CS4670/5670: Computer Vision

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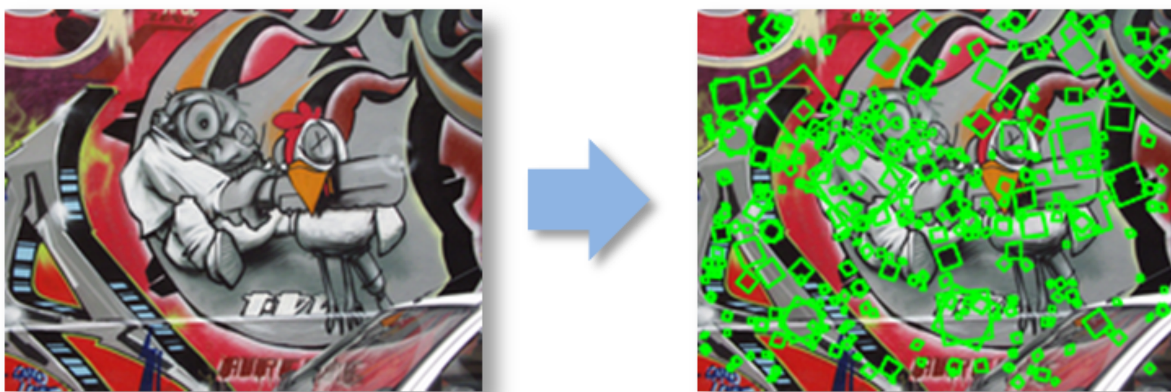
Lecture 13: Feature Descriptors and Matching

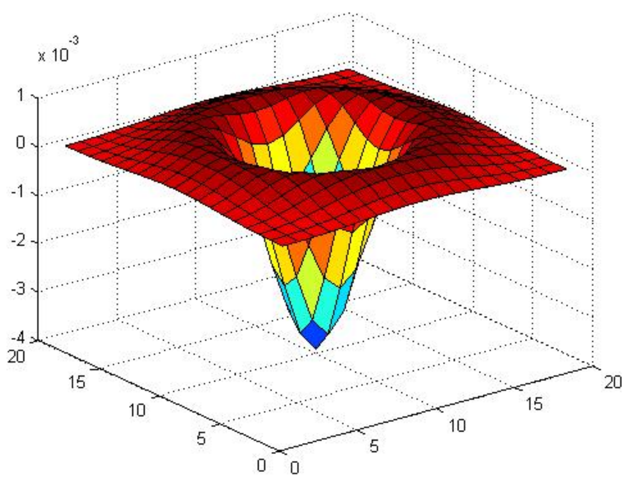


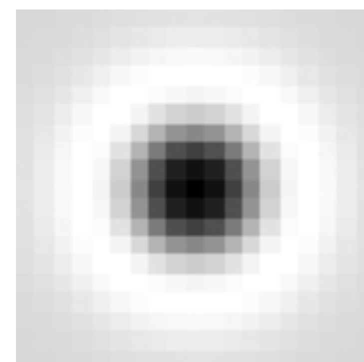
Announcements

- PA 2 out
- Artifact voting out: please vote
- Schedule will be updated shortly
- HW 1 out tonight
  - No slip days for HW 1
  - Due on Sunday Mar 13, answers released on Monday

Another type of feature

- The *Laplacian of Gaussian* (*LoG*)





$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

(very similar to a Difference of Gaussians (DoG) – i.e. a Gaussian minus a slightly smaller Gaussian)

Scale Invariant Detection

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

Kernels:

$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

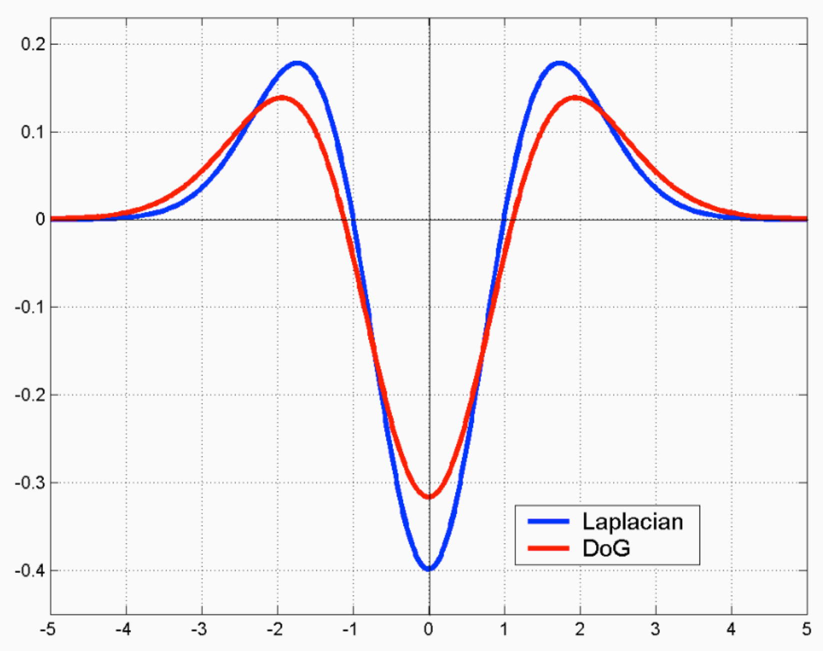
(Laplacian)

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

(Difference of Gaussians)

where Gaussian

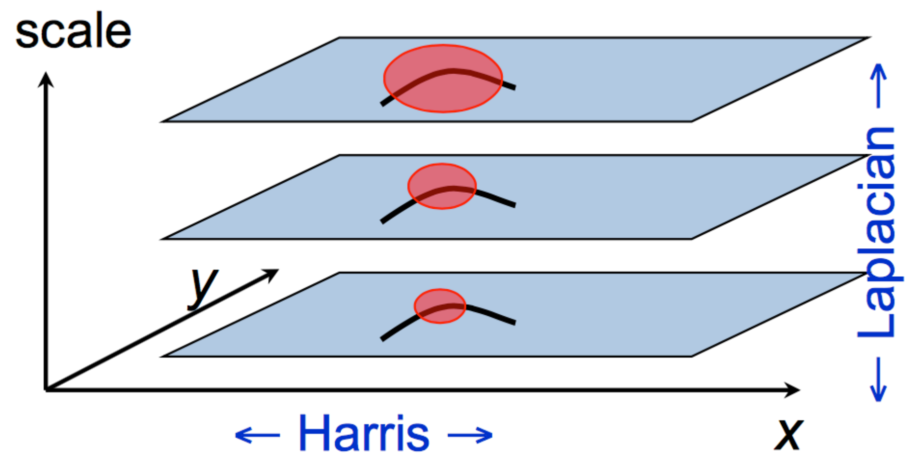
$$G(x, y, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$



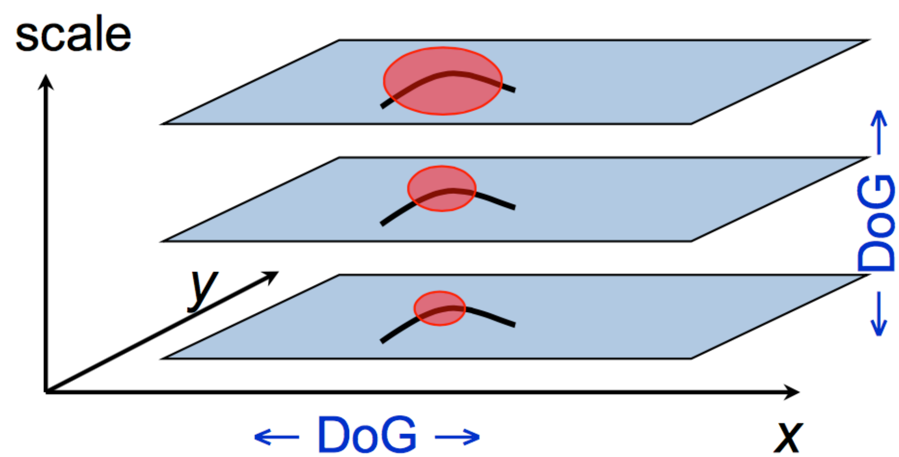
Note: both kernels are invariant to *scale* and *rotation*

Scale Invariant Detectors

- Harris-Laplacian[1]
  Find local maximum of:
  - Harris corner detector in space (image coordinates)
  - Laplacian in scale



- SIFT (Lowe)[2]
  Find local maximum of:
  - Difference of Gaussians in space and scale



[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

Comparison of Keypoint Detectors

Table 7.1 Overview of feature detectors.

Feature Detector	Corner	Blob	Region	Rotation invariant	Scale invariant	Affine invariant	Repeatability	Localization accuracy	Robustness	Efficiency
Harris	√			√			+++	+++	+++	++
Hessian		√		√			++	++	++	+
SUSAN	√			√			++	++	++	+++
Harris-Laplace	√	(√)		√	√		+++	+++	++	+
Hessian-Laplace	(√)	√		√	√		+++	+++	+++	+
DoG	(√)	√		√	√		++	++	++	++
SURF	(√)	√		√	√		++	++	++	+++
Harris-Affine	√	(√)		√	√	√	+++	+++	++	++
Hessian-Affine	(√)	√		√	√	√	+++	+++	+++	++
Salient Regions	(√)	√		√	√	(√)	+	+	++	+
Edge-based	√			√	√	√	+++	+++	+	+
MSER			√	√	√	√	+++	+++	++	+++
Intensity-based			√	√	√	√	++	++	++	++
Superpixels			√	√	(√)	(√)	+	+	+	+

Tuytelaars Mikolajczyk 2008

Choosing a detector

- What do you want it for?
  - Precise localization in x-y: Harris
  - Good localization in scale: Difference of Gaussian
  - Flexible region shape: e.g., Maximal Stable Extremal Regions

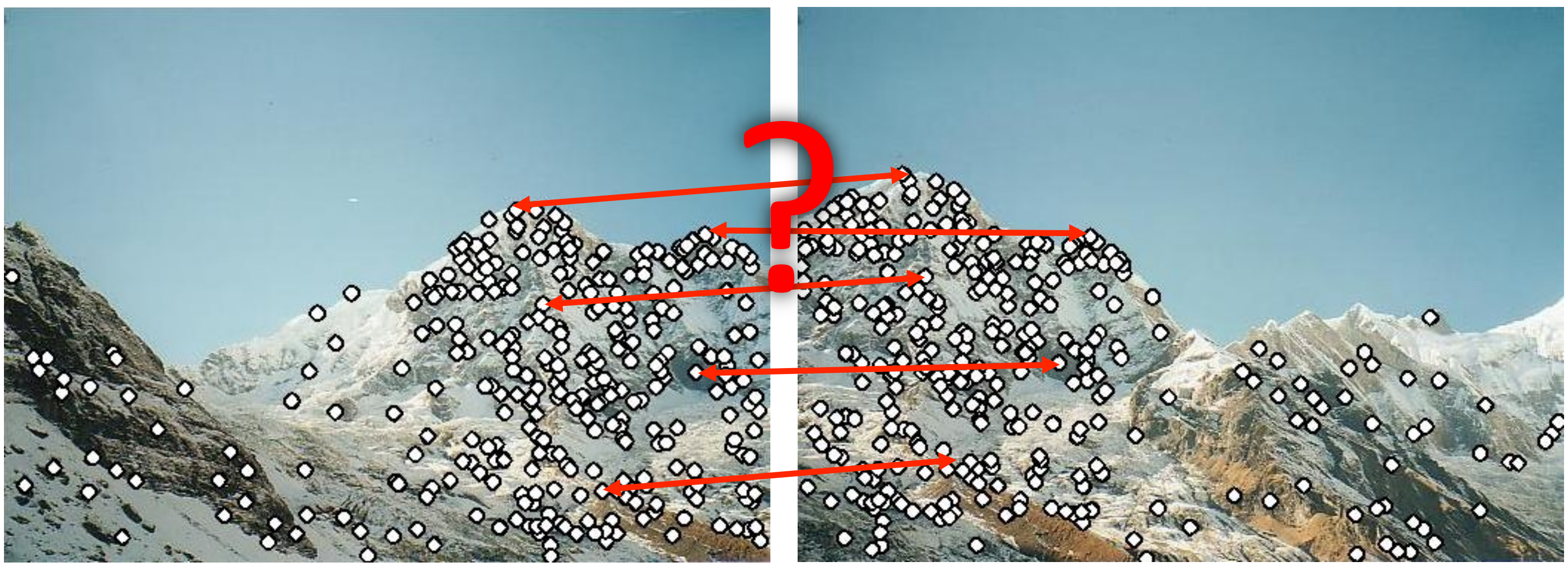
- Best choice often application dependent

- There have been extensive evaluations/comparisons
  - [Mikolajczyk et al., IJCV'05, PAMI'05]
  - All detectors/descriptors shown here work well

Feature descriptors

We know how to detect good points

Next question: **How to match them?**

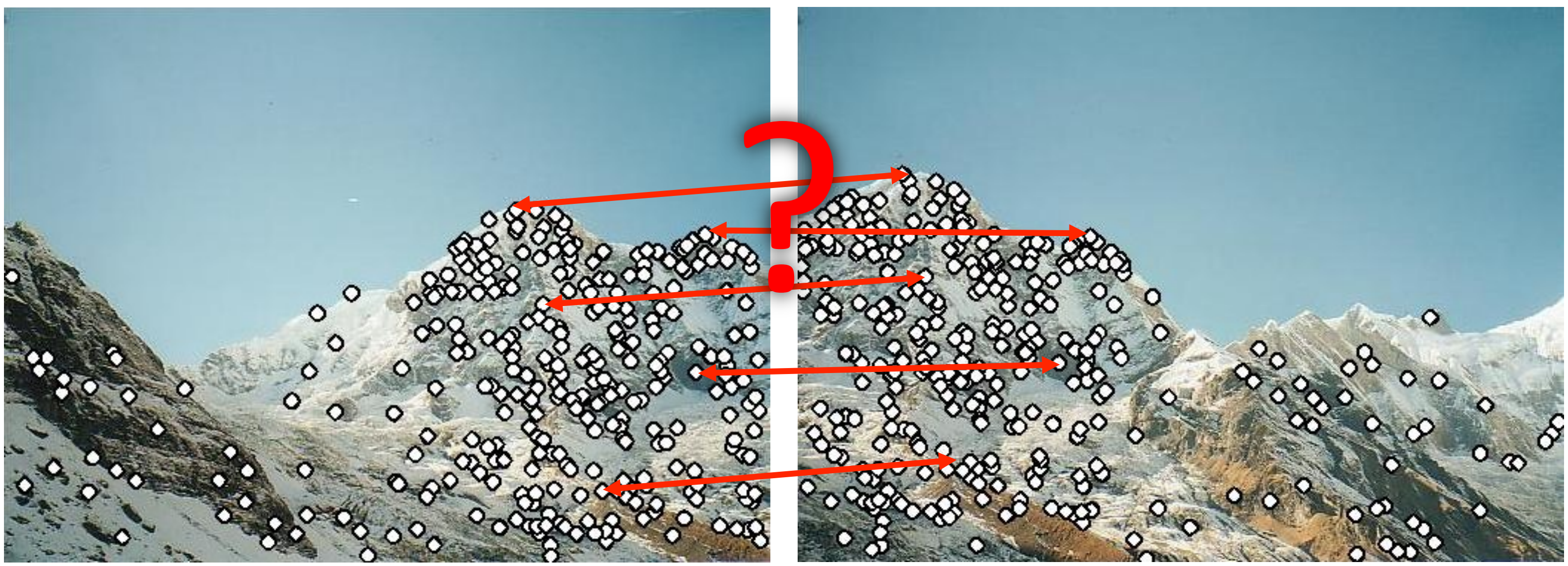


Answer: Come up with a *descriptor* for each point, find similar descriptors between the two images

Feature descriptors

We know how to detect good points

Next question: **How to match them?**



Lots of possibilities (this is a popular research area)

- Simple option: match square windows around the point
- State of the art approach: SIFT
  - David Lowe, UBC http://www.cs.ubc.ca/~lowe/keypoints/

Image representations

- Templates
  - Intensity, gradients, etc.

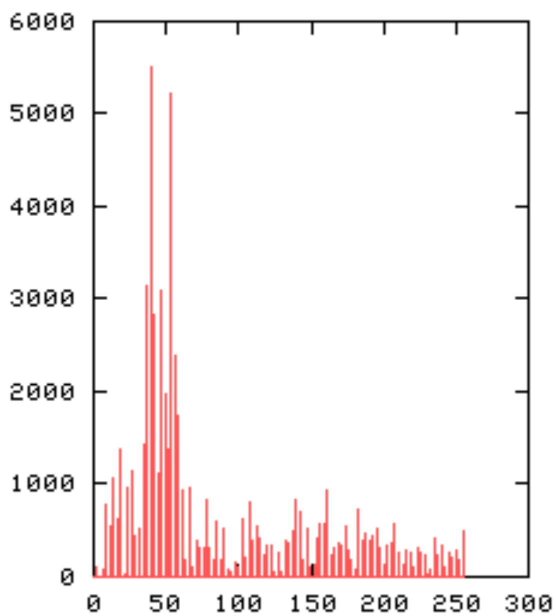
- Histograms
  - Color, texture, SIFT descriptors, etc.

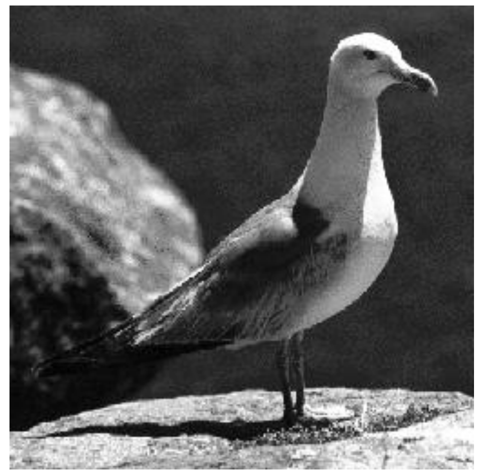
Local Descriptors

- Most features can be thought of as templates, histograms (counts), or combinations
- The ideal descriptor should be
  - Robust
  - Distinctive
  - Compact
  - Efficient
- Most available descriptors focus on edge/gradient information
  - Capture texture information

K. Grauman, B. Leibe

Image Representations: Histograms





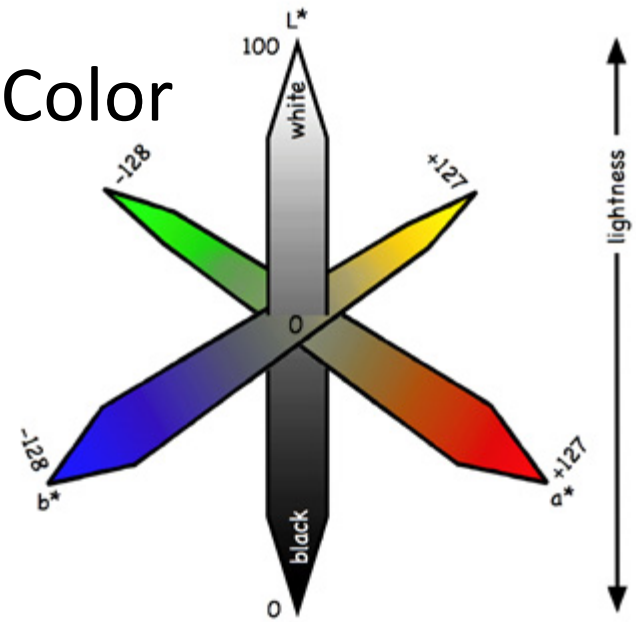
Global histogram

- Represent distribution of features
  - Color, texture, depth, …

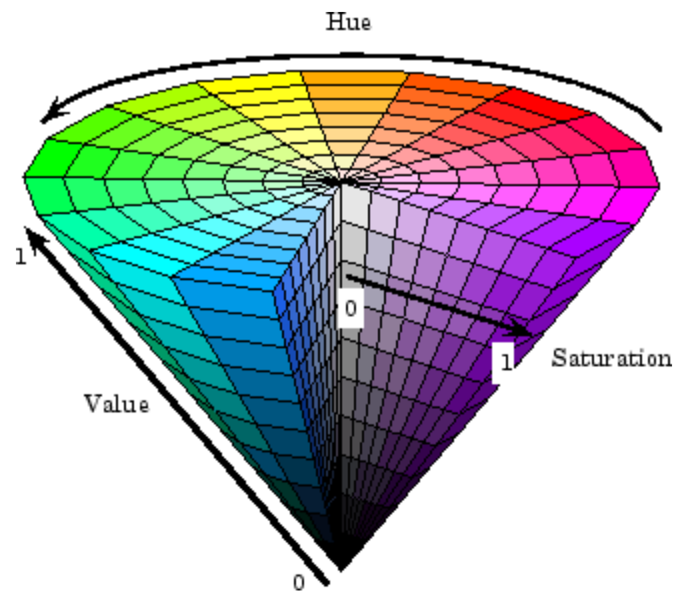
Images from Dave Kauchak

What kind of things do we compute histograms of?

- Color



L*a*b* color space



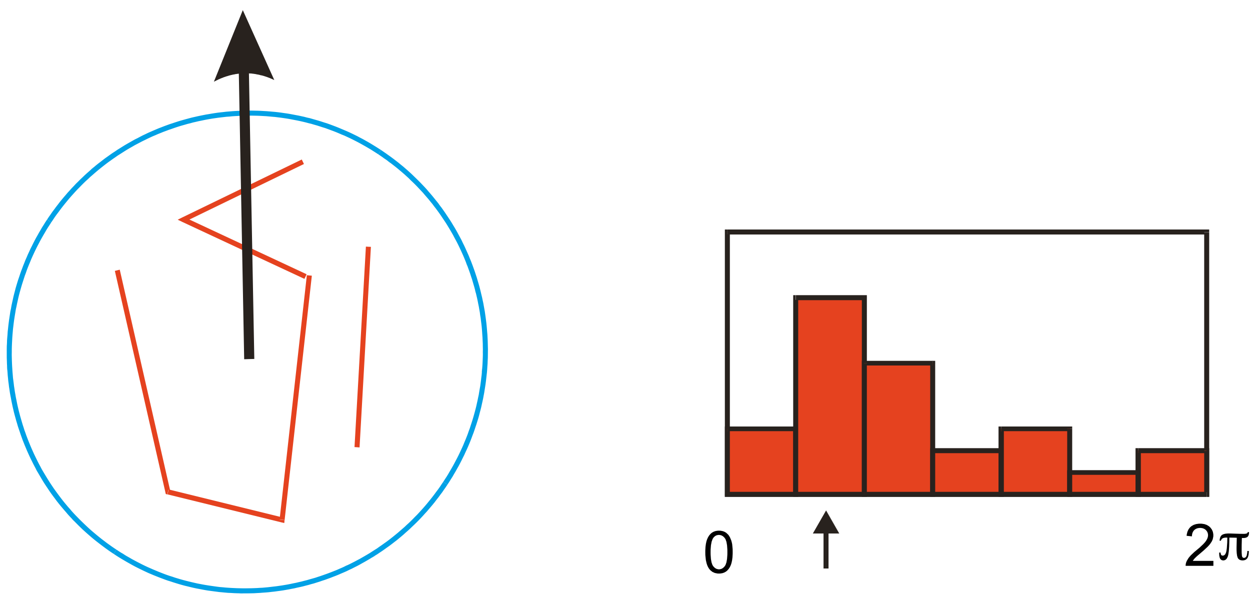
HSV color space

- Texture (filter banks or HOG over regions)
  - HOG: Histogram of Oriented Gradients

Orientation Normalization

[Lowe, SIFT, 1999]

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



Rotation invariance for feature descriptors

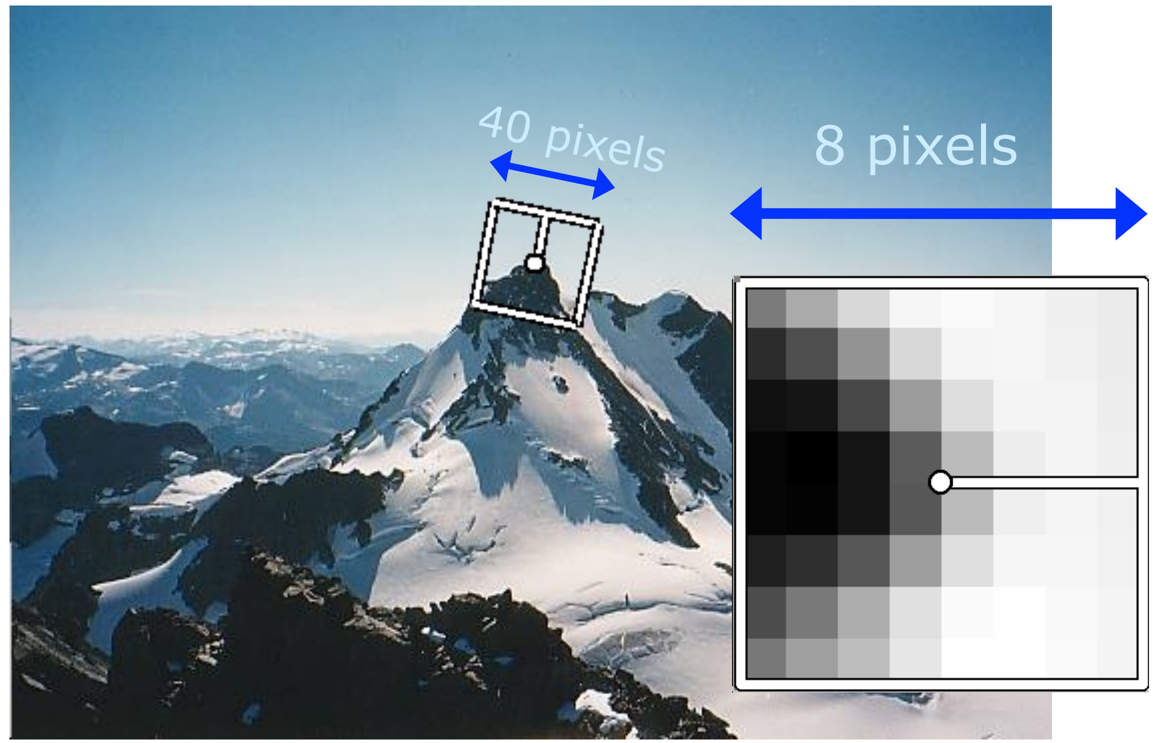
- Find dominant orientation of the image patch
  - This is given by $\mathbf{x}_{\mathbf{max}}$, the eigenvector of **M** corresponding to λ_{max} (the *larger* eigenvalue)
  - Rotate the patch according to this angle

Figure by Matthew Brown

Multiscale Oriented PatcheS descriptor

Take 40x40 square window around detected feature

- Scale to 1/5 size (using prefiltering)
- Rotate to horizontal
- Sample 8x8 square window centered at feature
- Intensity normalize the window by subtracting the mean, dividing by the standard deviation in the window



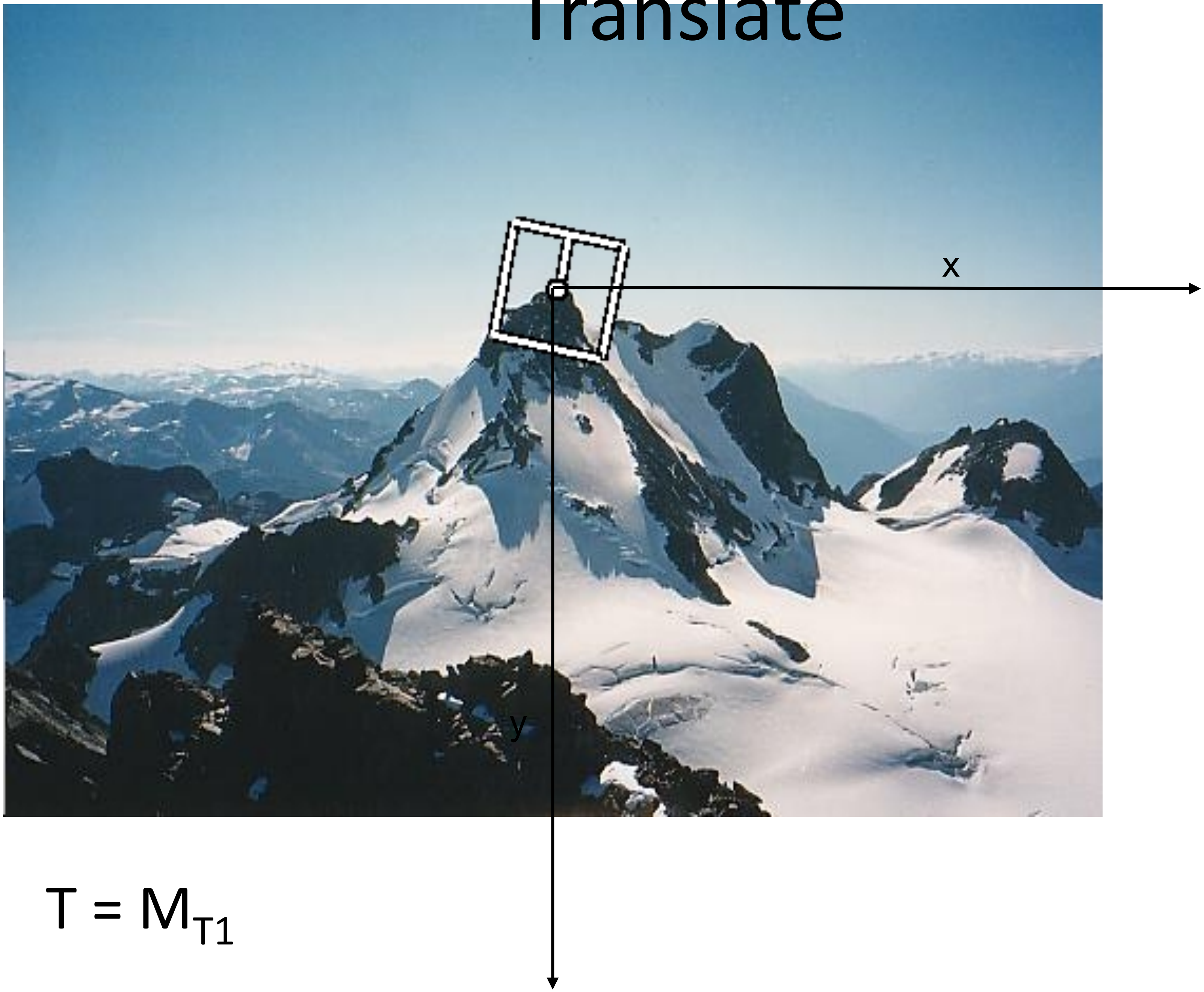
Adapted from slide by Matthew Brown

MOPS descriptor

•You can combine transformations together to get the final transformation

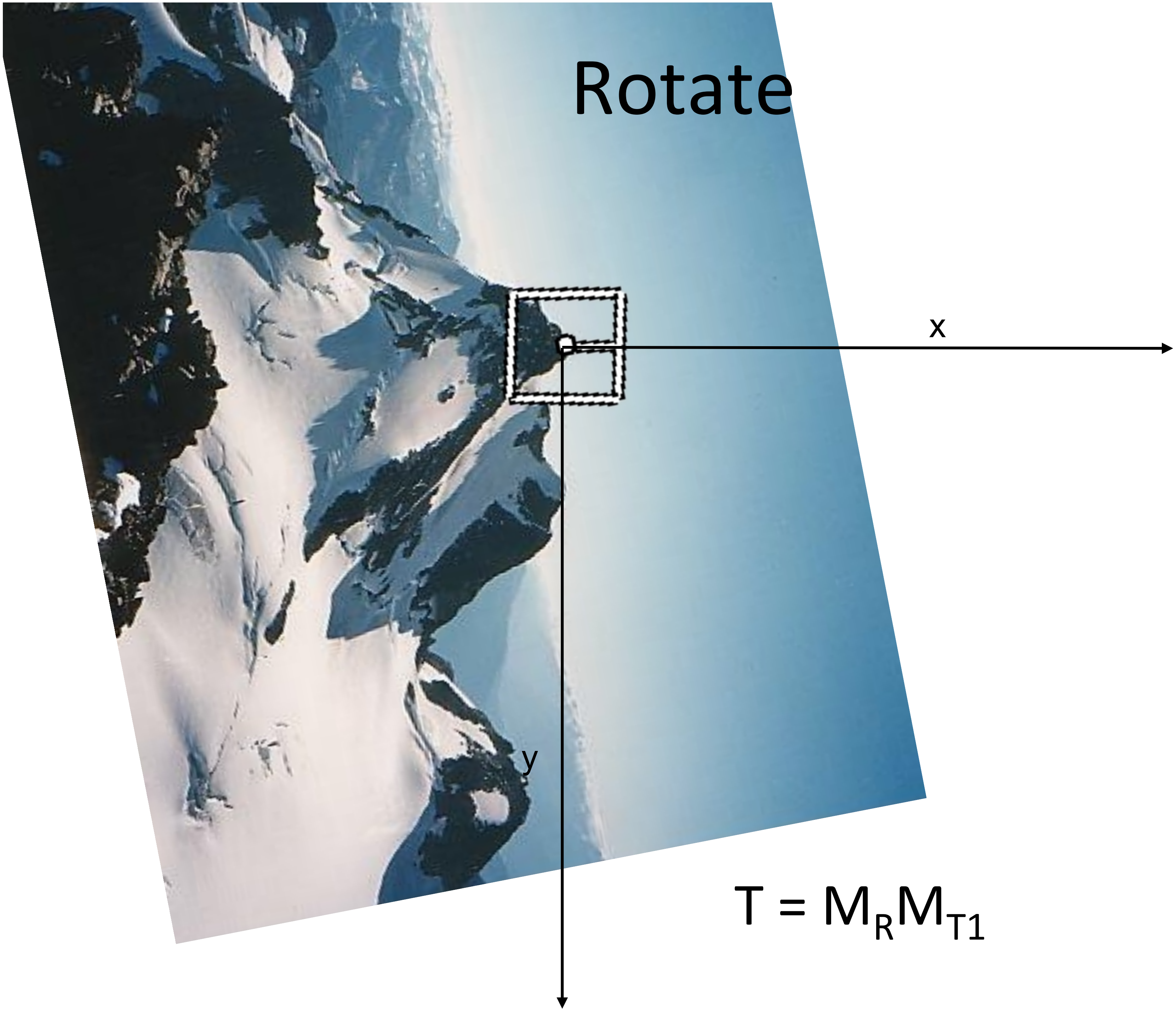
T = ?

Translate



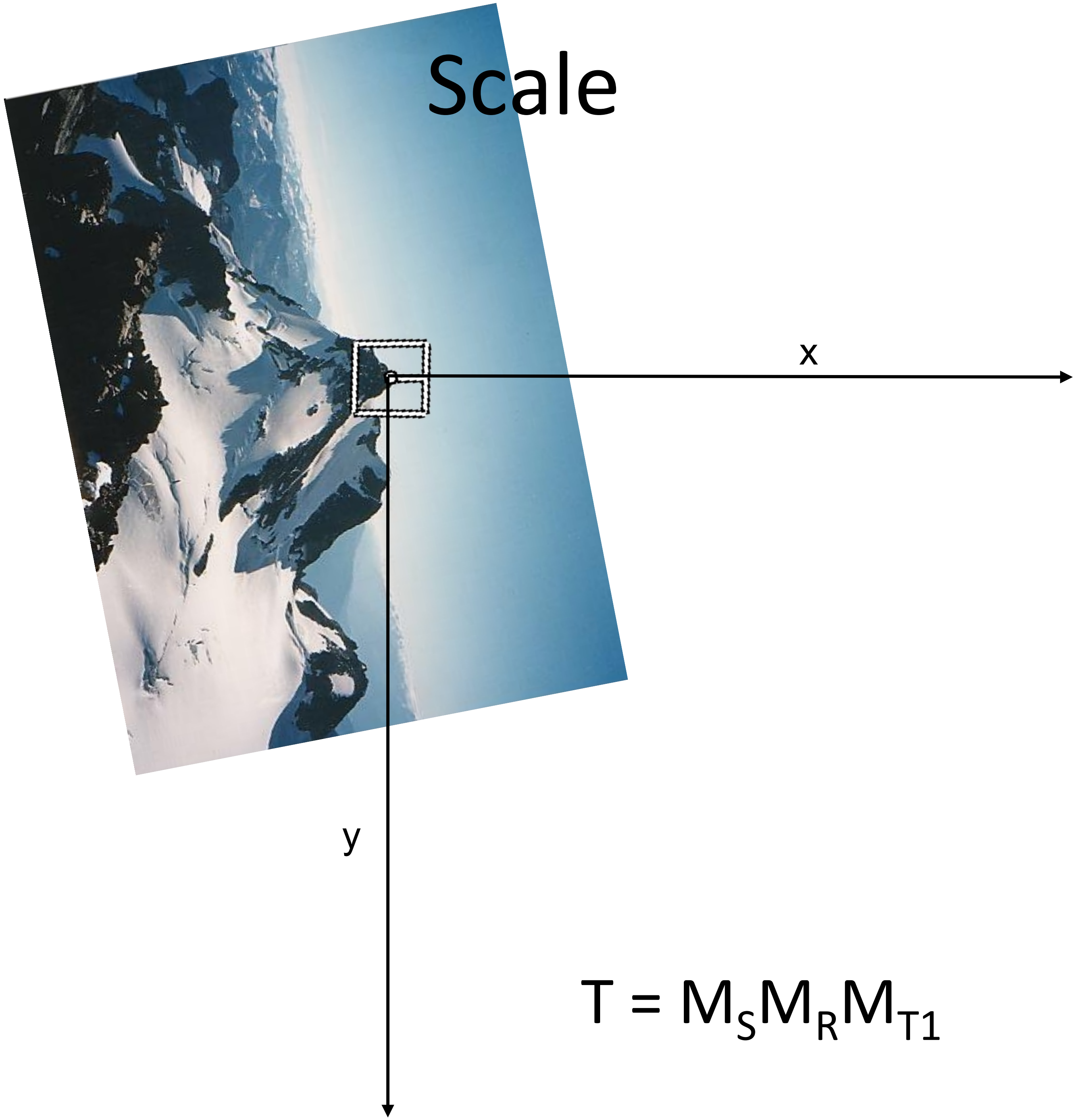
$T = M_{T1}$

Rotate



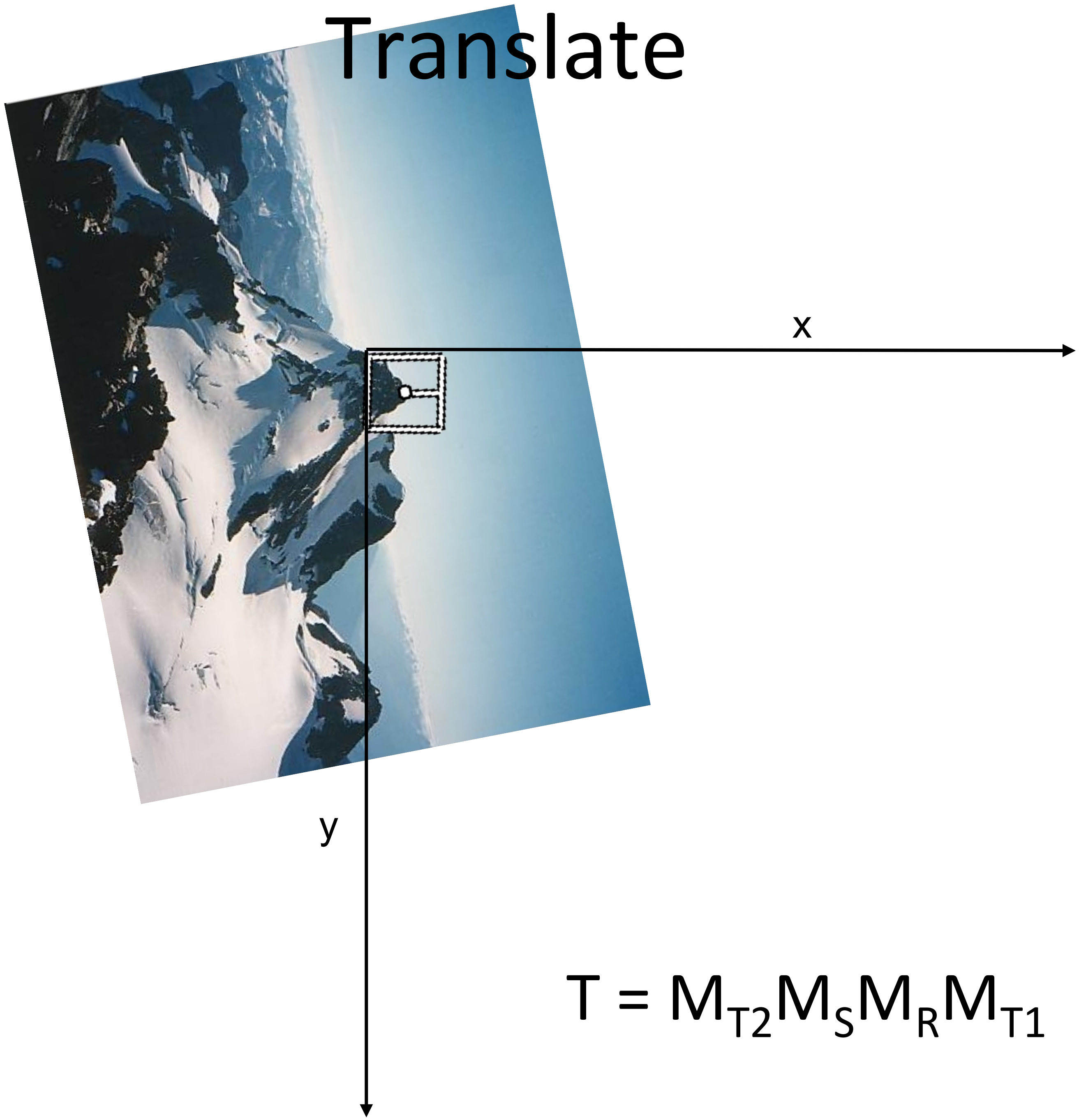
$$T = M_R M_{T1}$$

Scale



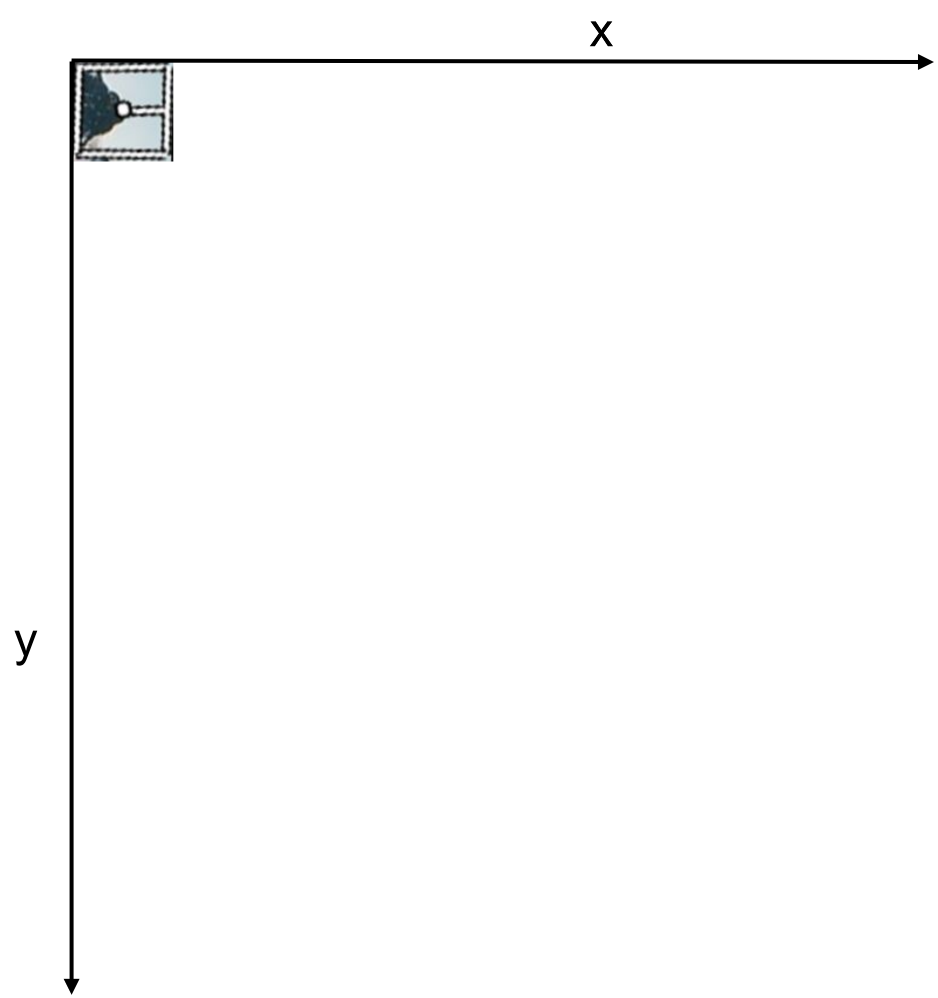
$$T = M_S M_R M_{T1}$$

Translate



$$T = M_{T2} M_S M_R M_{T1}$$

Crop



Detections at multiple scales

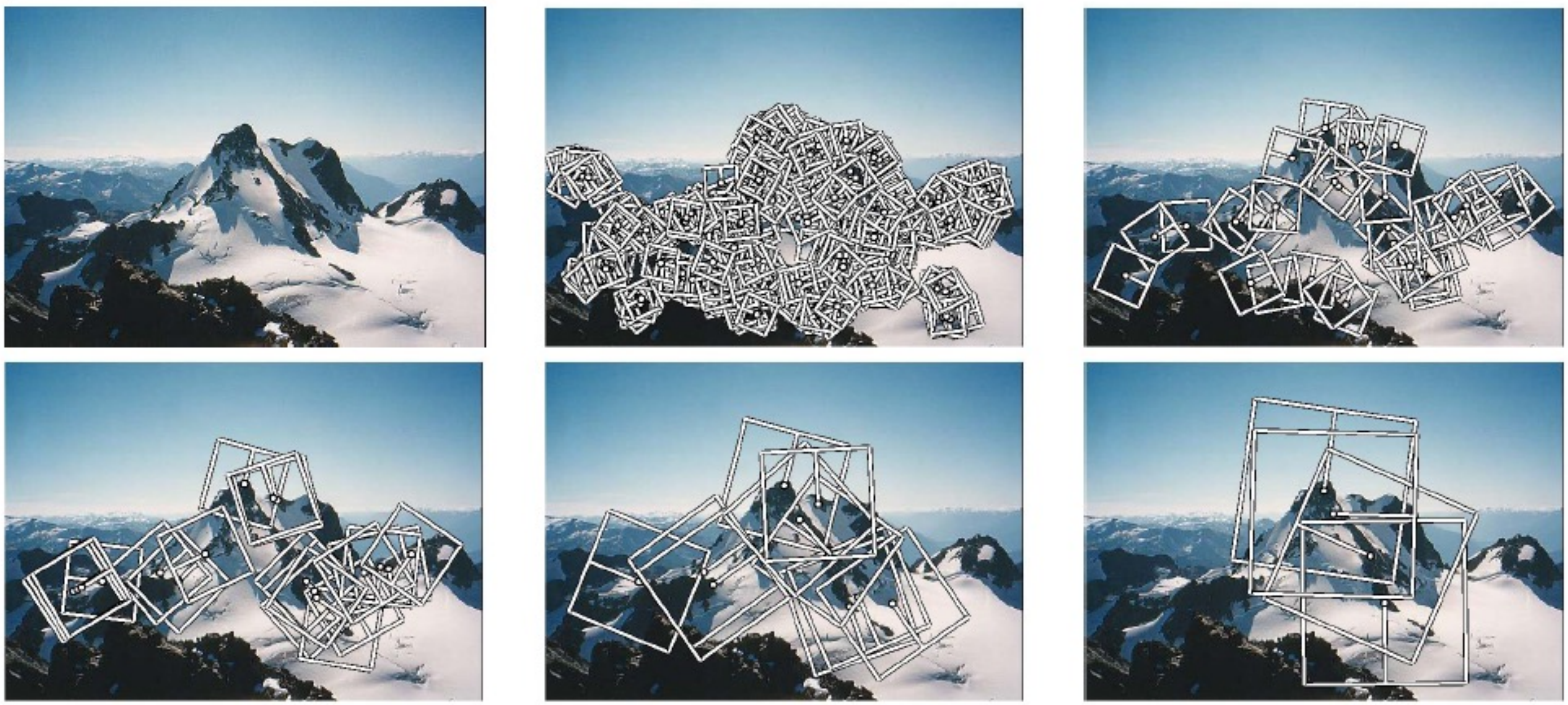
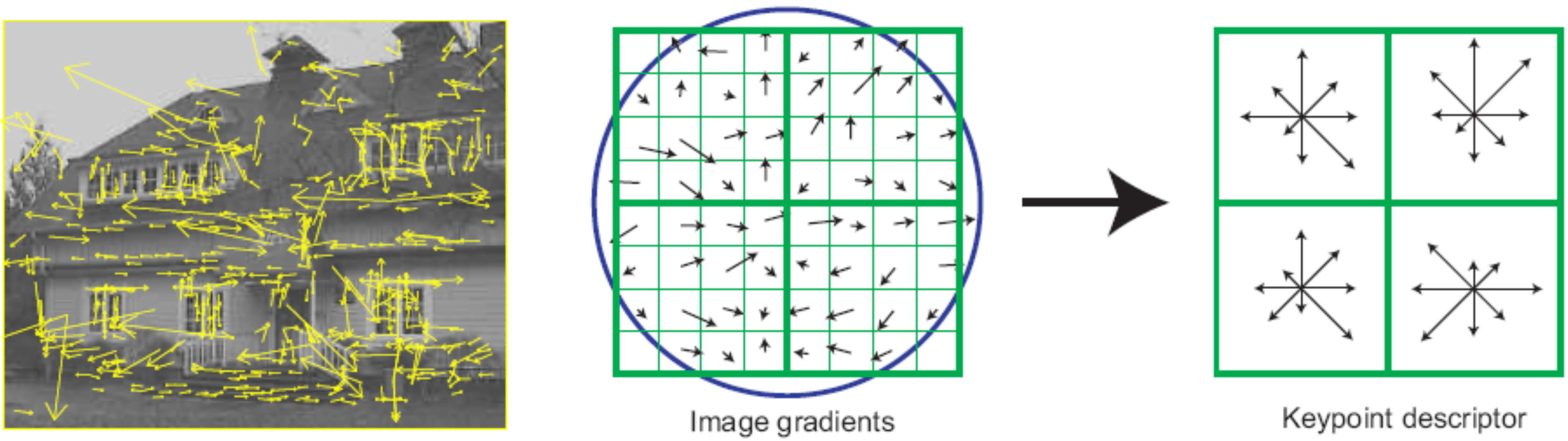


Figure 1. Multi-scale Oriented Patches (MOPS) extracted at five pyramid levels from one of the Matier images. The boxes show the feature orientation and the region from which the descriptor vector is sampled.

Invariance of MOPS

- Intensity
- Scale
- Rotation

What kind of things do we compute histograms of?

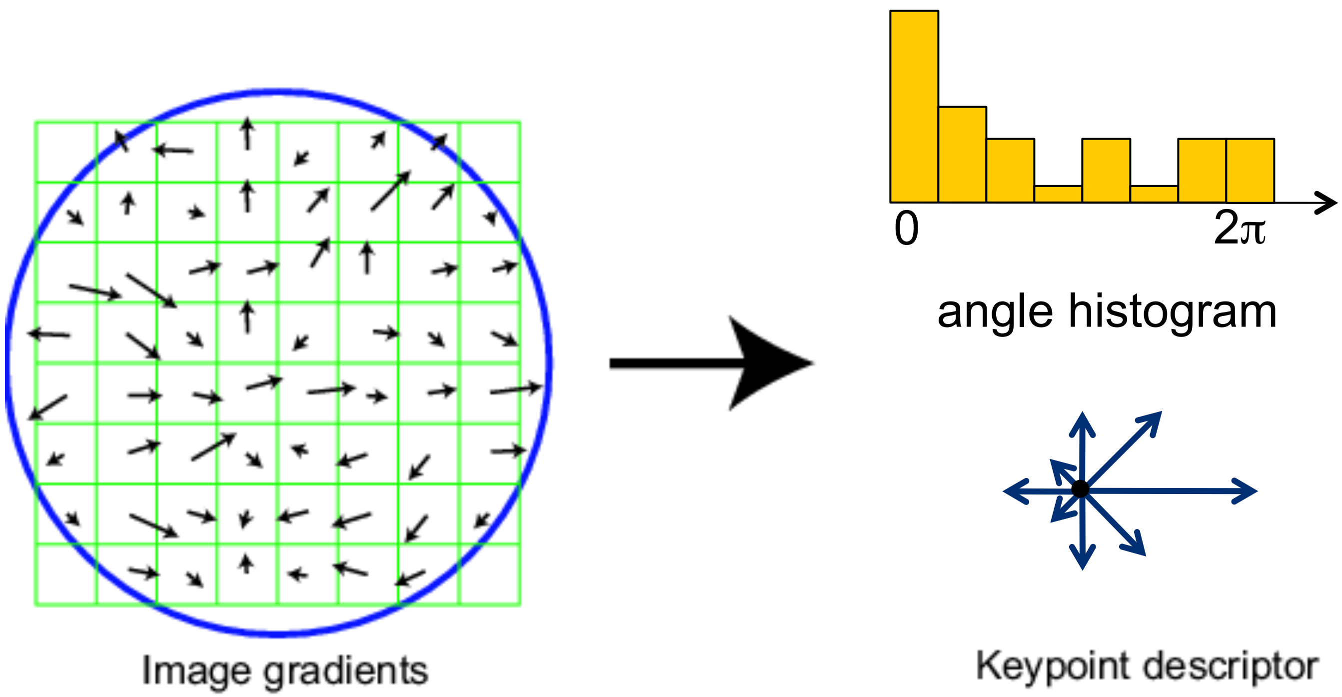


SIFT – Lowe IJCV 2004

Scale Invariant Feature Transform

Basic idea:

- DoG for scale-space feature detection
- Take 16x16 square window around detected feature
  - Compute gradient orientation for each pixel
  - Throw out weak edges (threshold gradient magnitude)
  - Create histogram of surviving edge orientations



Adapted from slide by David Lowe

SIFT descriptor

Create histogram

- Divide the 16x16 window into a 4x4 grid of cells (2x2 case shown below)
- Compute an orientation histogram for each cell
- 16 cells * 8 orientations = 128 dimensional descriptor

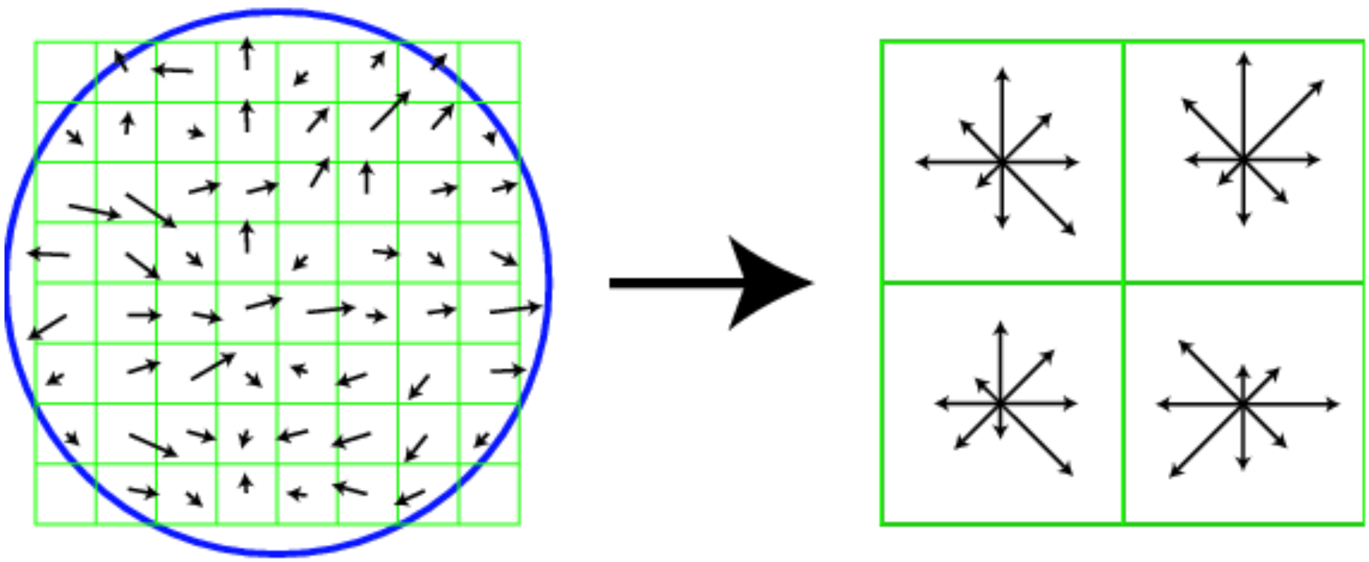


Image gradients   Keypoint descriptor

Adapted from slide by David Lowe

SIFT vector formation

- Computed on rotated and scaled version of window according to computed orientation & scale
  - resample the window
- Based on gradients weighted by a Gaussian

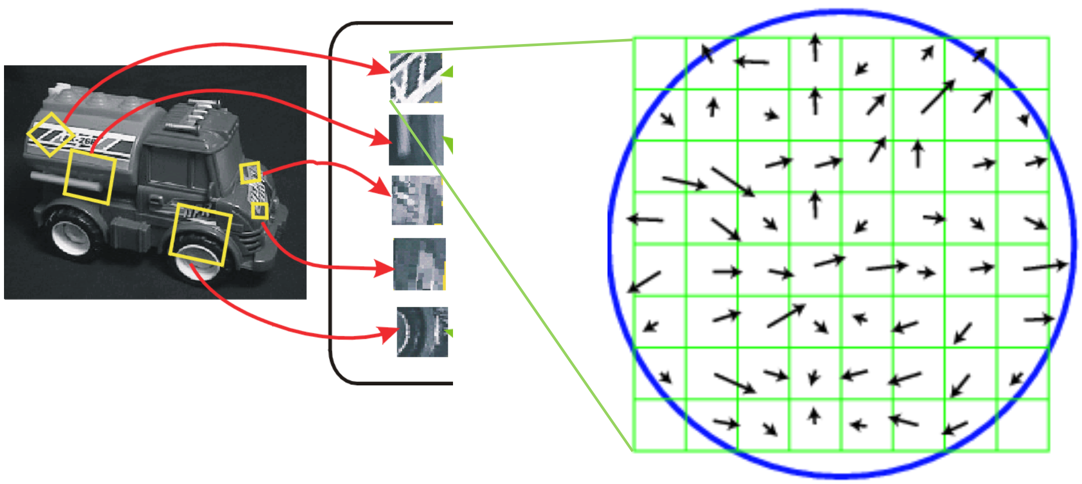
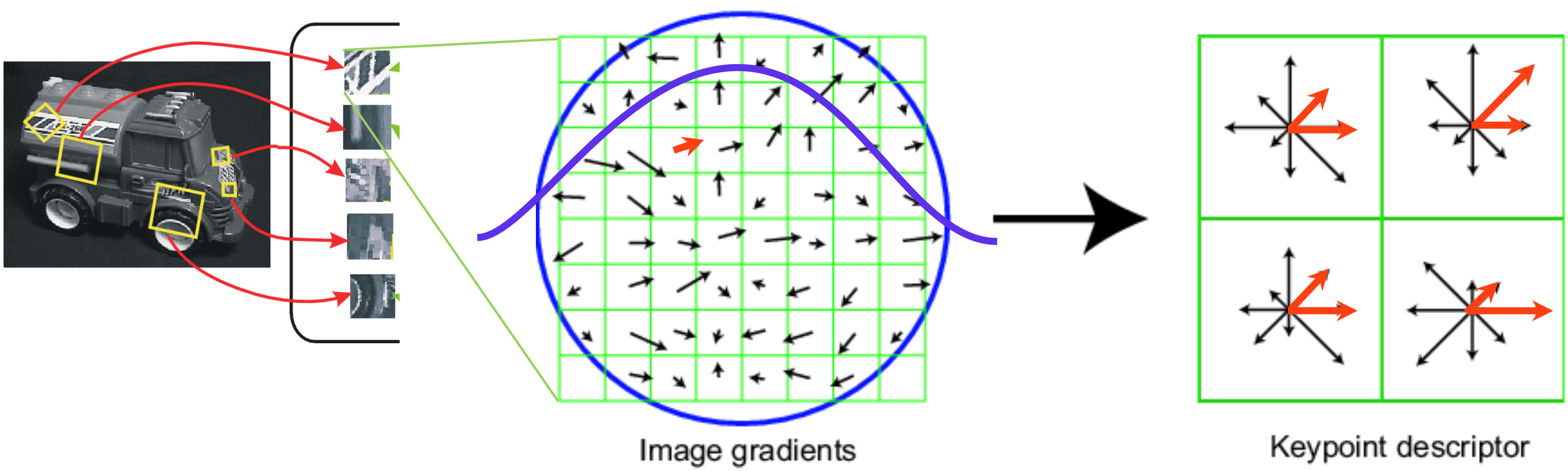


Image gradients

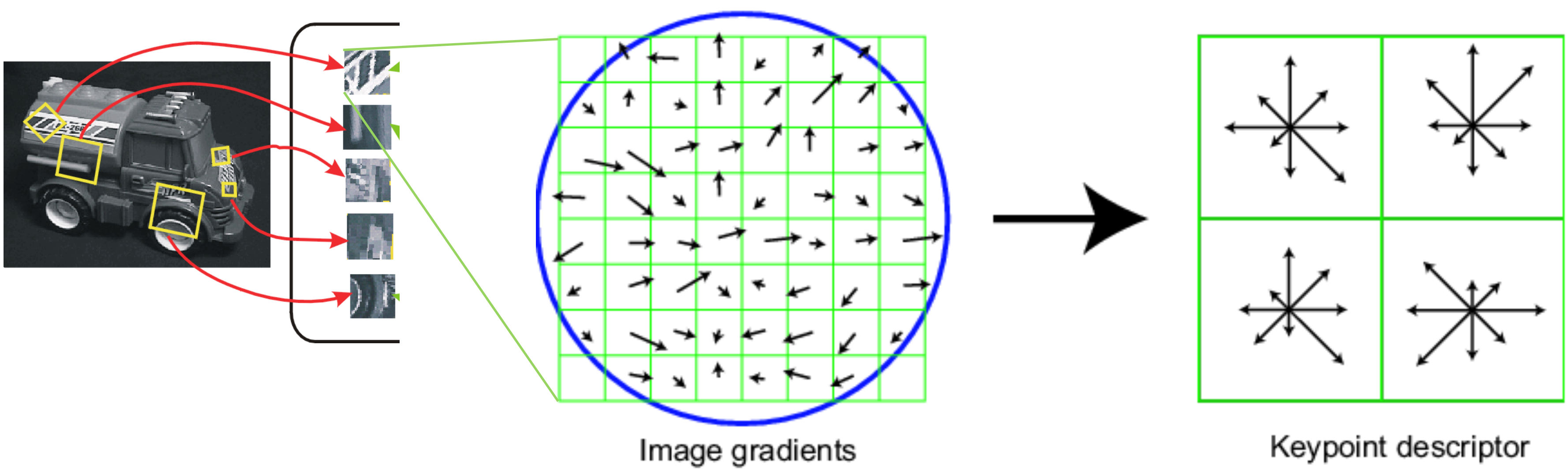
Ensure smoothness

- Trilinear interpolation
  - a given gradient contributes to 8 bins: 4 in space times 2 in orientation



Reduce effect of illumination

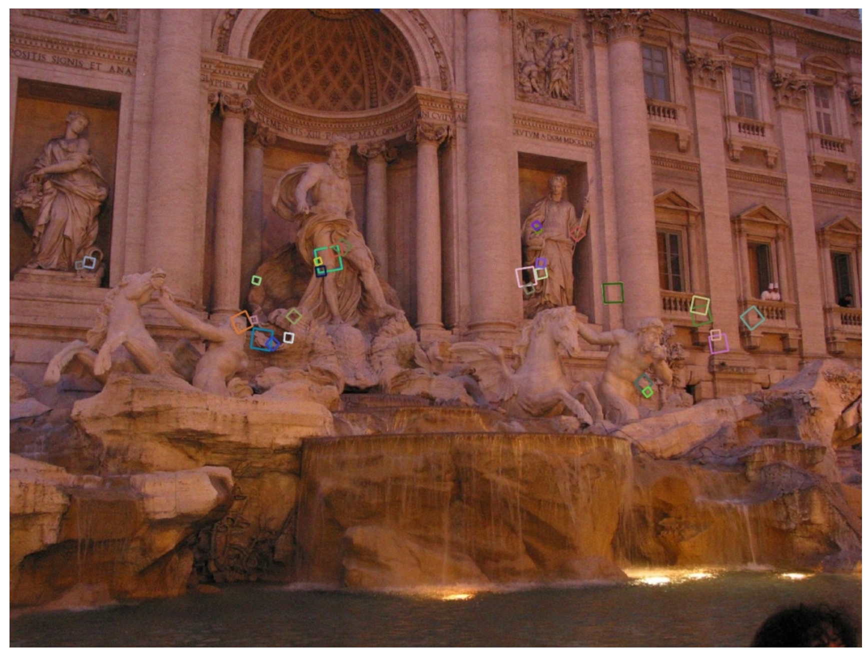
- 128-dim vector normalized to 1
- Threshold gradient magnitudes to avoid excessive influence of high gradients
  - after normalization, clamp gradients >0.2
  - renormalize



Properties of SIFT

Extraordinarily robust matching technique

- Can handle changes in viewpoint
  - Up to about 60 degree 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



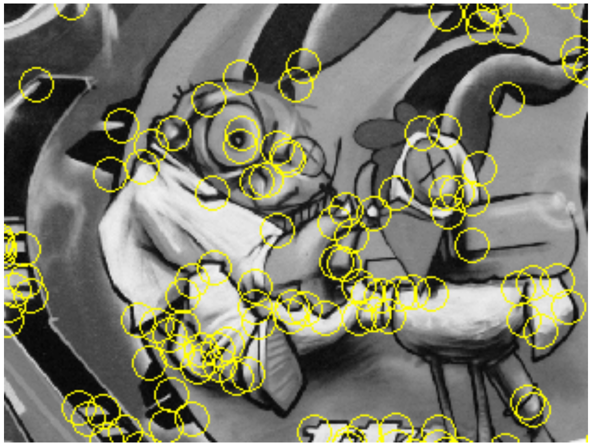
Other descriptors

- HOG: Histogram of Gradients (HOG)
  - Dalal/Triggs
  - Sliding window, pedestrian detection

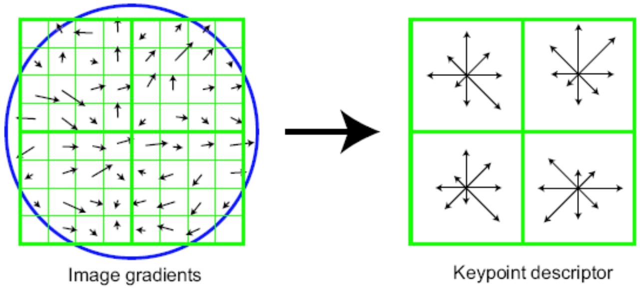
- FREAK: Fast Retina Keypoint
  - Perceptually motivated

Summary

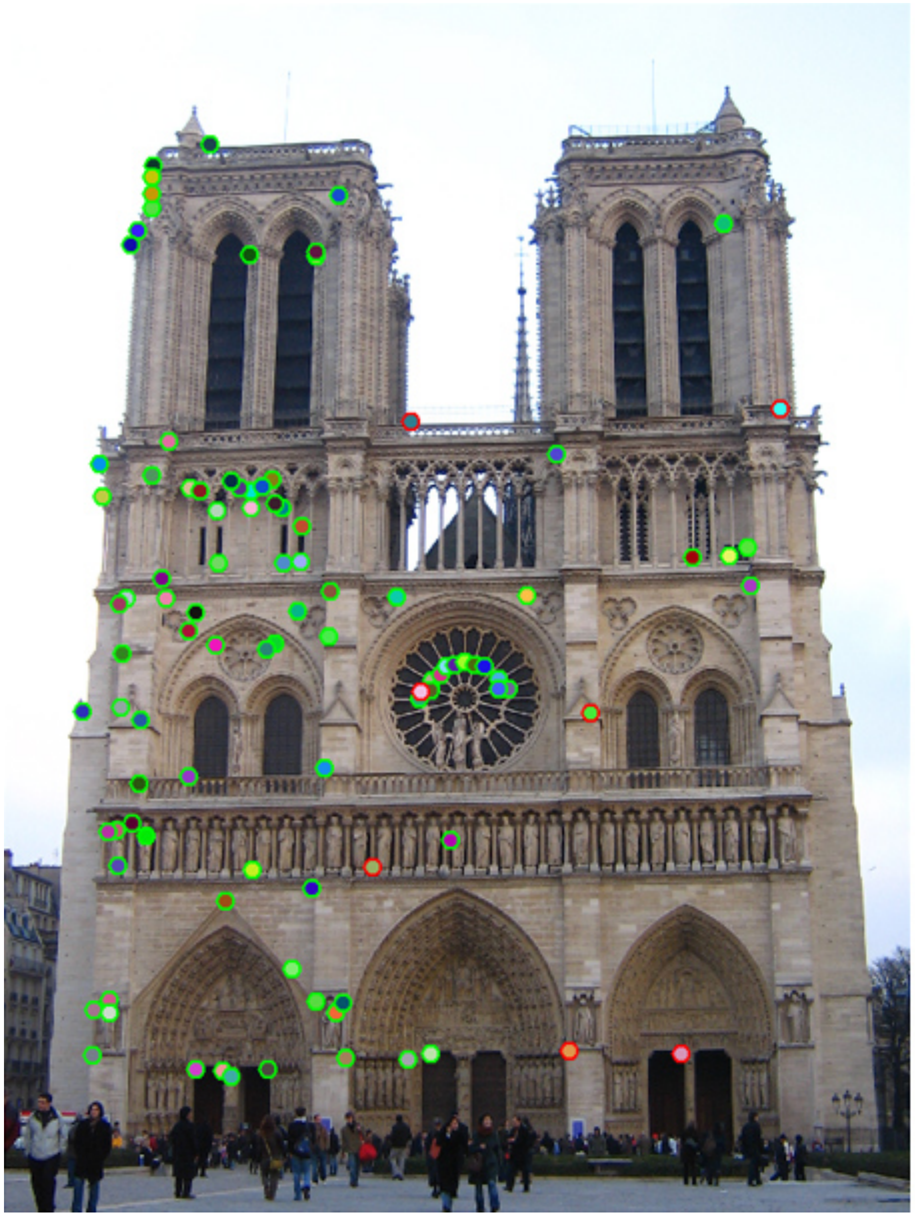
- Keypoint detection: repeatable and distinctive
  - Corners, blobs, stable regions
  - Harris, DoG

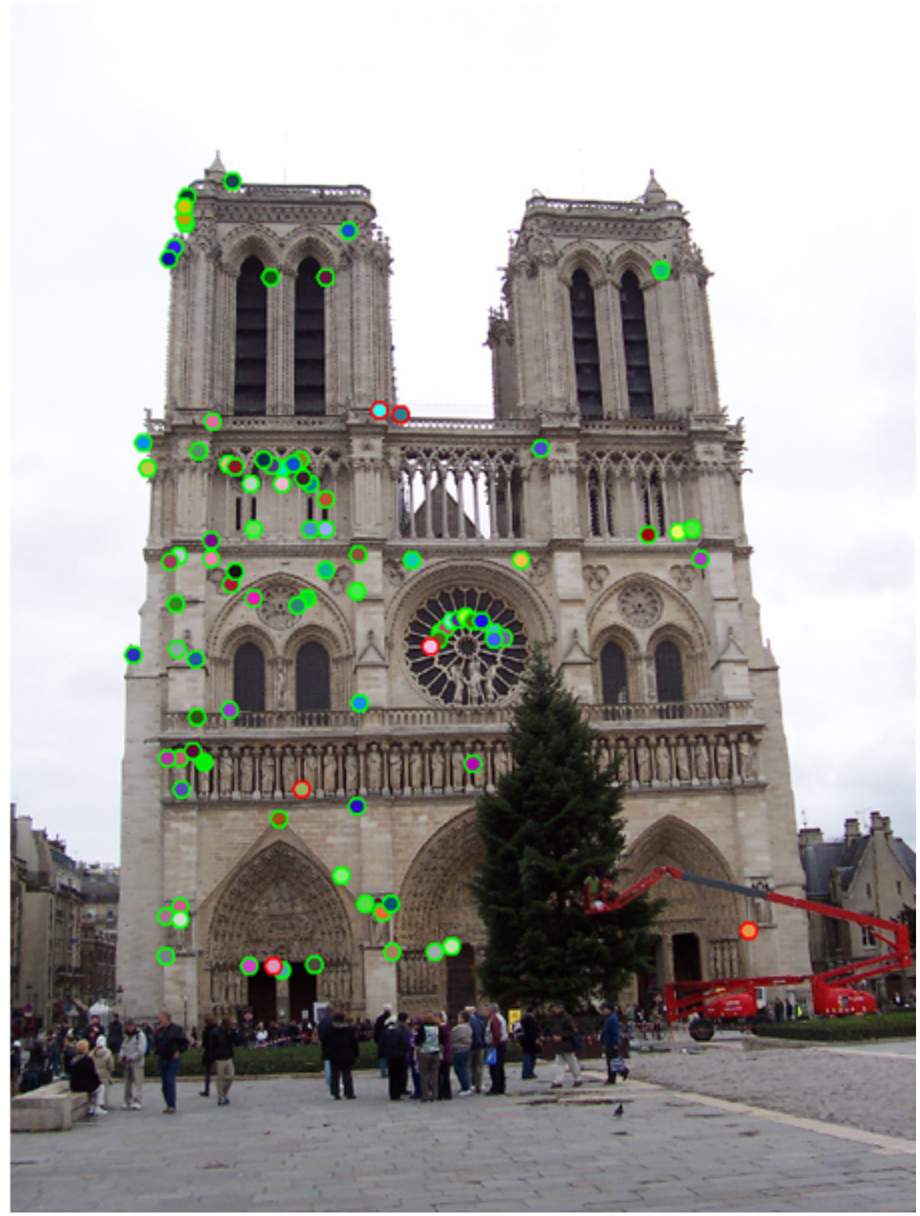


- Descriptors: robust and selective
  - spatial histograms of orientation
  - SIFT and variants are typically good for stitching and recognition
  - But, need not stick to one



Which features match?





Feature matching

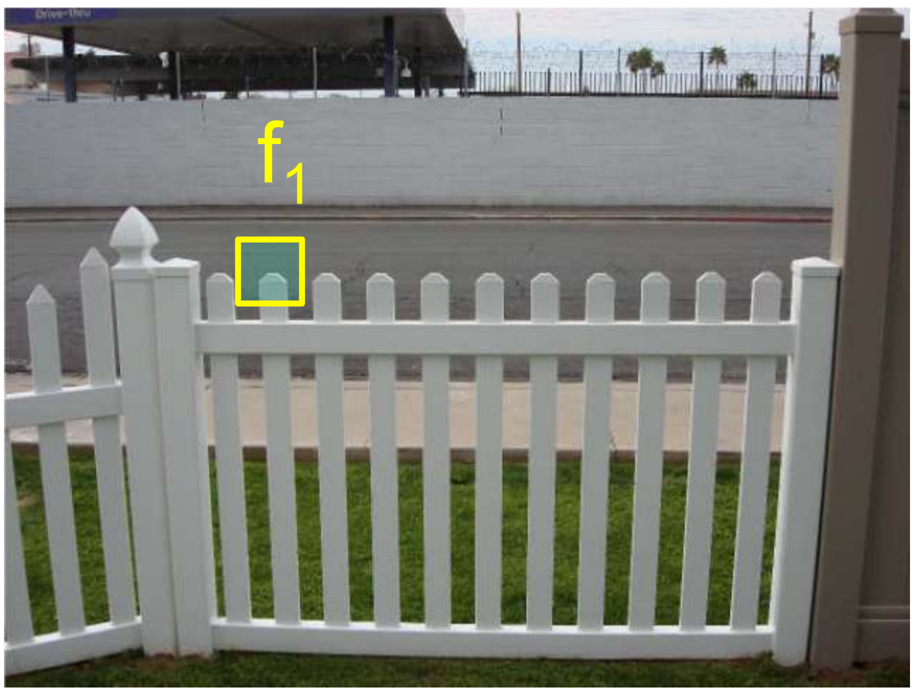
Given a feature in I_1, how to find the best match in I_2?

1. Define distance function that compares two descriptors
2. Test all the features in I_2, find the one with min distance

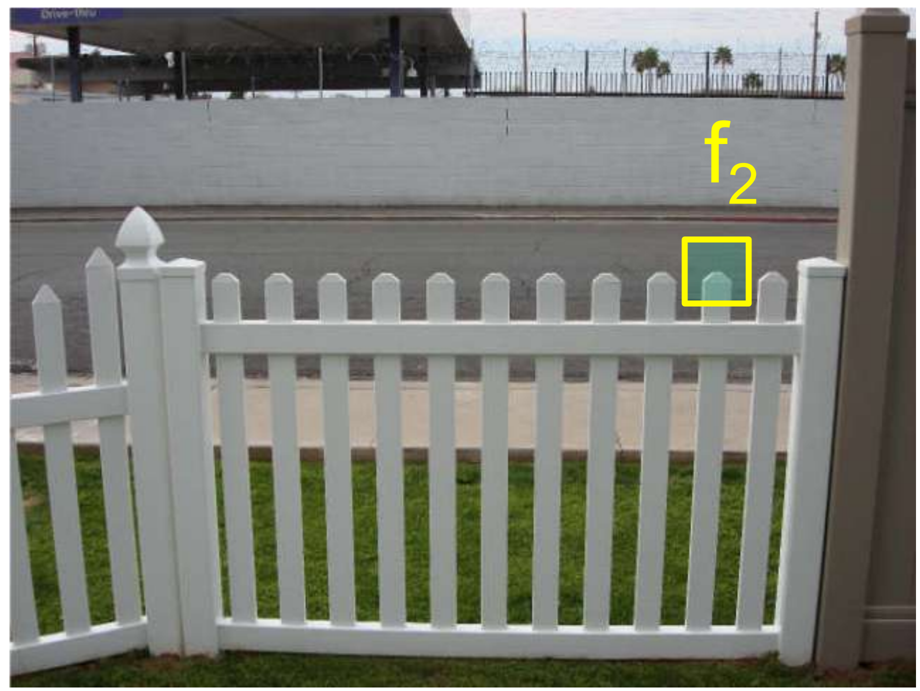
Feature distance

How to define the difference between two features f_1, f_2?

– Simple approach: L_2 distance, $||f_1 - f_2||$
– can give good scores to ambiguous (incorrect) matches



I_1

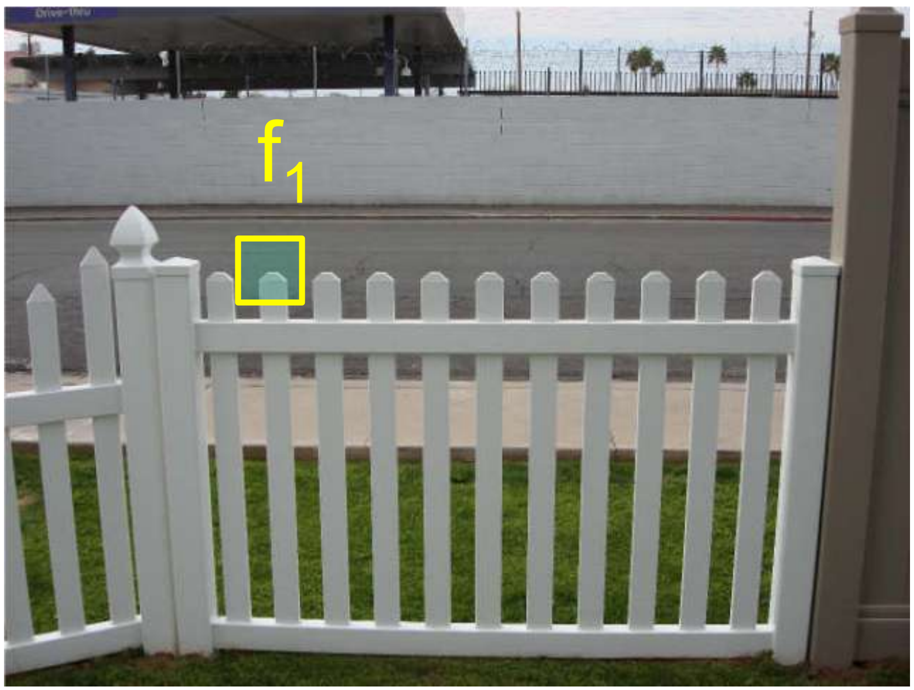


I_2

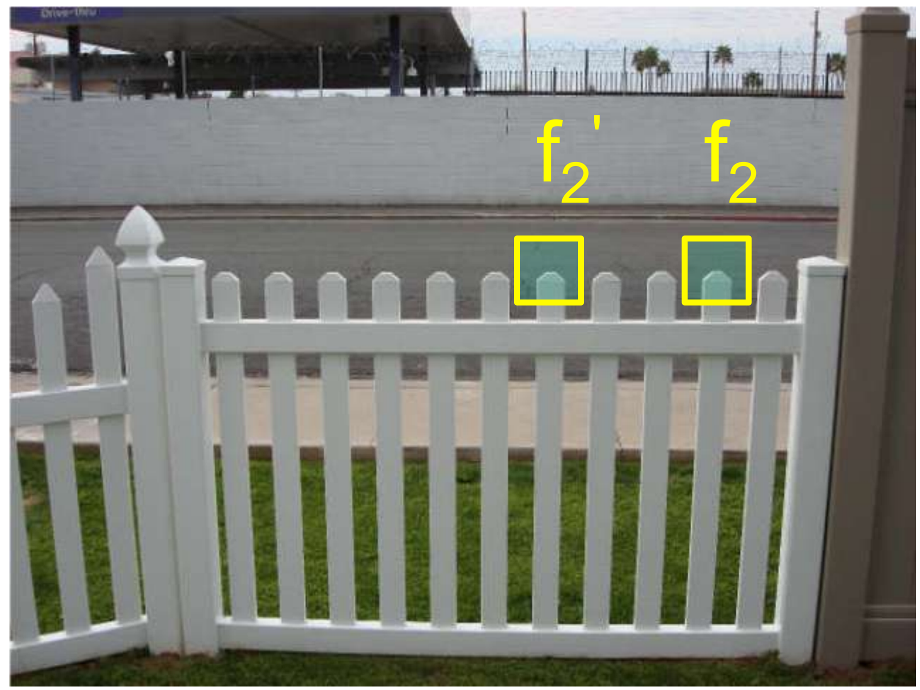
Feature distance

How to define the difference between two features f_1, f_2?

- Better approach: ratio distance = $||f_1 - f_2|| \,/\, ||f_1 - f_2'||$
  - f_2 is best SSD match to f_1 in I_2
  - f_2' is 2^{nd} best SSD match to f_1 in I_2
  - gives large values for ambiguous matches



I_1



I_2

PA2:
Feature detection and matching