CAP5415-Computer Vision

Lecture 4 - Finding Features

(introduction to feature engineering, local features)

Guest Lecturer: Prof. Boqing Gong

Outline

Non-Deep Learning Approaches (Introduction to Feature Engineering)

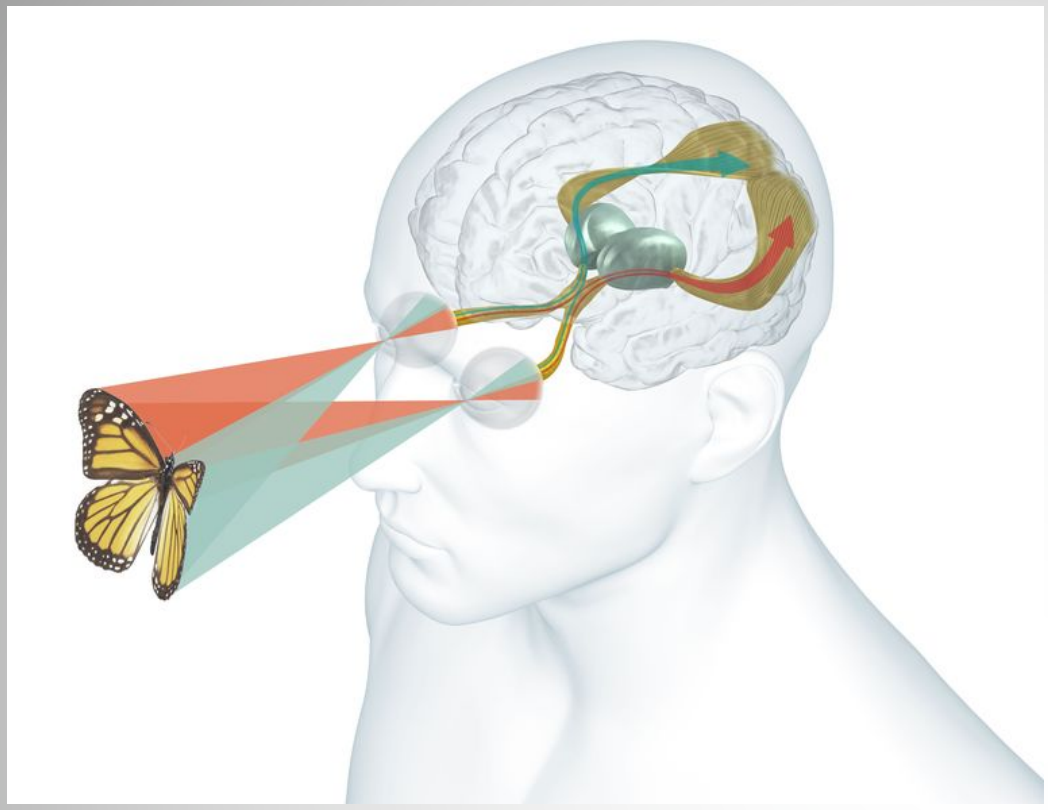
- Ex1. Key-point Features
  - Harris corner detection
- Ex2. Affine Invariance

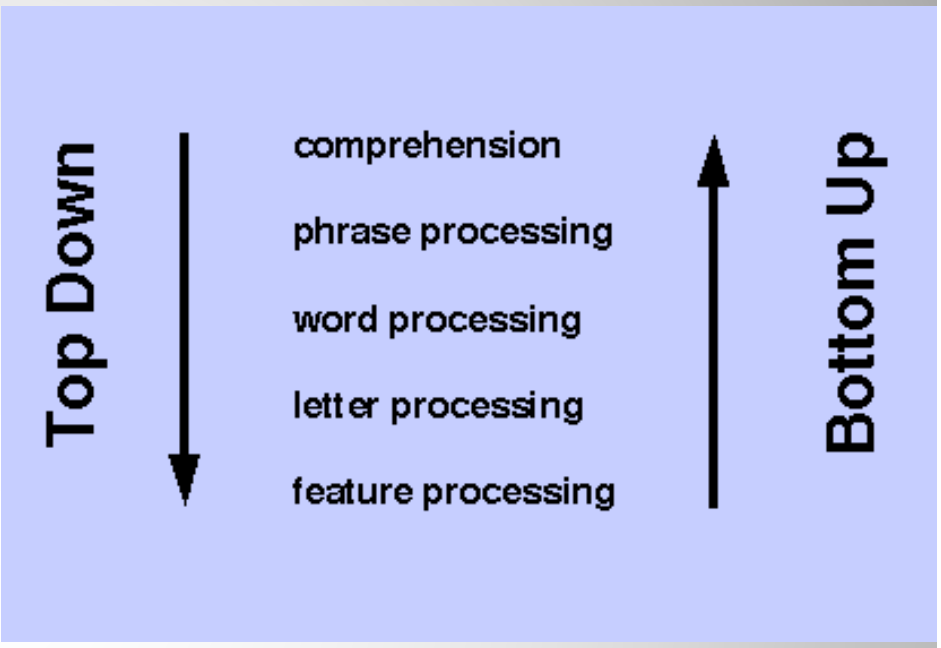
- *Read Szeliski, Chapter 4.*
- *Read Shah, Chapter 2.*
- *Read/Program CV with Python, Chapters 1 and 2.*

Motivation for Feature Finding: Matching

Motivation for Feature Finding: Harder case

Credit: Fei Fei Li

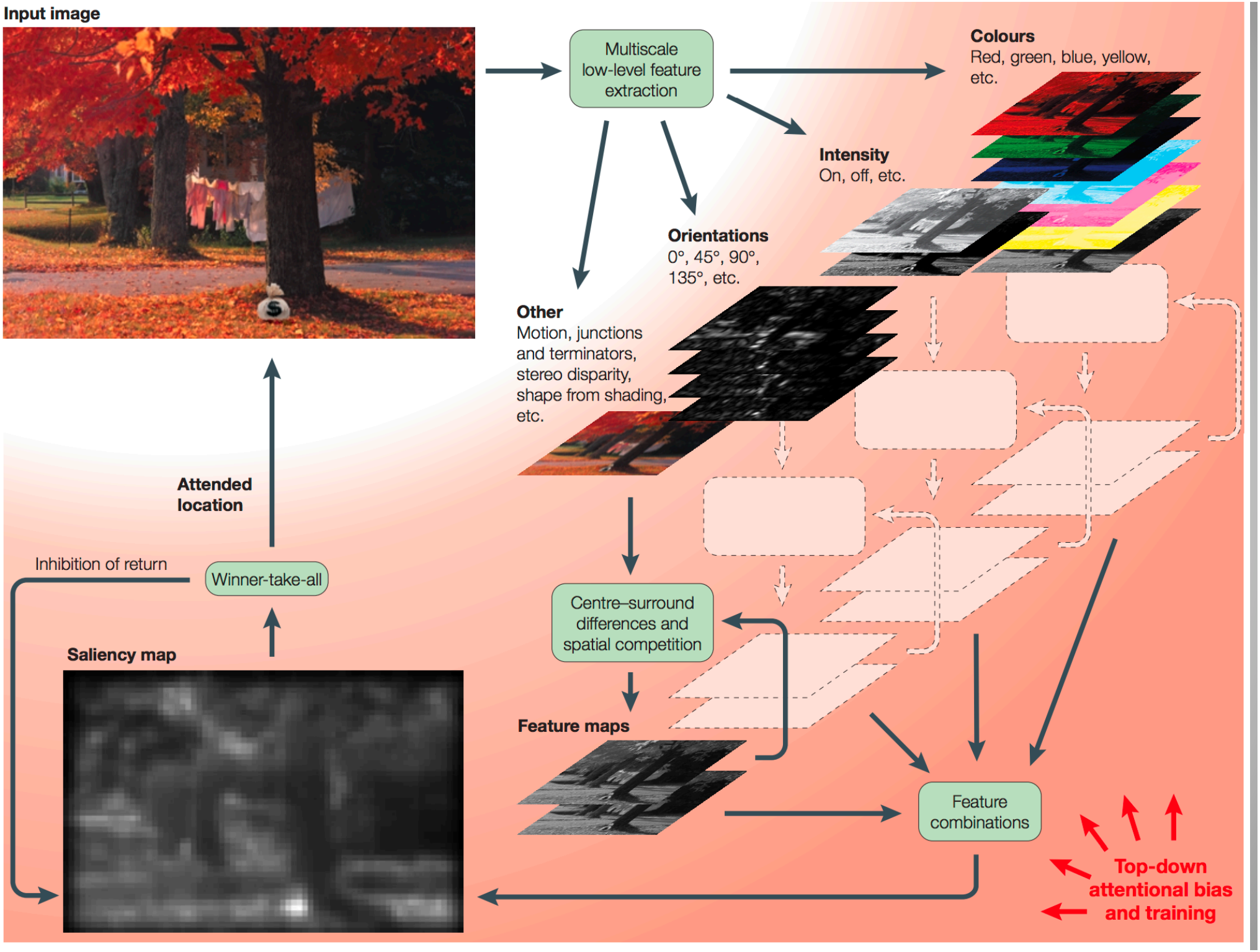


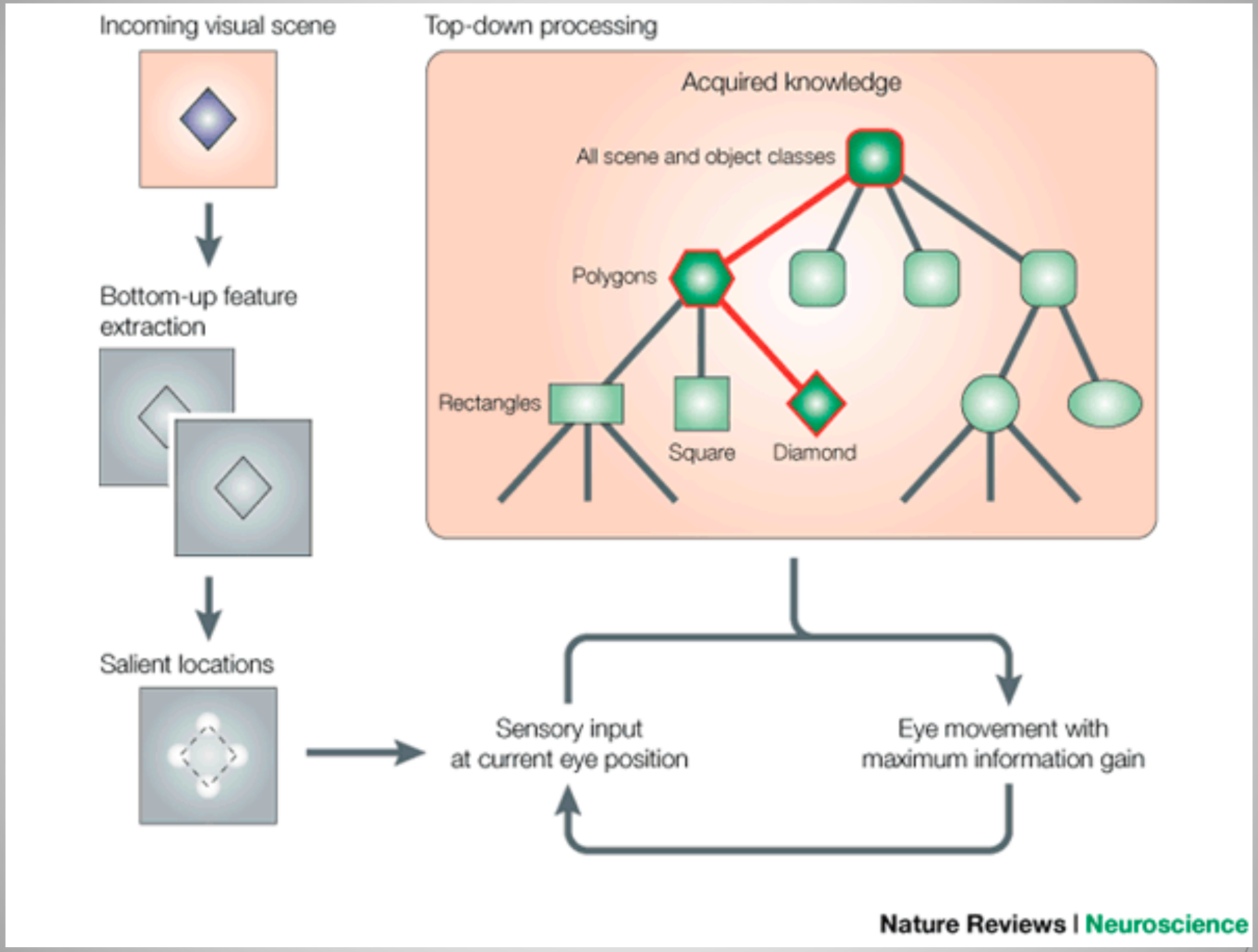


Top-down processing suggests that we form our perceptions starting with a larger object, concept or idea before working our way toward more detailed information.

In other words, top-down processing happens when we work from the **general to the specific;** the big picture to the tiny details.

In top-down processing, your abstract impressions can influence the sensory data that you gather.

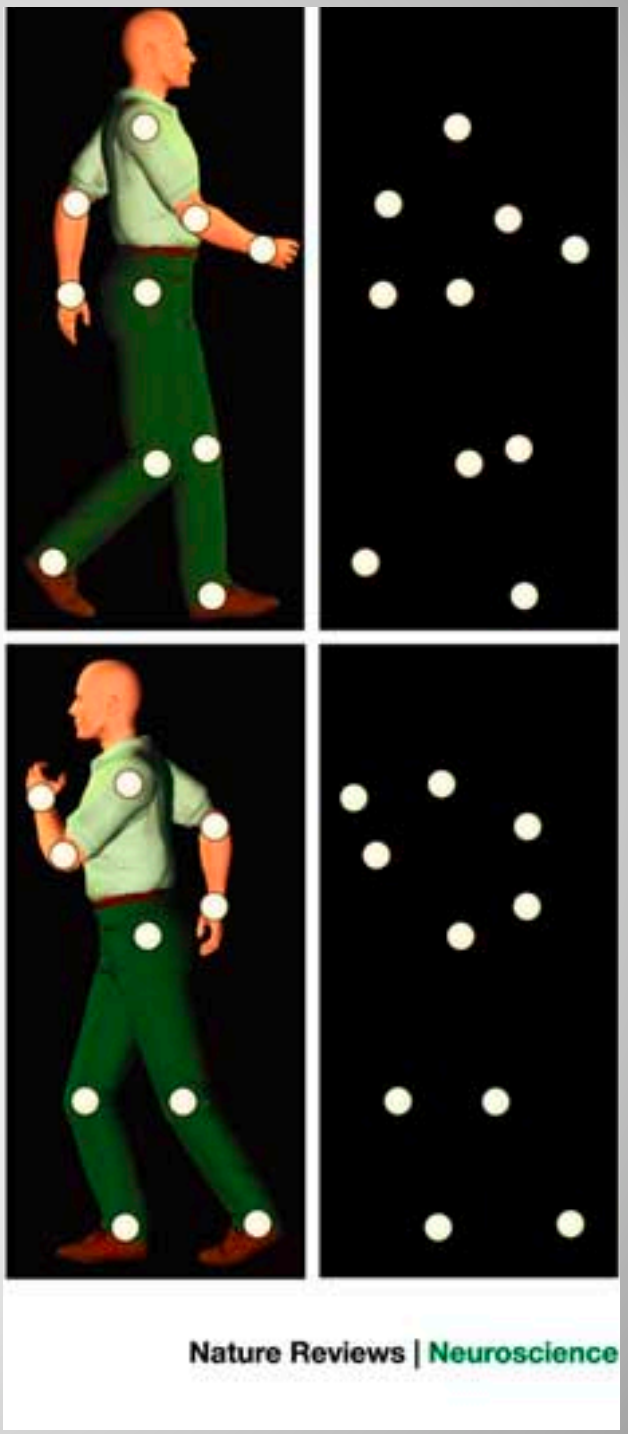

Input image
Multiscale low-level feature extraction
Colours
Red, green, blue, yellow, etc.
Intensity
On, off, etc.
Orientations
0°, 45°, 90°, 135°, etc.
Other
Motion, junctions and terminators, stereo disparity, shape from shading, etc.
Attended location
Inhibition of return
Winner-take-all
Saliency map
Centre–surround differences and spatial competition
Feature maps
Feature combinations
Top-down attentional bias and training

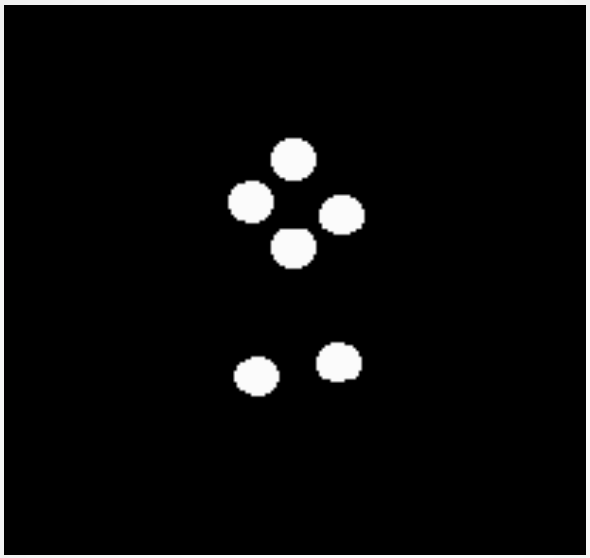

Incoming visual scene
Top-down processing
Acquired knowledge
All scene and object classes
Polygons
Rectangles
Square
Diamond
Bottom-up feature extraction
Salient locations
Sensory input at current eye position
Eye movement with maximum information gain
Nature Reviews | Neuroscience

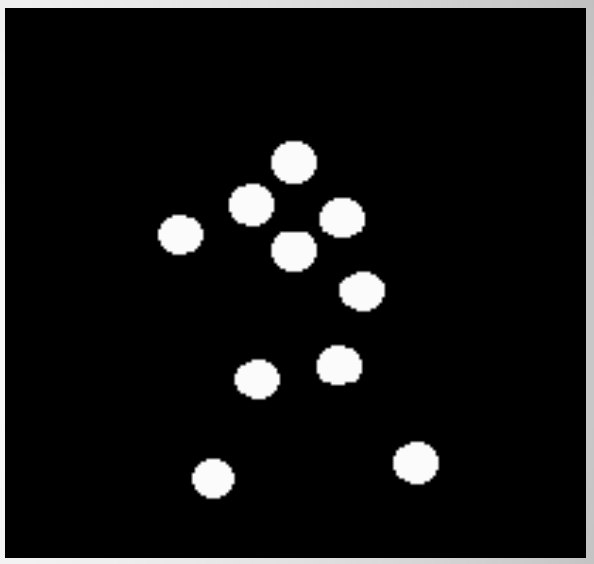
Finding Features in Videos

Subsequent studies have shown that many complex
actions can be recognized on the basis of such 'point-light displays', including

- facial expressions,
- Sign Language,
- arm movements,
- and various full-body actions.







Choosing interest points

Where would you tell your friend to meet you?

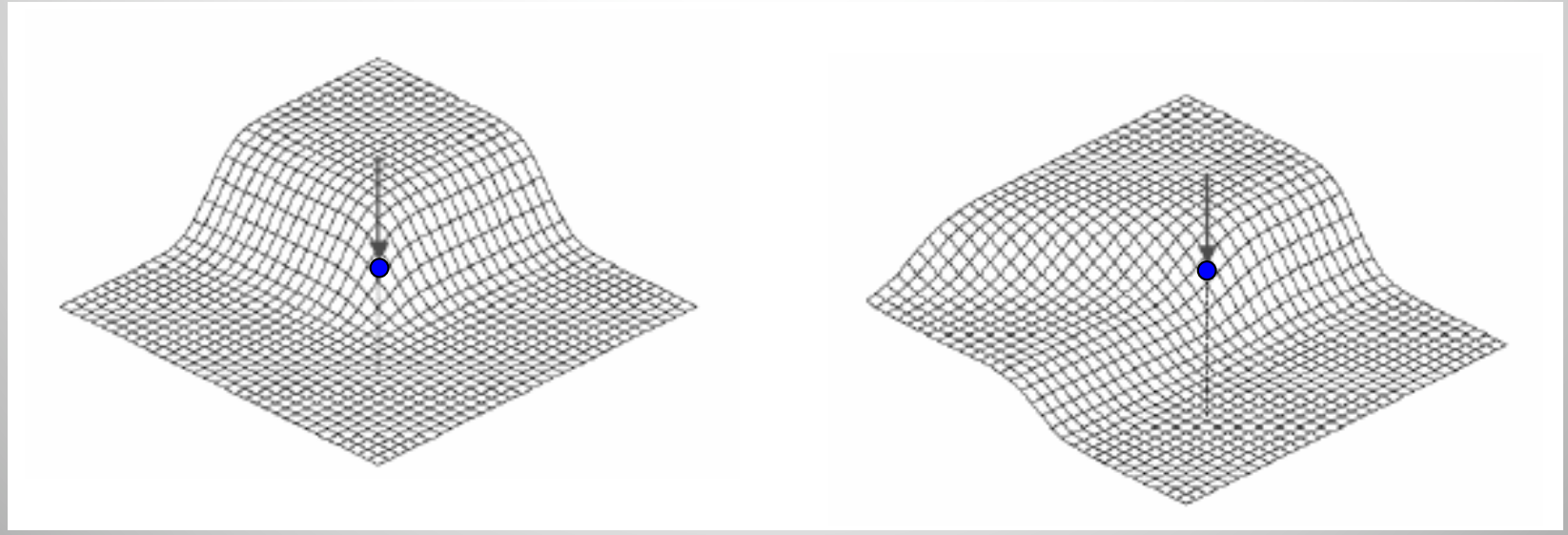
Slide Credit: James Hays

Features are used in …

- Automate object tracking
- Point matching for computing disparity
- Motion based segmentation
- Object Recognition
- 3D Object Reconstruction
- Robot Navigation
- Image Retrieval/Indexing
- ….

What is an interest point?

- Expressive texture
  - The point at which the direction of the boundary of object changes abruptly
  - Intersection point between two or more edge segments



What is an interest point?

Properties of Interest Points

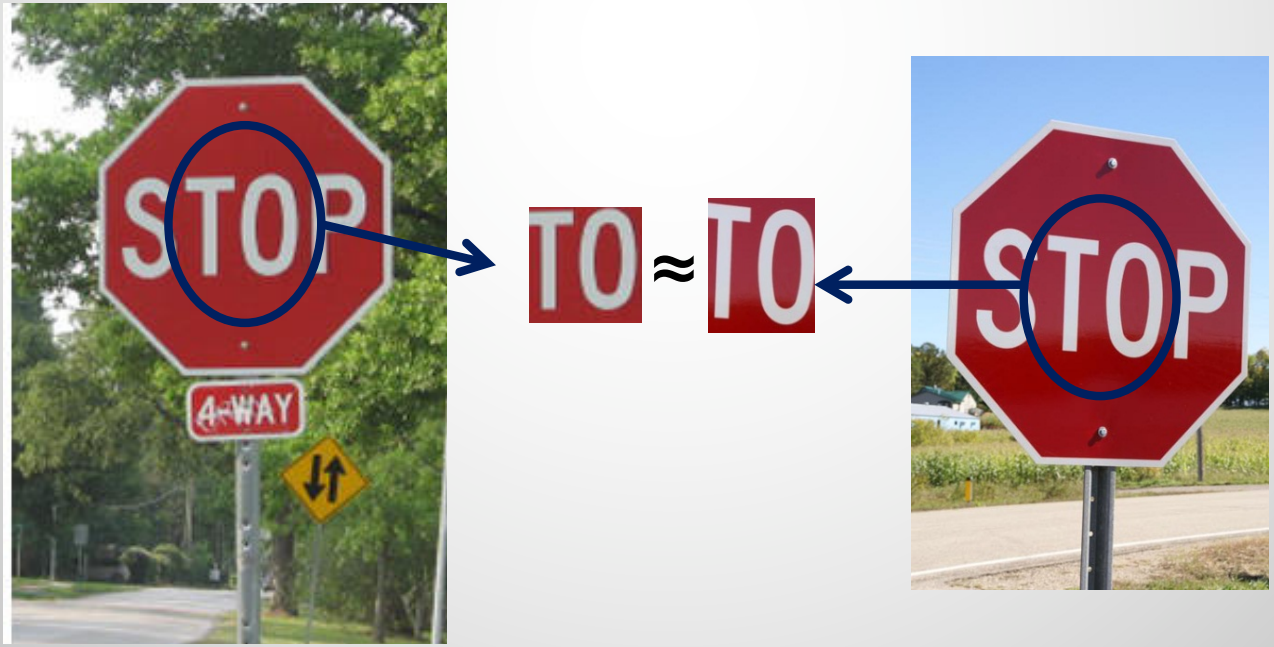
- Detect all (or most) true interest points
- No false interest points
- Well localized
- Robust with respect to noise
- Efficient detection

Possible Approaches for Corner Detection (ex. interest point)

- Based on brightness of images
  - Usually image derivatives
- Based on boundary extraction
  - First step edge detection
  - Curvature analysis of edges

Correspondence Across Views

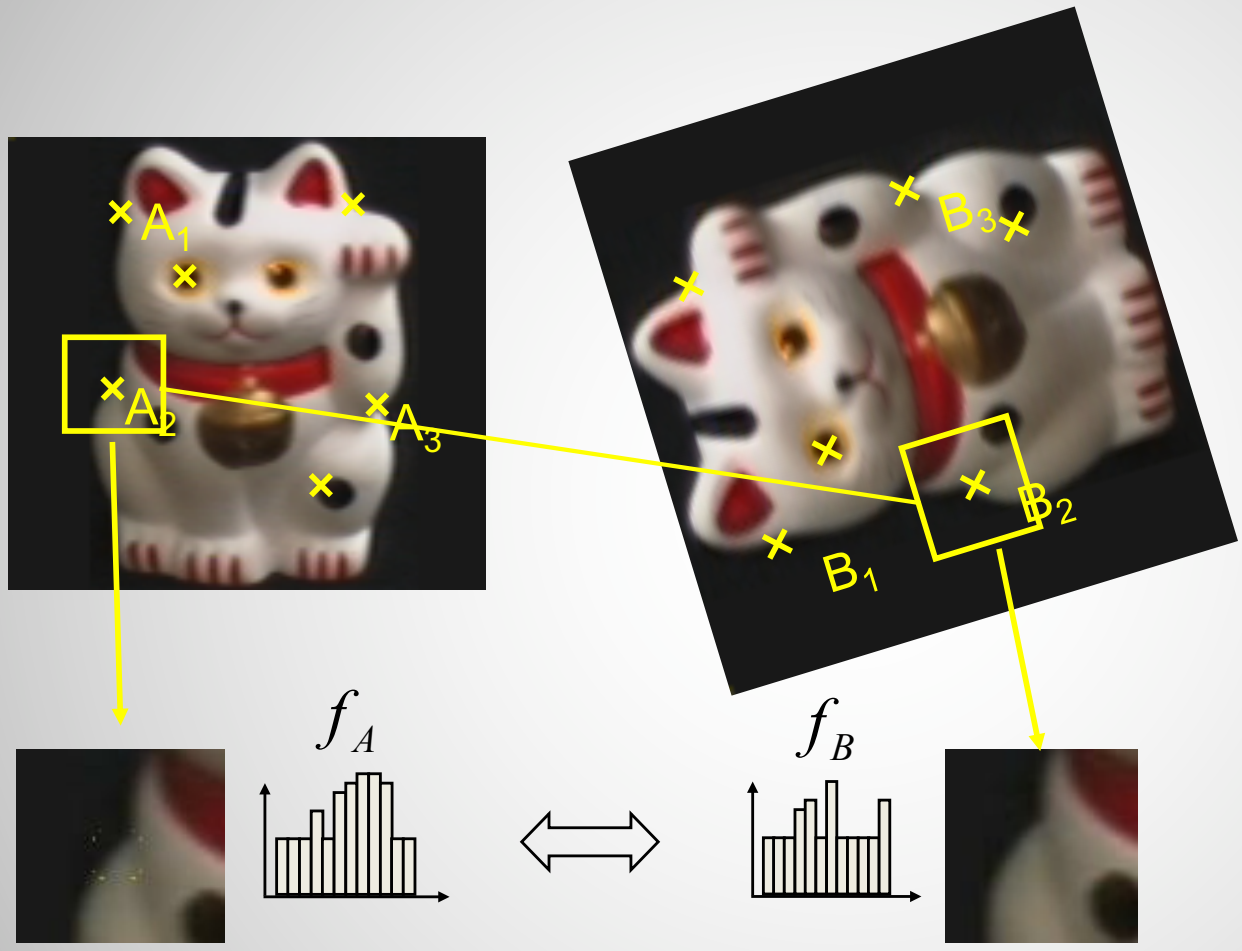
- Correspondence: matching points, patches, edges, or regions across images



Goals for KeyPoints

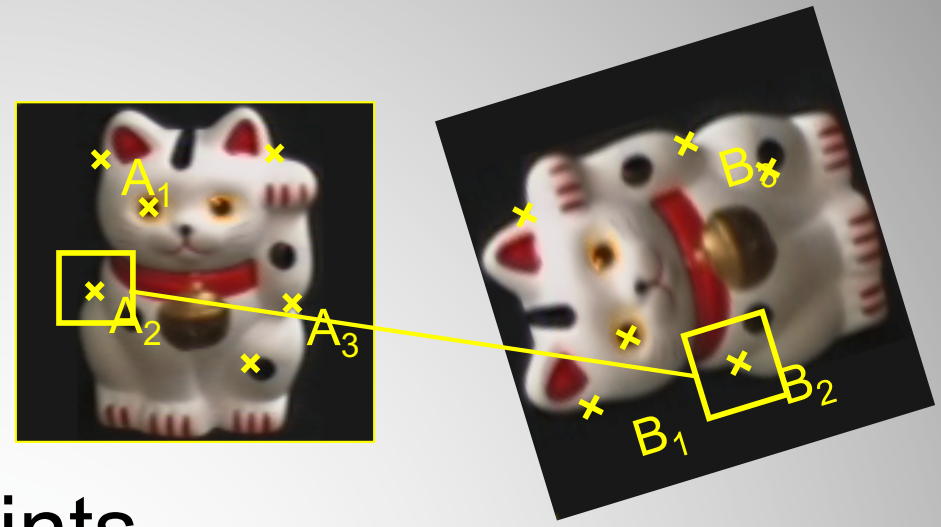
Detect points that are *repeatable* and *distinctive*

Overview of KeyPoint Matching



1. Find a set of distinctive key-points
2. Define a region around each keypoint
3. Extract and normalize the region content
4. Compute a local descriptor from the normalized region
5. Match local descriptors

Major Trade-offs



Detection of interest points

More Repeatable
- Robust detection
- Precise localization

More Interest Points
- Robust to occlusion
- Works with less texture

Description of patches

More Distinctive
- Minimize wrong matches

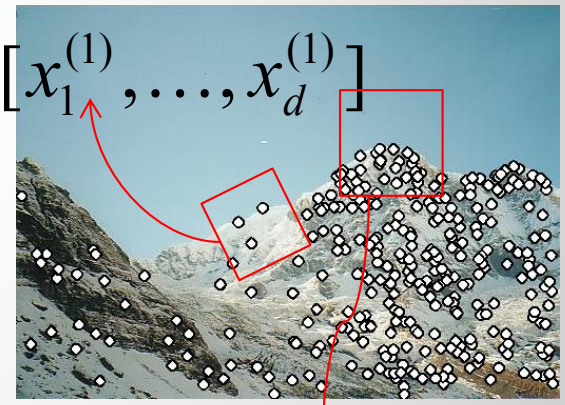
More Flexible

Local Features: Main Components

1) **Detection:** Identify the interest points

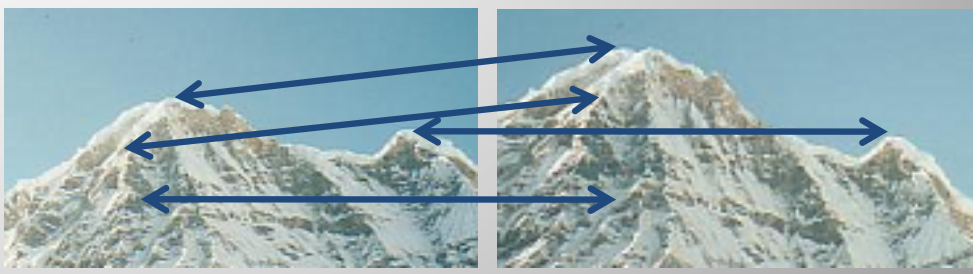
2) **Description:** Extract feature vector descriptor surrounding each interest point.

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



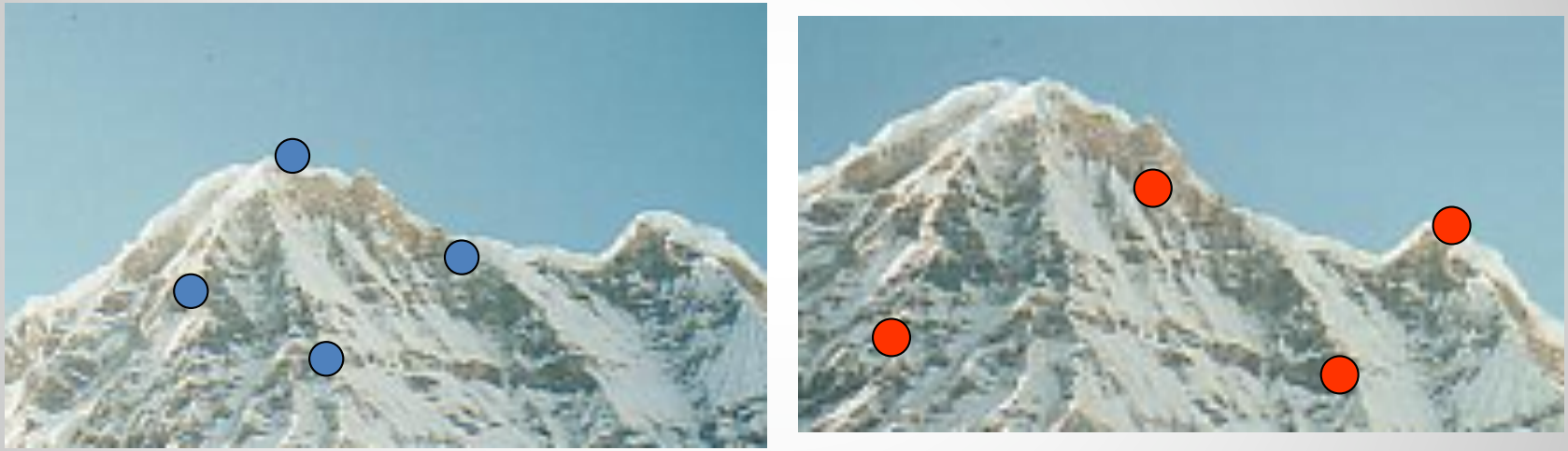
$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) **Matching:** Determine correspondence between descriptors in two views



Goal: interest operator repeatability

- We want to detect (at least some of) the same points in both images.

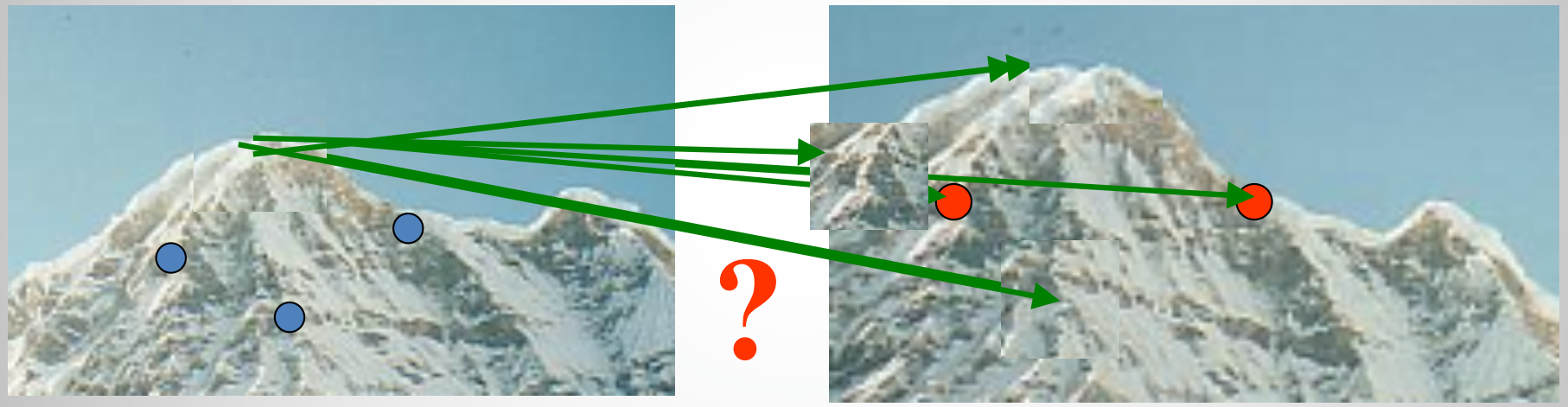


No chance to find true matches!

- Yet we have to be able to run the detection procedure *independently* per image.

Goal: descriptor distinctiveness

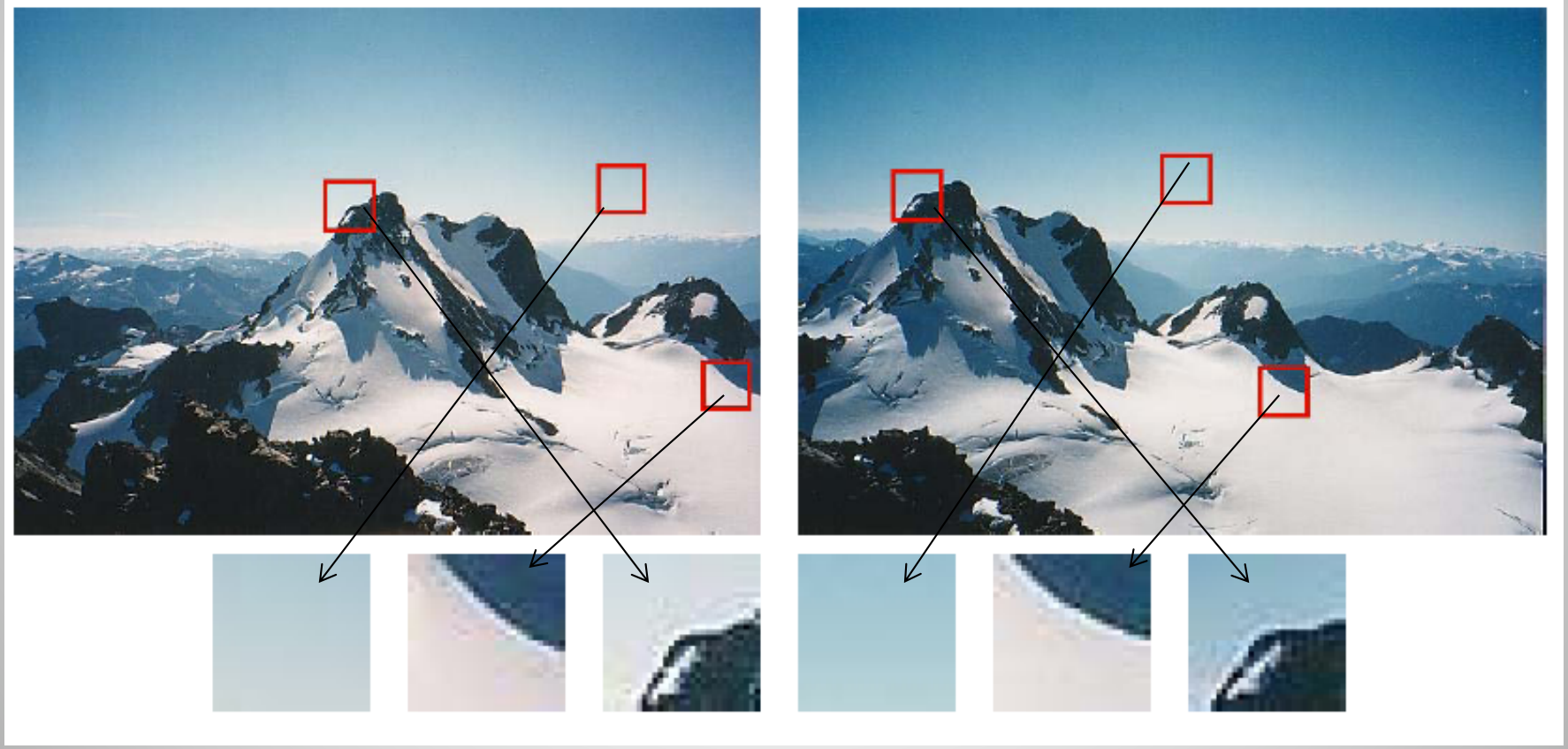
- We want to be able to reliably determine which point goes with which.



- Must provide some invariance to geometric and photometric differences between the two views.

Some patches can be localized or matched with higher accuracy than others

why ?



A COMBINED CORNER AND EDGE DETECTOR

Chris Harris & Mike Stephens

Plessey Research Roke Manor, United Kingdom

Consistency of image edge filtering is of prime importance for 3D interpretation of image sequences using feature tracking algorithms. To cater for image regions containing texture and isolated features, a combined corner and edge detector based on the local auto-correlation function is utilised, and it is shown to perform with good consistency on natural imagery.

INTRODUCTION

The problem we are addressing in Alvey Project MMI149 is that of using computer vision to understand the unconstrained 3D world, in which the viewed scenes will in general contain too wide a diversity of objects for top-down recognition techniques to work. For example, we desire to obtain an understanding of natural scenes, containing roads, buildings, trees, bushes, etc., as typified by the two frames from a sequence illustrated in Figure 1. The solution to this problem that we are pursuing is to use a computer vision system based upon motion analysis of a monocular image sequence from a mobile camera. By extraction and tracking of image features, representations of the 3D analogues of these features can be constructed.

To enable explicit tracking of image features to be performed, the image features must be discrete, and not form a continuum like texture, or edge pixels (edgels). For this reason, our earlier work[1] has concentrated on the extraction and tracking of feature-points or corners, since they are discrete, reliable and meaningful[2]. However, the lack of connectivity of feature-points is a major limitation in our obtaining higher level descriptions, such as surfaces and objects. We need the richer information that is available from edges[3].

THE EDGE TRACKING PROBLEM

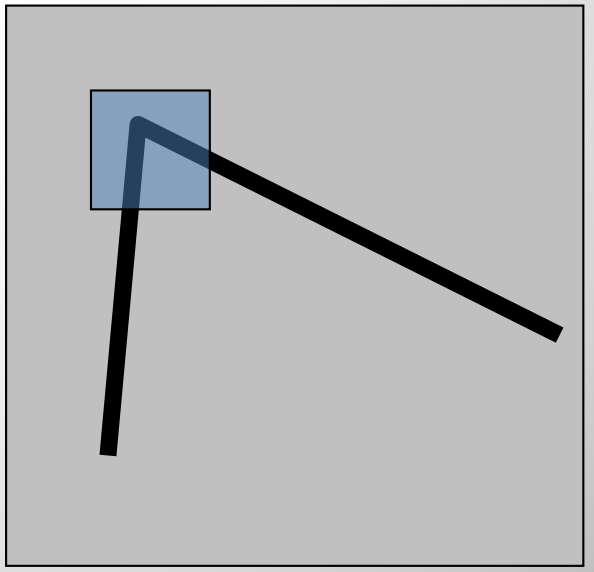
Matching between edge images on a pixel-by-pixel basis works for stereo, because of the known epi-polar camera geometry. However for the motion problem, where the camera motion is unknown, the aperture problem prevents us from undertaking explicit edgel matching. This could be overcome by solving for the motion beforehand, but we are still faced with the task of tracking each individual edge pixel and estimating its 3D location from, for example, Kalman Filtering. This approach is unattractive in comparison with assembling the edgels into edge segments, and tracking these segments as the features.

Now, the unconstrained imagery we shall be considering will contain both curved edges and texture of various scales. Representing edges as a set of straight line fragments[4], and using these as our discrete features will be inappropriate, since curved lines and texture edges can be expected to fragment differently on each image of the sequence, and so be untrackable. Because of ill-conditioning, the use of parametrised curves (eg. circular arcs) cannot be expected to provide the solution, especially with real imagery.

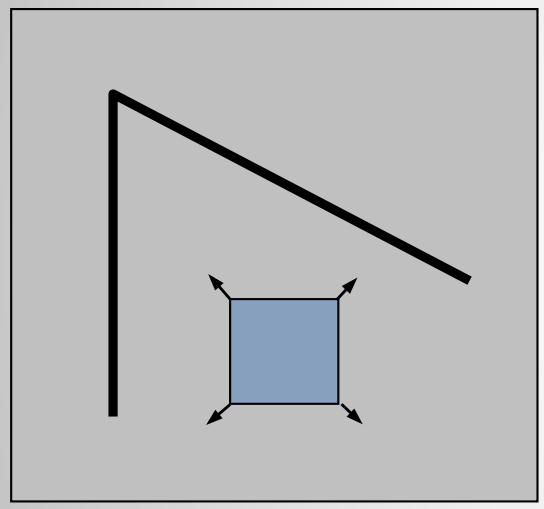
a *b*

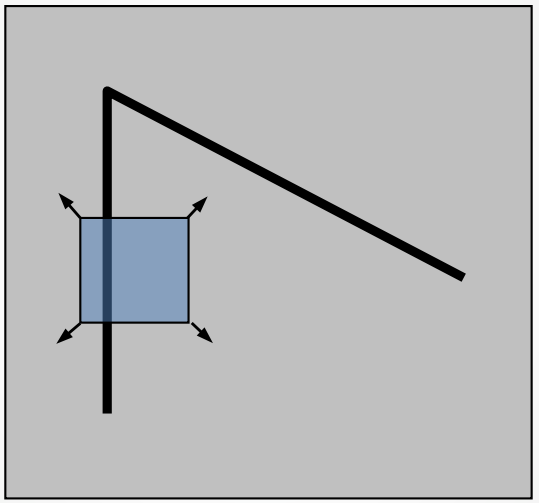
Figure 1. Pair of images from an outdoor sequence.

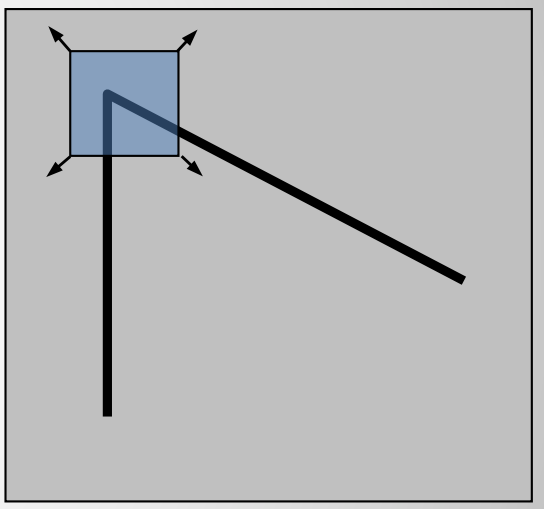
- Edge detectors often fail in corners. Why?
- Corner point can be recognized in a window
- Shifting a window in any direction should give a large change in intensity
- LOCALIZING and UNDERSTANDING shapes…



Basic Idea in Corner Detection







"flat" region:
no change in
all directions

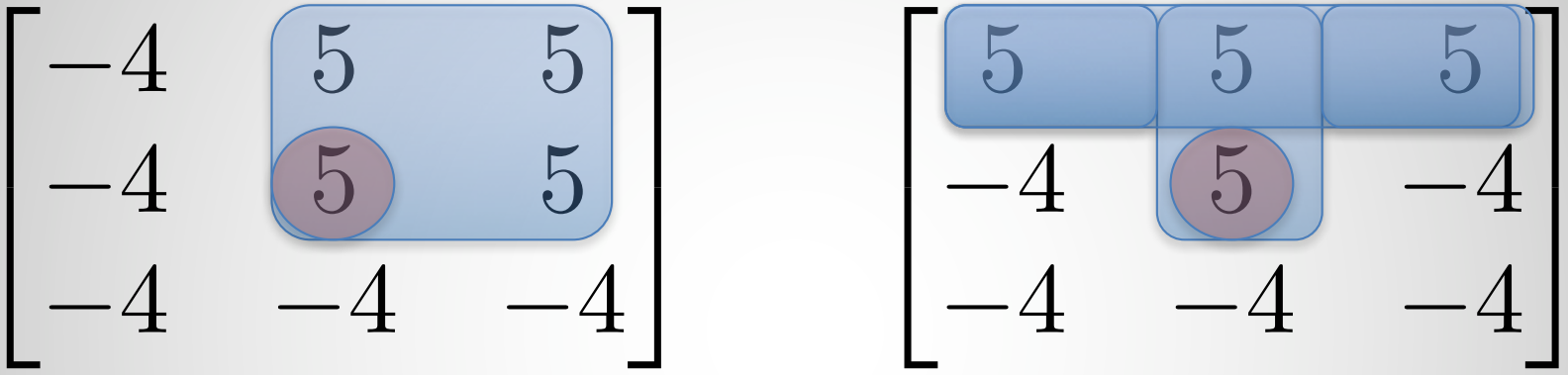
"edge":
no change along
the edge direction

"corner":
significant change
in all directions

Template Matching

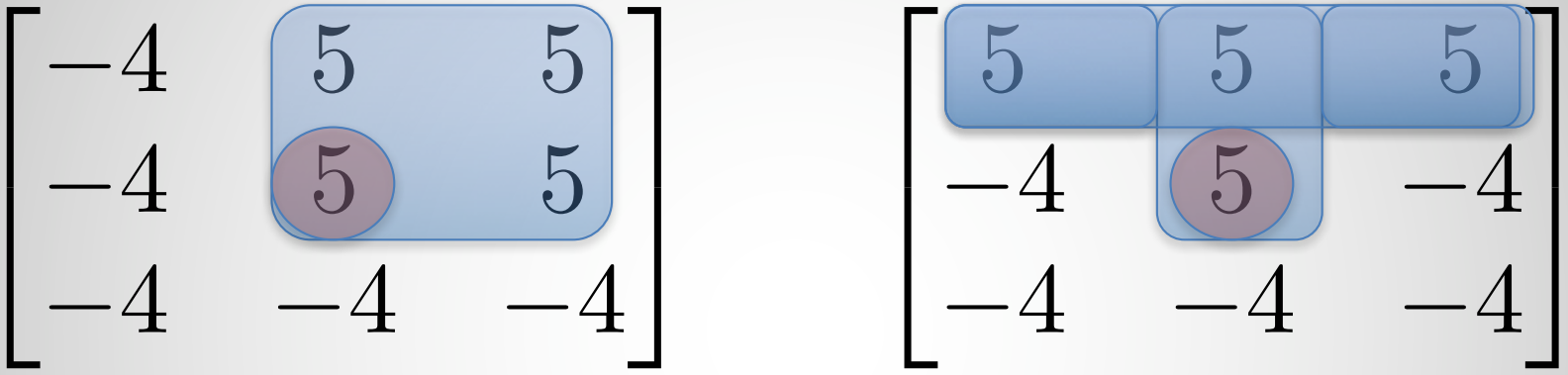
$$\begin{bmatrix} -4 & 5 & 5 \\ -4 & 5 & 5 \\ -4 & -4 & -4 \end{bmatrix} \qquad \begin{bmatrix} 5 & 5 & 5 \\ -4 & 5 & -4 \\ -4 & -4 & -4 \end{bmatrix}$$

Template Matching



Complete set of eight templates can be generated by successive 90 degree of rotations.

Template Matching



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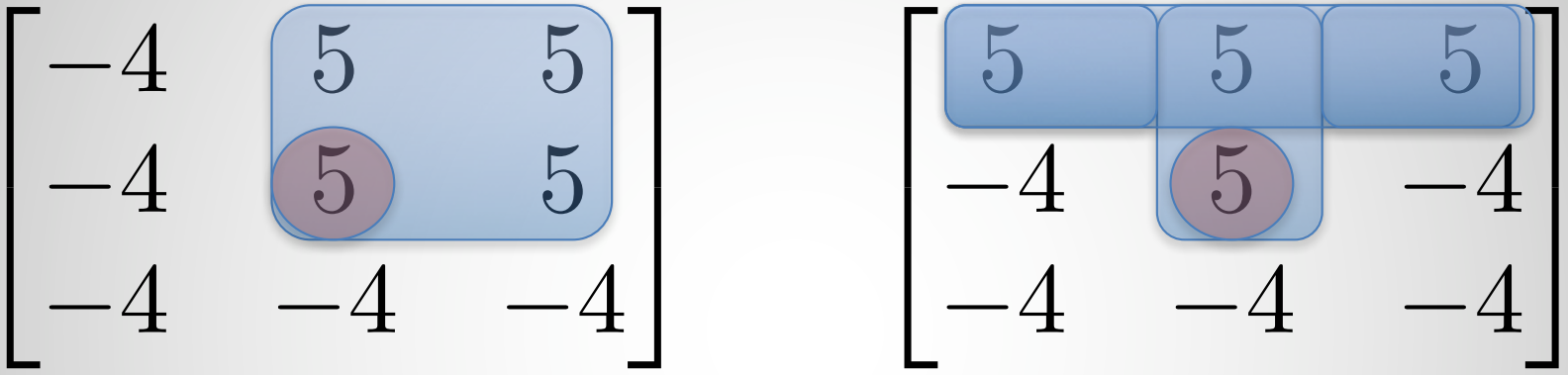
Why the summation of filter is 0?

Template Matching



Complete set of eight templates can be generated by successive 90 degree of rotations.

Why the summation of filter is 0? → Insensitive to absolute change In intensity!

Corner Detection using the Hessian Matrix

- Corners are characterized by high-curvature of intensity values.

$$H(p) = \begin{bmatrix} I_{xx}(p) & I_{xy}(p) \\ I_{xy}(p) & I_{yy}(p) \end{bmatrix}$$

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Hessian Matrix
at voxel p.

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Hessian Matrix at voxel p.

Eigenvalues of the Hessian indicate corner features if both eigenvalues are large!

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Eigenvalues of the Hessian indicate corner features if both eigenvalues are large!

One large, one small eigenvalues -> edge regions

Two small eigenvalues indicate -> flat regions

Corner Detection using the Hessian Matrix

- Corners are characterized by high-curvature of intensity values.

Hessian matrix summarizes Distribution of gradients.

$$H(p) = \begin{bmatrix} I_{xx}(p) & I_{xy}(p) \\ I_{xy}(p) & I_{yy}(p) \end{bmatrix}$$

Hessian Matrix at voxel p.

Eigenvalues of the Hessian indicate corner features if both eigenvalues are large!

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Reminder: Eigenvalues/Eigenvectors

$$H(p) = \begin{bmatrix} I_{xx}(p) & I_{xy}(p) \\ I_{xy}(p) & I_{yy}(p) \end{bmatrix}$$

$$det(H) = I_{xx}I_{yy} - I_{xy}^2$$

$$Tr(H) = I_{xx} + I_{yy}$$

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The eigenvalues of the matrix H are solutions of its characteristics polynomial

$$det(\mathbf{H} - \lambda \mathbf{1}_2) = 0$$

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$$det(\begin{bmatrix} I_{xx}(p) - \lambda & I_{xy}(p) \\ I_{xy}(p) & I_{yy}(p) - \lambda \end{bmatrix}) = 0$$

$$(I_{xx}(p) - \lambda)(I_{yy}(p) - \lambda) - I_{xy}(p)^2 = 0$$

Harris and Stephens Corner Detector

- Instead of using *Hessian* of image I, use first derivative of smoothed I (i.e., L)

$$G(p,\sigma) = \begin{bmatrix} L_x^2(p,\sigma) & L_x(p,\sigma)L_y(p,\sigma) \\ L_x(p,\sigma)L_y(p,\sigma) & L_y^2(p,\sigma) \end{bmatrix}$$

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- Instead of calculating eigenvalues, we will consider ***cornerness*** feature:

Harris and Stephens Corner Detector

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- Instead of calculating eigenvalues, we will consider ***cornerness*** feature:

$$\mathcal{H}(p,\sigma,\alpha) = det(G) - \alpha.Tr(G)$$

for small alpha (=1/25)

Harris and Stephens Corner Detector

$$\mathcal{H}(p, \sigma, \alpha) = \lambda_1 \lambda_2 - \alpha.(\lambda_1 + \lambda_2)$$

Harris and Stephens Corner Detector

$$\mathcal{H}(p, \sigma, \alpha) = \lambda_1 \lambda_2 - \alpha.(\lambda_1 + \lambda_2)$$

- The same behavior as Hessian based detector, but now we directly use simple determinant and trace functions!

$$\mathcal{H}(p, \sigma, \alpha) = det(G) - \alpha.Tr(G)$$

Harris and Stephens Corner Detector

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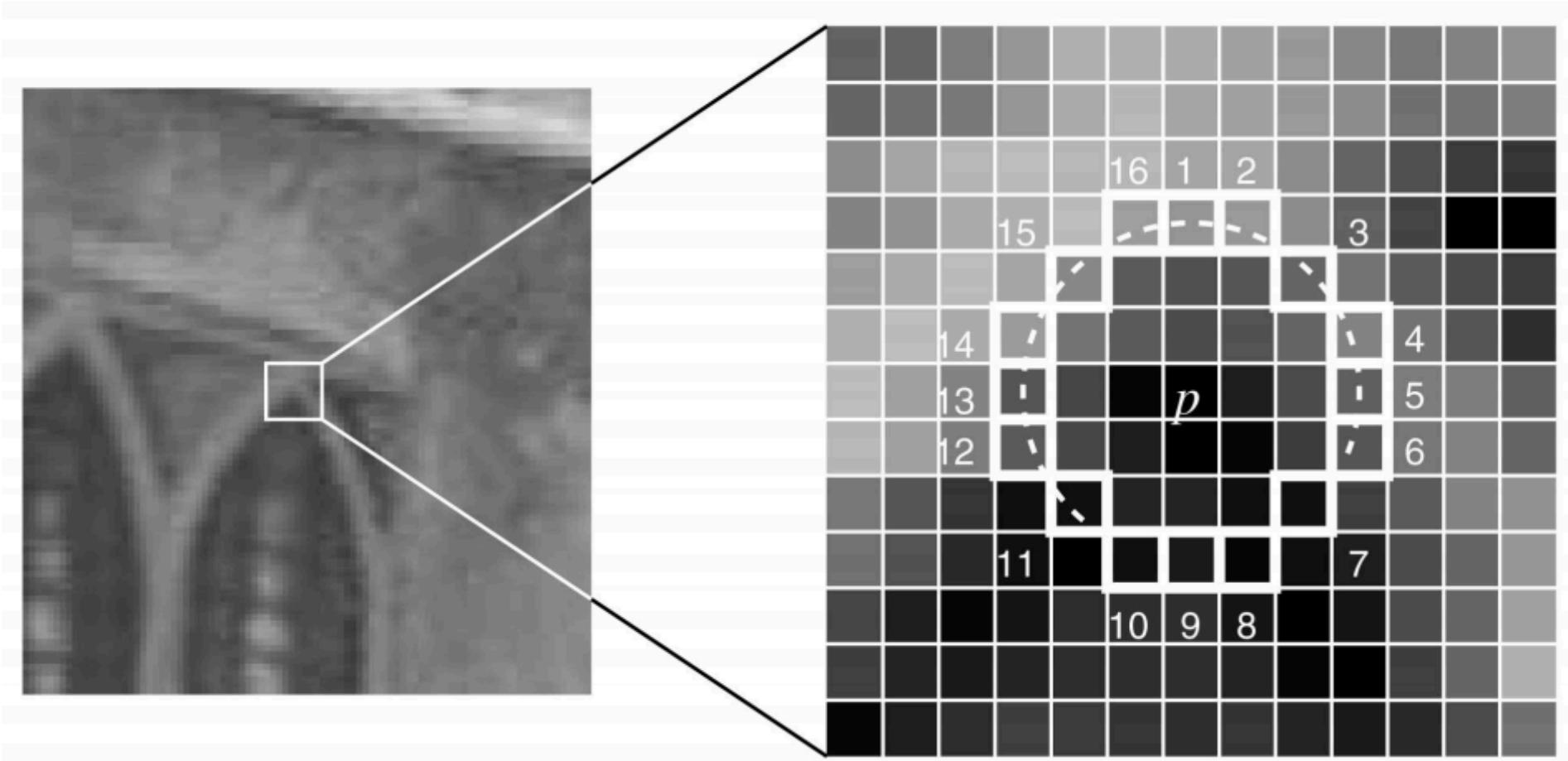
- The same behavior as Hessian based detector, but now we directly use simple determinant and trace functions!

$$\mathcal{H}(p,\sigma,\alpha) = det(G) - \alpha.Tr(G)$$

Other **cornerness** measures: $\dfrac{\lambda_1\lambda_2}{\lambda_1 + \lambda_2}$ Harmonic mean or $\lambda_1 - \alpha\lambda_2$ Triggs


16
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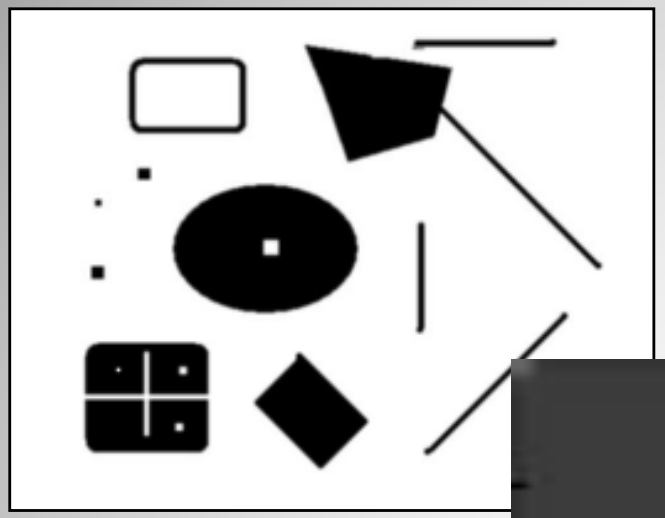


I_x

I_y

Square of derivatives

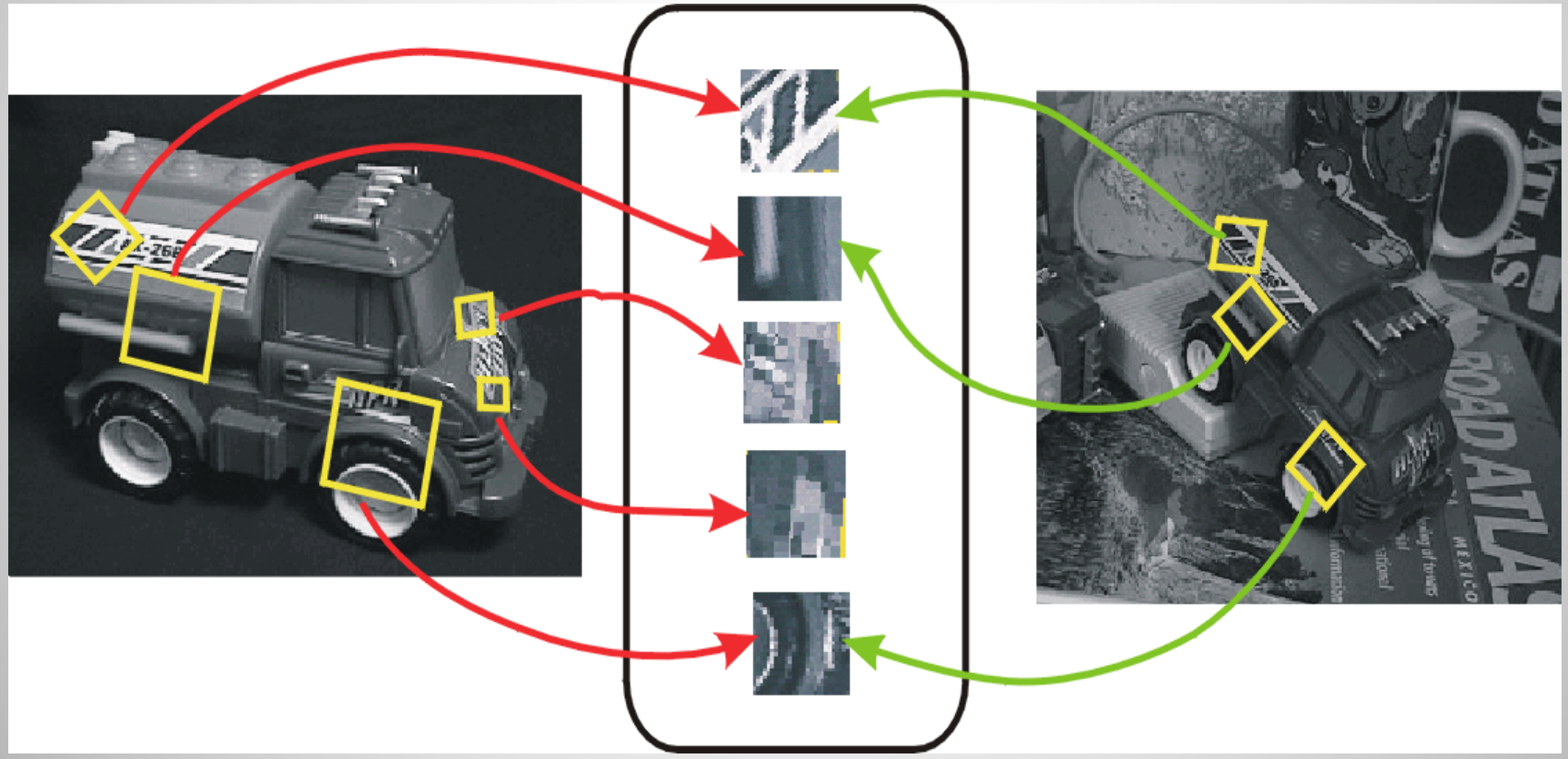
I_y

Gaussian Smoothing

Feature Extraction: Corners

Invariant Local Features

•Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters

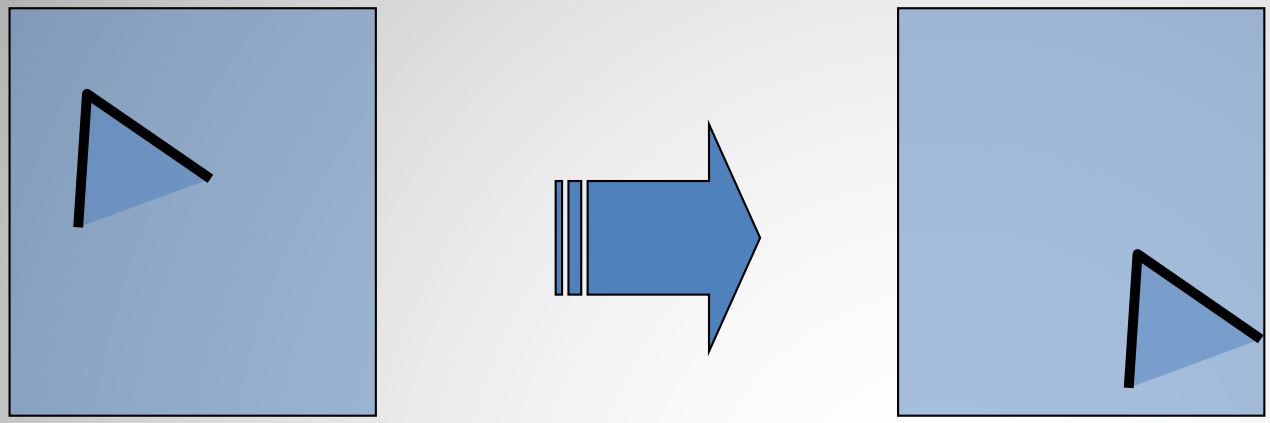


Features Descriptors

Invariance and Covariance

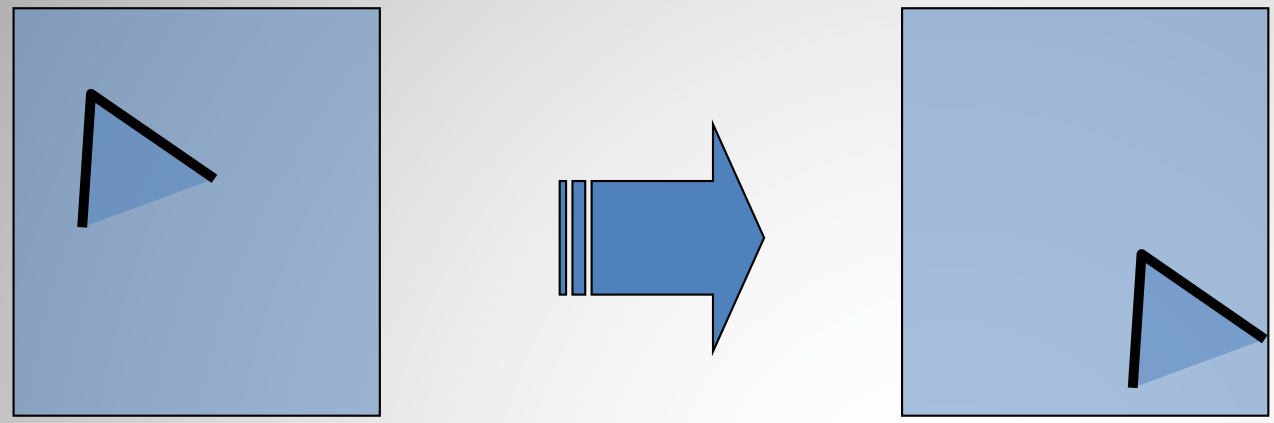
- We want corner locations to be ***invariant*** to photometric transformations and ***covariant*** to geometric transformations
  - **Invariance:** image is transformed and corner locations do not change
  - **Covariance:** if we have two transformed versions of the same image, features should be detected in corresponding locations

Affine Transformation

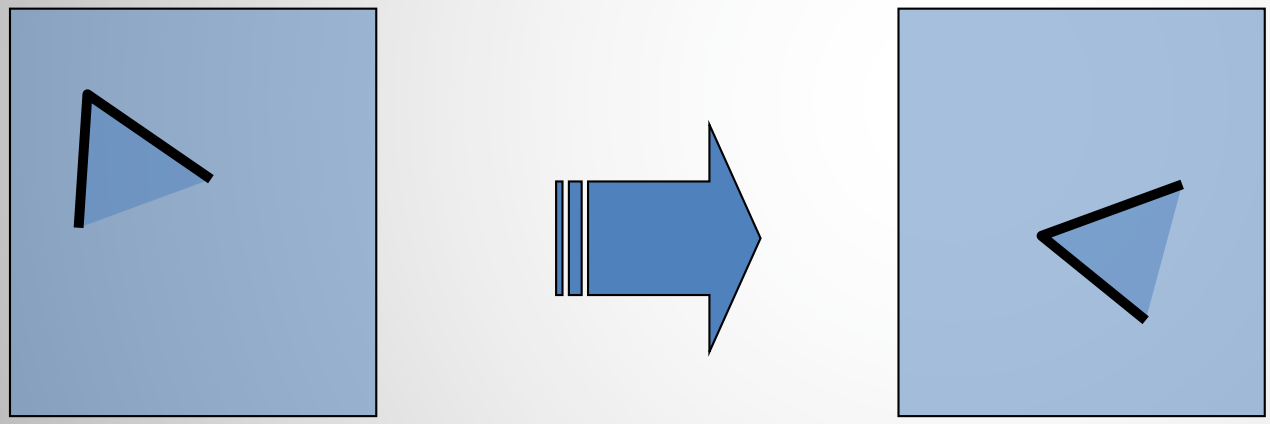


translation

Affine Transformation

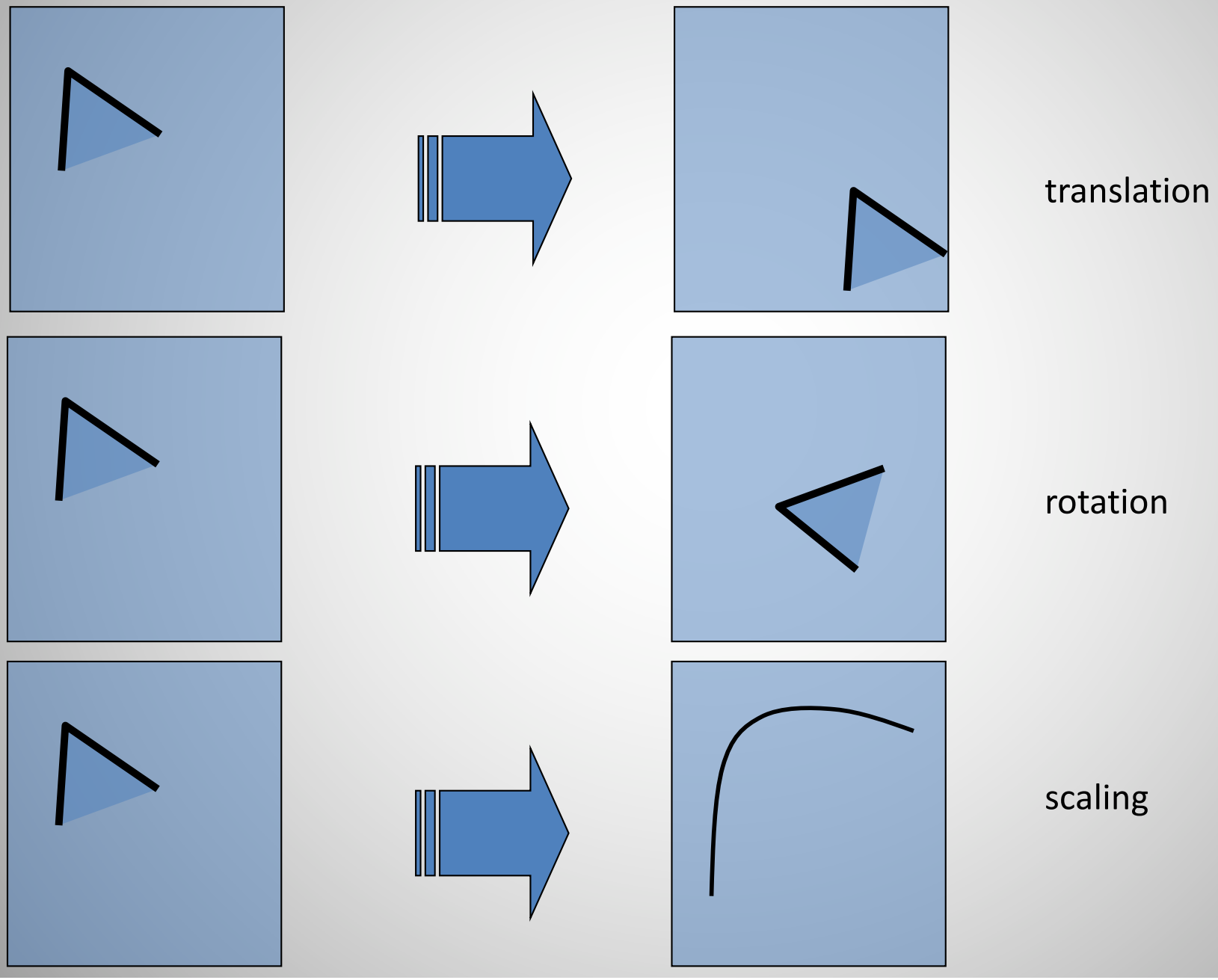


translation

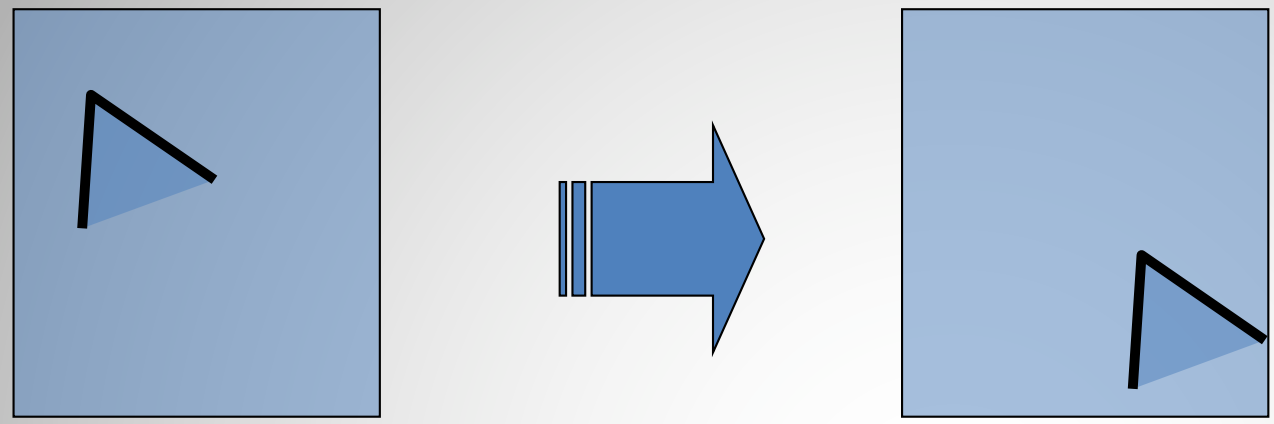


rotation

Affine Transformation

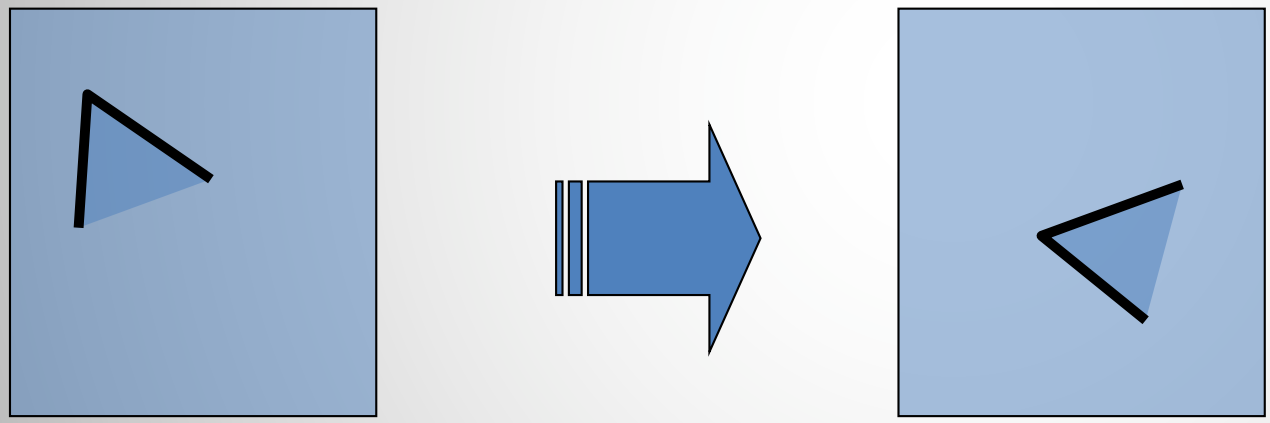


Affine Transformation

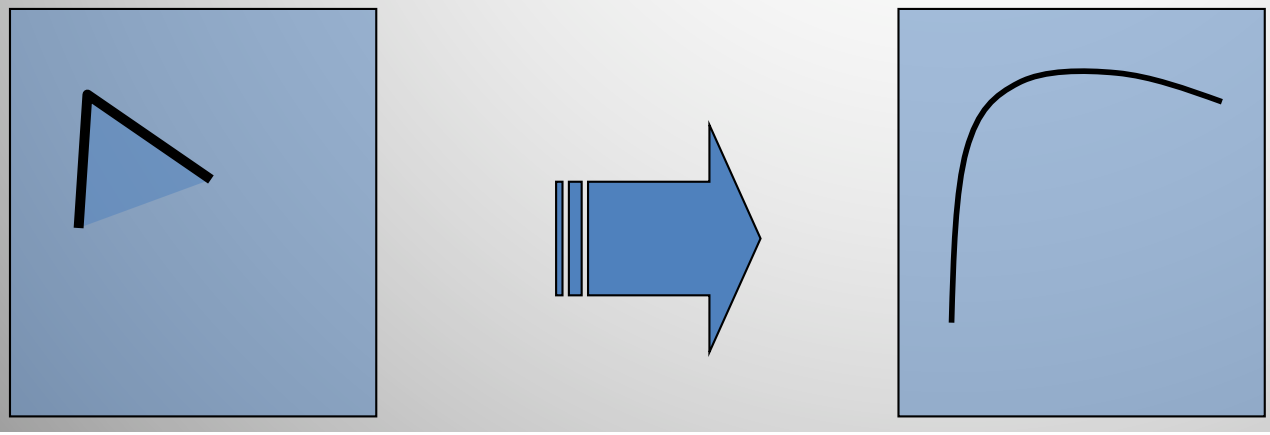


Corners are invariant to

translation ✔



rotation ✔



scaling ✖

Next Lecture

- We will continue Affine Invariance concept
- Introduce the concept of scale-space approaches
- Introduce “famous” SIFT algorithm (Lowe’s Scale invariant feature transform)

Questions?