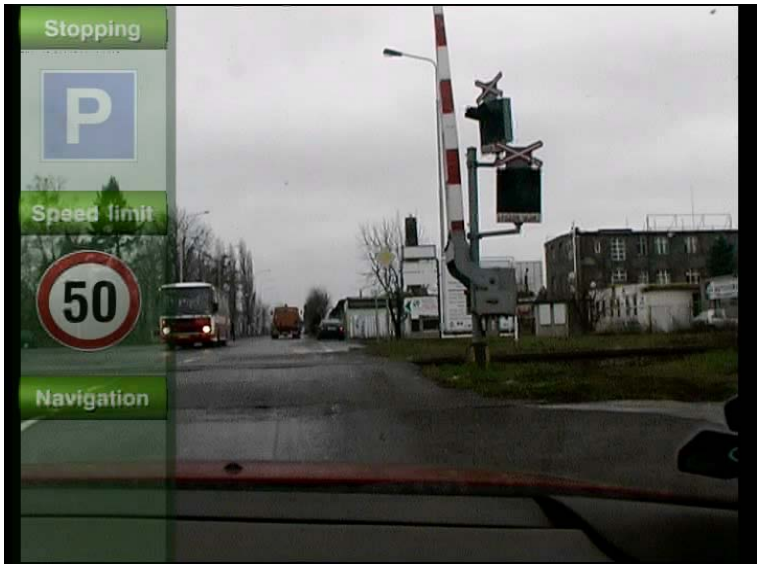
- Output: list of objects identified in the tray

Local Features : Application Examples

- Traffic sign recognition from a moving car
- Database: images of known signs

- Output: identification of signs in images taken by an in-car camera (scene-interpretation is not part of the system)





Local Features : Application Examples

- Detection of product logos in scanned commercials

- Detection of advertising side-boards in TV coverage of sport events. "For how long was my commercial actually broadcasted?"

- Detection of company logos in automatic fax processing

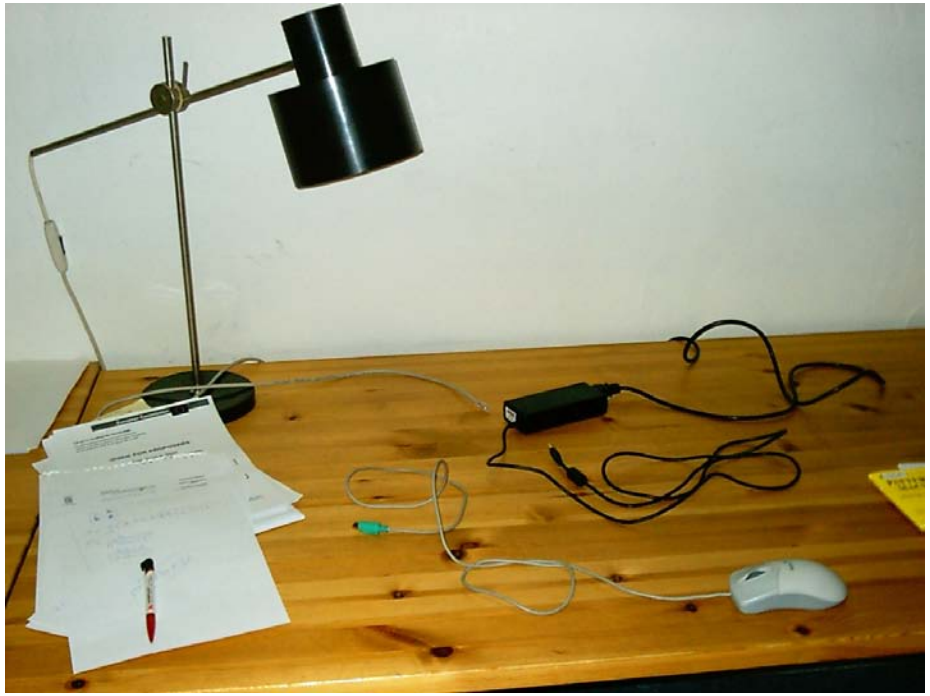
Local Feature Methods: Analysis

1. Methods work well for a non-negligible class of objects, that are locally approximately planar, compact and have surface markings or where 3D effects are negligible (e.g. stitching photographs taken from a similar viewpoint)

2. They are *correspondence based methods*
   - insensitive to occlusion, background clutter
   - very fast
   - handles very large dataset
   - model-building is automatic

3. **The space of problems and object where it does not work is HUGE (examples are all around us).**

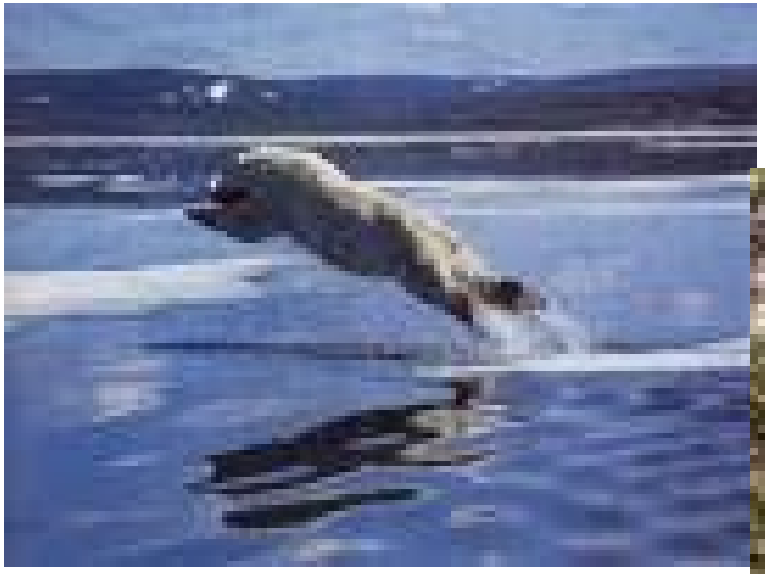
Where Local Features Fail:



Challenge: Elongated, Wirey and Flexible Objects

In this case: “no recognition without segmentation”?

Where Local Features Fail:



Camouflage: No distinguished regions !
Very few animals can afford to be distinguishable ....

Thank you for your attention.

OPPA European Social Fund
Prague & EU: We invest in your future.