



Perception VI: Homography. SIFT

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Perception VI: Affine & Projective Transformations (Homography)

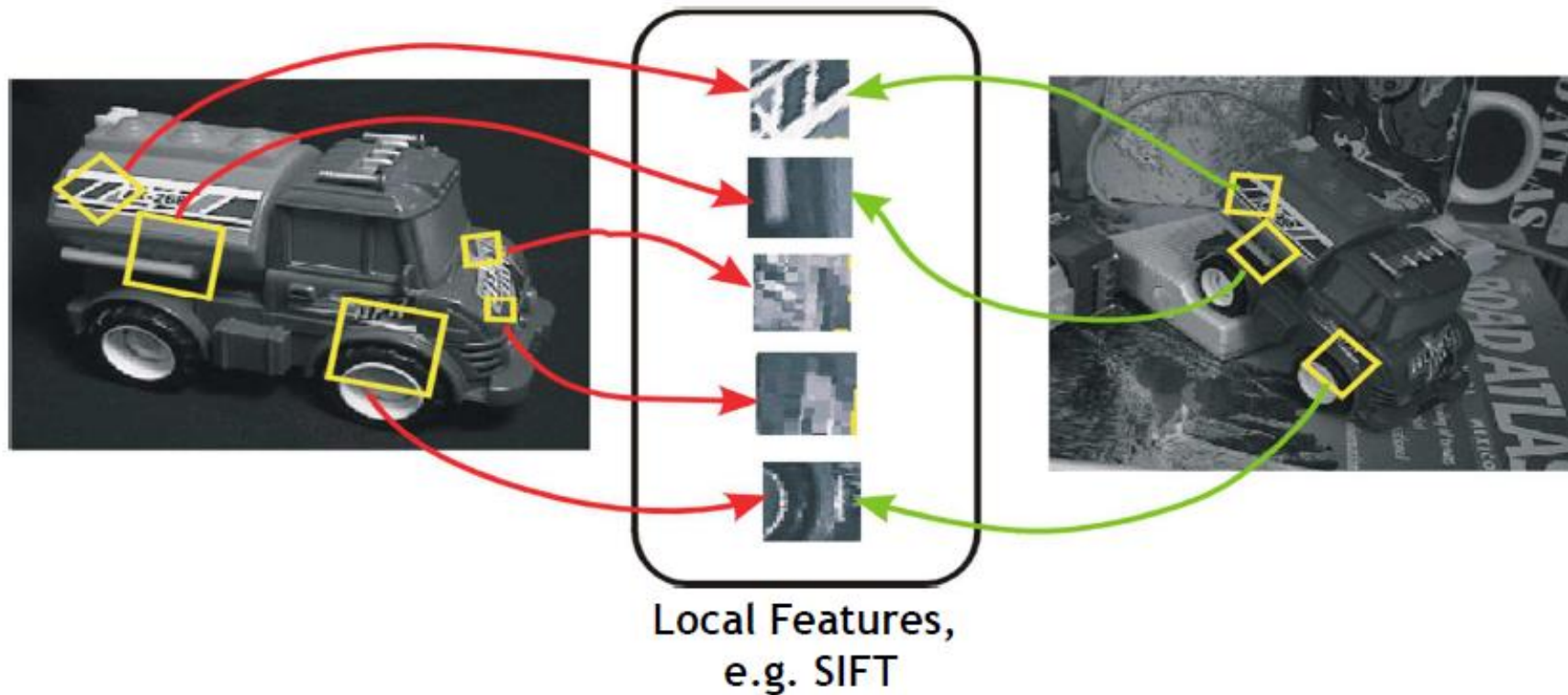
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Contents

- Matching images:
 - Affine Transformation
 - Projective Transformation (Homography)

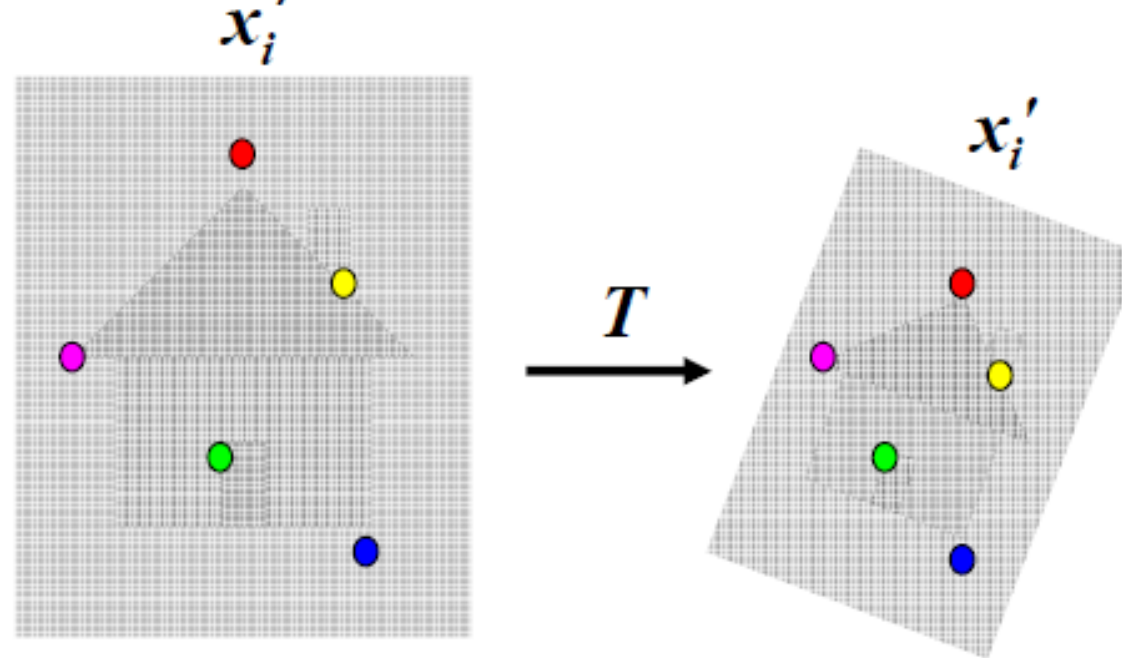
Recognition with Local Features

- Image content is transformed into local features that are invariant to translation, rotation, and scale
- Goal: Verify if they belong to a consistent configuration



Alignment Problem

- In alignment, we will fit the parameters of some transformation according to a set of matching feature pairs (“correspondences”).



Basic 2D Transformations

- Basic 2D transformations as 3x3 matrices

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Translation

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Scaling

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Rotation

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & sh_x & 0 \\ sh_y & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Shearing

What Can be Represented by a 2x2 Matrix?

- 2D Scaling?

$$x' = s_x * x$$

$$y' = s_y * y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

- 2D Rotation around (0,0)?

$$x' = \cos \theta * x - \sin \theta * y$$

$$y' = \sin \theta * x + \cos \theta * y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

- 2D Shearing?

$$x' = x + sh_x * y$$

$$y' = sh_y * x + y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & sh_x \\ sh_y & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

What Can be Represented by a 2x2 Matrix?

- 2D Mirror about y axis?

$$x' = -x$$

$$y' = y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

- 2D Mirror over (0,0)?

$$x' = -x$$

$$y' = -y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

- 2D Translation?

$$x' = x + t_x$$

$$y' = y + t_y$$

NO!

2D Linear Transform

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

- Only linear 2D transformations can be represented with a 2x2 matrix.
- Linear transformations are combinations of ...
 - Scale,
 - Rotation,
 - Shear, and
 - Mirror

Homogeneous Coordinates

- Q: How can we represent translation as a 3x3 matrix using homogeneous coordinates?

$$x' = x + t_x$$

$$y' = y + t_y$$

- A: Using the rightmost column:

$$\text{Translation} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix}$$

Spatial transformations

2D Affine Transformation

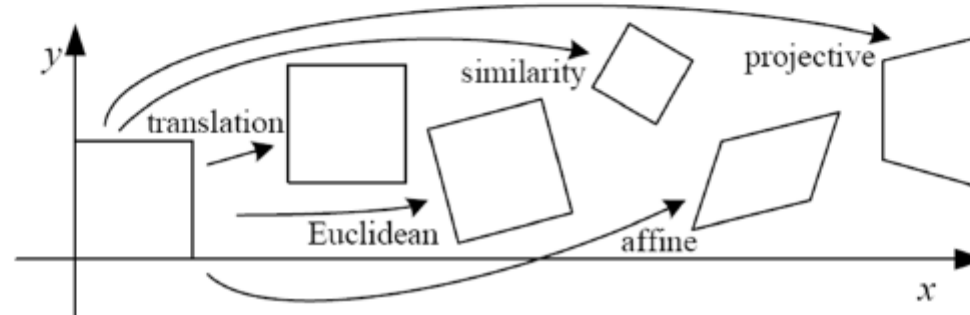
$$\begin{bmatrix} x' \\ y' \\ w \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ w \end{bmatrix}$$

- **Affine transformations:**
 - Linear transformations
 - Translations
- Parallel lines remain parallel

Projective Transformation

$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x \\ y \\ w \end{bmatrix}$$

- **Projective transformations:**
 - Affine transformations, and
 - Projective warps
- Parallel lines do not necessarily remain parallel



Let's Start with Affine Transformations

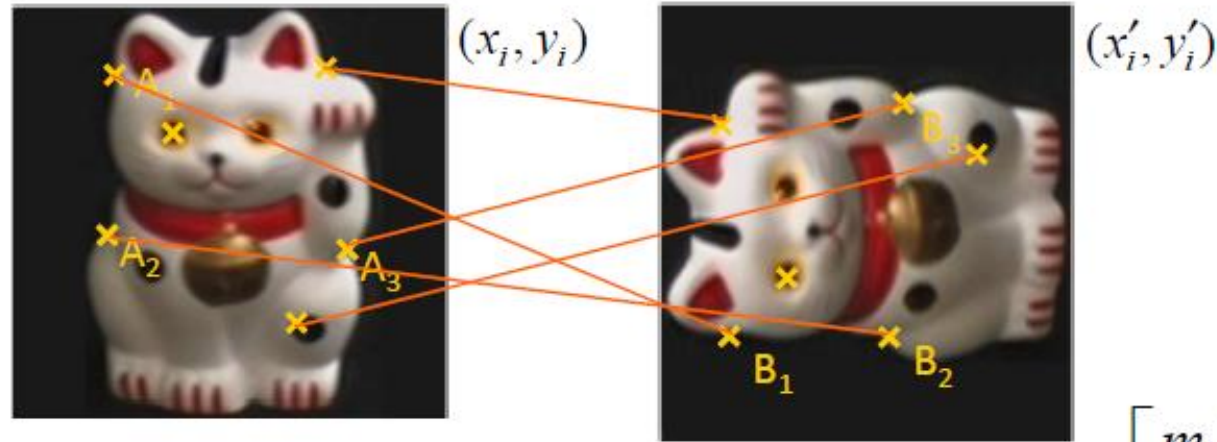
- Simple fitting procedure (linear least squares)
- Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras
- Can be used to initialize fitting for more complex models



© Slide credit: Svetlana Lazebnik, David Lowe

Fitting an Affine Transformation

- Assuming we know the correspondences, how do we get the transformation?



$$\begin{bmatrix} x'_i \\ y'_i \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} \Rightarrow \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \end{bmatrix}$$

Fitting an Affine Transformation

- Assuming we know the correspondences, how do we get the transformation?

$$\begin{bmatrix} x'_i \\ y'_i \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} \Rightarrow \begin{bmatrix} x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ \dots & & & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \dots \\ x'_i \\ y'_i \\ \dots \end{bmatrix}$$

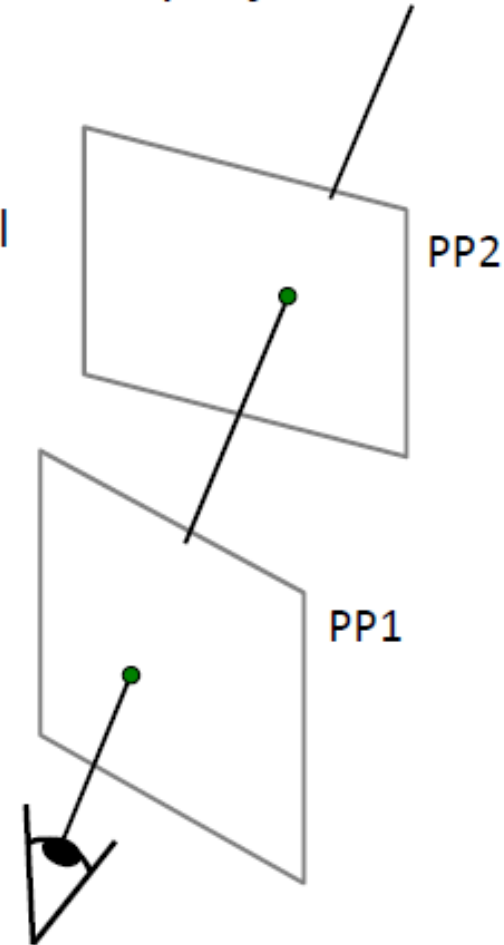
- How many matches (correspondence pairs) do we need to solve for the transformation parameters?
- Once we have solved for the parameters, how do we compute the coordinates of the corresponding point for (x_{new}, y_{new}) ?

Fitting a Projective Transformation

- A projective transform is a mapping between any two perspective projections with the same center of projection.
 - I.e. two planes in 3D along the same sight ray
- Properties
 - Rectangle should map to arbitrary quadrilateral
 - Parallel lines aren't
 - but must preserve straight lines
- This is called a **homography**

$$\begin{bmatrix} wx' \\ wy' \\ w \\ p' \end{bmatrix} = \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \\ p \end{bmatrix}$$

H



Fitting a Projective Transformation

- A projective transform is a mapping between any two perspective projections with the same center of projection.
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- Properties
 - Rectangle should map to arbitrary quadrilateral
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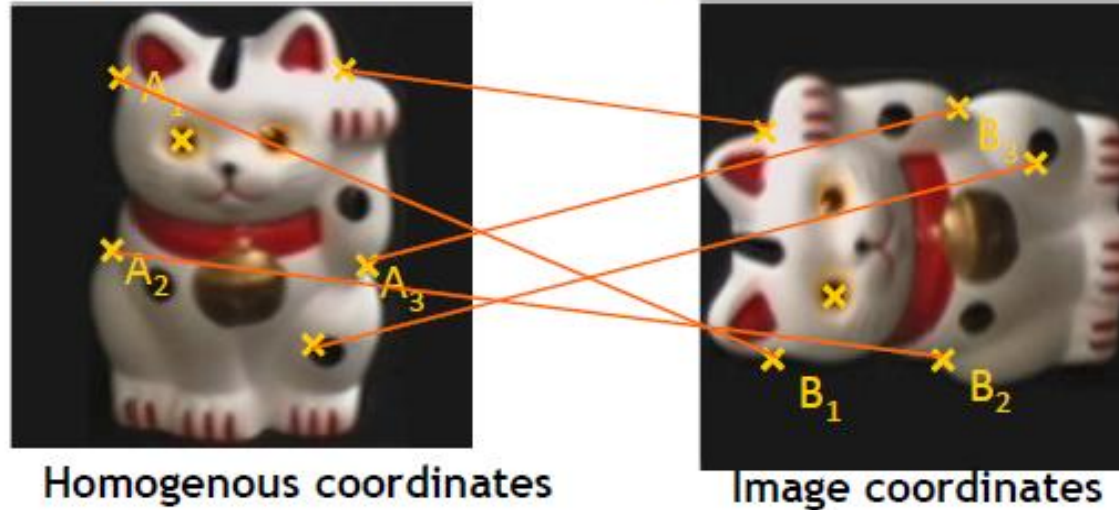
$$\begin{bmatrix} wx' \\ wy' \\ w \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & \textcircled{1} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

p' H p

Set scale factor to 1
 \Rightarrow 8 parameters left.

Projective Transformation (Homography)

- Estimating the transformation



$$\begin{aligned} \mathbf{X}_{A_1} &\leftrightarrow \mathbf{X}_{B_1} \\ \mathbf{X}_{A_2} &\leftrightarrow \mathbf{X}_{B_2} \\ \mathbf{X}_{A_3} &\leftrightarrow \mathbf{X}_{B_3} \\ &\vdots \end{aligned}$$

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x'' \\ y'' \\ 1 \end{bmatrix} = \frac{1}{z'} \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix}$$

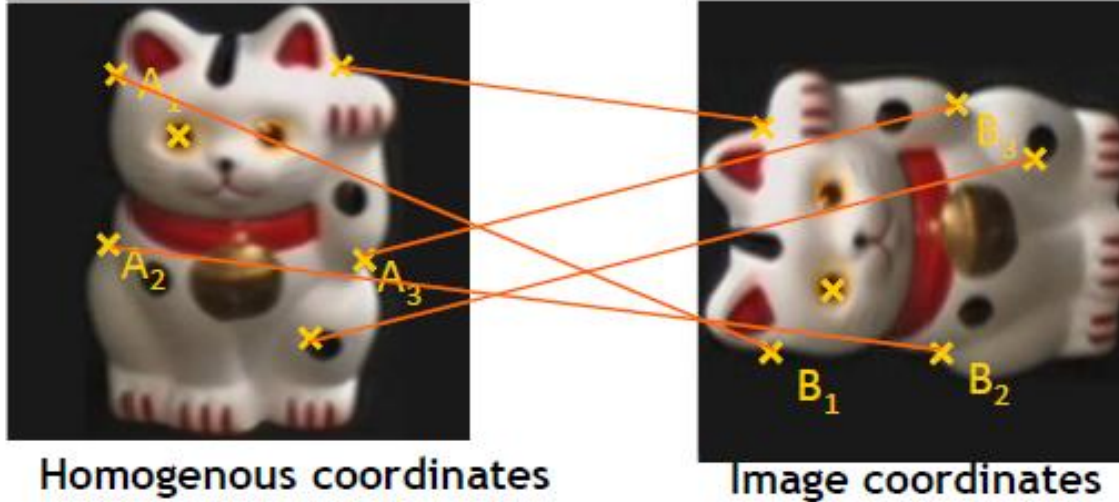
Matrix notation

$$x' = Hx$$

$$x'' = \frac{1}{z'} x'$$

Projective Transformation (Homography)

- Estimating the transformation



$$\begin{aligned} \mathbf{X}_{A_1} &\leftrightarrow \mathbf{X}_{B_1} \\ \mathbf{X}_{A_2} &\leftrightarrow \mathbf{X}_{B_2} \\ \mathbf{X}_{A_3} &\leftrightarrow \mathbf{X}_{B_3} \\ &\vdots \end{aligned}$$

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$x_{A_1} = \frac{h_{11} x_{B_1} + h_{12} y_{B_1} + h_{13}}{h_{31} x_{B_1} + h_{32} y_{B_1} + 1}$$

$$\begin{bmatrix} x'' \\ y'' \\ 1 \end{bmatrix} = \frac{1}{z'} \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix}$$

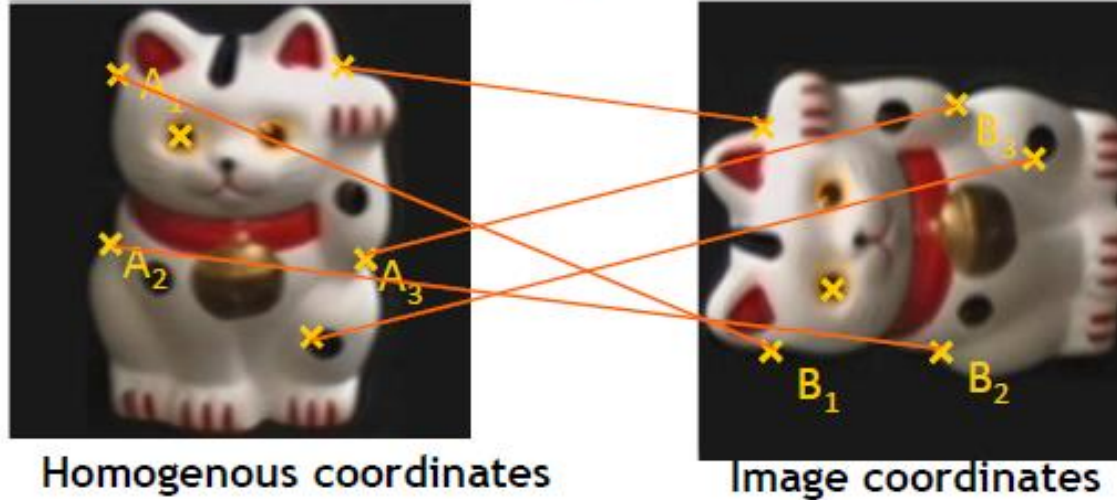
Matrix notation

$$x' = Hx$$

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Projective Transformation (Homography)

- Estimating the transformation



$$\begin{aligned} \mathbf{X}_{A_1} &\leftrightarrow \mathbf{X}_{B_1} \\ \mathbf{X}_{A_2} &\leftrightarrow \mathbf{X}_{B_2} \\ \mathbf{X}_{A_3} &\leftrightarrow \mathbf{X}_{B_3} \\ &\vdots \end{aligned}$$

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$x_{A_1} = \frac{h_{11} x_{B_1} + h_{12} y_{B_1} + h_{13}}{h_{31} x_{B_1} + h_{32} y_{B_1} + 1}$$

$$y_{A_1} = \frac{h_{21} x_{B_1} + h_{22} y_{B_1} + h_{23}}{h_{31} x_{B_1} + h_{32} y_{B_1} + 1}$$

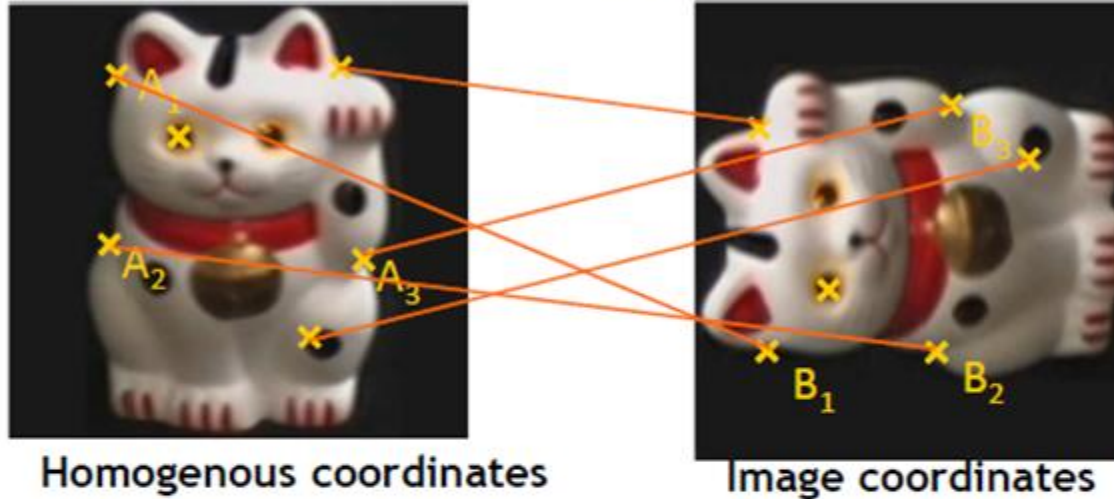
Matrix notation

$$x' = Hx$$

$$x'' = \frac{1}{z'} x'$$

Projective Transformation (Homography)

- Estimating the transformation



$$\mathbf{X}_{A_1} \leftrightarrow \mathbf{X}_{B_1}$$

$$\mathbf{X}_{A_2} \leftrightarrow \mathbf{X}_{B_2}$$

$$\mathbf{X}_{A_3} \leftrightarrow \mathbf{X}_{B_3}$$

$$\vdots$$

$$x_{A_1} = \frac{h_{11} x_{B_1} + h_{12} y_{B_1} + h_{13}}{h_{31} x_{B_1} + h_{32} y_{B_1} + 1}$$

$$y_{A_1} = \frac{h_{21} x_{B_1} + h_{22} y_{B_1} + h_{23}}{h_{31} x_{B_1} + h_{32} y_{B_1} + 1}$$

$$x_{A_1} h_{31} x_{B_1} + x_{A_1} h_{32} y_{B_1} + x_{A_1} = h_{11} x_{B_1} + h_{12} y_{B_1} + h_{13}$$

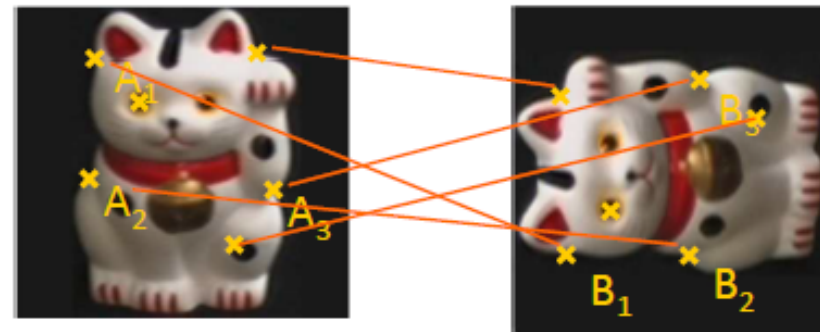
$$h_{11} x_{B_1} + h_{12} y_{B_1} + h_{13} - x_{A_1} h_{31} x_{B_1} - x_{A_1} h_{32} y_{B_1} - x_{A_1} = 0$$

$$h_{21} x_{B_1} + h_{22} y_{B_1} + h_{23} - y_{A_1} h_{31} x_{B_1} - y_{A_1} h_{32} y_{B_1} - y_{A_1} = 0$$

Projective Transformation (Homography)

- Estimating the transformation

$$\begin{aligned} h_{11} x_{B_1} + h_{12} y_{B_1} + h_{13} - x_{A_1} h_{31} x_{B_1} - x_{A_1} h_{32} y_{B_1} - x_{A_1} &= 0 \\ h_{21} x_{B_1} + h_{22} y_{B_1} + h_{23} - y_{A_1} h_{31} x_{B_1} - y_{A_1} h_{32} y_{B_1} - y_{A_1} &= 0 \end{aligned}$$

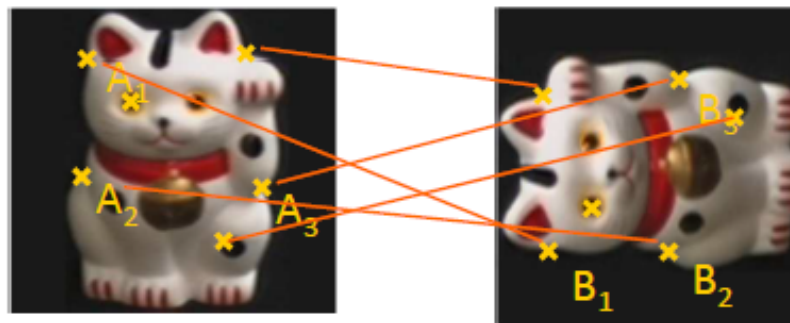


$$\begin{aligned} \mathbf{X}_{A_1} &\leftrightarrow \mathbf{X}_{B_1} \\ \mathbf{X}_{A_2} &\leftrightarrow \mathbf{X}_{B_2} \\ \mathbf{X}_{A_3} &\leftrightarrow \mathbf{X}_{B_3} \\ &\vdots \end{aligned} \quad \begin{bmatrix} x_{B_1} & y_{B_1} & 1 & 0 & 0 & 0 & -x_{A_1}x_{B_1} & -x_{A_1}y_{B_1} & -x_{A_1} \\ 0 & 0 & 0 & x_{B_1} & y_{B_1} & 1 & -y_{A_1}x_{B_1} & -y_{A_1}y_{B_1} & -y_{A_1} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \end{bmatrix} \cdot \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \cdot \\ \cdot \\ \cdot \end{bmatrix}$$

$$Ah = 0$$

Projective Transformation (Homography)

- Estimating the transformation
- Solution:
 - Null-space vector of A
 - Corresponds to smallest eigenvector



$$\begin{aligned}
 & \mathbf{x}_{A_1} \leftrightarrow \mathbf{x}_{B_1} \\
 & \mathbf{x}_{A_2} \leftrightarrow \mathbf{x}_{B_2} \\
 & \mathbf{x}_{A_3} \leftrightarrow \mathbf{x}_{B_3} \\
 & \vdots
 \end{aligned}$$

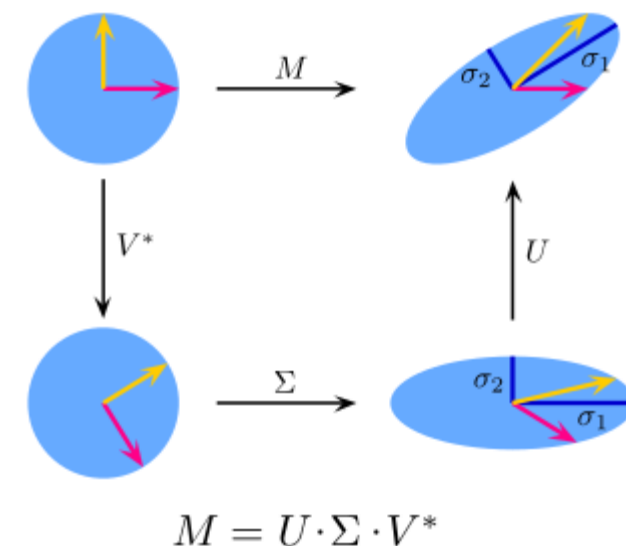
SVD

$$\mathbf{A} = \mathbf{U}\mathbf{D}\mathbf{V}^T = \mathbf{U} \begin{bmatrix} d_{11} & \cdots & d_{19} \\ \vdots & \ddots & \vdots \\ d_{91} & \cdots & d_{99} \end{bmatrix} \begin{bmatrix} v_{11} & \cdots & v_{19} \\ \vdots & \ddots & \vdots \\ v_{91} & \cdots & v_{99} \end{bmatrix}^T$$

$Ah = 0$

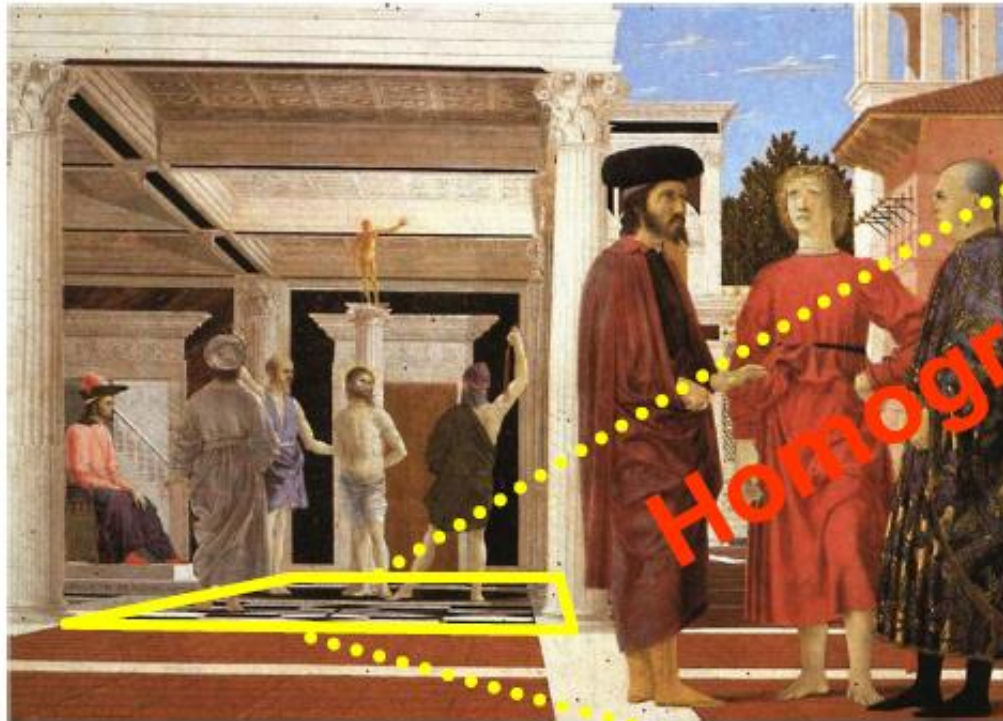
$$\mathbf{h} = \frac{[v_{19}, \dots, v_{99}]}{v_{99}}$$

Minimizes least square error



Uses: Analyzing Patterns and Shapes

- What is the shape of the b/w floor pattern?

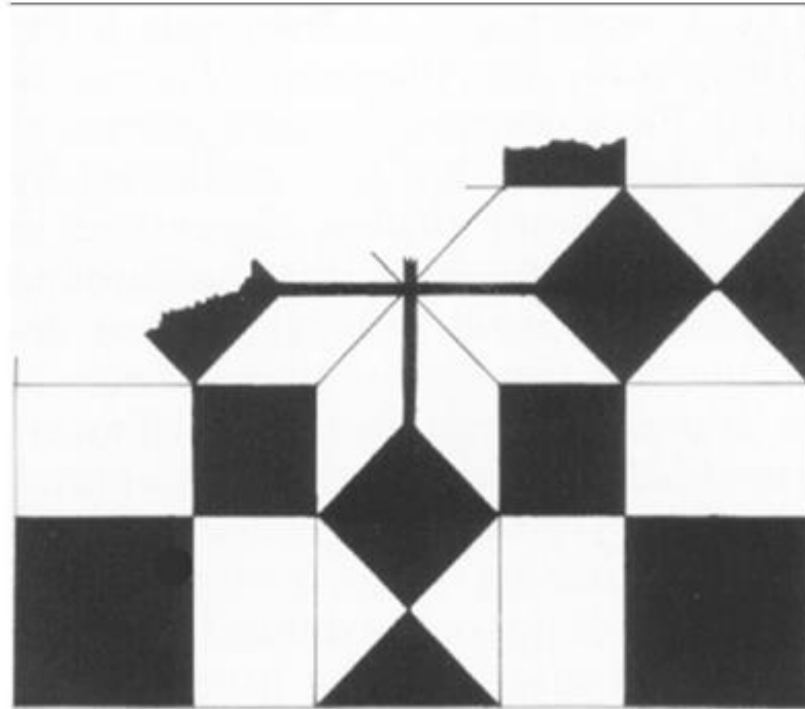


The floor (enlarged)



Homography

Uses: Analyzing Patterns and Shapes



From Martin Kemp *The Science of Art*
(*manual reconstruction*)

Automatic rectification





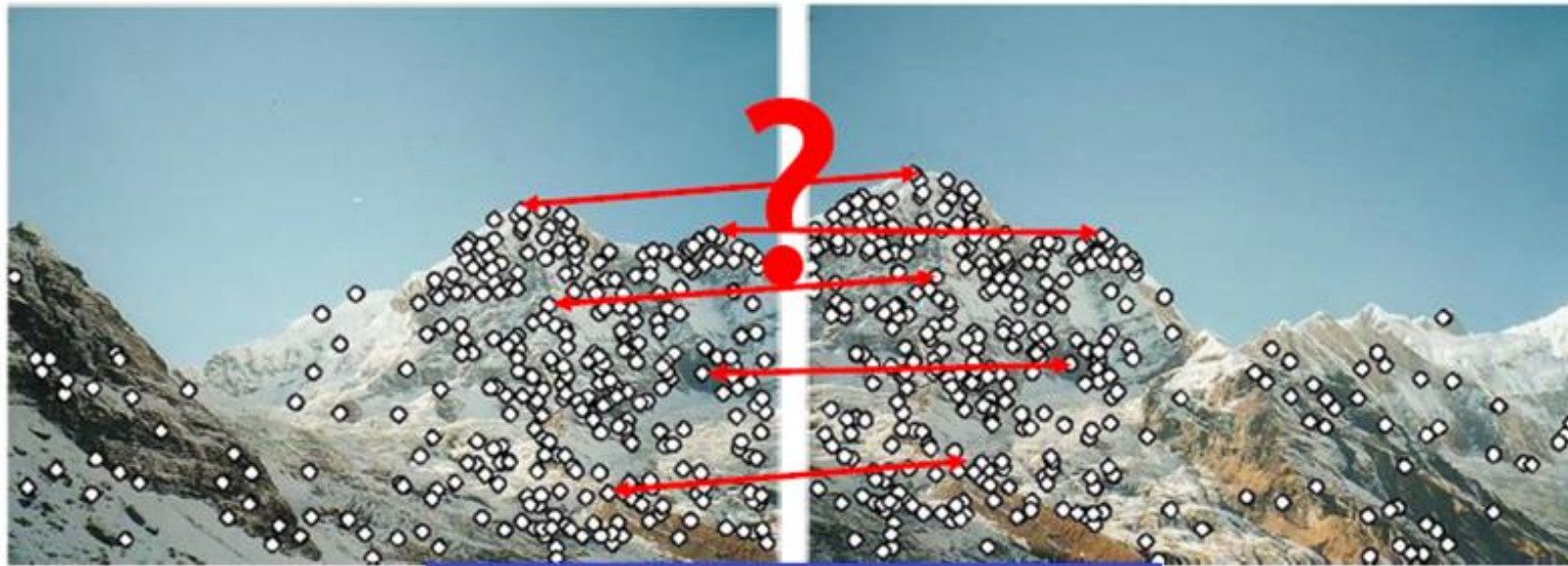
Perception VI: Descriptors. SIFT

[Dr. Ilya Afanasyev, i.afanasyev@innopolis.ru](mailto:i.afanasyev@innopolis.ru)

Local Descriptors

- We know how to detect points
- Next question:

How to describe them for matching?

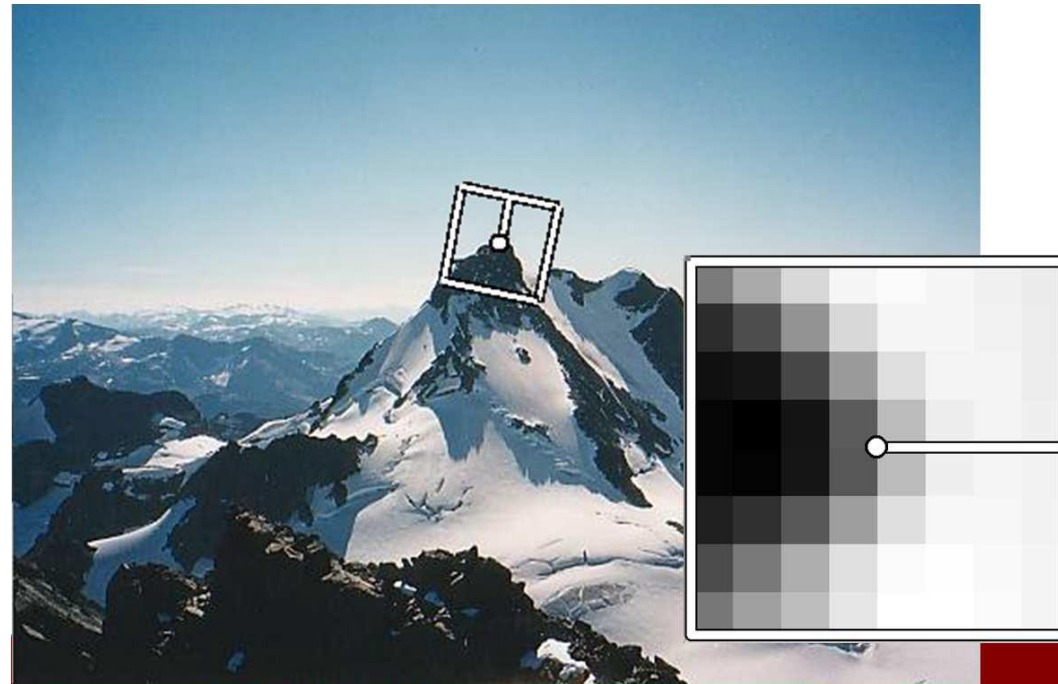
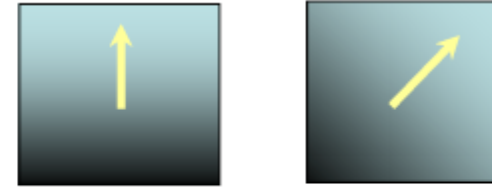


Point descriptor should be:

1. Invariant
2. Distinctive

Rotation Invariant Descriptors

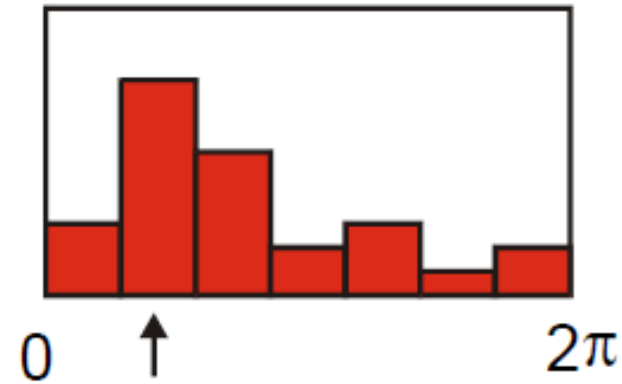
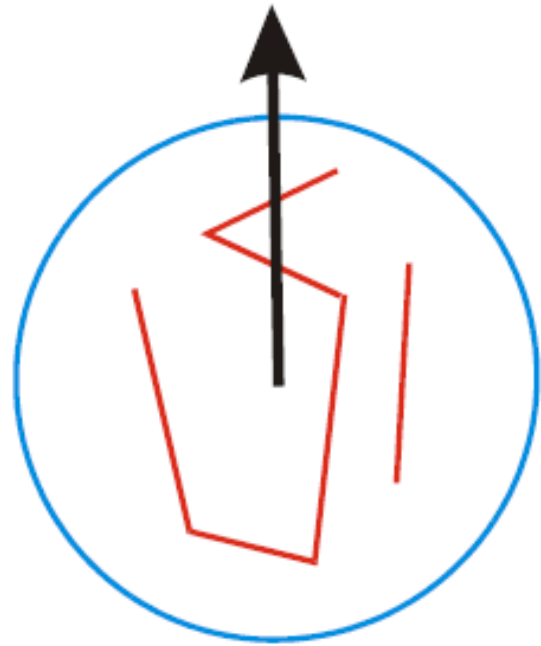
- Find local orientation
 - Dominant direction of gradient for the image patch
- Rotate patch according to this angle
 - This puts the patches into a canonical orientation.



© Slide credit: Svetlana Lazebnik, Matthew Brown

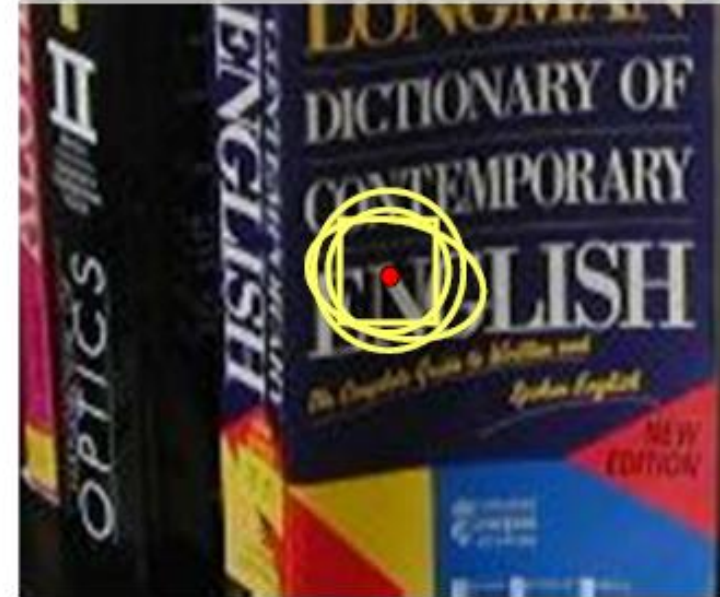
Orientation Normalization: Computation

- Compute orientation histogram
- Select dominant orientation
- Normalize: rotate to fixed orientation



© Slide credit: David Lowe [Lowe, SIFT, 1999]

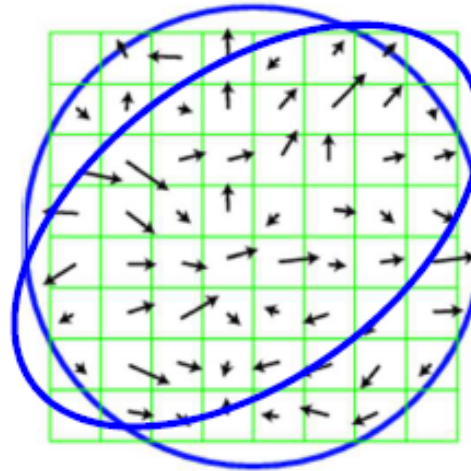
The Need for Invariance



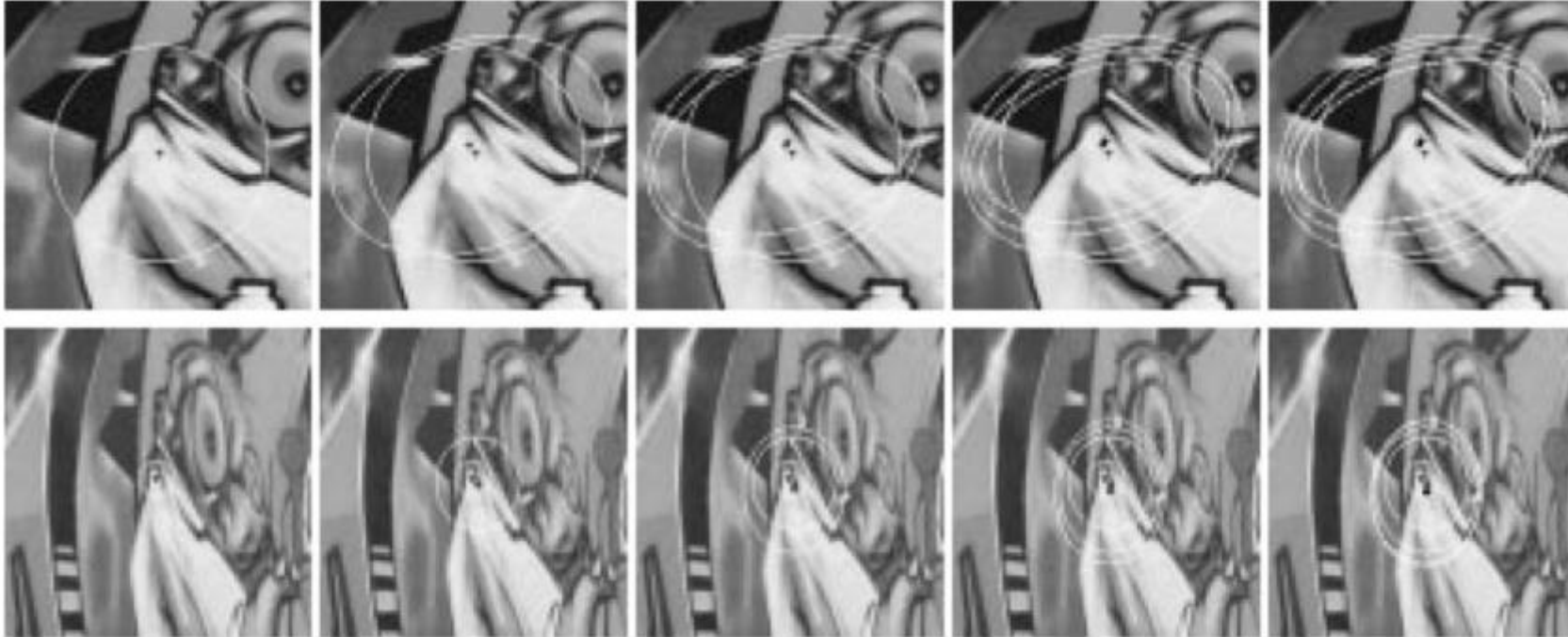
- Up to now, we had invariance to
 - Translation
 - Scale
 - Rotation
- Not sufficient to match regions under viewpoint changes
 - For this, we need also affine adaptation

Affine Adaptation

- Problem:
 - Determine the characteristic shape of the region.
 - Assumption: shape can be described by “local affine frame”.
- Solution: iterative approach
 - Use a circular window to compute second moment matrix.
 - Compute eigenvectors to adapt the circle to an ellipse.
 - Recompute second moment matrix using new window and iterate...



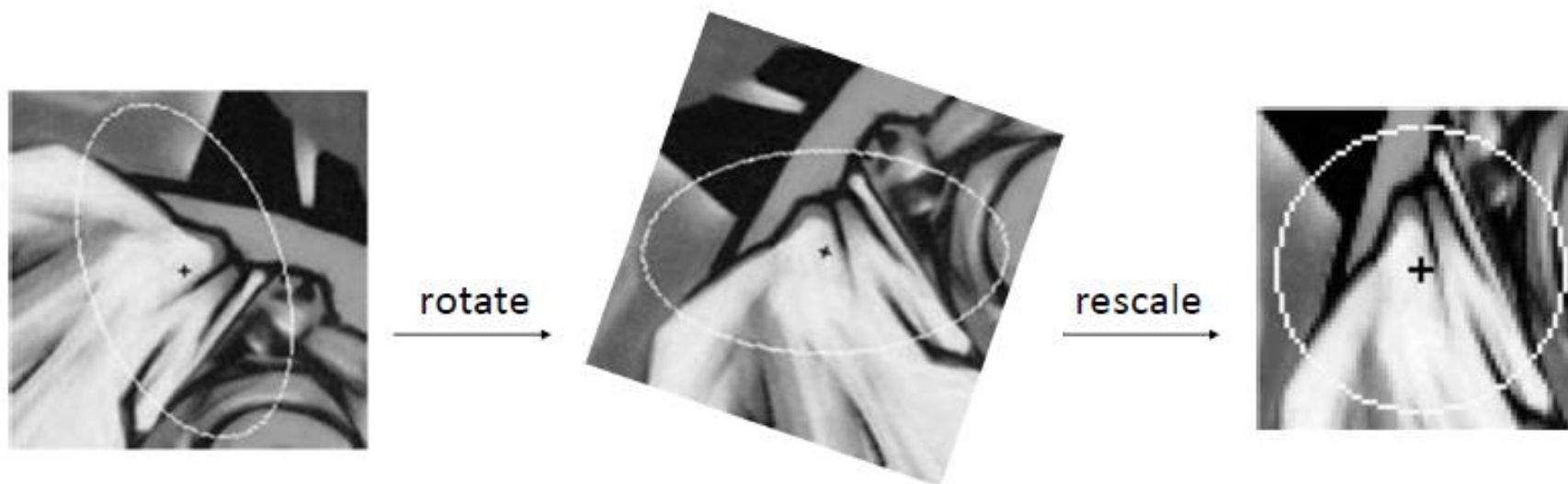
Iterative Affine Adaptation



1. Detect keypoints, e.g. multi-scale Harris
2. Automatically select the scales
3. Adapt affine shape based on second order moment matrix
4. Refine point location

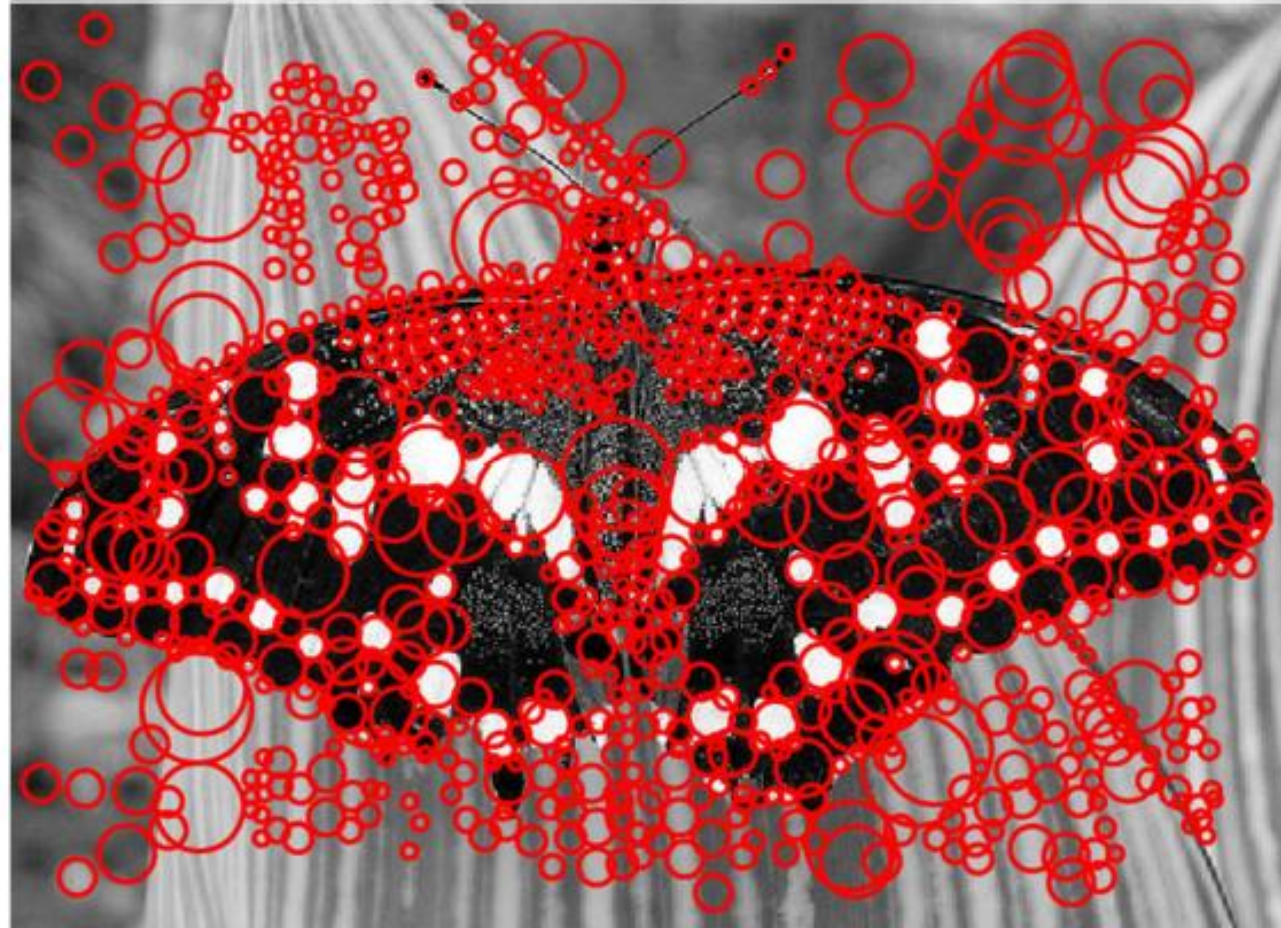
© Slide credit: Tinne Tuytelaars. K. Mikolajczyk and C. Schmid, Scale and affine invariant interest point detectors, IJCV 60(1):63-86, 2004.

Affine Normalization/Deskewing



- Steps
 - Rotate the ellipse's main axis to horizontal
 - Scale the x axis, such that it forms a circle

Affine Adaptation Example



Scale-invariant regions (blobs)

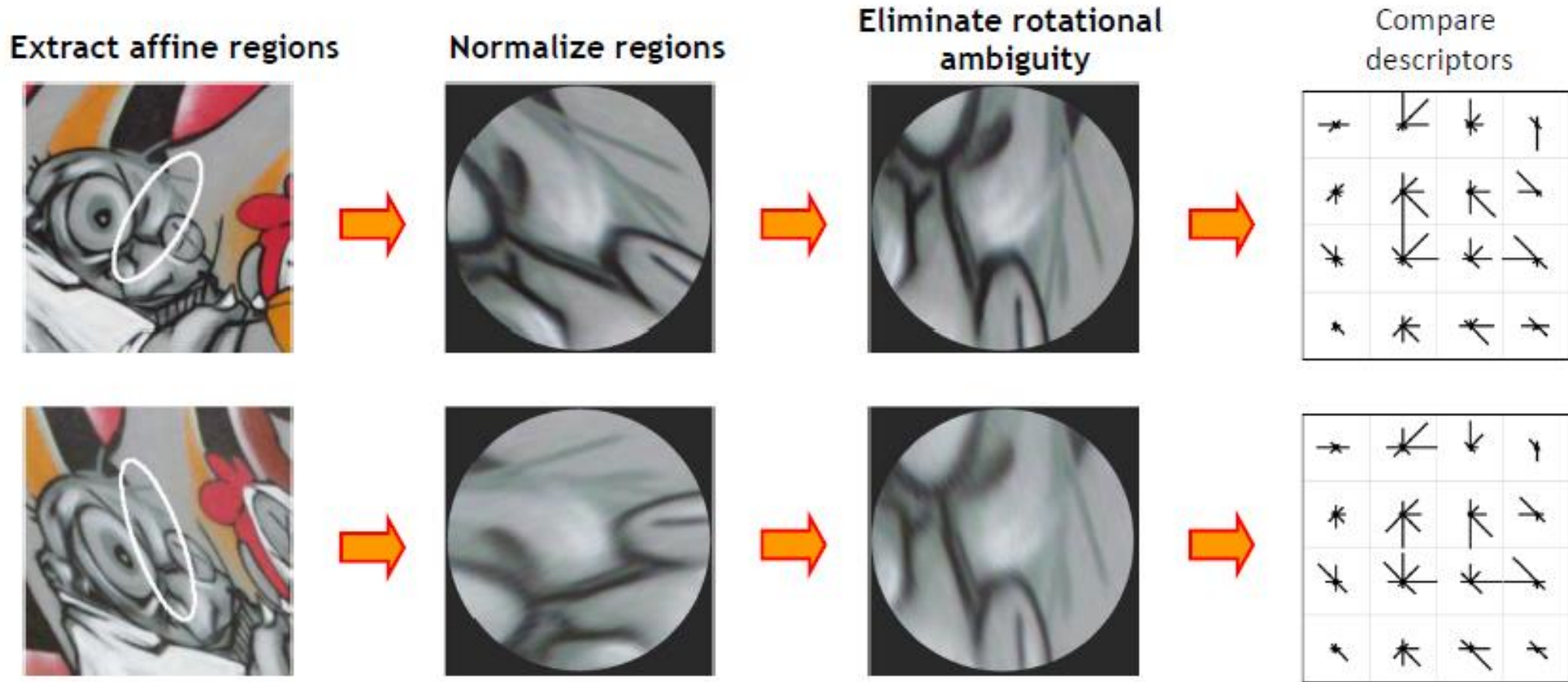
Affine Adaptation Example



Affine-adapted blobs

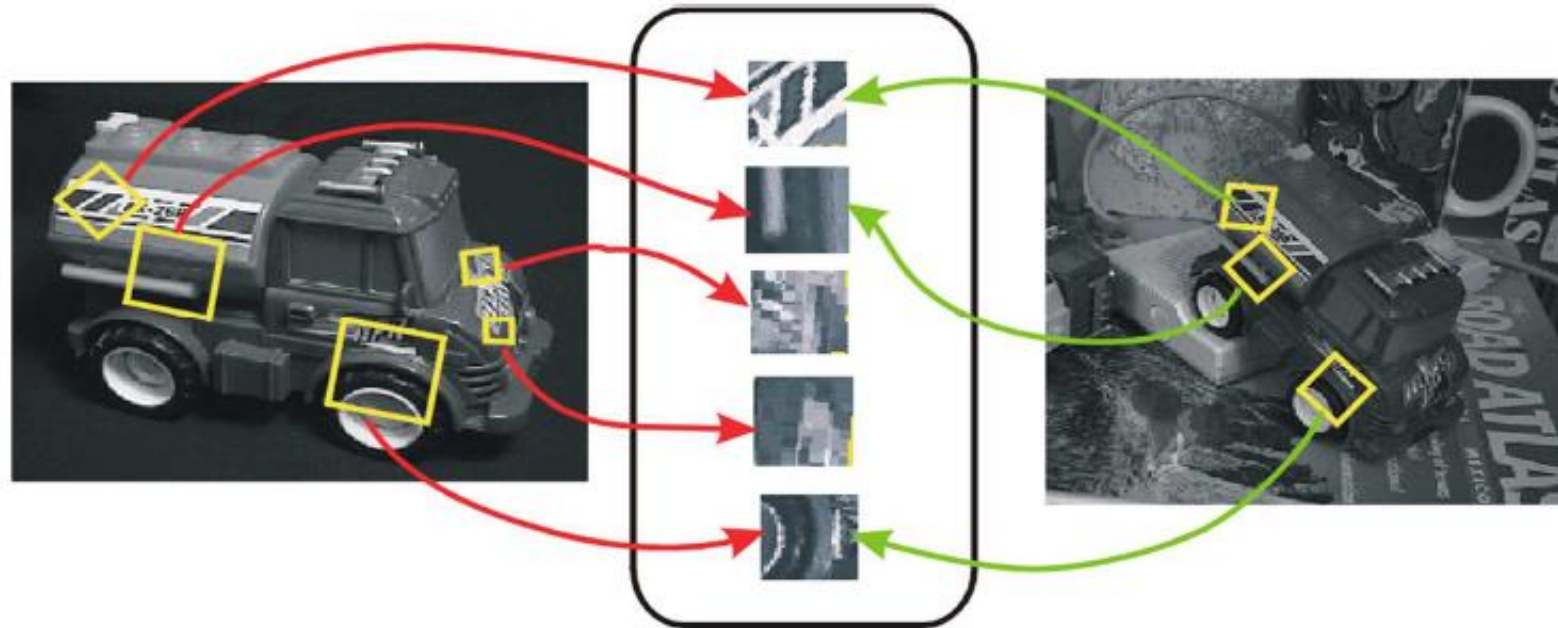
© Slide credit: Svetlana Lazebnik

Summary: Affine-Inv. Feature Extraction



Summary: Affine-Inv. Feature Extraction

- Invariance:
 - $\text{features}(\text{transform}(\text{image})) = \text{features}(\text{image})$
- Covariance:
 - $\text{features}(\text{transform}(\text{image})) = \text{transform}(\text{features}(\text{image}))$

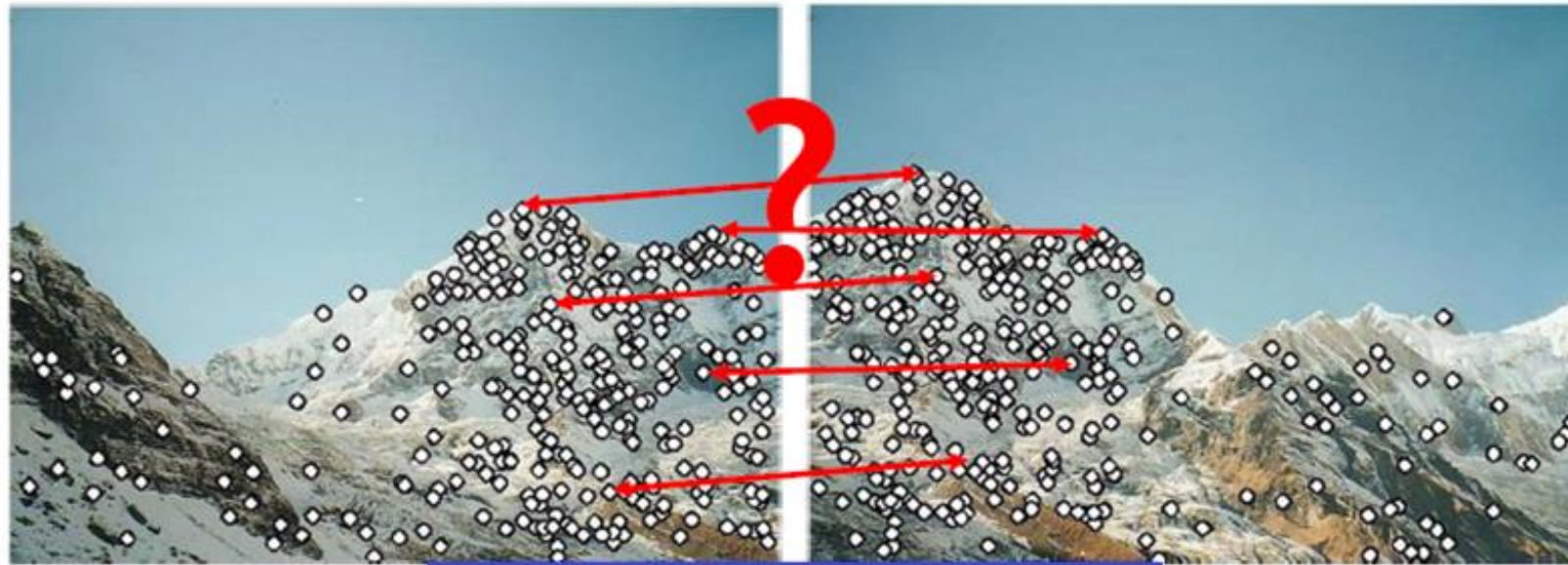


Covariant detection \Rightarrow invariant description

Local Descriptors

- We know how to detect points
- Next question:

How to describe them for matching?



Point descriptor should be:

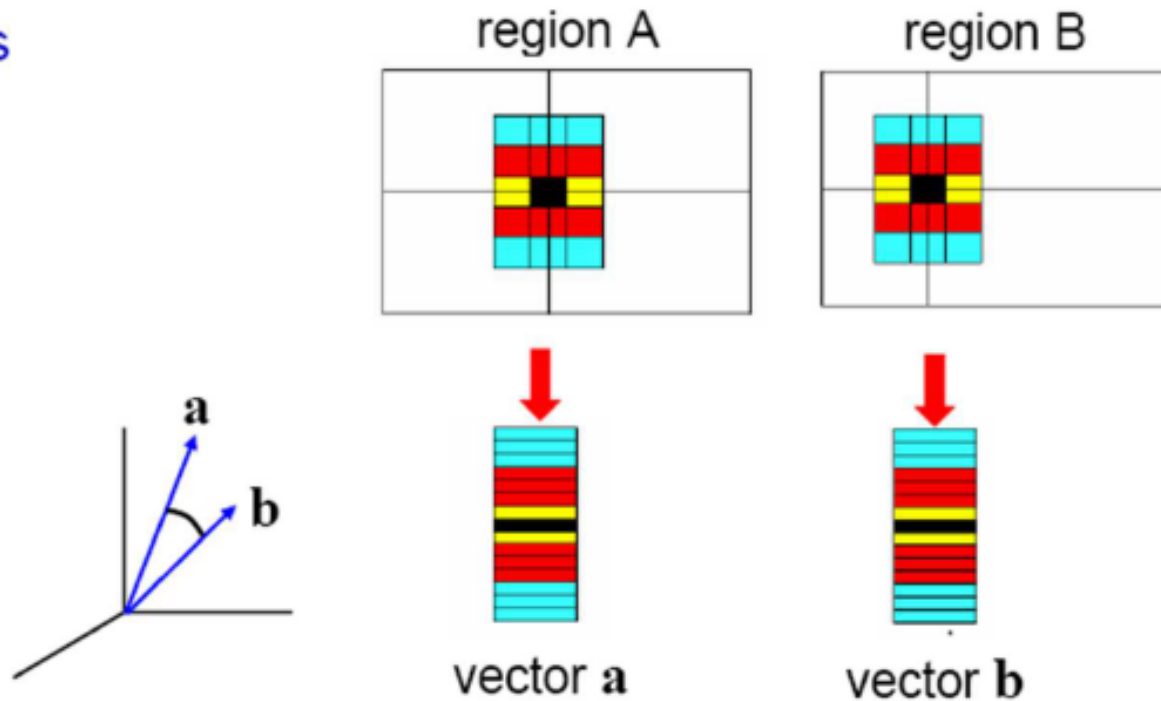
1. Invariant
2. Distinctive

Local Descriptors

- Simplest descriptor: list of intensities within a patch.
- What is this going to be invariant to?

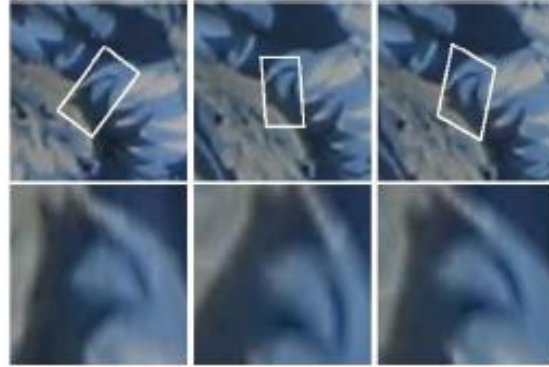
Write regions as vectors

$A \rightarrow \mathbf{a}, B \rightarrow \mathbf{b}$

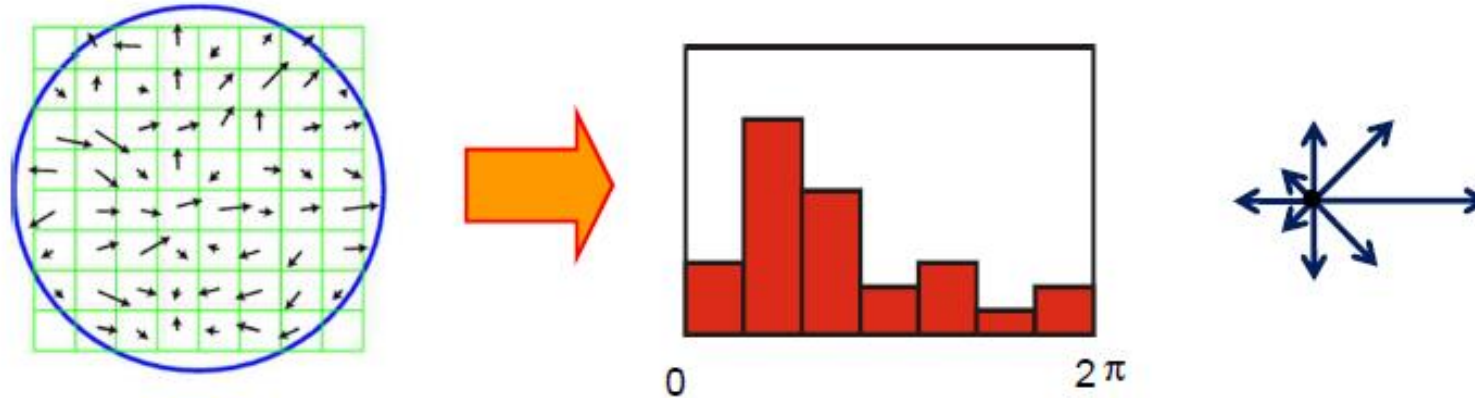


Feature Descriptors

- Disadvantage of patches as descriptors:
 - Small shifts can affect matching score a lot



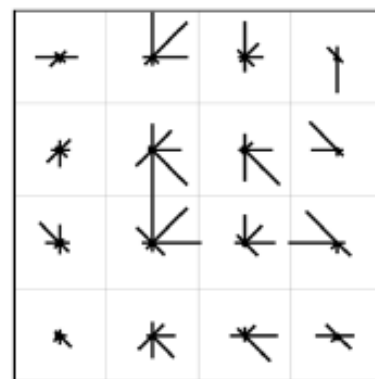
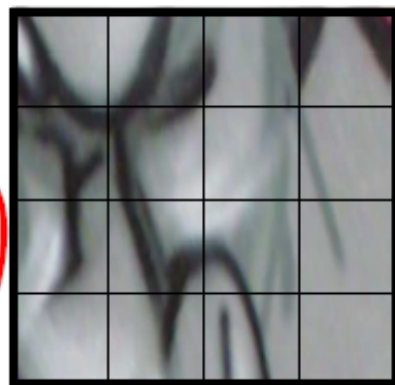
- Solution: histograms



Feature Descriptors: SIFT

- Scale Invariant Feature Transform
- Descriptor computation:
 - Divide patch into 4x4 sub-patches: 16 cells
 - Compute histogram of gradient orientations (8 reference angles) for all pixels inside each sub-patch
 - Resulting descriptor: $4 \times 4 \times 8 = 128$ dimensions

(optional)
subtract
from dominant
orientation
(normalize orient.)



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

Overview: SIFT

- Extraordinarily robust matching technique
 - Can handle changes in viewpoint up to ~ 60 deg. out-of-plane rotation
 - Can handle significant changes in illumination
 - Sometimes even day vs. night (below)
 - Fast and efficient—can run in real time
 - Lots of code available
 - http://people.csail.mit.edu/albert/ladypack/wiki/index.php/Known_implementations_of_SIFT



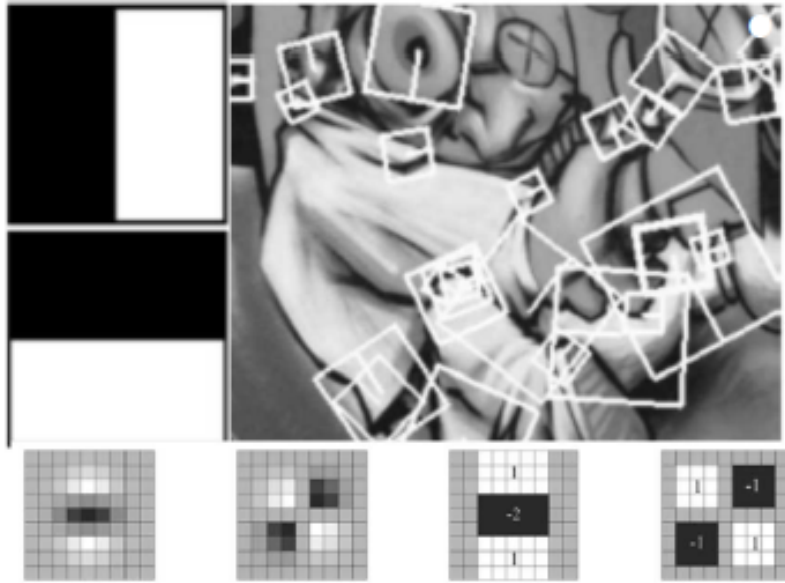
© Slide credit: Steve Seitz

Working with SIFT Descriptors

- One image yields:
 - n 128-dimensional descriptors: each one is a histogram of the gradient orientations within a patch
 - $[n \times 128 \text{ matrix}]$
 - n scale parameters specifying the size of each patch
 - $[n \times 1 \text{ vector}]$
 - n orientation parameters specifying the angle of the patch
 - $[n \times 1 \text{ vector}]$
 - n 2D points giving positions of the patches
 - $[n \times 2 \text{ matrix}]$



Local Descriptors: SURF



Fast approximation of SIFT idea

Efficient computation by 2D box filters & integral images

⇒ 6 times faster than SIFT

Equivalent quality for object identification

<http://www.vision.ee.ethz.ch/~surf>

GPU implementation available

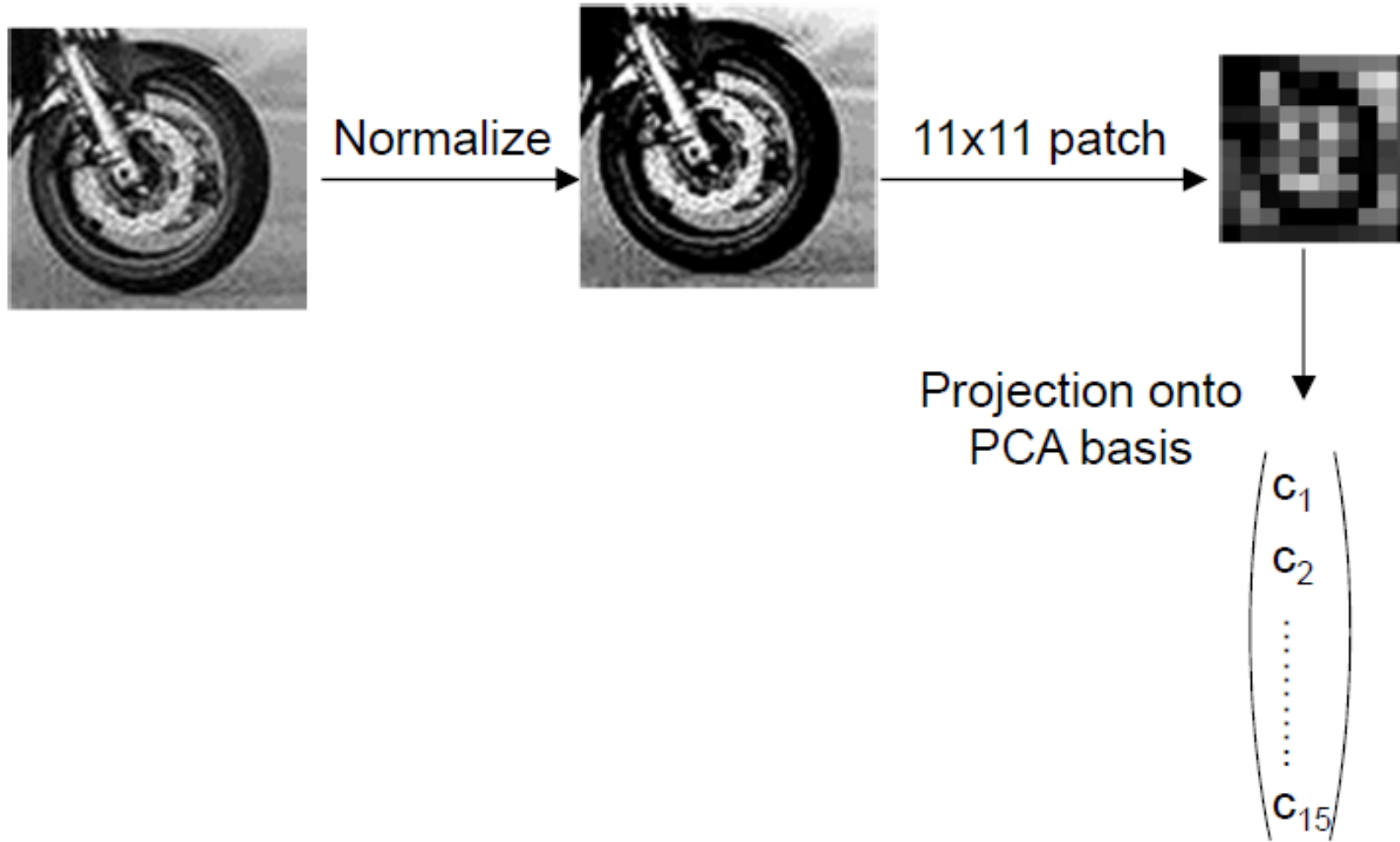
Feature extraction @ 100Hz
(detector + descriptor, 640×480 img)

<http://homes.esat.kuleuven.be/~ncorneli/gpusurf/>

[Bay, ECCV'06], [Cornelis, CVGPU'08]

<http://www.vision.ee.ethz.ch/~surf>

Other local descriptors: Gray-scale intensity



Matching features: Learned Invariant Feature Transform (LIFT)

LIFT: Learned Invariant Feature Transform

K.M. Yi, E. Trulls, V. Lepetit, P. Fua
ECCV 2016

© Sculdo, K.M. Yi, E. Trulls, V. Lepetit, P. Fua, LIFT: Learned Invariant Feature Transform, ECCV, 2016, <https://www.youtube.com/watch?v=hxxAttChmCo>

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THANK YOU!

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