

# **ECE468/CS519**

## **Digital Image Processing**

### **Feature Descriptors**

**Prof. Sinisa Todorovic**

**[sinisa@eecs.oregonstate.edu](mailto:sinisa@eecs.oregonstate.edu)**

# Outline

- Point descriptors -- SIFT, HOG

# Affine Invariant Feature Detection

# Affine Invariant Feature Detection

Given two images of the same scene  
and related by an affine transform

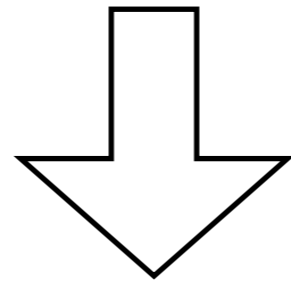
$$I_2(x, y) = T[I_1(x, y)]$$

Features detected in both images should be the same

$$\begin{aligned} F\{I_1(x, y)\} &= F\{I_2(x, y)\} \\ &= F\{T[I_1(x, y)]\} \\ &= T'[F\{I_2(x, y)\}] \end{aligned}$$

# Affine Invariant Feature Detection

$$F\{I_1(x, y)\} = T'[F\{I_2(x, y)\}]$$



$$T_1[F\{I_1(x, y)\}] = T_2[F\{I_2(x, y)\}]$$

Each detected feature is normalized to a canonical view

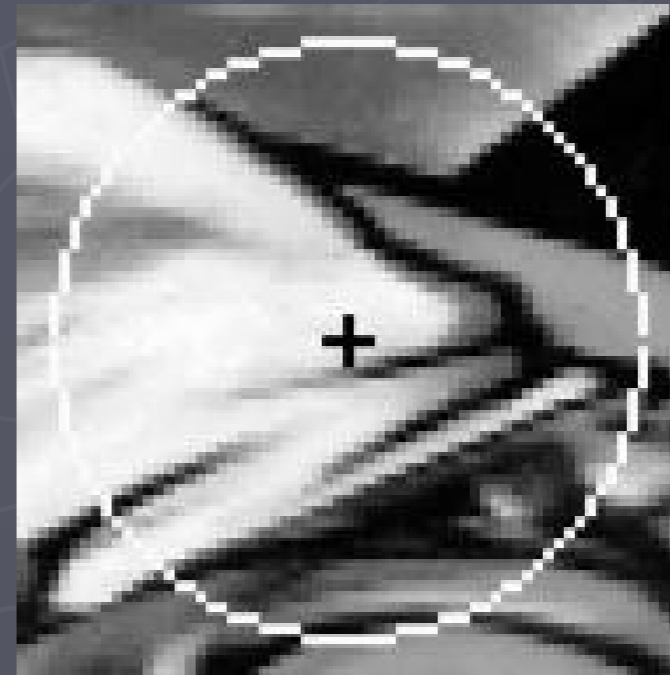
# Affine normalization ('deskewing')



rotate →

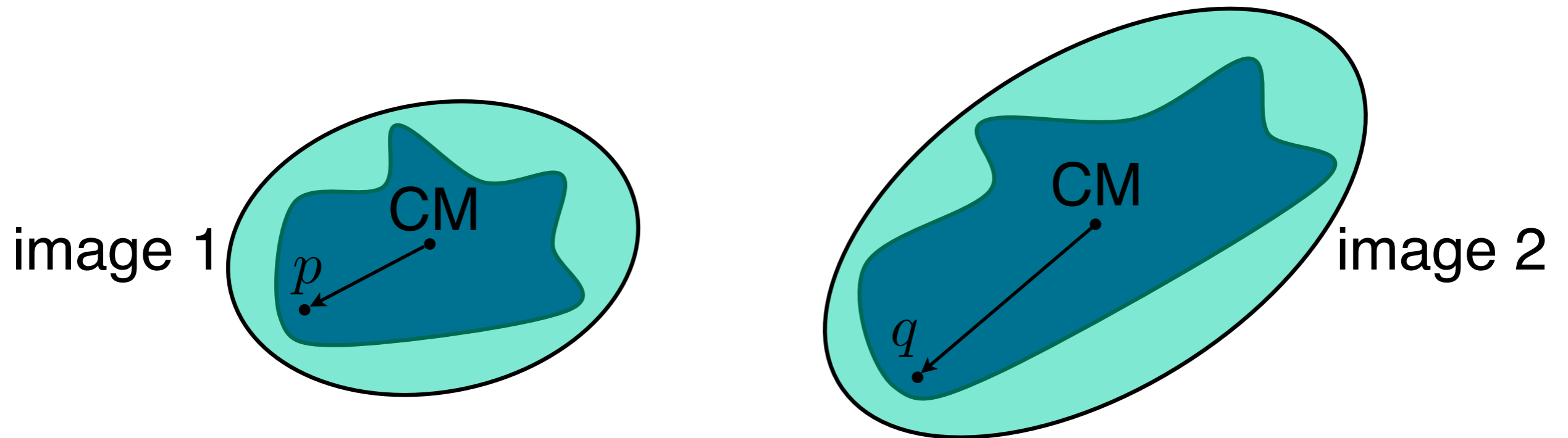


↓ rescale



Source: Tuytelaars

# How to Normalize to a Canonical View?



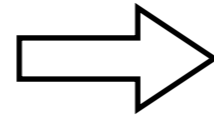
If the points in two images are related by a transform  
their covariance matrices are also related by that transform

$$q = Tp$$

$$\Sigma_2 = T\Sigma_1T^T$$

# Affine Normalization

Ellipse in image 1



Unit circle in image 2

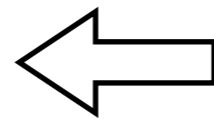
$$p^T M^{-1} p = 1$$

$$q^T I^{-1} q = 1$$

the amount of intensity changes at  
detected interest point

where

$$I = T M T^T$$



$$q = T p$$

$$I = T \Phi \Lambda \Phi^T T^T$$

$$T = ?$$

$$I = T \Phi \Lambda^{\frac{1}{2}} (T \Phi \Lambda^{-\frac{1}{2}})^T$$

$$T = \Phi^T \Lambda^{-\frac{1}{2}}$$



# Descriptors

# Point Descriptors

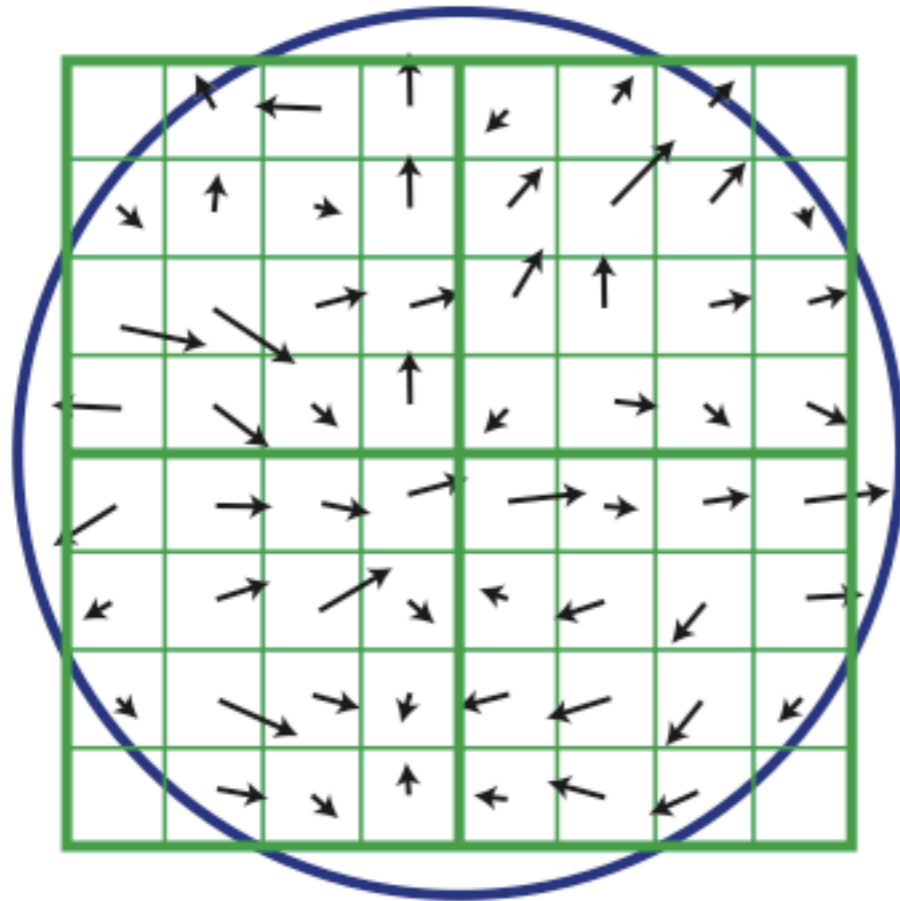
- Describe image properties in the neighborhood of a keypoint
- Descriptors = Vectors that are ideally affine invariant
- Popular descriptors:
  - Scale invariant feature transform (SIFT)
  - Steerable filters
  - Shape context and geometric blur
  - Gradient location and orientation histogram (GLOH)
  - Histogram of Oriented Gradients (HOGs)
  - DAISY

# SIFT and HOG

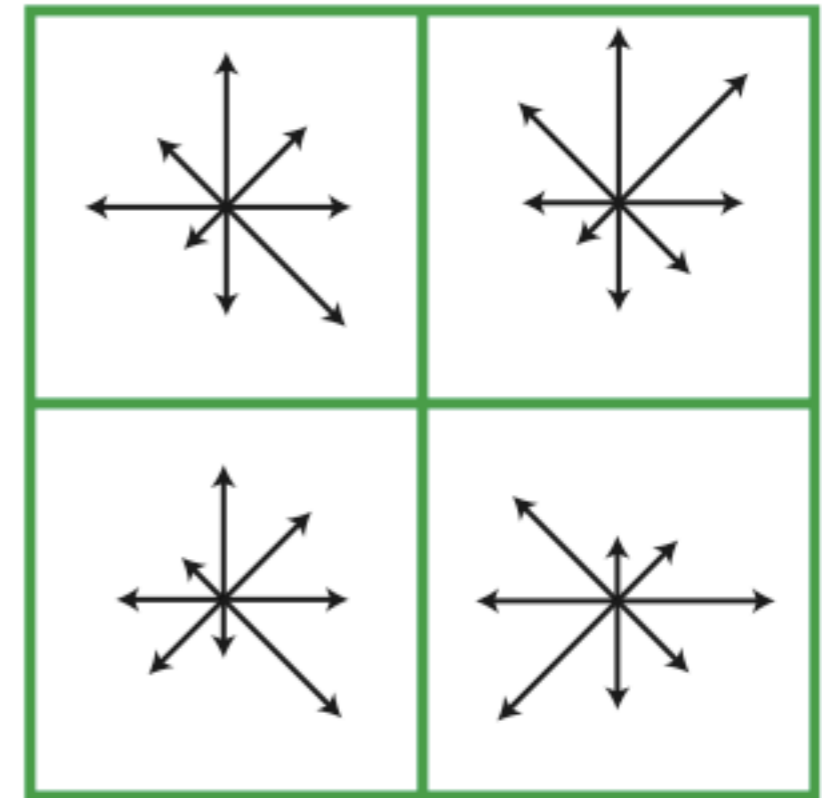
The key idea is that local object appearance and shape can be described by the distribution of intensity gradients or edge directions.

# SIFT Descriptor

128-D vector = (4x4 blocks) x (8 bins of histogram)



gradients of a 16x16  
patch centered at  
the point



histogram of gradients  
at certain angles  
of a 4x4 subpatch

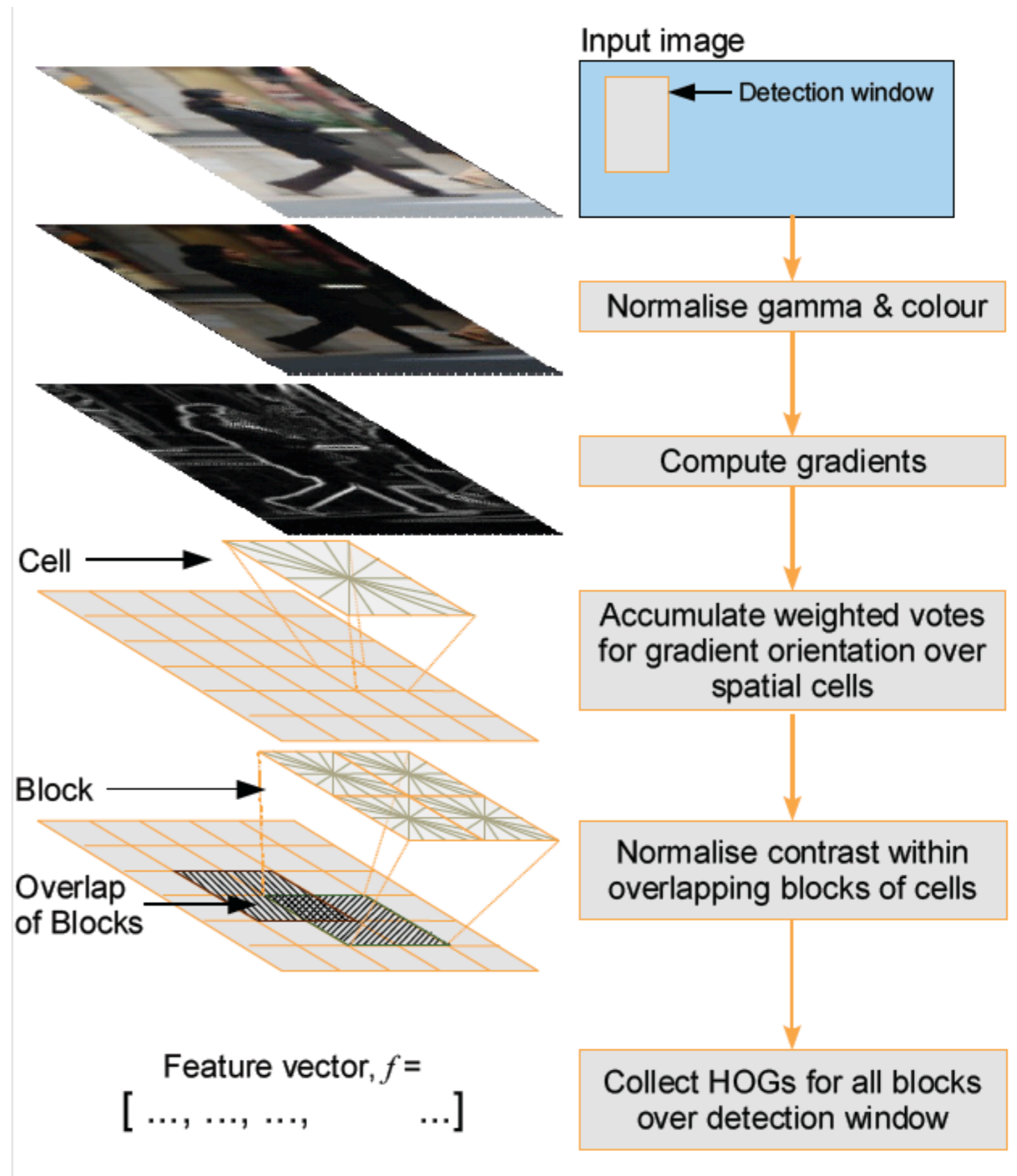
The figure illustrates only 8x8 pixel neighborhood  
that is transformed into 2x2 blocks, for visibility

# PCA-SIFT

- Instead of using 8 fixed bins for the histogram of gradients
- Learn the principal axes of all gradients observed in training images
- For a given interest point
  - Compute SIFT with
  - Gradients in the vicinity of the point projected onto the principal axes

# Histogram of Oriented Gradients

HOG is a histogram of orientations of the image gradients within a patch



# Evaluation of Feature Detectors and Descriptors

# Evaluation of Detectors

- Find corresponding points in two images showing the same scene.
- After projecting image 2 to image 1:
- Corresponding features have an overlap defined by the ratio of intersection and union of their associated ellipses:
- $\text{Similarity} = \text{intersection} / \text{union}$



# Repeatability of Detectors



image 1



image 2

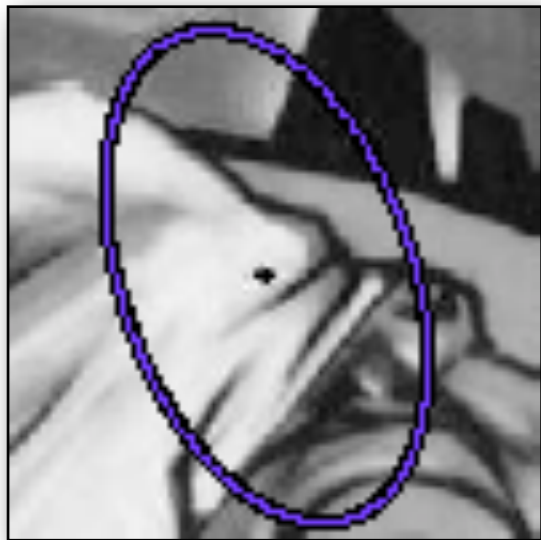
# Evaluation of Detectors



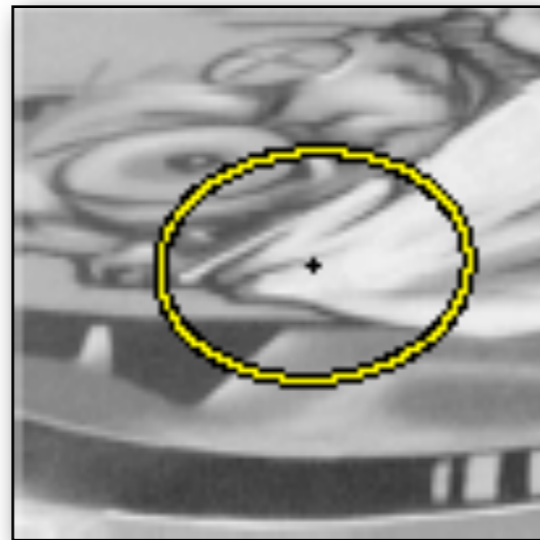
image 1



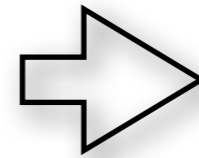
image 2



point detected  
in image 1



point detected  
in image 2



projection of  
image 2 to image 1

# Evaluation of Descriptors -- Task Driven

- Match points in two images showing the same scene
- Matches are nearest neighbors in the descriptor space
- Precision: percentage of correctly matched feature points of the total number of matches

# Matching Cost of Two Descriptors

- Euclidean distance:  $\psi(\mathbf{d}_1, \mathbf{d}_2) = \|\mathbf{d}_1 - \mathbf{d}_2\|^2$
- Chi-squared distance:  $\psi(\mathbf{d}_1, \mathbf{d}_2) = \sum_i \frac{(\mathbf{d}_{1i} - \mathbf{d}_{2i})^2}{\mathbf{d}_{1i} + \mathbf{d}_{2i}}$

# Matching Formulation

Given two sets of descriptors to be matched

$$V = \{\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_N\}, \text{ and } V' = \{\mathbf{d}'_1, \mathbf{d}'_2, \dots, \mathbf{d}'_M\}$$

Find the legal mapping  $f \in \mathcal{F}$

$$f := \{(\mathbf{d}, \mathbf{d}') : \mathbf{d} \in V, \mathbf{d}' \in V'\}$$

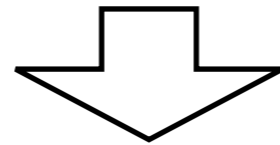
Which minimizes the total cost of matching

$$\hat{f} = \min_{f \in \mathcal{F}} \sum_{(\mathbf{d}, \mathbf{d}') \in f} \psi(\mathbf{d}, \mathbf{d}'), \quad \psi(\mathbf{d}, \mathbf{d}') \geq \mathbf{0}$$

# Total Cost of Matching

$$A = \begin{bmatrix} \psi_{11'} & \psi_{12'} & \psi_{13'} & \dots & \psi_{1M} \\ \psi_{21'} & \psi_{22'} & \psi_{23'} & \dots & \psi_{2M} \\ \dots & & & & \\ & & & & \end{bmatrix}_{N \times M}$$

cost matrix



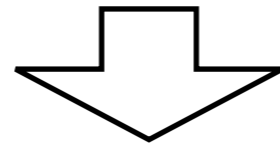
$$\sum_{(\mathbf{d}, \mathbf{d}')} \psi(\mathbf{d}, \mathbf{d}') = \text{tr}(A^T I)$$

identity matrix

# Total Cost of Matching

$$A = \begin{bmatrix} \psi_{11'} & \psi_{12'} & \psi_{13'} & \dots & \psi_{1M} \\ \psi_{21'} & \psi_{22'} & \psi_{23'} & \dots & \psi_{2M} \\ \dots & & & & \end{bmatrix}_{N \times M}$$

cost matrix



$$\sum_{(\mathbf{d}, \mathbf{d}')} \psi(\mathbf{d}, \mathbf{d}') = \text{tr}(A^T I)$$

identity matrix

$$\sum_{(\mathbf{d}, \mathbf{d}') \in f} \psi(\mathbf{d}, \mathbf{d}') = ?$$

# Linearization

Linearization by introducing an indicator matrix

$$X = \begin{bmatrix} 0 & 0 & 1 & \dots & 0 & 0 \\ 0 & 1 & 0 & \dots & 0 & 0 \\ & & \dots & & & \\ & & & & & \end{bmatrix}_{N \times M}$$

$x(\mathbf{d}, \mathbf{d}') = 1$ , if  $(\mathbf{d}, \mathbf{d}') \in f$  matched pair

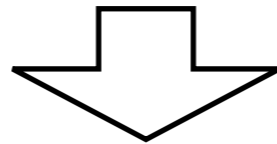
$x(\mathbf{d}, \mathbf{d}') = 0$ , if  $(\mathbf{d}, \mathbf{d}') \notin f$  unmatched pair



# Linearization

$$A = \begin{bmatrix} \psi_{11'} & \psi_{12'} & \psi_{13'} & \dots & \psi_{1M} \\ \psi_{21'} & \psi_{22'} & \psi_{23'} & \dots & \psi_{2M} \\ \dots & & & & \end{bmatrix}_{N \times M}$$

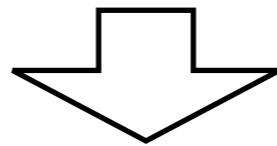
$$X = \begin{bmatrix} 0 & 0 & 1 & \dots & 0 & 0 \\ 0 & 1 & 0 & \dots & 0 & 0 \\ \dots & & & & & \end{bmatrix}_{N \times M}$$



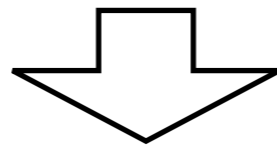
$$\sum_{(\mathbf{d}, \mathbf{d}') \in f} \psi(\mathbf{d}, \mathbf{d}') = \sum_{(\mathbf{d}, \mathbf{d}')} \psi_{\mathbf{d}, \mathbf{d}'} x_{\mathbf{d}, \mathbf{d}'} = \text{tr}(A^T X)$$

# Matching Formulation

$$\hat{X} = \min_X \text{tr}(A^T X)$$



$$\hat{X} = \mathbf{0} \quad \text{trivial solution}$$



we need to constrain the formulation

# Matching Formulation

$$\min_X \operatorname{tr}(A^T X)$$

subject to:

$$\forall \mathbf{d} \in V, \forall \mathbf{d}' \in V', x_{\mathbf{d}\mathbf{d}'} \in \{0, 1\}$$

$$\forall \mathbf{d}, \sum_{\mathbf{d}'} x_{\mathbf{d}\mathbf{d}'} = 1$$

$$\forall \mathbf{d}', \sum_{\mathbf{d}} x_{\mathbf{d}\mathbf{d}'} = 1$$

what is the meaning of this constraint?

# Matching Formulation

$$\min_X \operatorname{tr}(A^T X)$$

subject to:

$$\forall \mathbf{d} \in V, \forall \mathbf{d}' \in V', x_{\mathbf{d}\mathbf{d}'} \in \{0, 1\}$$

$$\forall \mathbf{d}, \sum_{\mathbf{d}'} x_{\mathbf{d}\mathbf{d}'} = 1$$

**one-to-one  
matching**

$$\forall \mathbf{d}', \sum_{\mathbf{d}} x_{\mathbf{d}\mathbf{d}'} = 1$$

# Relaxation

$$\min_X \operatorname{tr}(A^T X)$$

subject to:

$$\forall \mathbf{d} \in V, \forall \mathbf{d}' \in V', x_{\mathbf{d}\mathbf{d}'} \in [0, 1]$$

$$\forall \mathbf{d}, \sum_{\mathbf{d}'} x_{\mathbf{d}\mathbf{d}'} = 1$$

$$\forall \mathbf{d}', \sum_{\mathbf{d}} x_{\mathbf{d}\mathbf{d}'} = 1$$

**one-to-one  
matching**

# Linear Assignment Problem

$$\min_X \operatorname{tr}(A^T X)$$

subject to:

$$\forall \mathbf{d} \in V, \forall \mathbf{d}' \in V', x_{\mathbf{d}\mathbf{d}'} \in [0, 1]$$

$$\forall \mathbf{d}, \sum_{\mathbf{d}'} x_{\mathbf{d}\mathbf{d}'} = 1$$

**one-to-one  
matching**

$$\forall \mathbf{d}', \sum_{\mathbf{d}} x_{\mathbf{d}\mathbf{d}'} = 1$$

Hungarian algorithm for the balanced problem  $|V| = |V'|$

# Hungarian Algorithm

# The Hungarian Algorithm

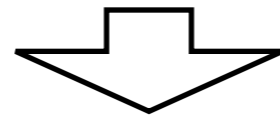
1. Find the min element along each row (column) of  $A$ , and subtract it from all elements in the respective rows (columns). Replace  $A$  with the resulting matrix.
2. Cross out the minimum number of rows and columns in  $A$  to cover all zero elements of  $A$
3. If  $\min(N, M)$  rows and columns of  $A$  are crossed out, then go to step 5.
4. Otherwise, find the minimal entry of  $A$  that is not crossed out. Add this entry to all elements that are doubly crossed out (by both a horizontal and vertical line), and subtract it from all entries of  $A$  that are not crossed out. Return to step 2 with the new matrix.
5. Solutions are zero elements of  $A$ . Go first for the zero element which is unique in its row and column. Then, delete that row and column from  $A$ . Repeat until you delete all rows or columns from  $A$ .



# Example -- The Hungarian Algorithm

given a  
cost matrix

$$A = \begin{bmatrix} 14 & 5 & 8 & 7 \\ 2 & 12 & 6 & 5 \\ 7 & 8 & 3 & 9 \\ 2 & 4 & 6 & 10 \end{bmatrix}$$



step 1: find minimums  
in each row and subtract

$$A = \begin{bmatrix} 9 & 0 & 3 & 2 \\ 0 & 10 & 4 & 3 \\ 4 & 5 & 0 & 6 \\ 0 & 2 & 4 & 8 \end{bmatrix}$$

# Example -- The Hungarian Algorithm -- Solution

go for the unique solution first

step 5:

$$A = \begin{bmatrix} 10 & 0 & 3 & 0 \\ 0 & 9 & 3 & 0 \\ 5 & 5 & \boxed{0} & 4 \\ 0 & 1 & 3 & 5 \end{bmatrix}$$

↑

$$f = \{(\mathbf{d}_3, \mathbf{d}'_3)\}$$

# Example -- The Hungarian Algorithm -- Solution

go for the unique solution first

step 5:

$$A = \begin{bmatrix} 10 & 0 & 3 & 0 \\ 0 & 9 & 3 & 0 \\ 5 & 5 & \boxed{0} & 4 \\ \rightarrow \boxed{0} & 1 & 3 & 5 \\ \uparrow & & & \end{bmatrix}$$

$$f = \{(d_3, d'_3), (d_4, d'_1)\}$$

# Example -- The Hungarian Algorithm -- Solution

go for the unique solution first

step 5:

$$A = \begin{bmatrix} \rightarrow & 10 & \boxed{0} & 3 & 0 \\ & 0 & 9 & 3 & 0 \\ & 5 & 5 & \boxed{0} & 4 \\ & \boxed{0} & 1 & 3 & 5 \\ & & \uparrow & & \end{bmatrix}$$

$$f = \{(\mathbf{d}_3, \mathbf{d}'_3), (\mathbf{d}_4, \mathbf{d}'_1), (\mathbf{d}_1, \mathbf{d}'_2)\}$$

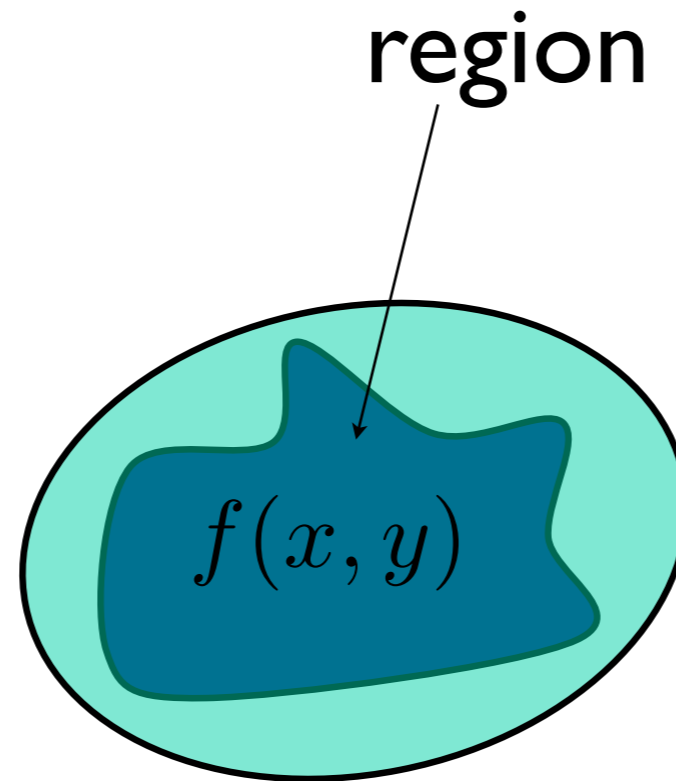
# Example -- The Hungarian Algorithm -- Solution

go for the unique solution first

step 5:  $A =$   $\left[ \begin{array}{ccccc} & 10 & \boxed{0} & 3 & 0 \\ \rightarrow & 0 & 9 & 3 & \boxed{0} \\ & 5 & 5 & \boxed{0} & 4 \\ & \boxed{0} & 1 & 3 & 5 \\ & & & & \uparrow \end{array} \right]$

$$f = \{(\mathbf{d}_3, \mathbf{d}'_3), (\mathbf{d}_4, \mathbf{d}'_1), (\mathbf{d}_1, \mathbf{d}'_2), (\mathbf{d}_2, \mathbf{d}'_4)\}$$

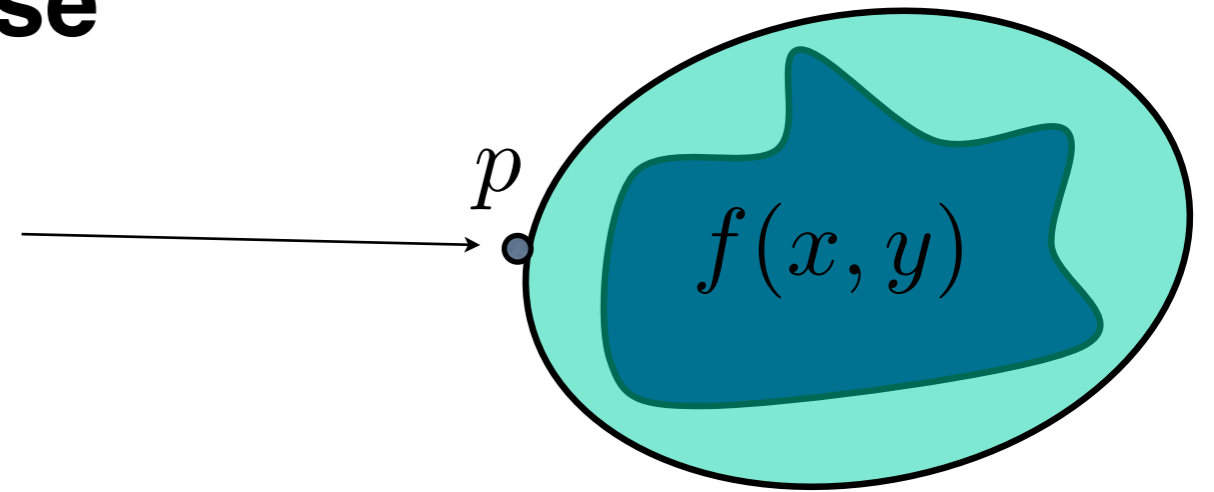
# How to Fit an Ellipse to a Region



$$f(x, y) = \left[ \begin{array}{ll} 1 & \text{inside the region} \\ 0 & \text{otherwise} \end{array} \right]$$

# Ellipse

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



$$\Sigma = \begin{bmatrix} m_{20} & m_{11} \\ m_{11} & m_{02} \end{bmatrix}$$

CM = center of mass

$$CM_x = \int_{\mathbb{R}^2} x f(x, y) dx$$

$$CM_y = \int_{\mathbb{R}^2} y f(x, y) dx$$

$$m_{pq} = \int_{\mathbb{R}^2} (x - CM_x)^p (y - CM_y)^q f(x, y) dx dy$$

# Next Class

- Shape Descriptors
- Image segmentation