Feature Descriptors

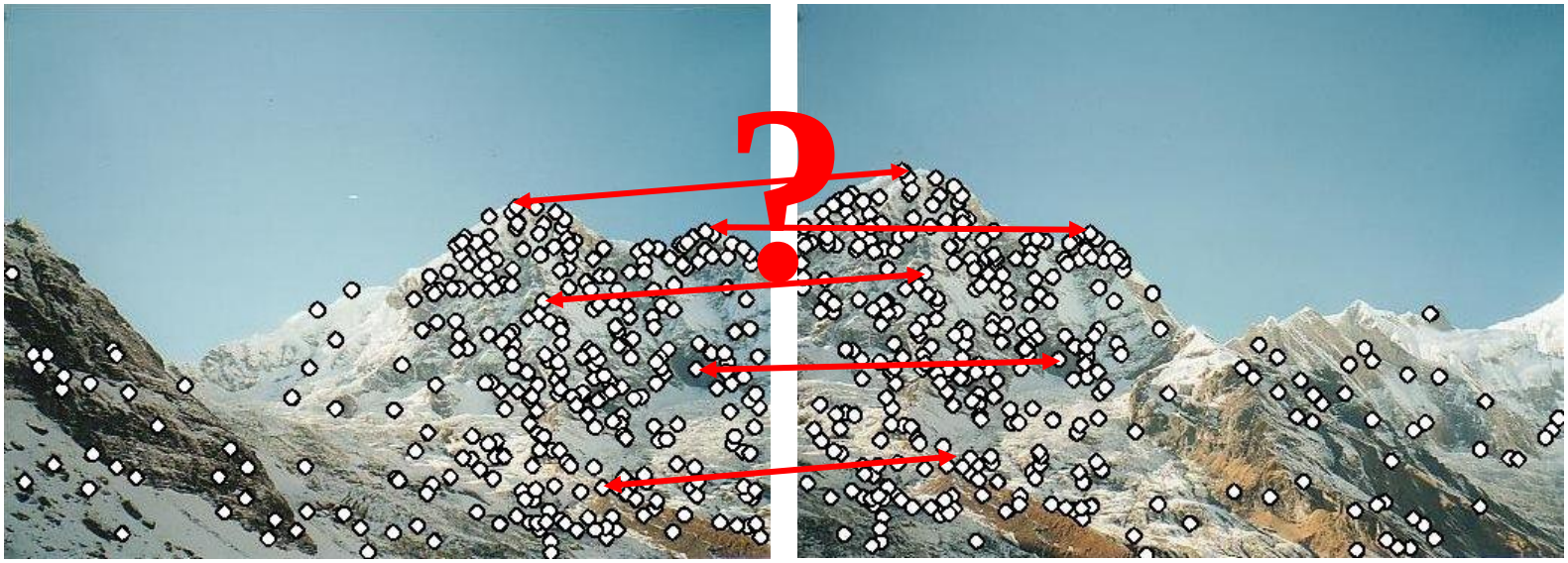
Main questions

- Where will the interest points come from?
  - What are salient features that we'll *detect* in multiple views?
- How to *describe* a local region?
- How to establish *correspondences*, i.e., compute matches?

Local descriptors

- We know how to detect points
- Next question:

How to *describe* them for matching?



Point descriptor should be:

1. Invariant
2. Distinctive

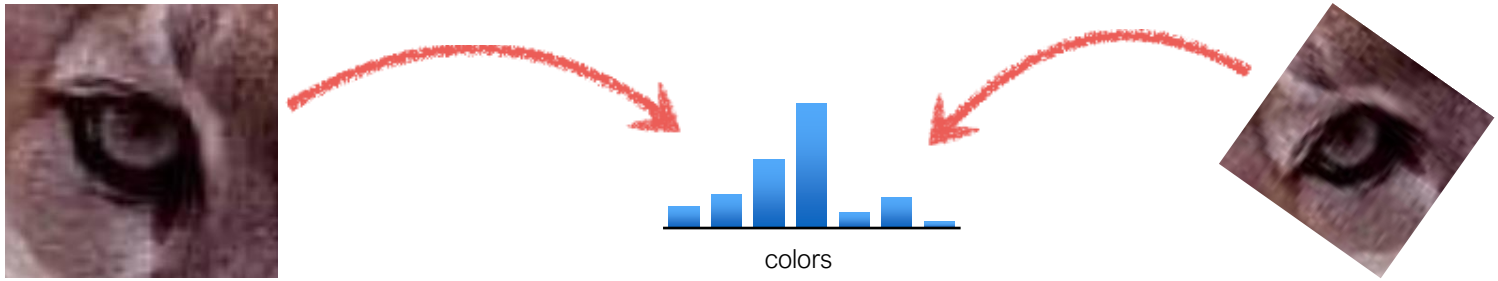
Image patch

Just use the pixel values of the patch

Perfectly fine if geometry and appearance is unchanged (a.k.a. template matching)

Color histogram

Count the colors in the image using a histogram

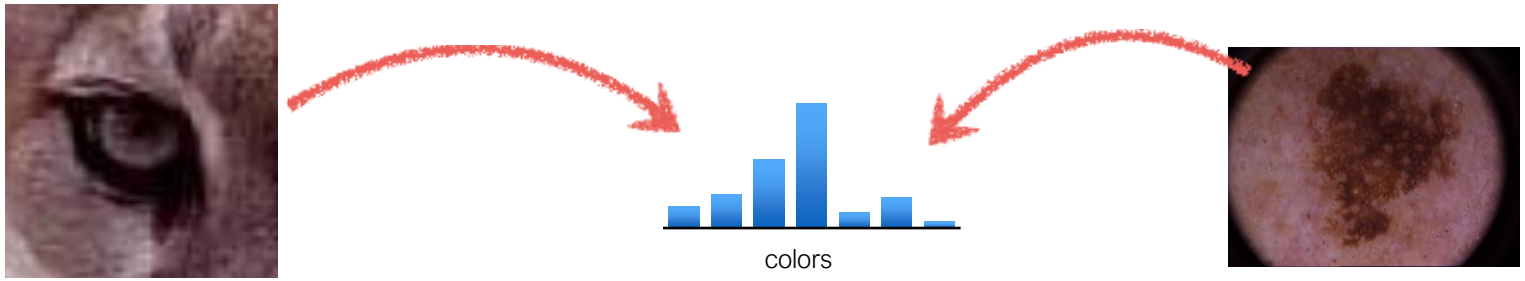


Invariant to changes in scale and rotation

What are the problems?

Color histogram

Count the colors in the image using a histogram

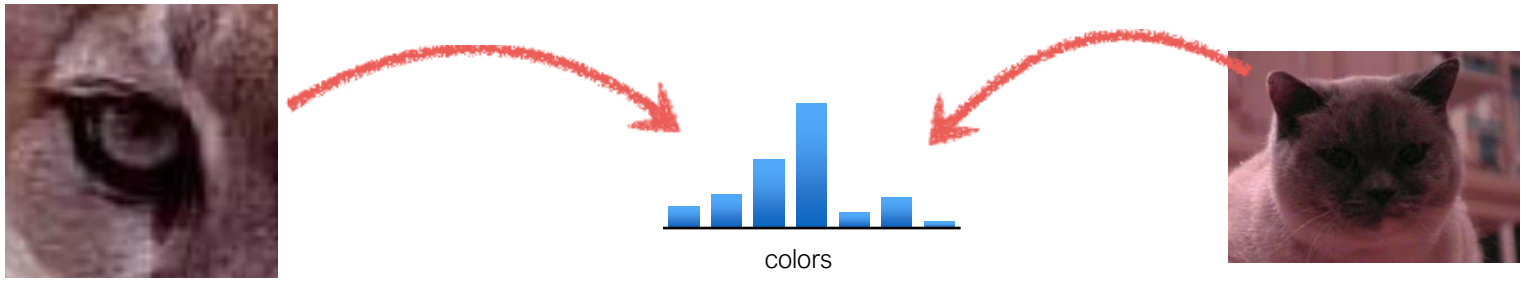


Invariant to changes in scale and rotation

What are the problems?

Color histogram

Count the colors in the image using a histogram



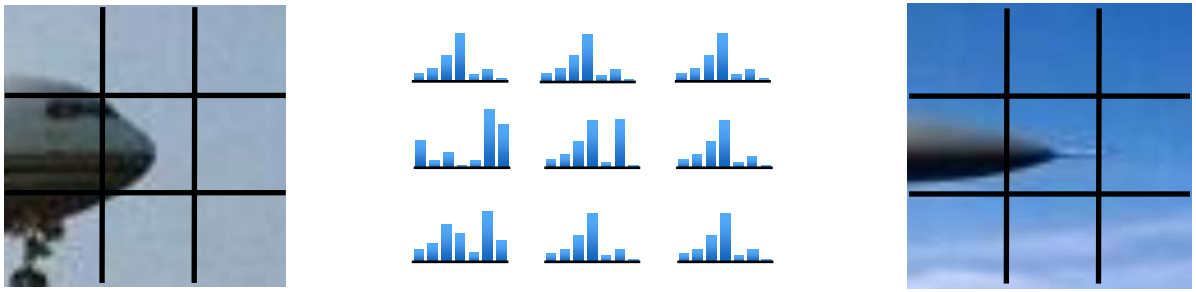
Invariant to changes in scale and rotation

What are the problems?

How can you be more sensitive to spatial layout?

Spatial histograms

Compute histograms over spatial ‘cells’

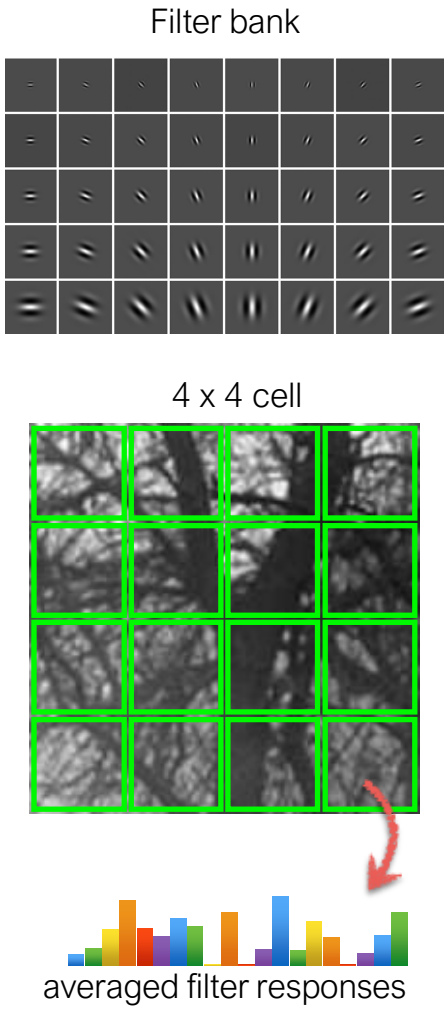


Retains rough spatial layout

Some invariance to deformations

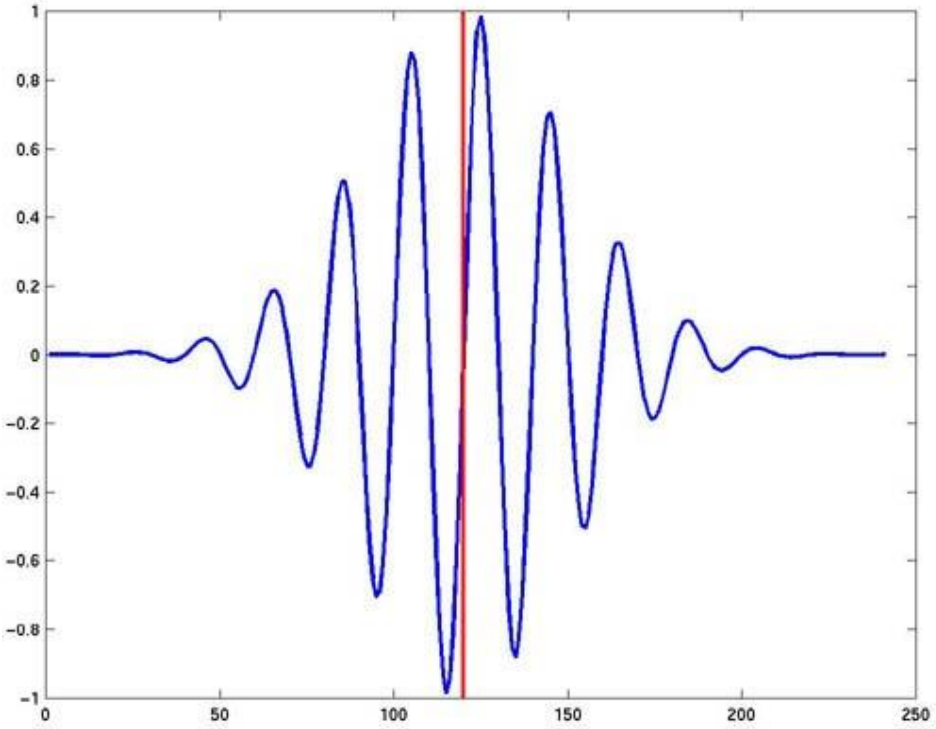
GIST

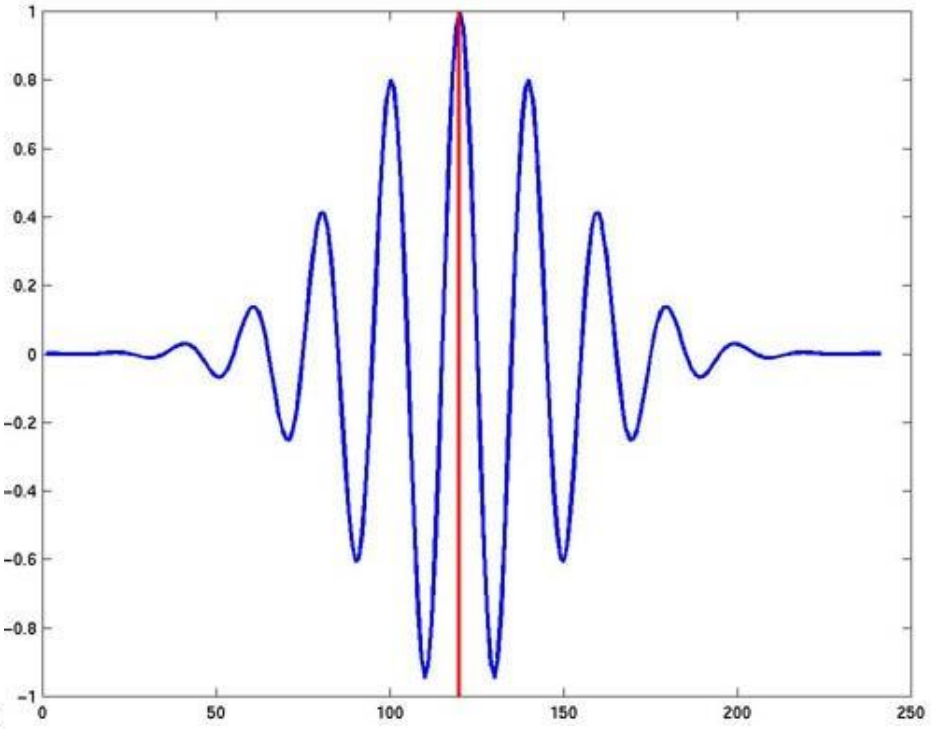
1. Compute filter responses (filter bank of Gabor filters)
2. Divide image patch into 4 x 4 cells
3. Compute filter response averages for each cell
4. Size of descriptor is 4 x 4 x N, where N is the size of the filter bank



Gabor Filters

(1D examples)



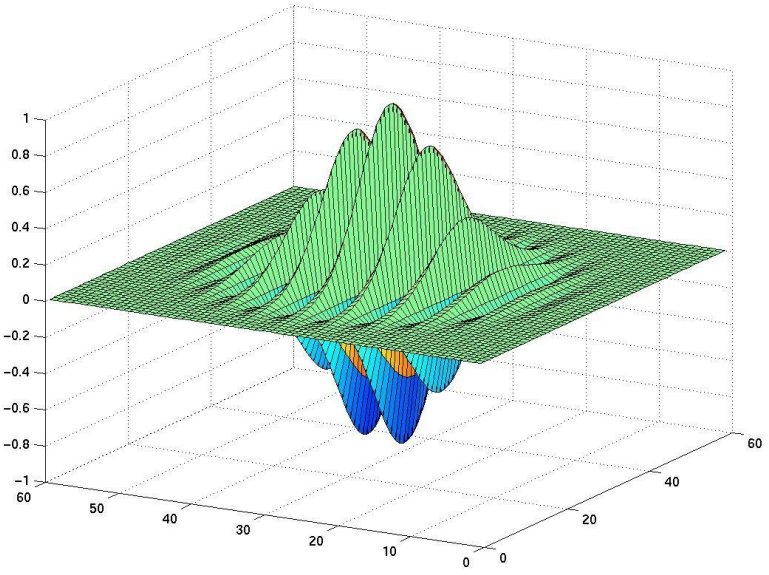


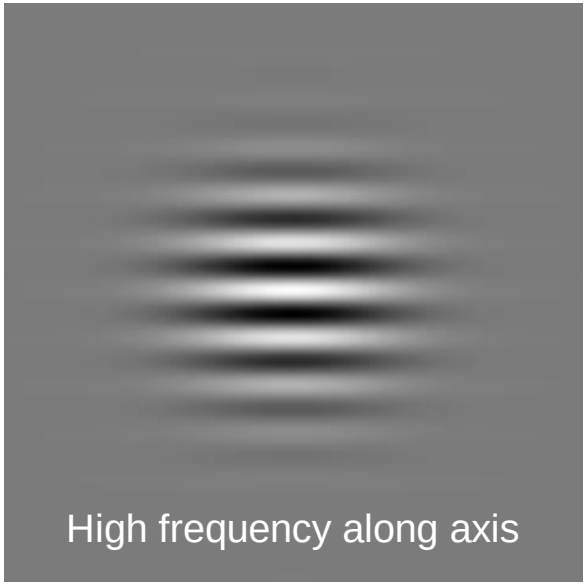
$$e^{-\frac{x^2}{2\sigma^2}} \sin(2\pi\omega x)$$

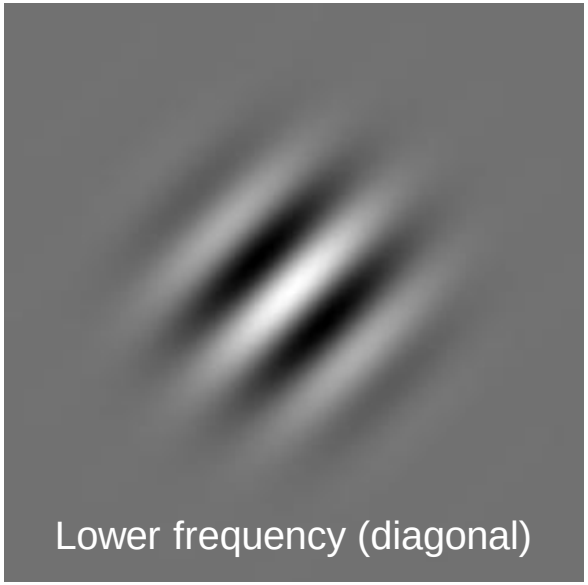
$$e^{-\frac{x^2}{2\sigma^2}} \cos(2\pi\omega x)$$

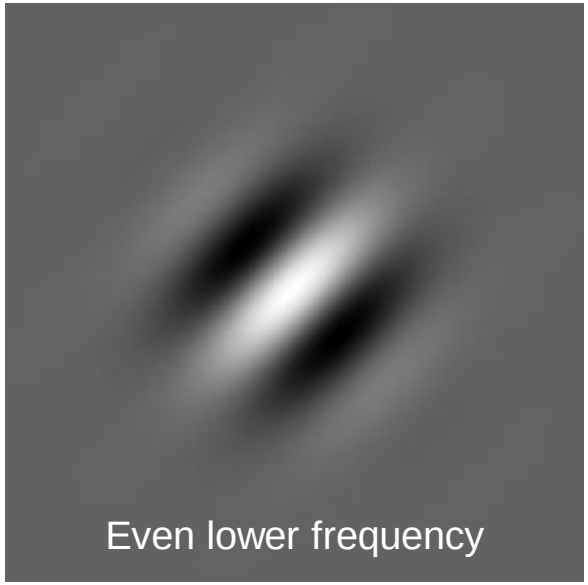
2D Gabor Filters

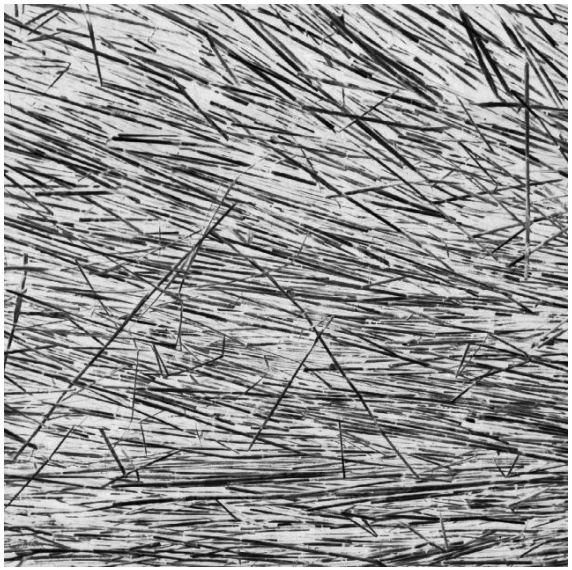
$$e^{-\frac{x^2+y^2}{2\sigma^2}} \cos\left(2\pi\left(k_x x + k_y y\right)\right)$$

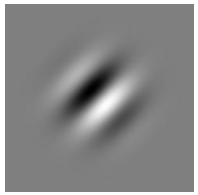


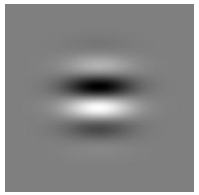


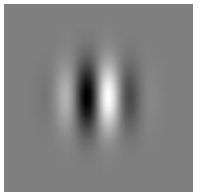


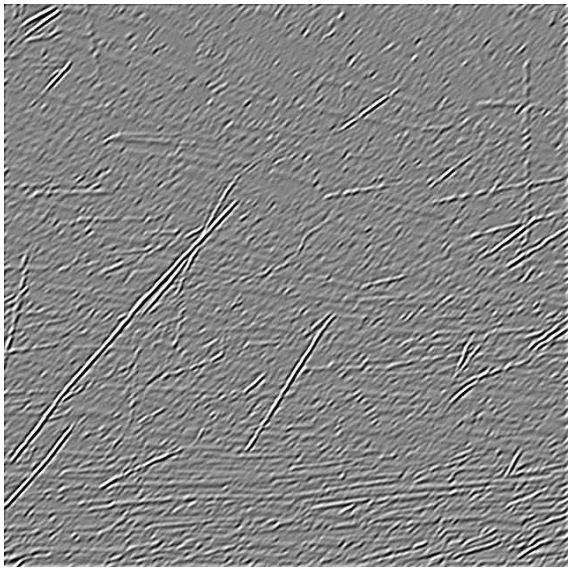


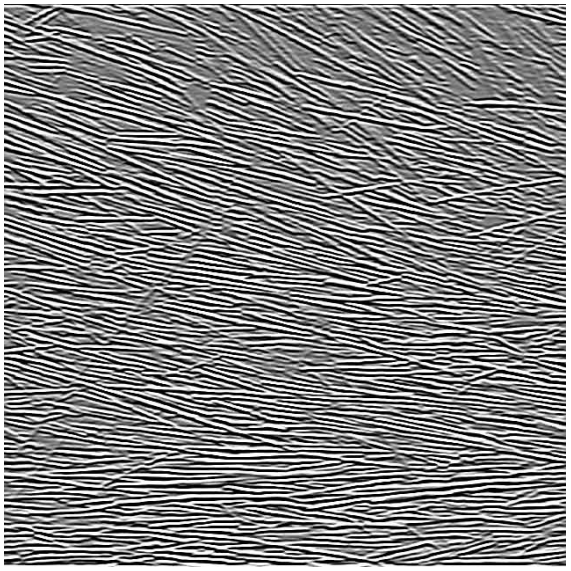


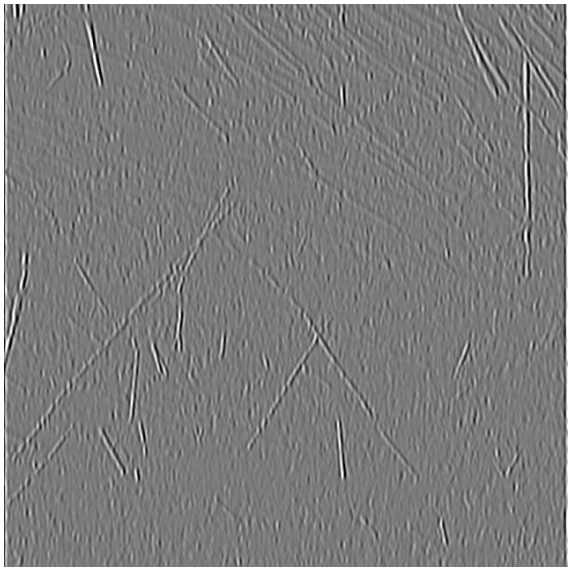


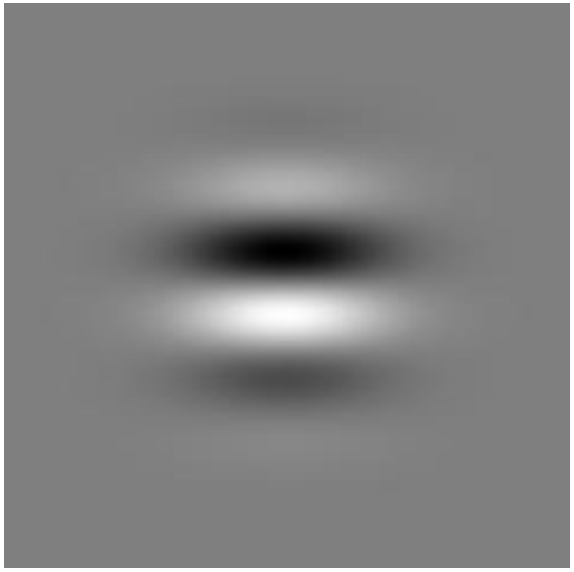




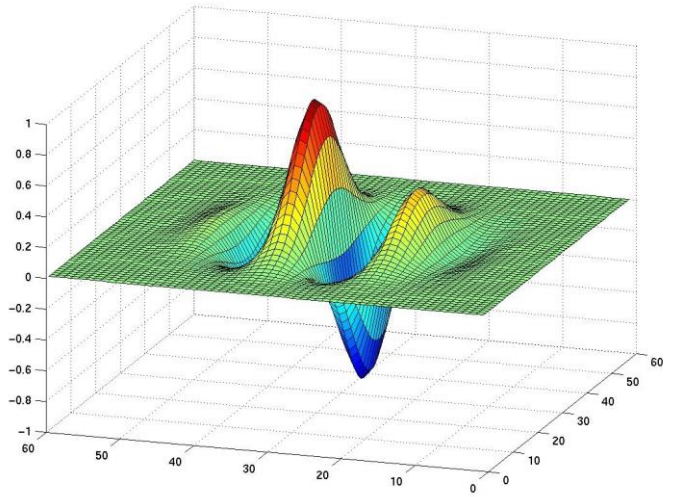




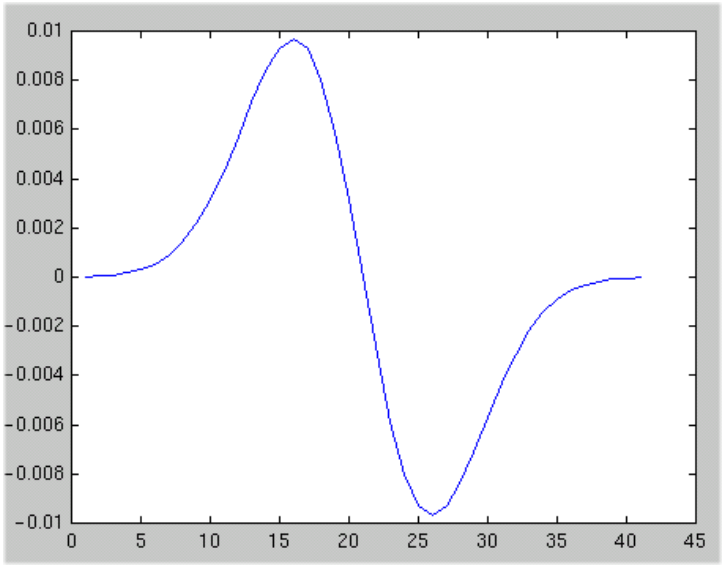




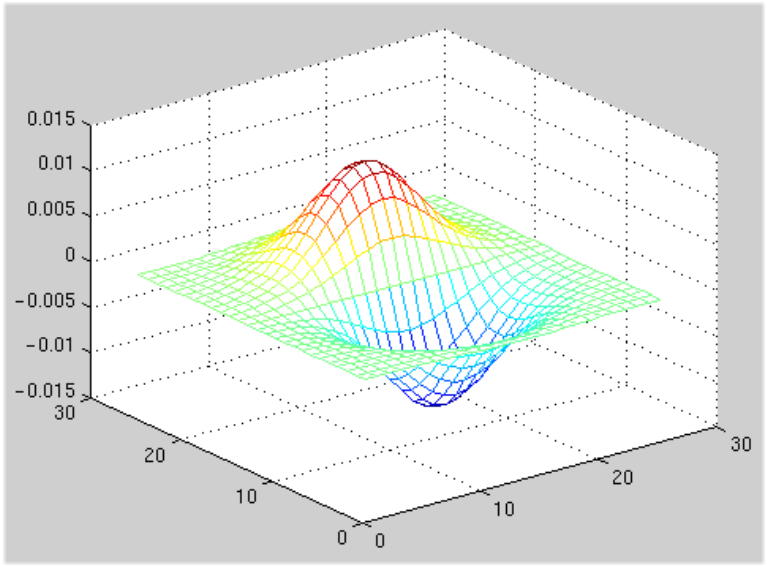
Odd
Gabor
filter

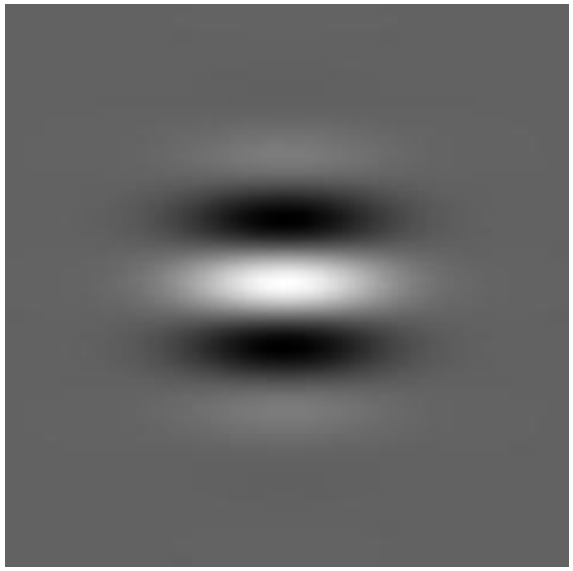


… looks a lot like…

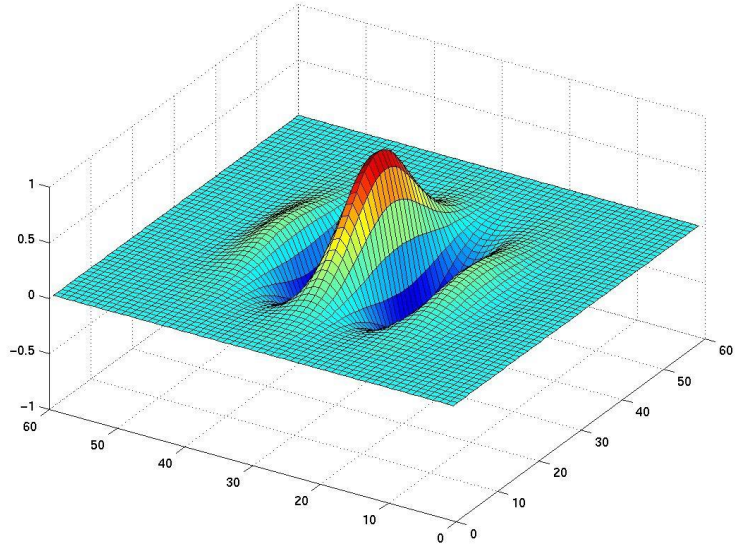


Gaussian
Derivative

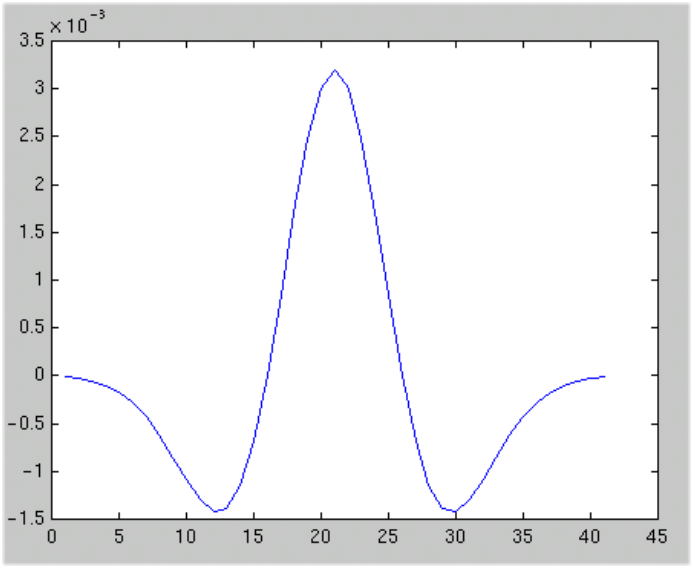




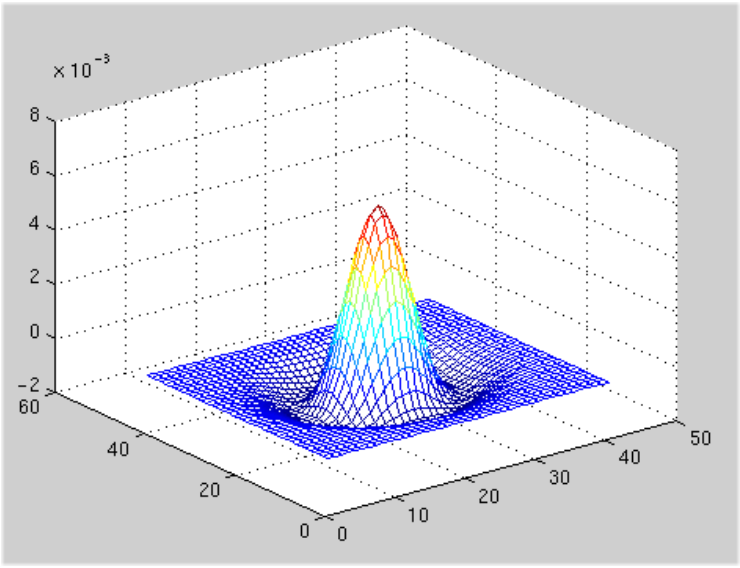
Even
Gabor
filter



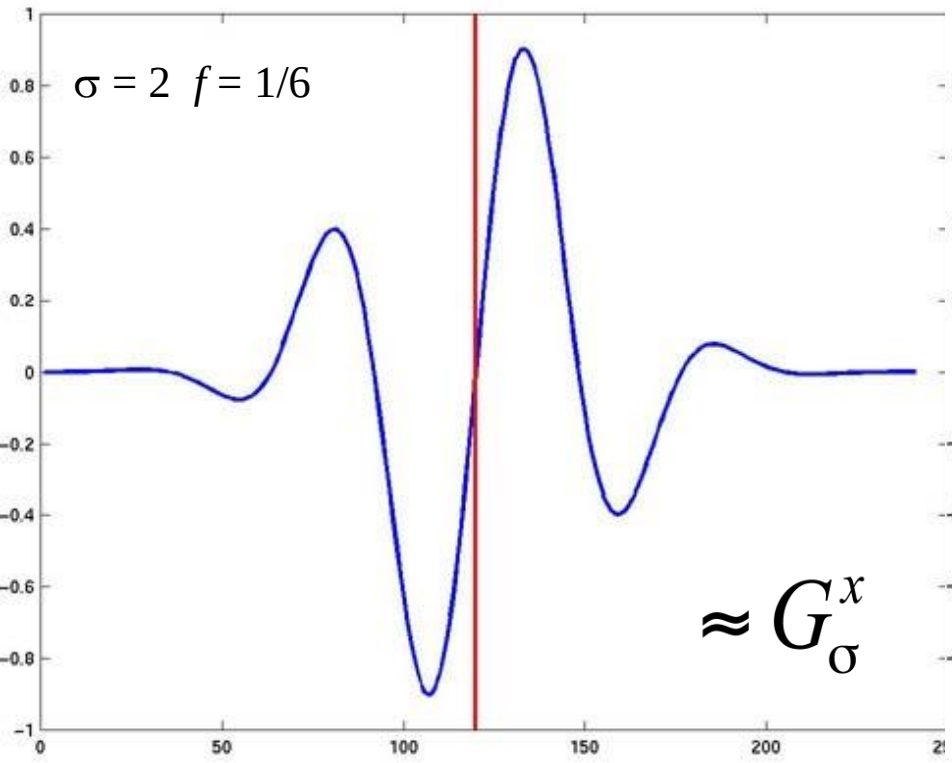
… looks a lot like…

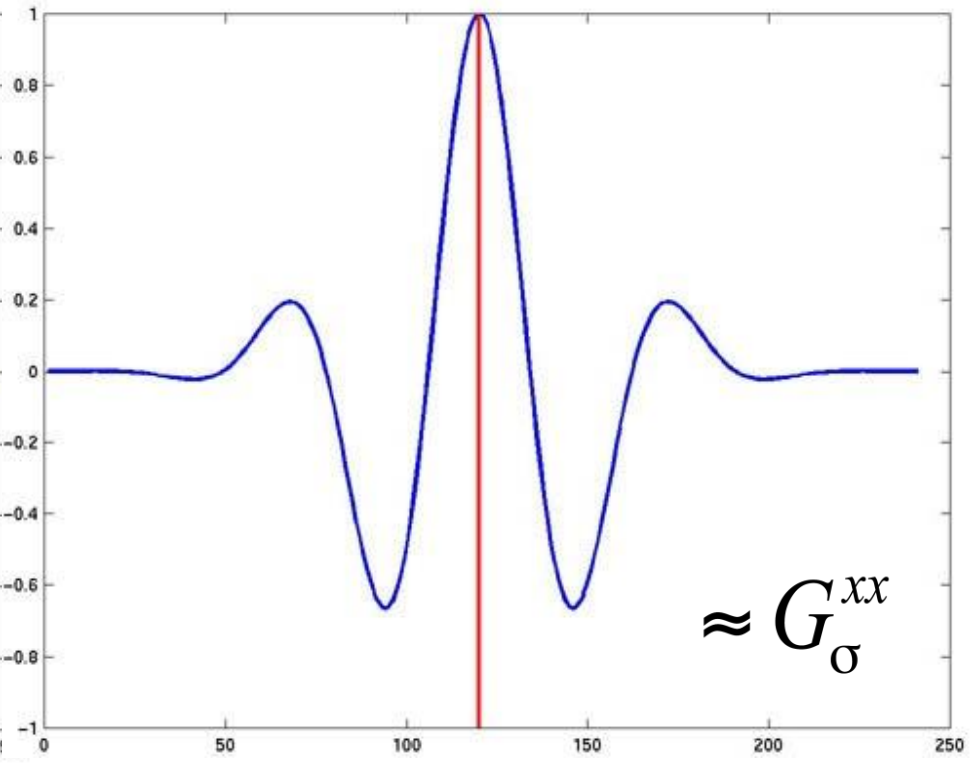


Laplacian

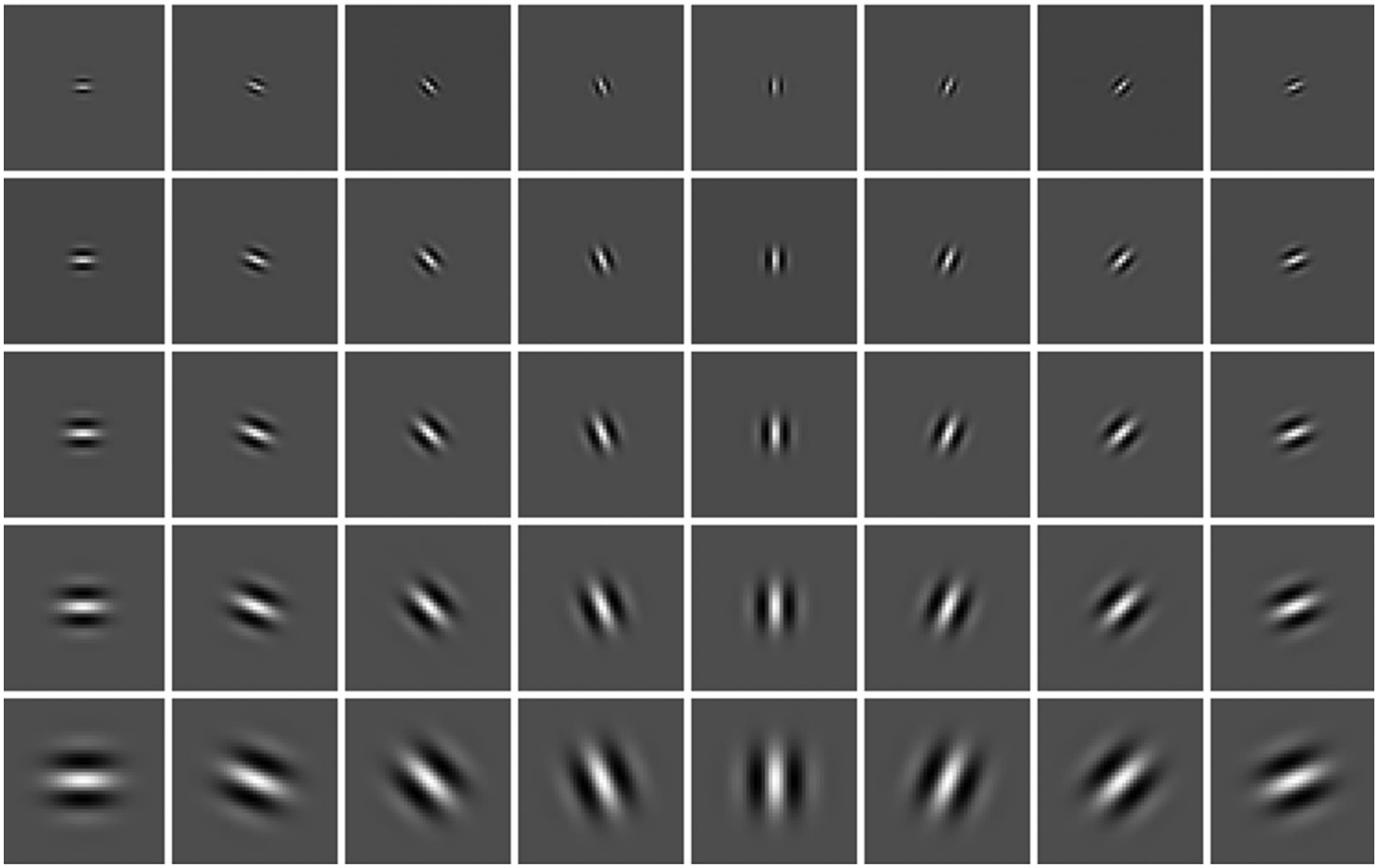


If scale small compared to inverse frequency, the Gabor filters become derivative operators





Directional edge detectors

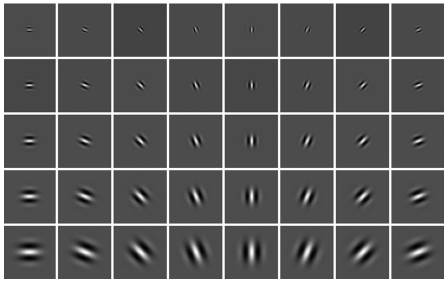


GIST

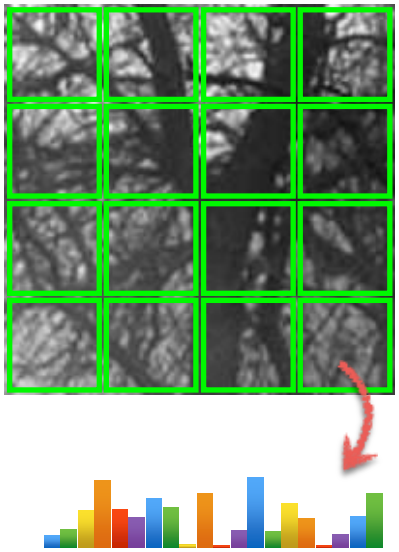
1. Compute filter responses (filter bank of Gabor filters)
2. Divide image patch into 4 x 4 cells
3. Compute filter response averages for each cell
4. Size of descriptor is 4 x 4 x N, where N is the size of the filter bank

What is the GIST descriptor encoding?

Filter bank

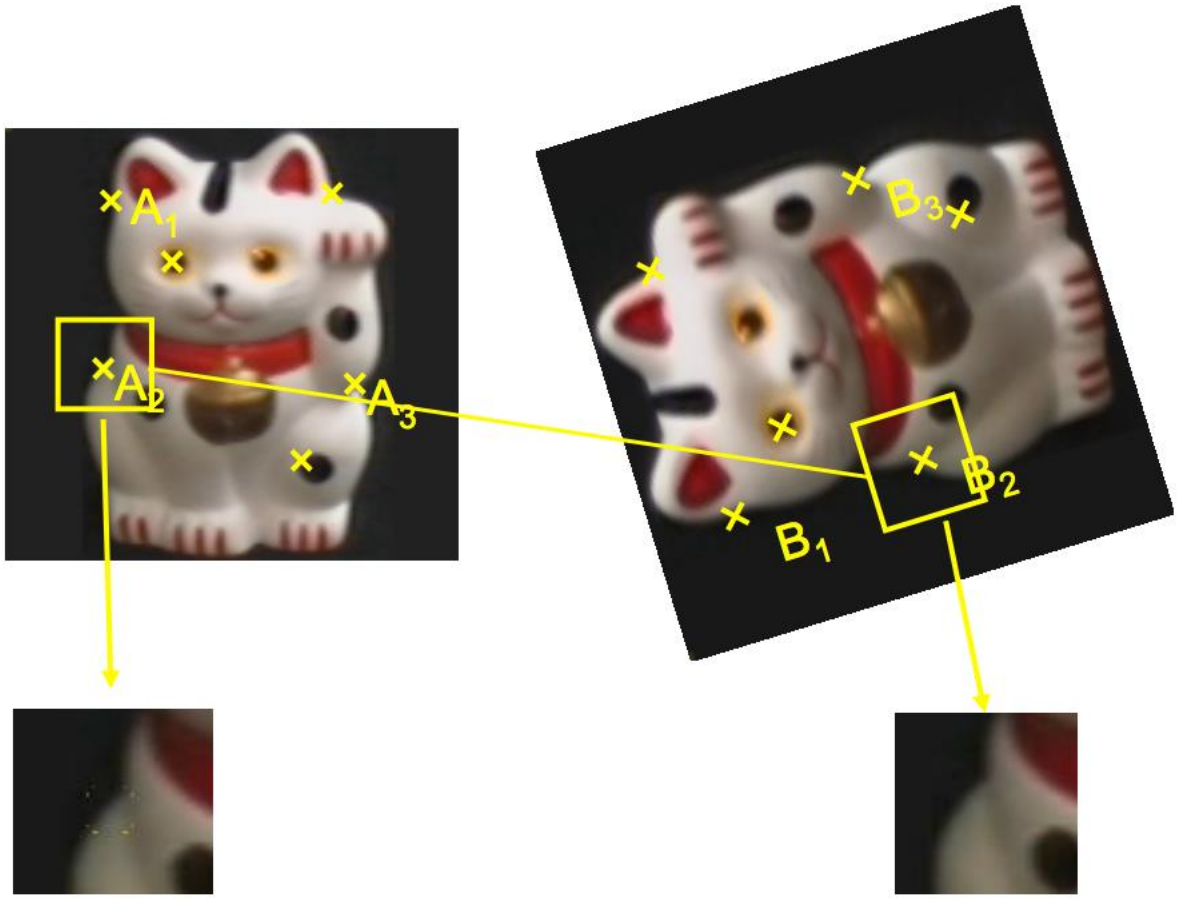


4 x 4 cell



averaged filter responses

Becoming rotation invariant



Orientation Assignment

- Use scale of point to choose correct image:

$$L(x, y) = G(x, y, \sigma) * I(x, y)$$

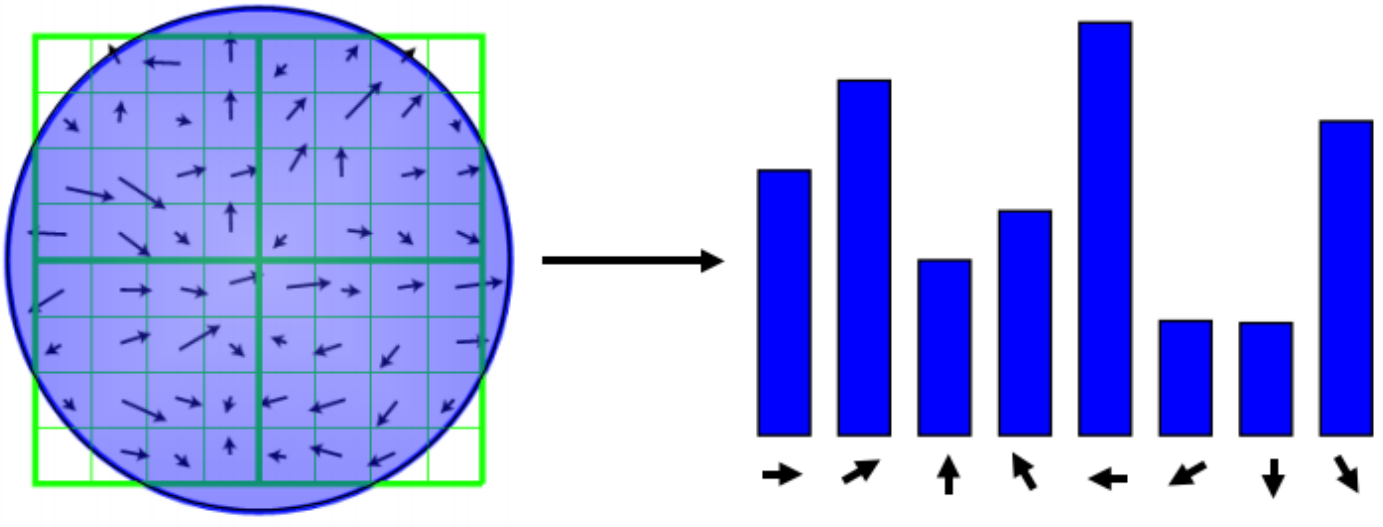
- Compute gradient magnitude and orientation using finite differences:

$$m(x, y) = \sqrt{\left(L(x+1, y) - L(x-1, y)\right)^2 + \left(L(x, y+1) - L(x, y-1)\right)^2}$$

$$\theta(x, y) = \tan^{-1}\left(\frac{\left(L(x, y+1) - L(x, y-1)\right)}{\left(L(x+1, y) - L(x-1, y)\right)}\right)$$

Orientation Assignment

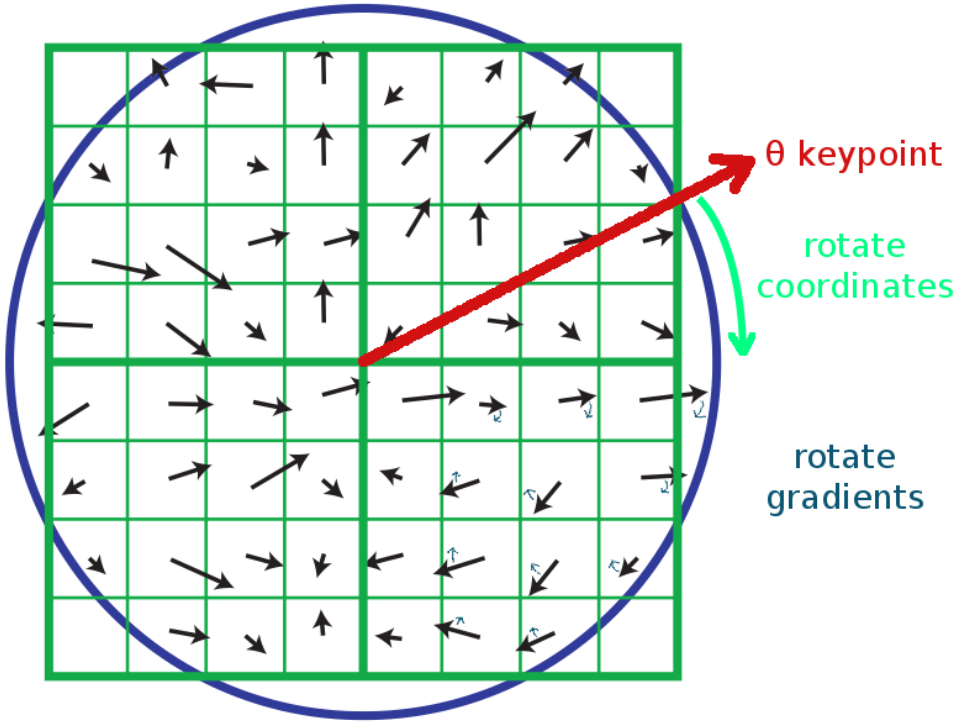
- Create gradient histogram (36 bins)
  - Weighted by magnitude and Gaussian window (σ is 1.5 times that of the scale of a keypoint)



Orientation Assignment

- Any peak within 80% of the highest peak is used to create a keypoint with that orientation
- ~15% assigned multiplied orientations, but contribute significantly to the stability
- Finally a parabola is fit to the 3 histogram values closest to each peak to interpolate the peak position for better accuracy

SIFT descriptor formation



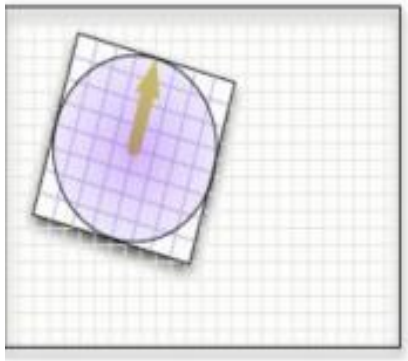
- To become rotation invariant, rotate the gradient directions AND locations by (-keypoint orientation)
  - Now we've cancelled out rotation and have gradients expressed at locations **relative** to keypoint orientation θ
  - We could also have just rotated the whole image by -θ, but that would be slower.

SIFT descriptor formation

- Each point so far has x, y, σ, m, θ
- Now we need a descriptor for the region
  - Could sample intensities around point, but…
    - Sensitive to lighting changes
    - Sensitive to slight errors in x, y, θ

SIFT descriptor formation

- 4x4 Gradient window
- Histogram of 4x4 samples per window in 8 directions
- Gaussian weighting around center(σ is 0.5 times that of the scale of a keypoint)
- 4x4x8 = 128 dimensional feature vector



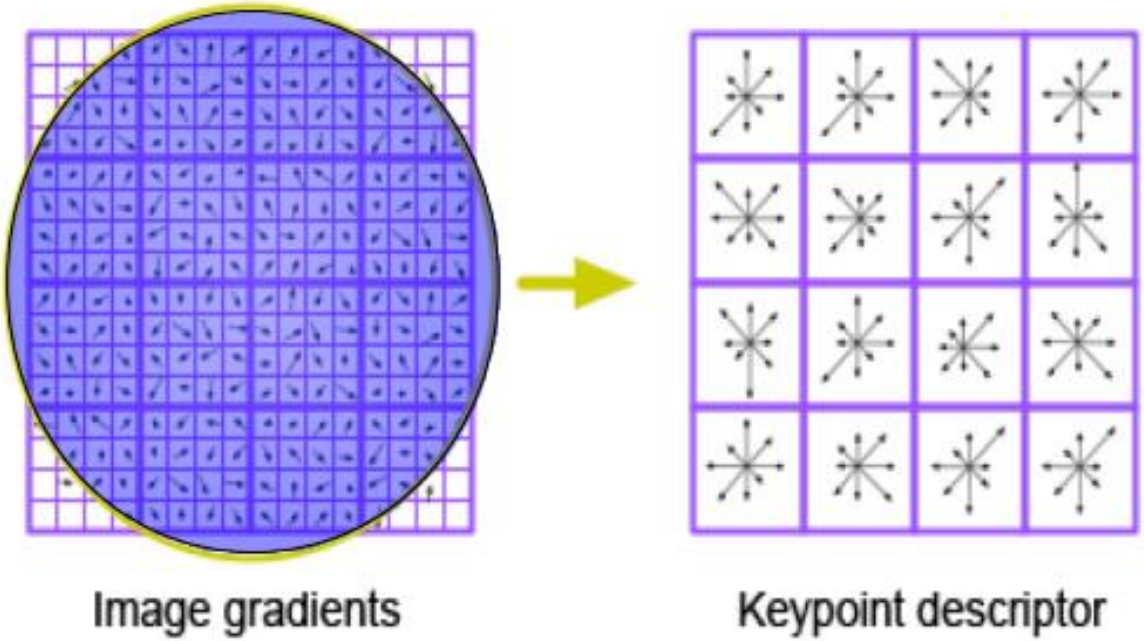
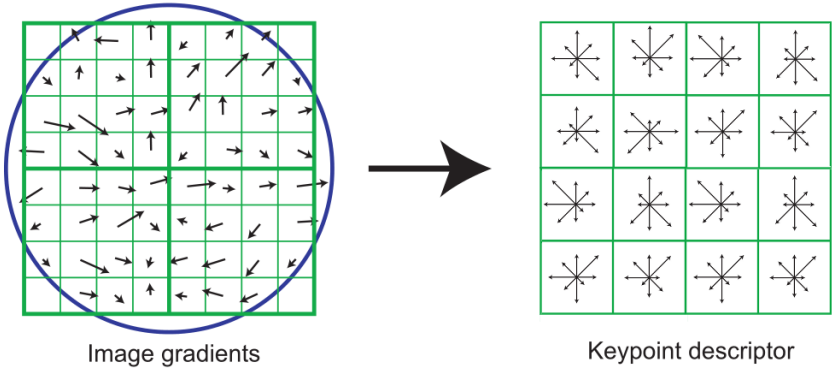


Image gradients

Keypoint descriptor

SIFT descriptor formation

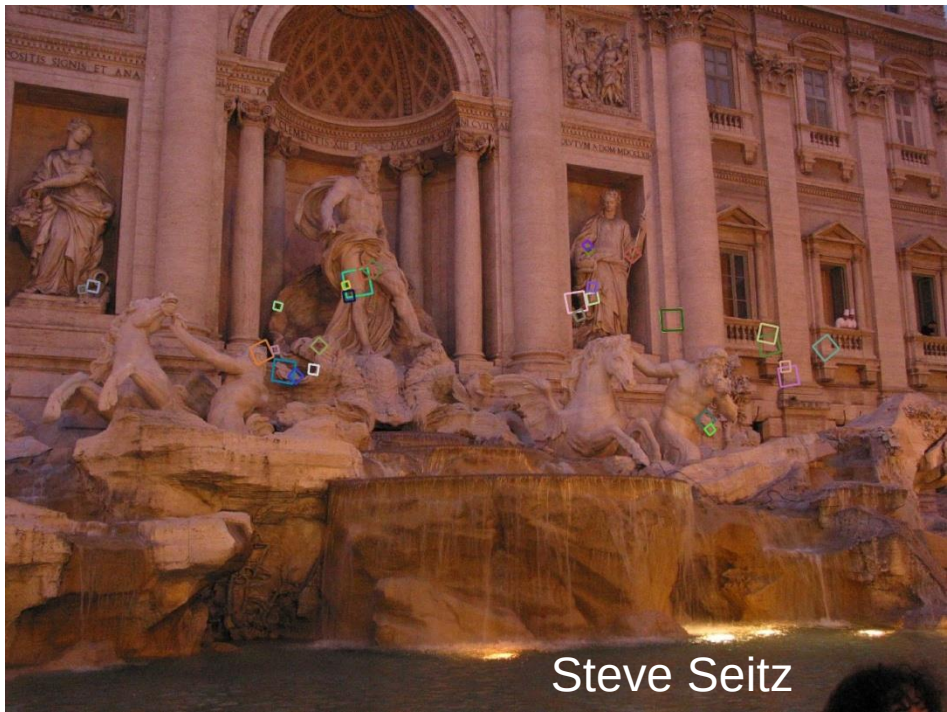


- Adding robustness to illumination changes:
- Remember that the descriptor is made of gradients (differences between pixels), so it's already invariant to changes in brightness (e.g. adding 10 to all image pixels yields the exact same descriptor)
- A higher-contrast photo will increase the magnitude of gradients linearly. So, to correct for contrast changes, normalize the vector (scale to length 1.0)
- Very large image gradients are usually from unreliable 3D illumination effects (glare, etc). So, to reduce their effect, clamp all values in the vector to be ≤ 0.2 (an experimentally tuned value). Then normalize the vector again.
- Result is a vector which is fairly invariant to illumination changes.

Feature descriptors: 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



Histogram of Oriented Gradients

Find robust feature set that allows object form to be discriminated.

Challenges

- Wide range of pose and large variations in appearances
- Cluttered backgrounds under different illumination
- “Speed” for mobile vision

References

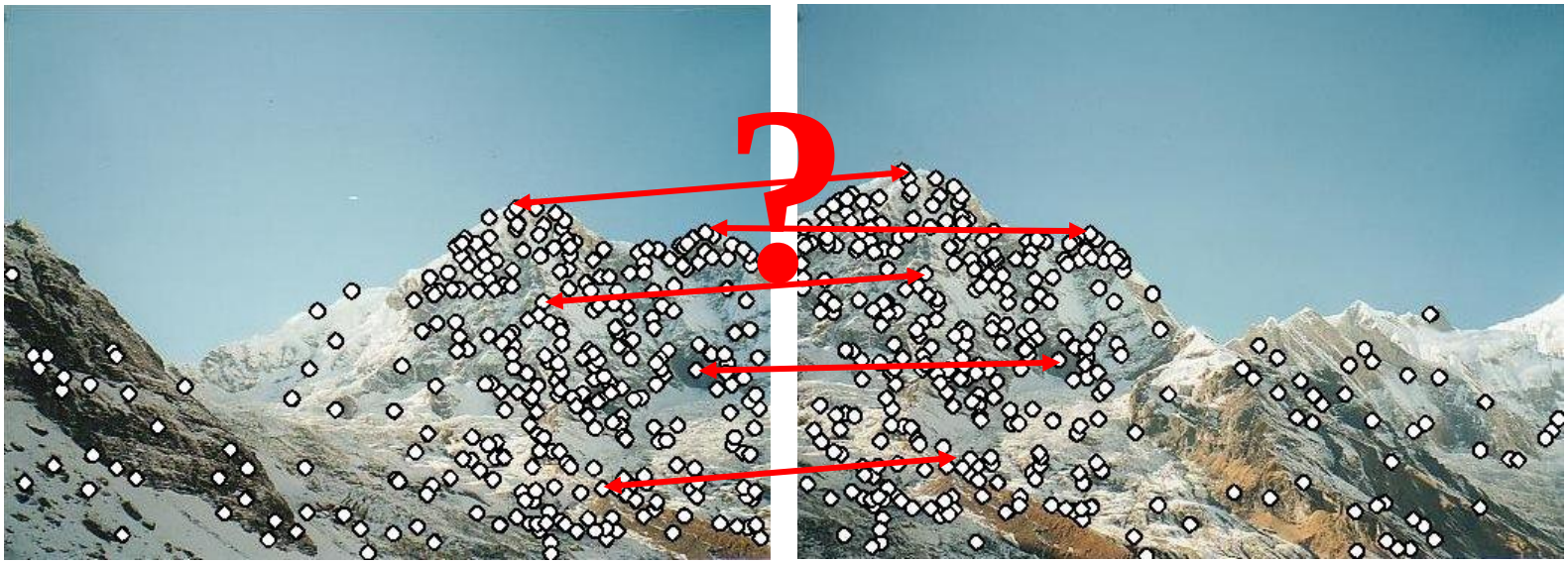
– [1] N. Dalal and B. Triggs. Histograms of Oriented Gradients for Human Detection. In CVPR, pages 886-893, 2005
– [2] Chandrasekhar et al. CHoG: Compressed Histogram of Gradients - A low bit rate feature descriptor, CVPR 2009

Main questions

- Where will the interest points come from?
  - What are salient features that we'll *detect* in multiple views?
- How to *describe* a local region?
- How to establish *correspondences*, i.e., compute matches?

Feature descriptors

We know how to detect **and describe** good points
Next question: **How to match them?**



Feature matching

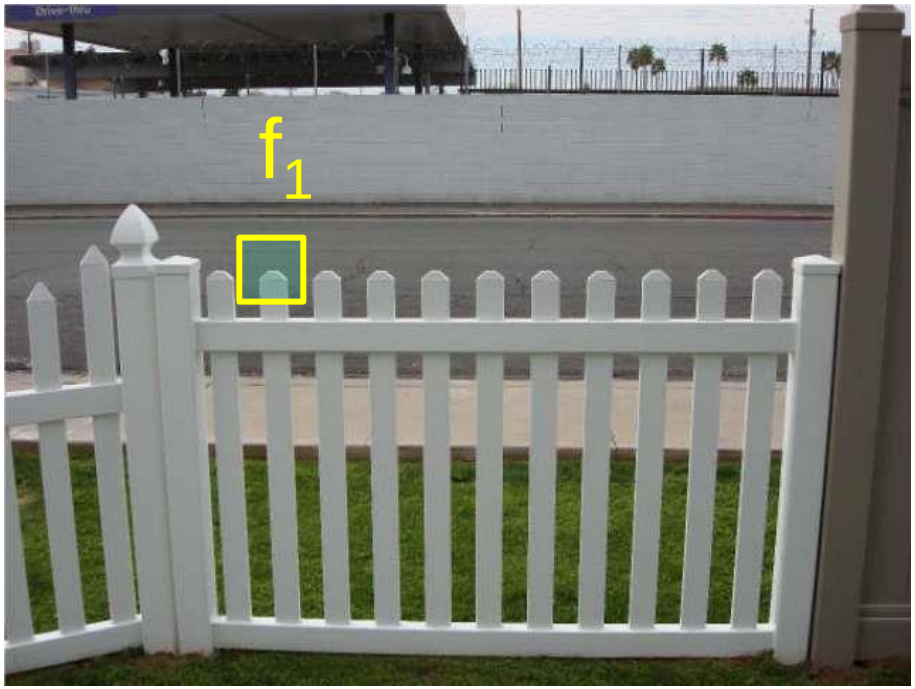
Given a feature in I_1, how to find the best match in I_2?

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

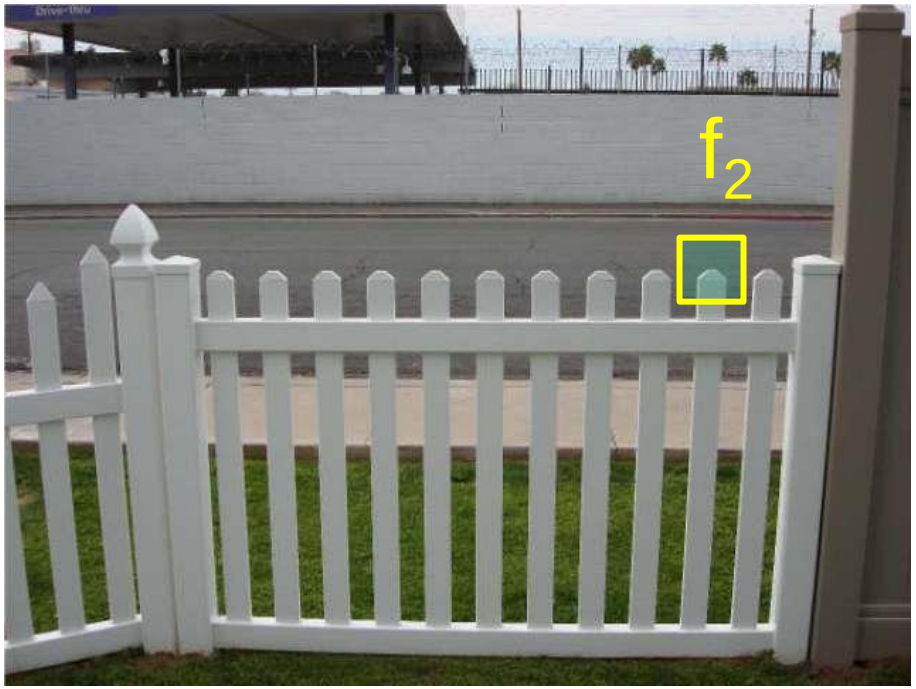
Feature distance

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

- Simple approach is SSD(f_1, f_2)
  - sum of square differences between entries of the two descriptors
  - can give good scores to very ambiguous (bad) matches



I_1

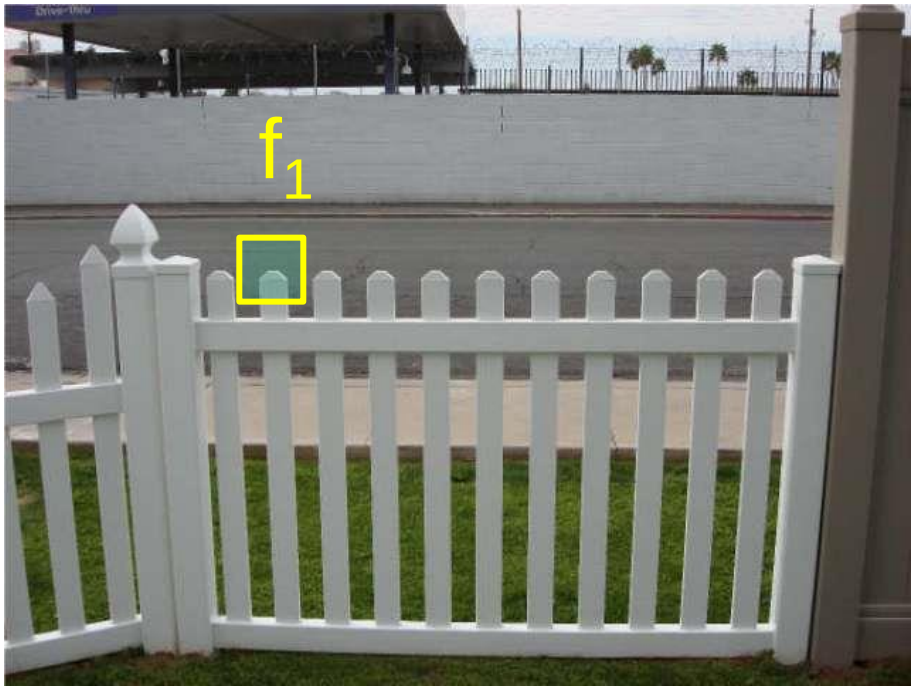


I_2

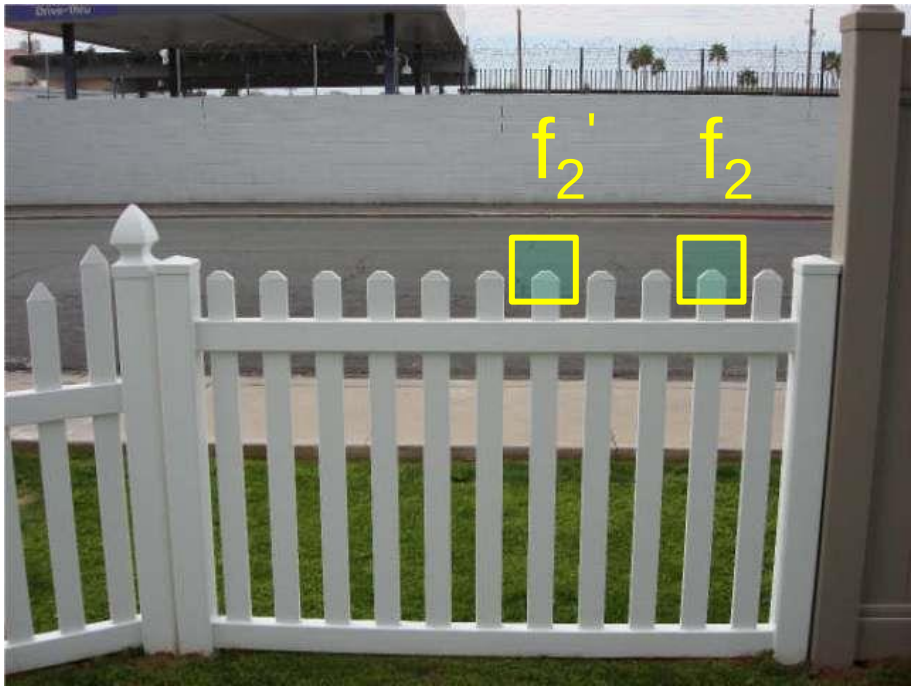
Feature distance

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

- Better approach: ratio distance = SSD(f_1, f_2) / SSD(f_1, f_2')
  - f_2 is best SSD match to f_1 in I_2
  - f_2' is 2nd best SSD match to f_1 in I_2
  - An ambiguous/bad match will have ratio close t
  - Look for unique matches which have low ratio



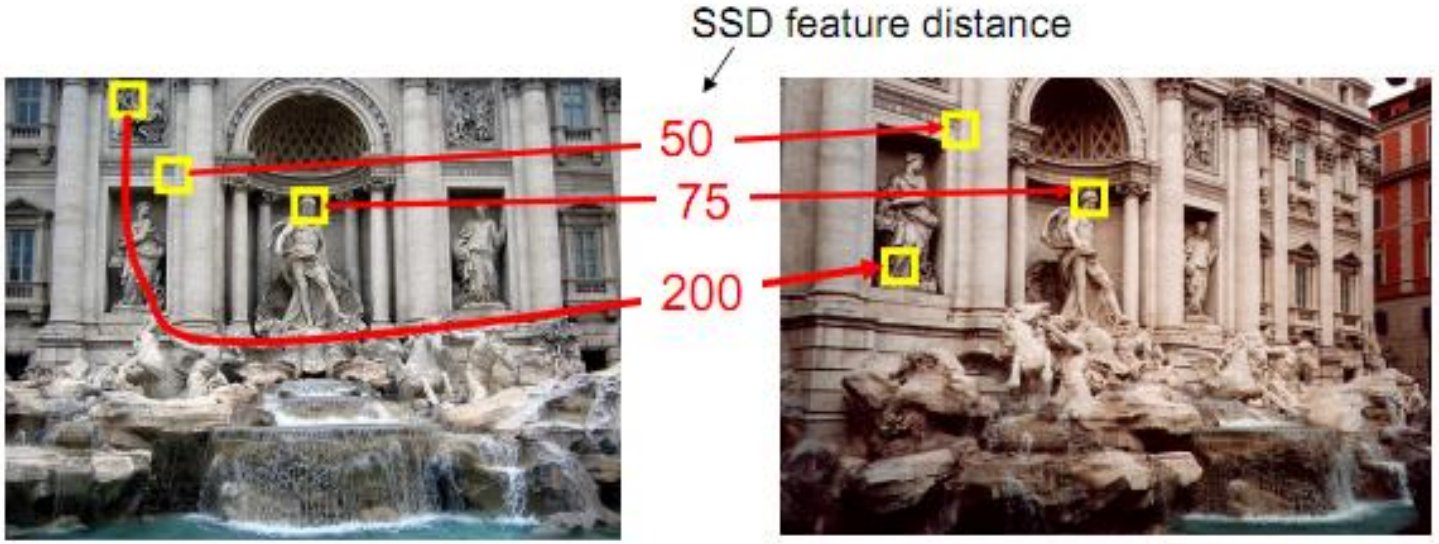
I_1



I_2

Evaluating the results

How can we measure the performance of a feature matcher?



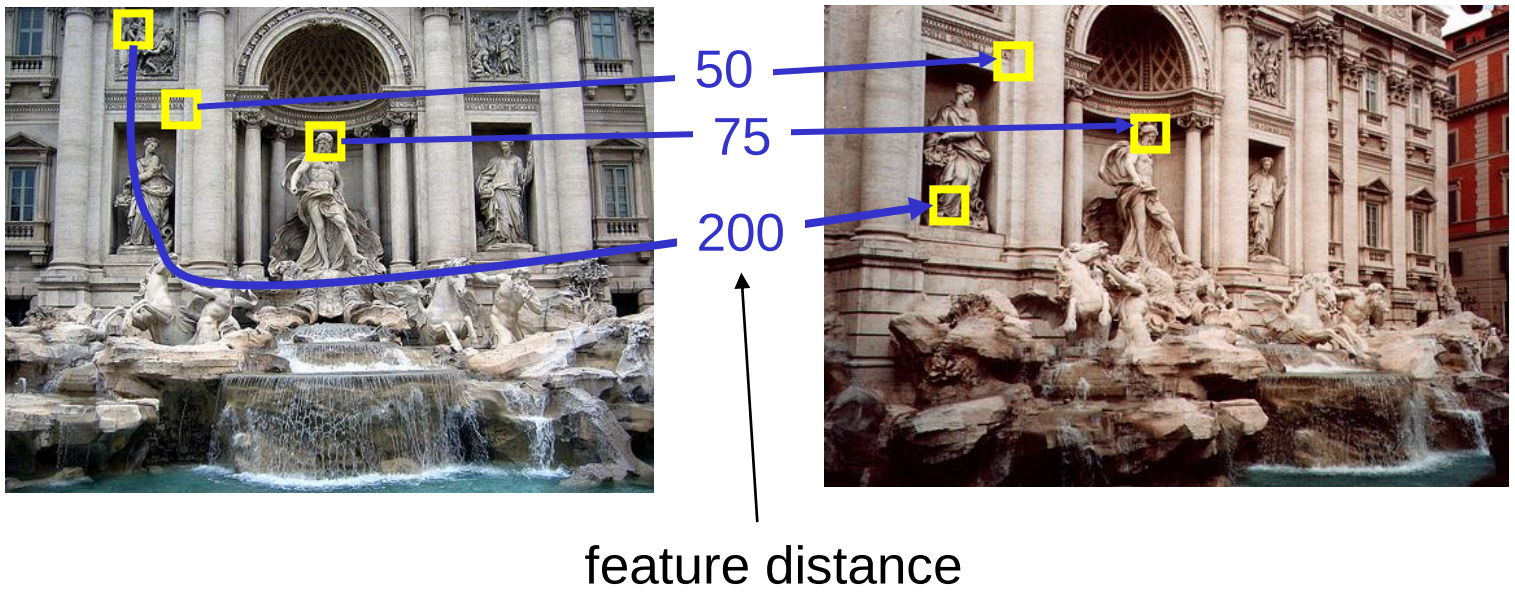
Suppose we use SSD
Small values are possible matches but how small?

Decision rule: Accept match if SSD < T
where T is a threshold

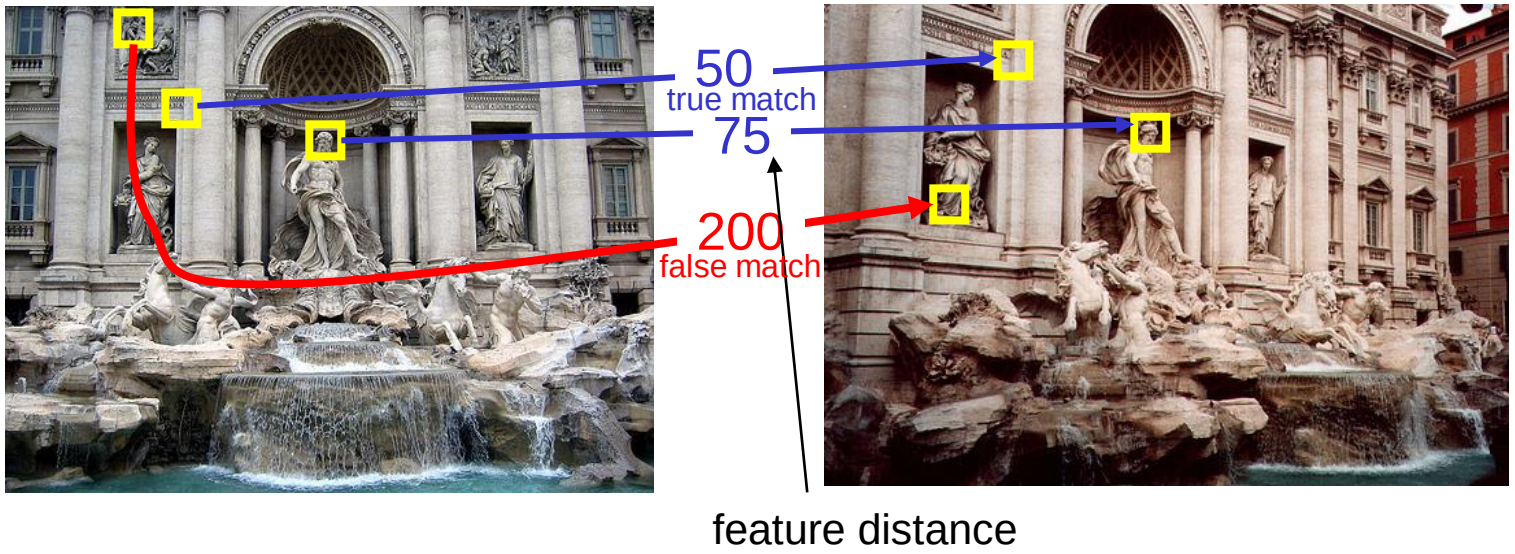
What is the effect of choosing a particular T?

Evaluating the results

How can we measure the performance of a feature matcher?



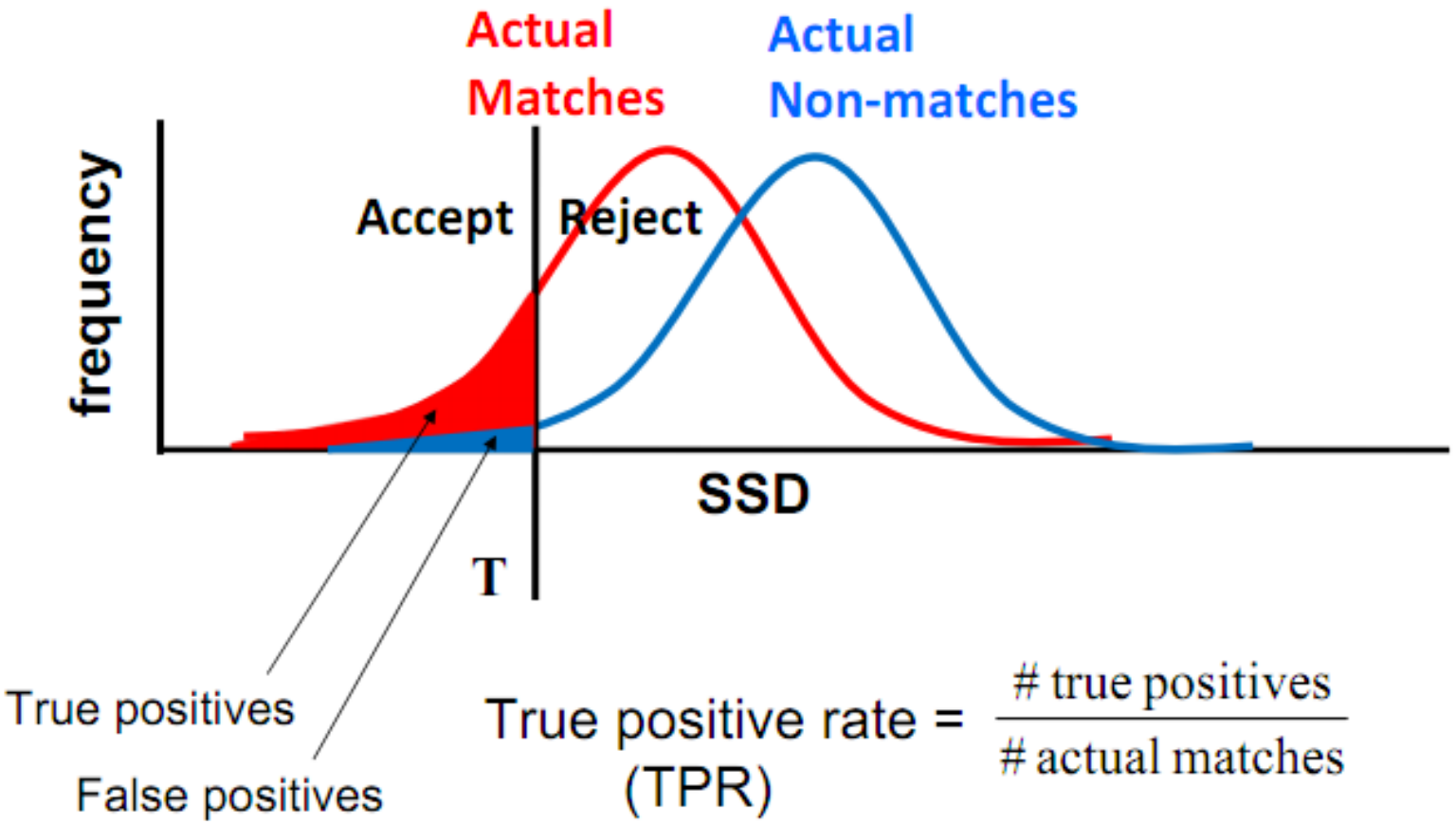
True/false positives



The distance threshold affects performance

- True positives = # of detected matches that are correct
  - Suppose we want to maximize these—how to choose threshold?
- False positives = # of detected matches that are incorrect
  - Suppose we want to minimize these—how to choose threshold?

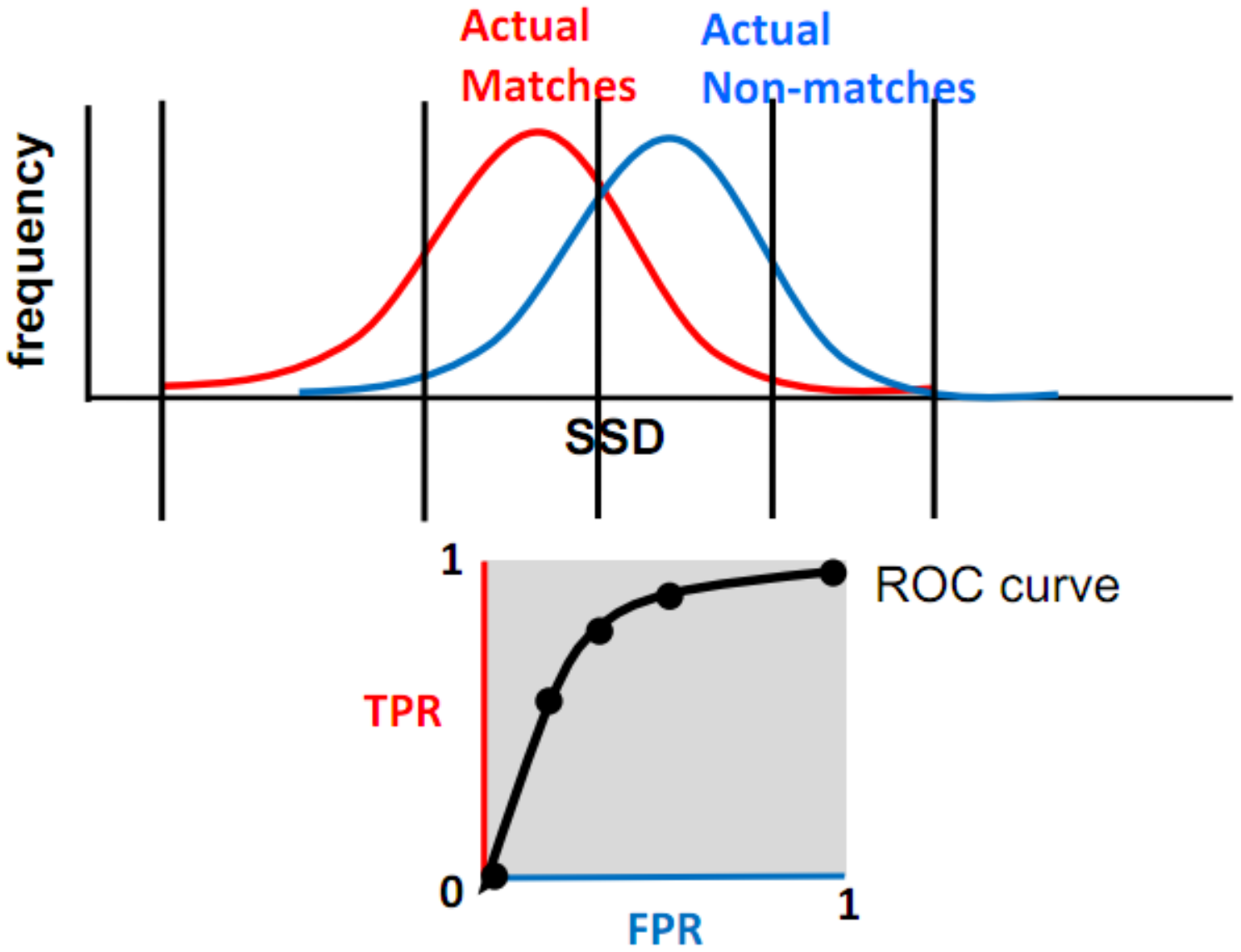
True/false positives



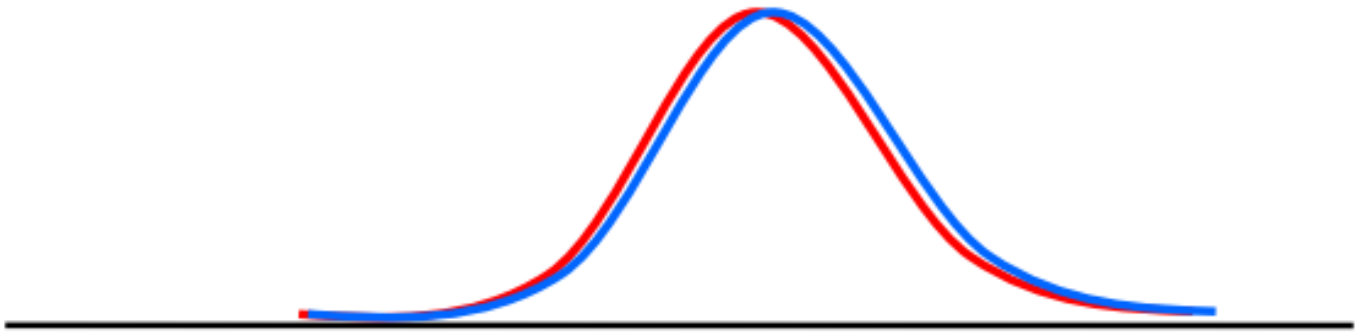
True positive rate (TPR) = $\frac{\text{\# true positives}}{\text{\# actual matches}}$

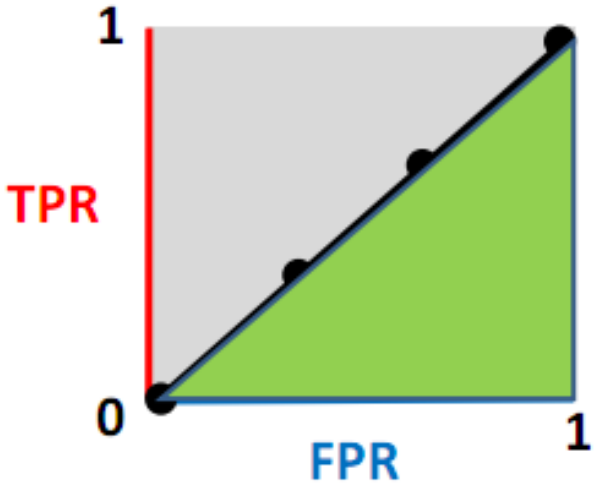
False positive rate (FPR) = $\frac{\text{\# false positives}}{\text{\# actual nonmatches}}$

Receiver Operating Characteristic (ROC) curve



Bad feature

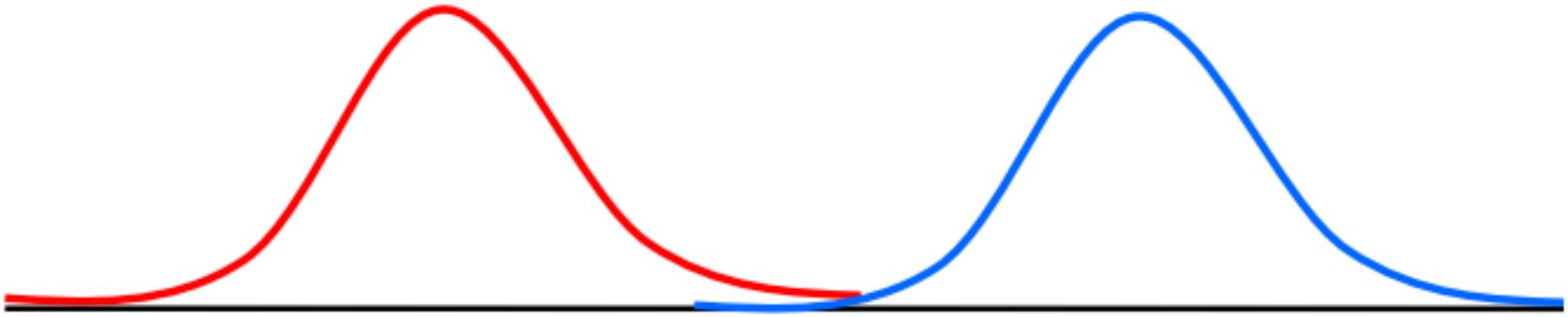


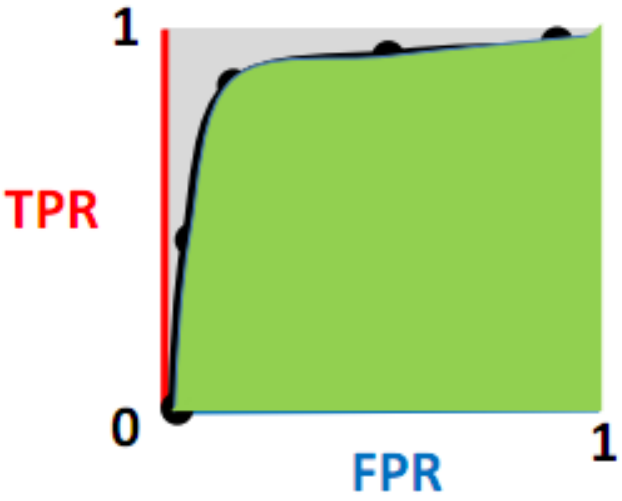


Area ≈ 0.5

Adapted from a slide by Shin Kira

Good feature



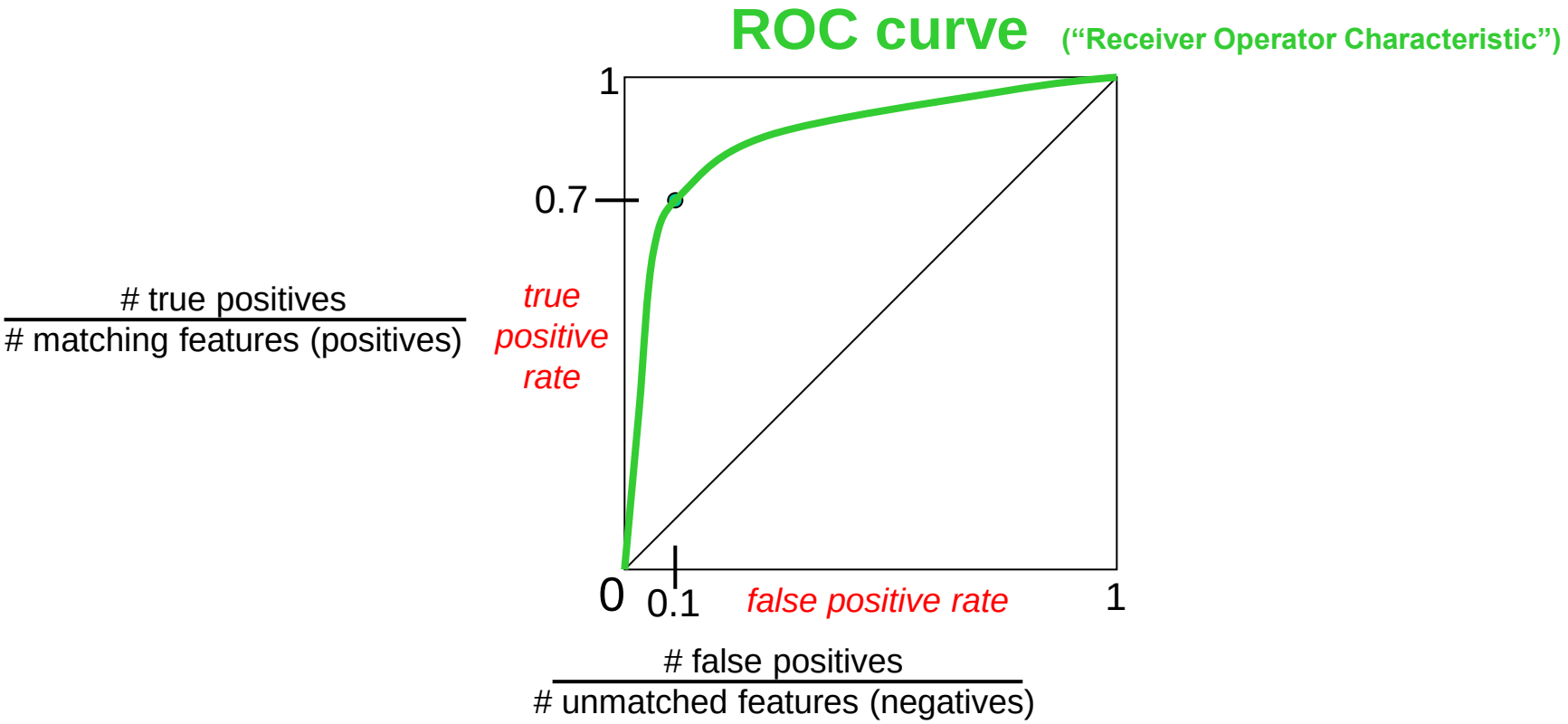


Area ≈ 1.0

Adapted from a slide by Shin Kira

Evaluating the results

How can we measure the performance of a feature matcher?



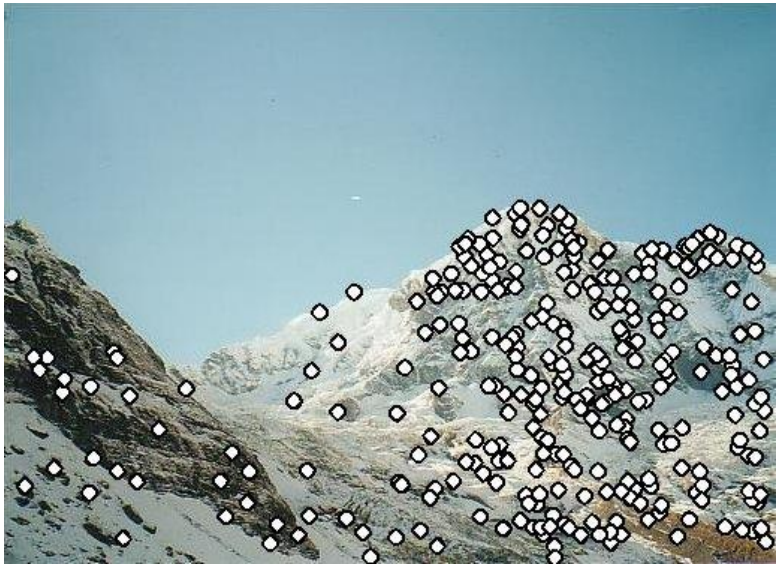
ROC Curves

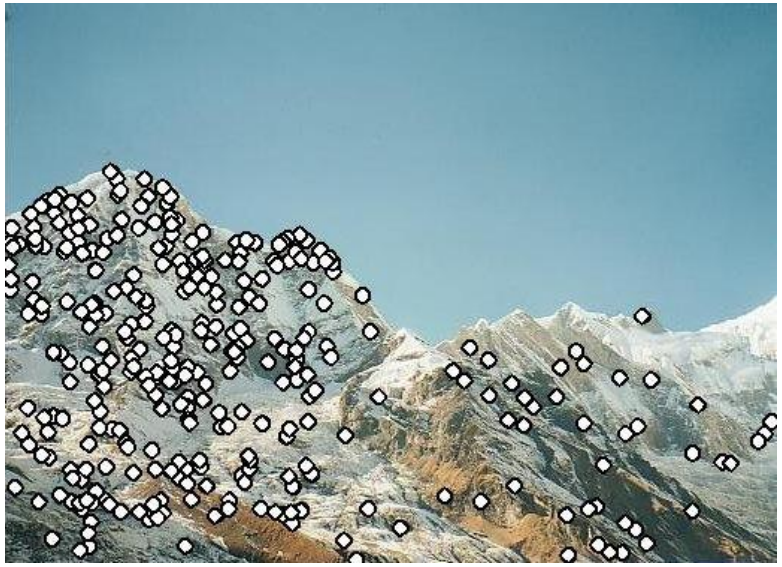
- Generated by counting # current/incorrect matches, for different threholds
- Want to maximize area under the curve (AUC)
- Useful for comparing different feature matching methods
- For more info: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

Application: Image Stitching

Slide credit: Darya Frolova, Denis Simakov

Application: Image Stitching

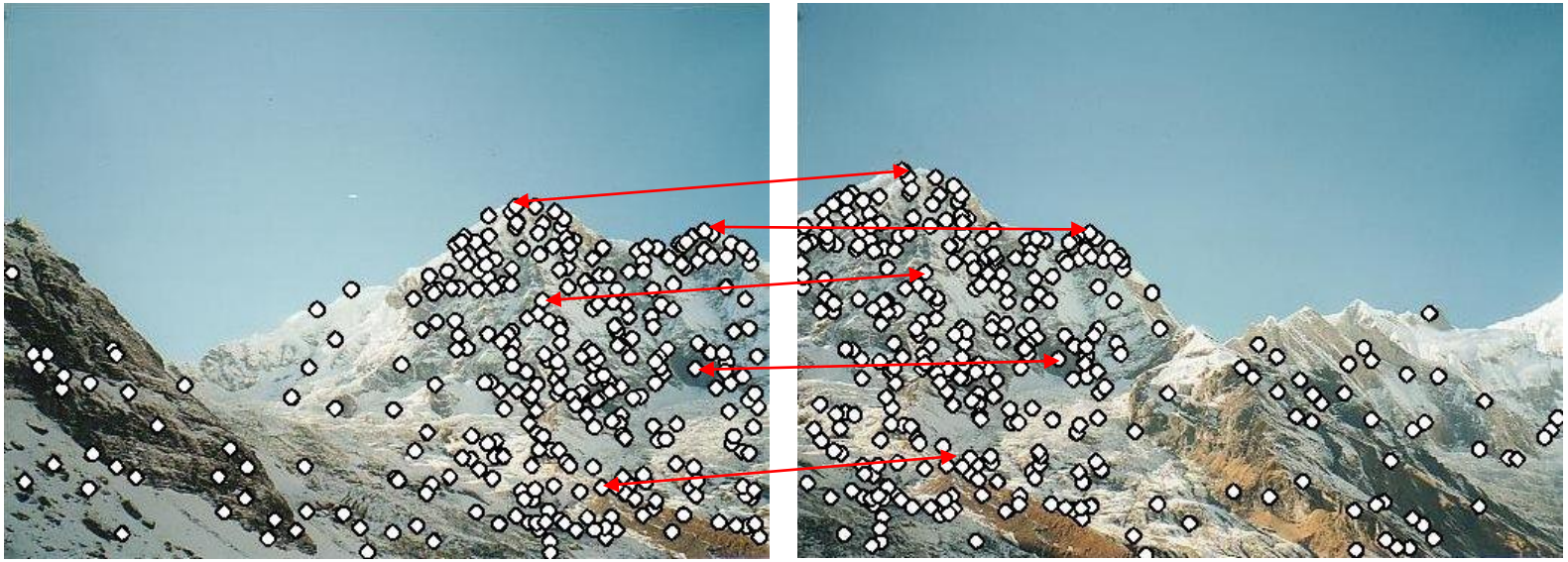




- Procedure:
  - Detect feature points in both images

Slide credit: Darya Frolova, Denis Simakov

Application: Image Stitching



- Procedure:
  - Detect feature points in both images
  - Find corresponding pairs

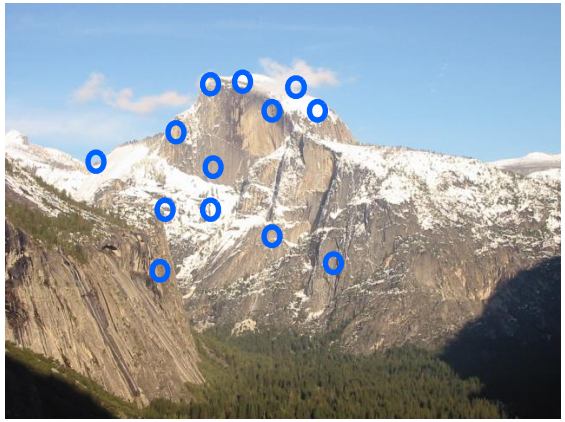
Slide credit: Darya Frolova, Denis Simakov

Application: Image Stitching

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

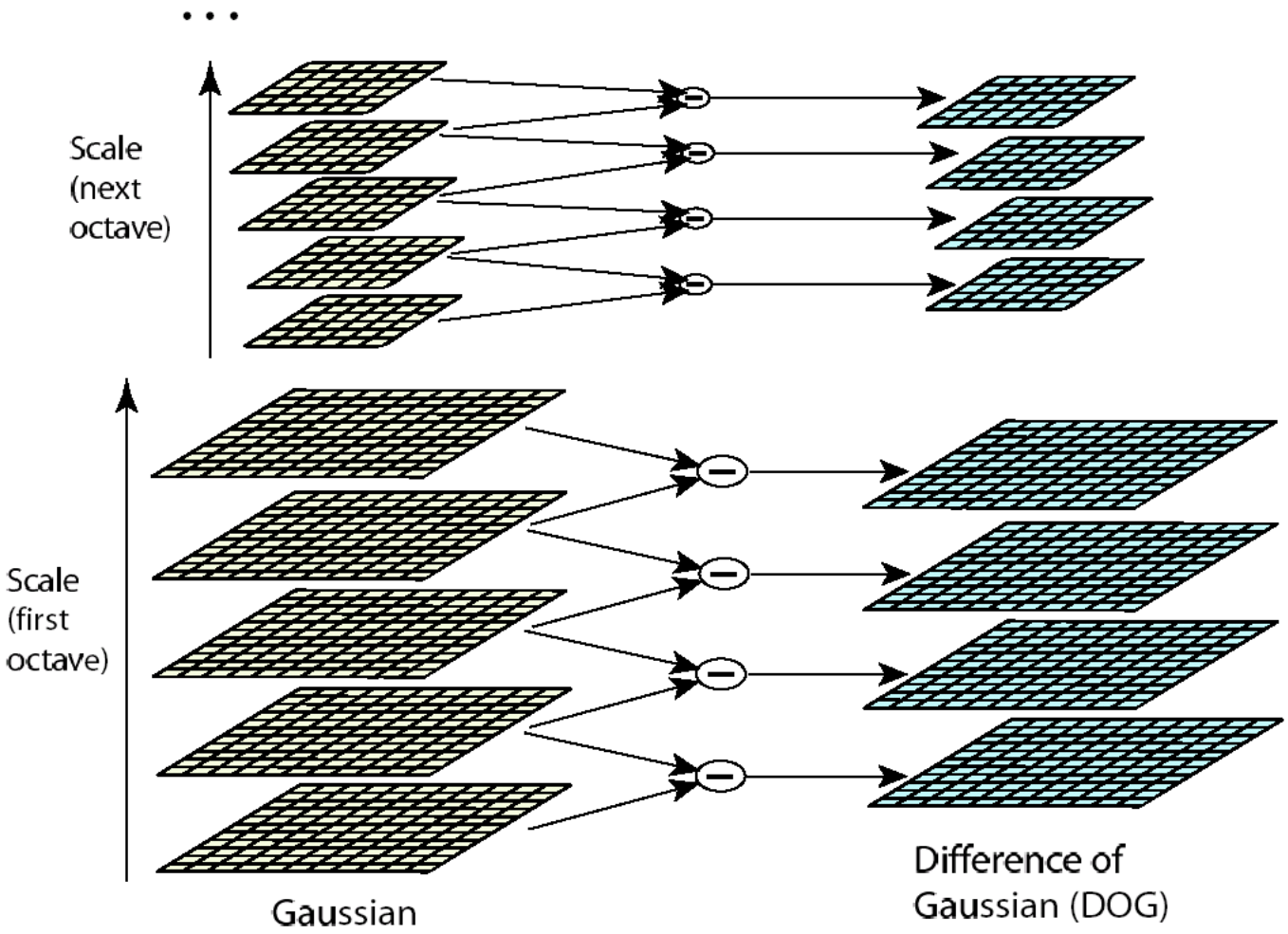
Slide credit: Darya Frolova, Denis Simakov

Main Flow



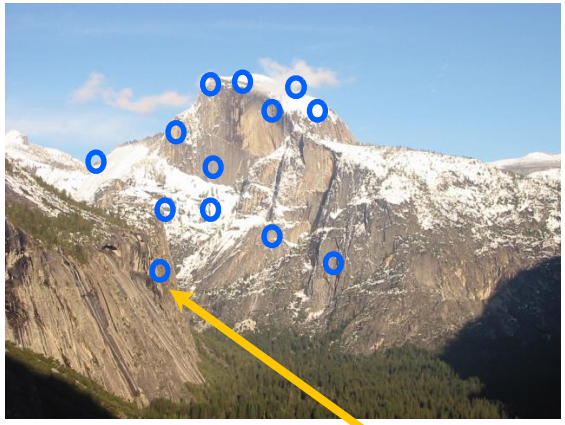
- Detect key points

Detect Key Points



Main Flow

$(u_1, u_2, \ldots, u_{128})$



$(v_1, v_2, \ldots, v_{128})$

- Detect key points
- Build the SIFT descriptors

Build the SIFT Descriptors

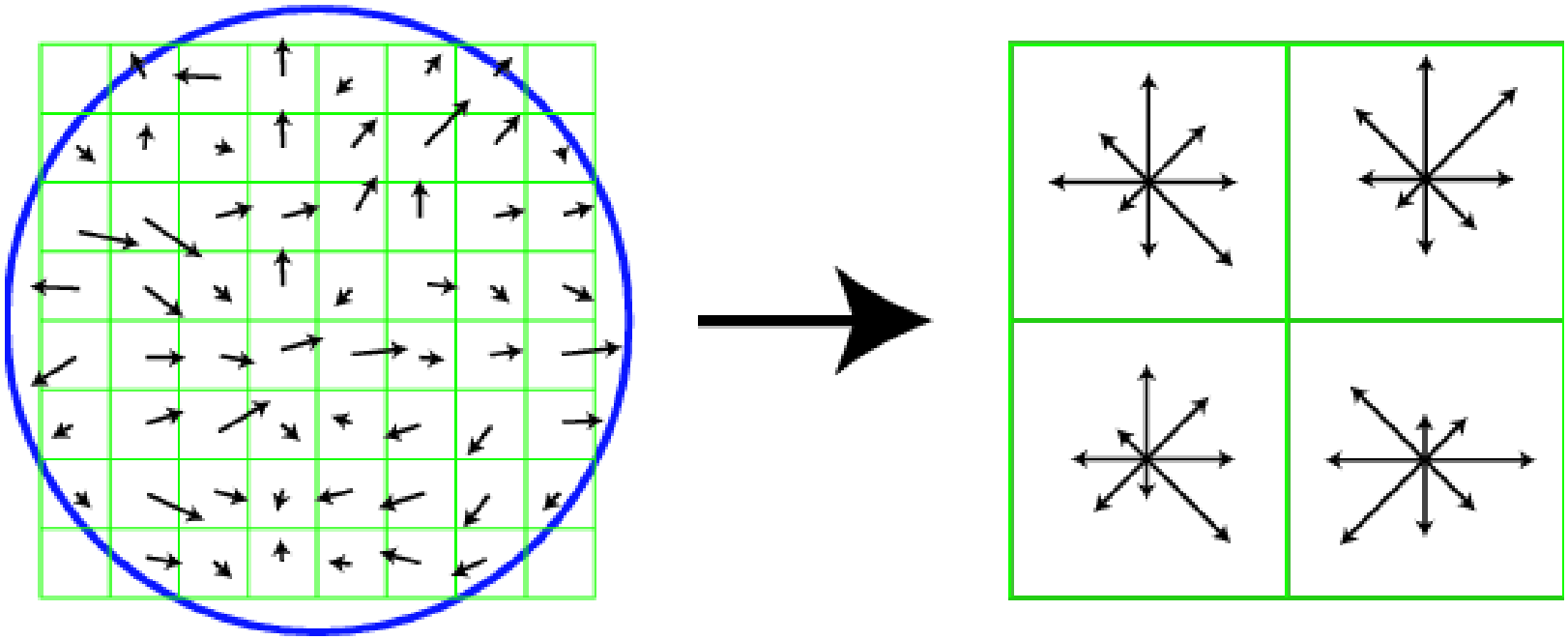
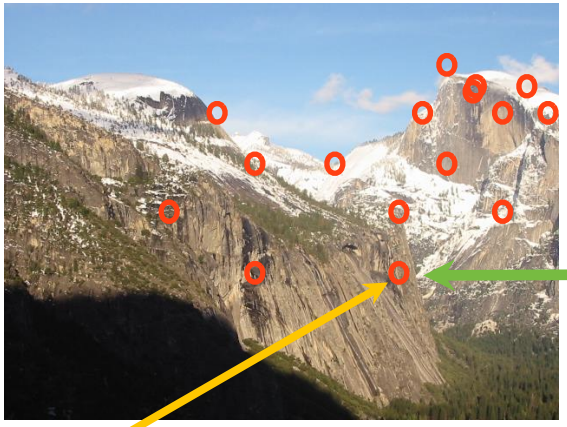
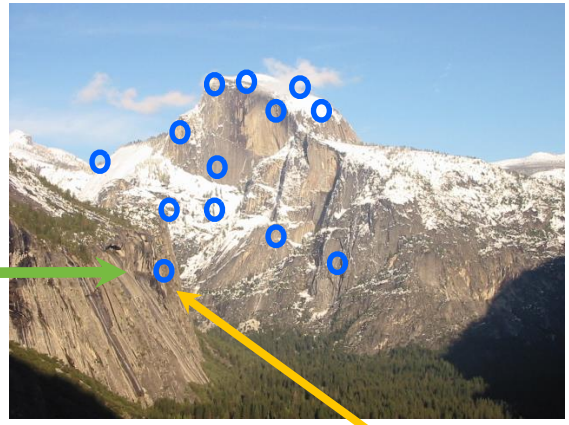


Image gradients

Keypoint descriptor

Main Flow





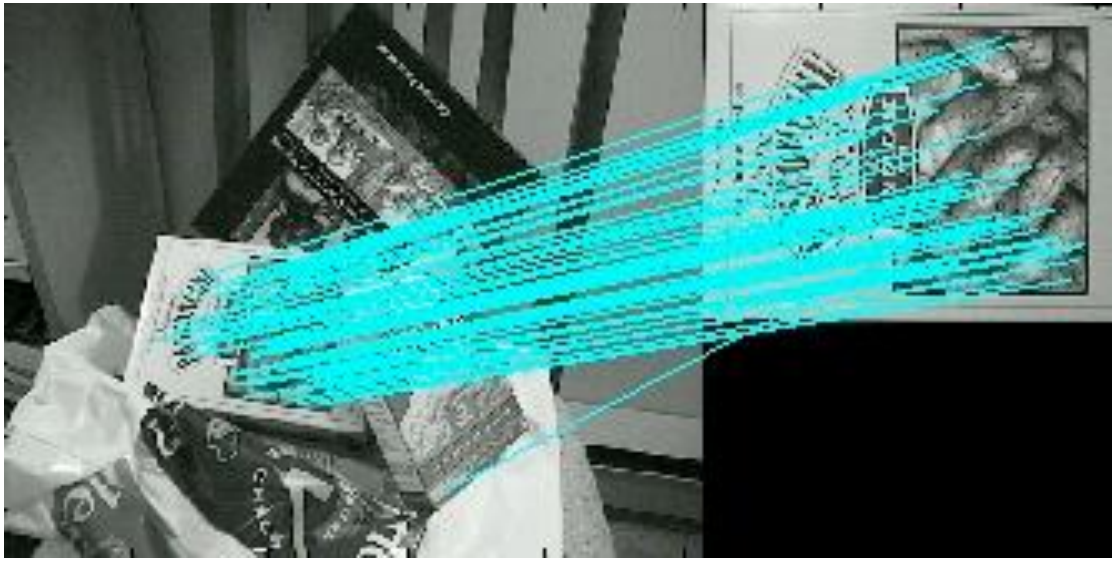
$(u_1, u_2, \ldots, u_{128})$

$(v_1, v_2, \ldots, v_{128})$

- Detect key points
- Build the SIFT descriptors
- Match SIFT descriptors

Match SIFT Descriptors

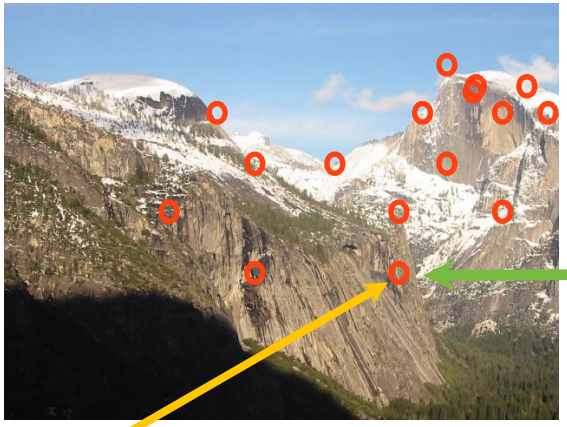
- Euclidean distance between descriptors

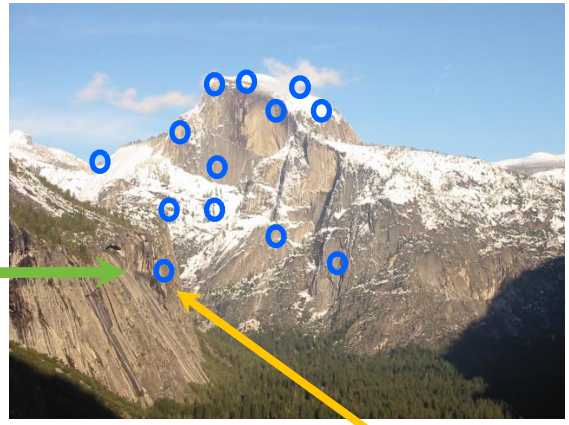


Skeleton Code

- Match SIFT descriptors (6 lines of code)
  - Input: D1, D2, thresh (default 0.7)
  - Output: match [D1's index, D2's index]
  - Try to use *one* *for* loop

Main Flow





$(u_1, u_2, \ldots, u_{128})$

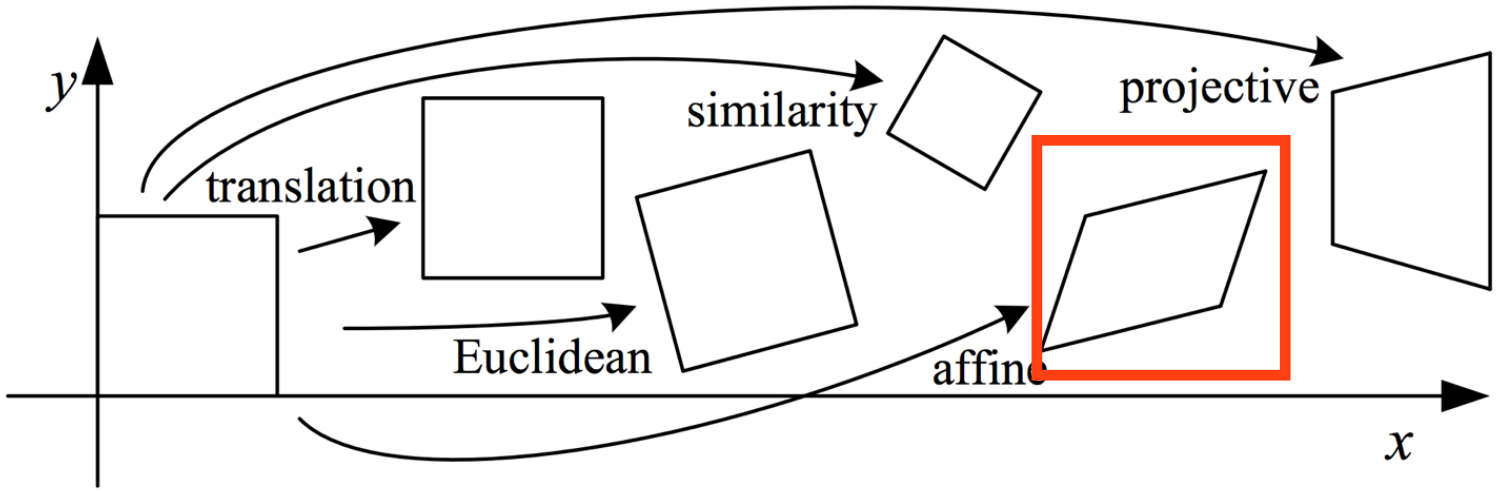
$(v_1, v_2, \ldots, v_{128})$

- Detect key points
- Build the SIFT descriptors
- Match SIFT descriptors
- Fitting the transformation

$$T = \begin{bmatrix} t_{11} & t_{12} & t_{13} \\ t_{21} & t_{22} & t_{23} \\ 0 & 0 & 1 \end{bmatrix}$$

Fitting the transformation

- 2D transformations



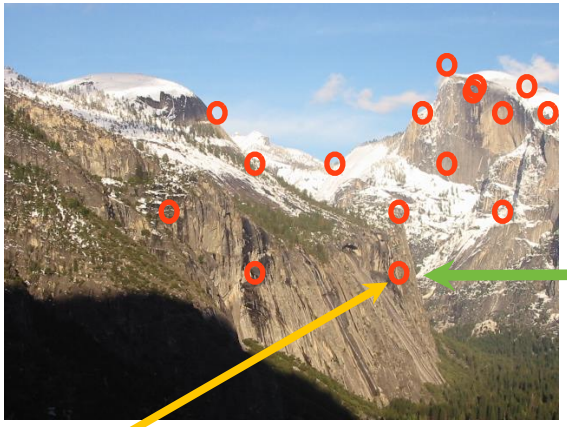
Skeleton Code

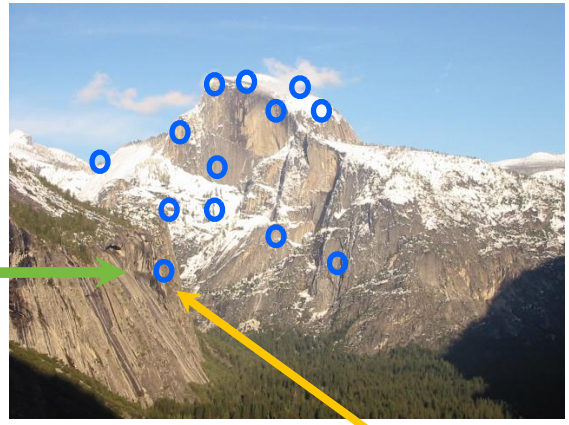
- Fit the transformation matrix

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ 0 & 0 & 1 \end{bmatrix}$$

- Six variables
  - each point give two equations
  - at least three points
- Least squares

Main Flow





$(u_1, u_2, \ldots, u_{128})$

$(v_1, v_2, \ldots, v_{128})$

- Detect key points
- Build the SIFT descriptors
- Match SIFT descriptors
- Fitting the transformation
- RANSAC

RANSAC [Fischler & Bolles 1981]

- RANdom SAmple Consensus
- Approach: we want to avoid the impact of outliers, so let's look for "inliers", and use only those.
- Intuition: if an outlier is chosen to compute the current fit, then the resulting line won't have much support from rest of the points.

Slide credit: Kristen Grauman

RANSAC [Fischler & Bolles 1981]

- The RANSAC algorithm is used for estimating the parameters of models in images (i.e., model fitting). The basic idea behind RANSAC is to solve the fitting problem many times using randomly selected minimal subsets of the data and choosing the best performing fit.
- The RANSAC algorithm can be used to estimate parameters of different models; this is proven beneficial in image stitching, outlier detection, lane detection (linear model estimation), and stereo camera calculations.

Slide credit: Kristen Grauman

RANSAC [Fischler & Bolles 1981]

RANSAC loop:

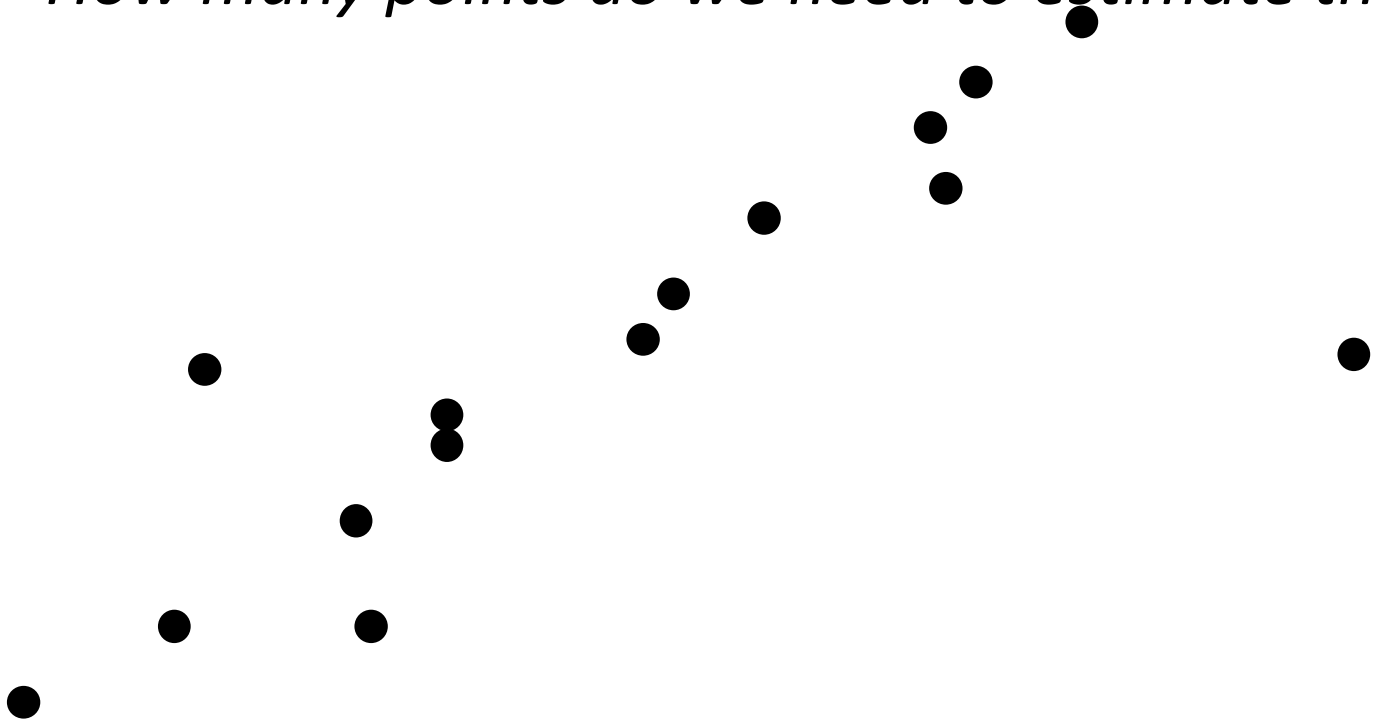
1. Randomly select a *seed group* of points on which to base transformation estimate
2. Compute transformation from seed group
3. Find *inliers* to this transformation
4. If the number of inliers is sufficiently large, re-compute least-squares estimate of transformation on all of the inliers

- Keep the transformation with the largest number of inliers

Slide credit: Kristen Grauman

RANSAC Line Fitting Example

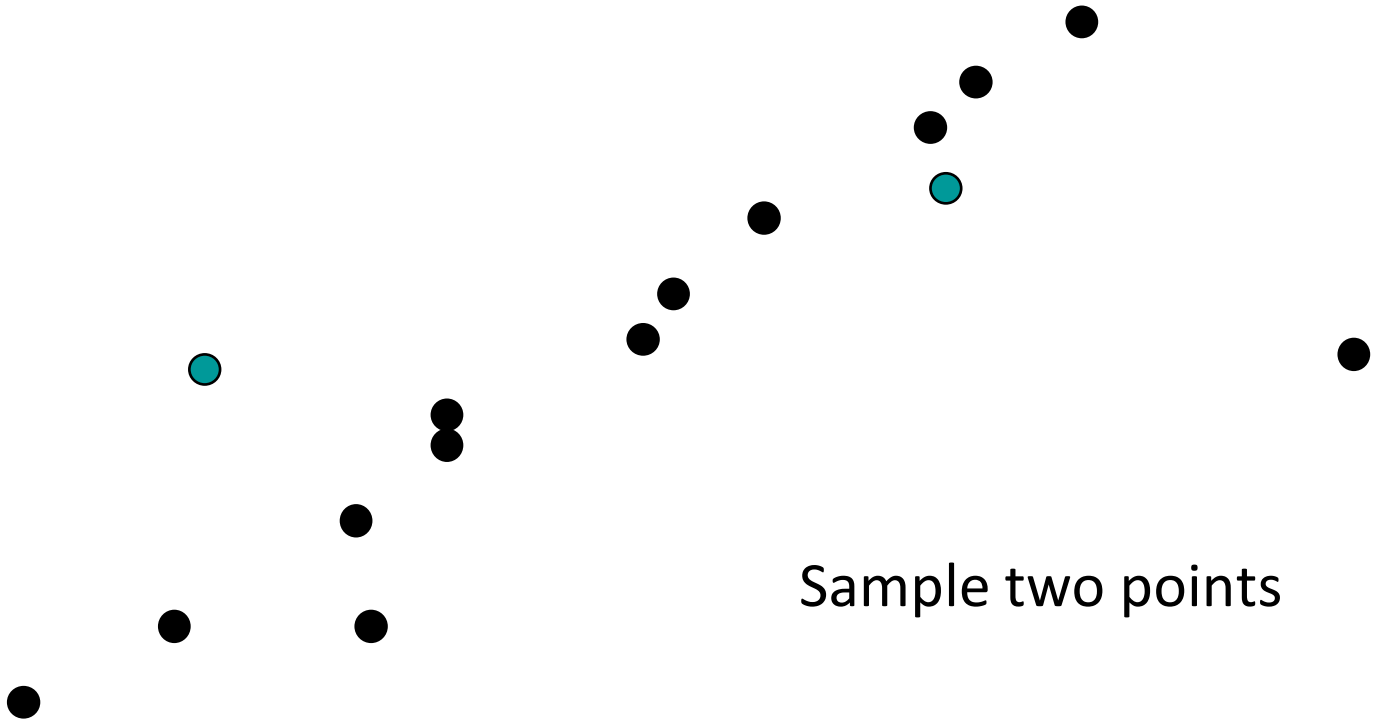
- Task: Estimate the best line
  - *How many points do we need to estimate the line?*



Slide credit: Jinxiang Chai

RANSAC Line Fitting Example

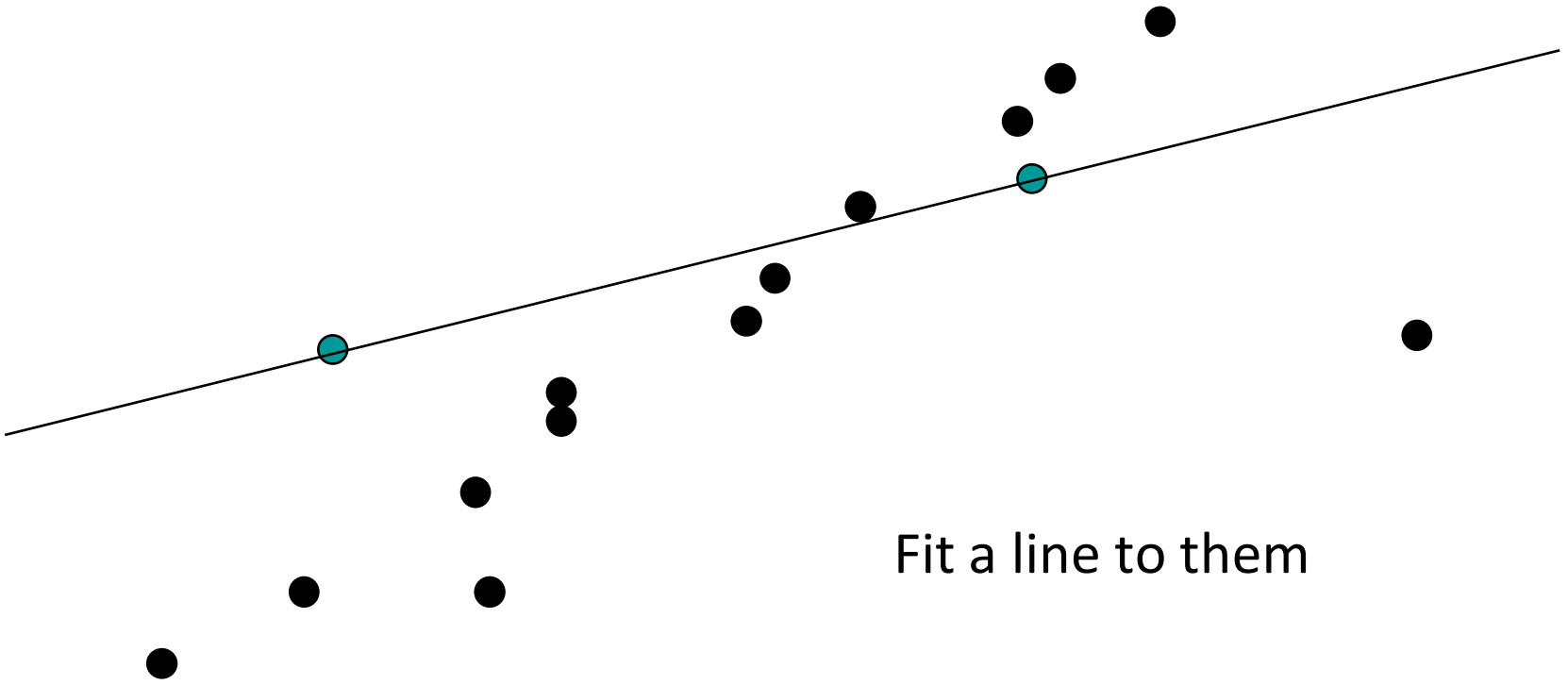
- Task: Estimate the best line



Slide credit: Jinxiang Chai

RANSAC Line Fitting Example

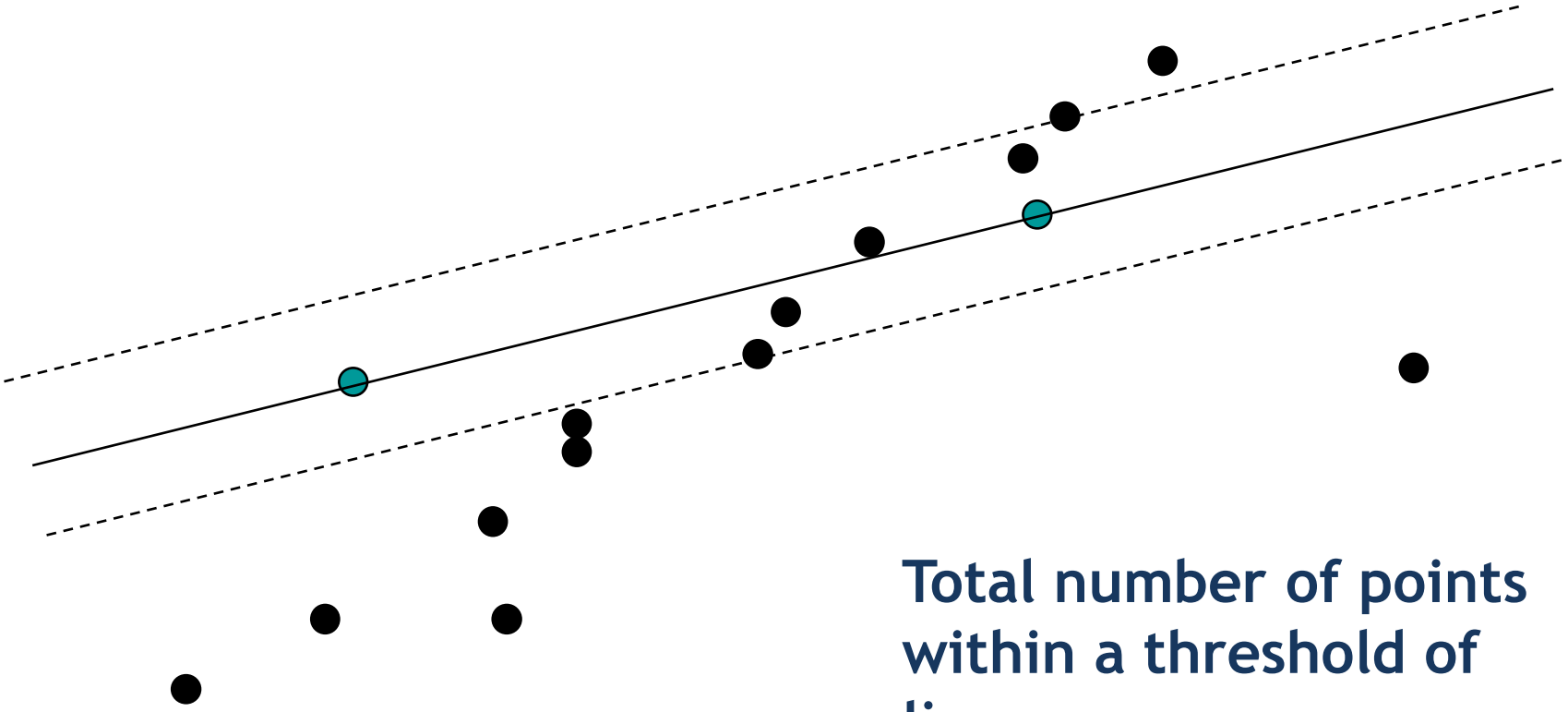
- Task: Estimate the best line



Slide credit: Jinxiang Chai

RANSAC Line Fitting Example

- Task: Estimate the best line

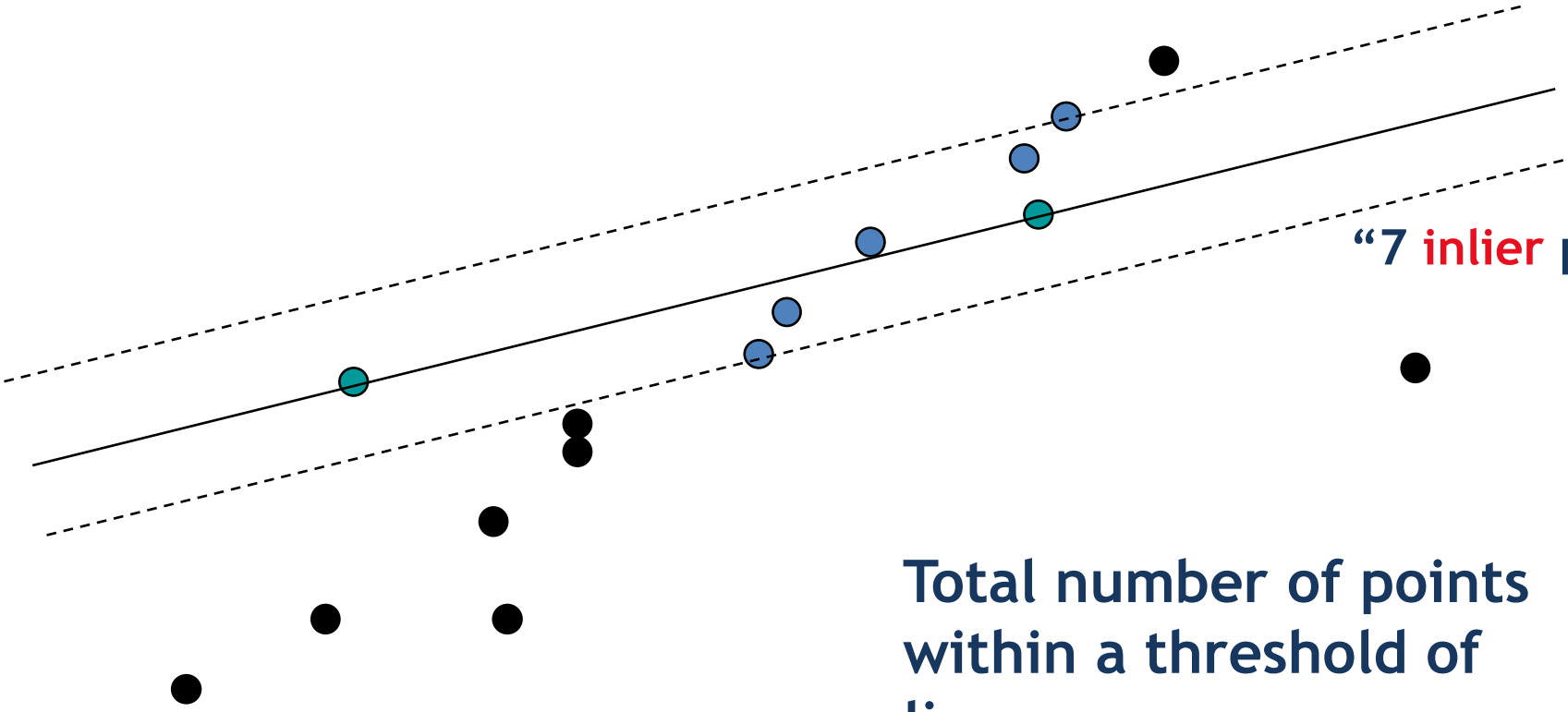


Total number of points within a threshold of line.

Slide credit: Jinxiang Chai

RANSAC Line Fitting Example

- Task: Estimate the best line



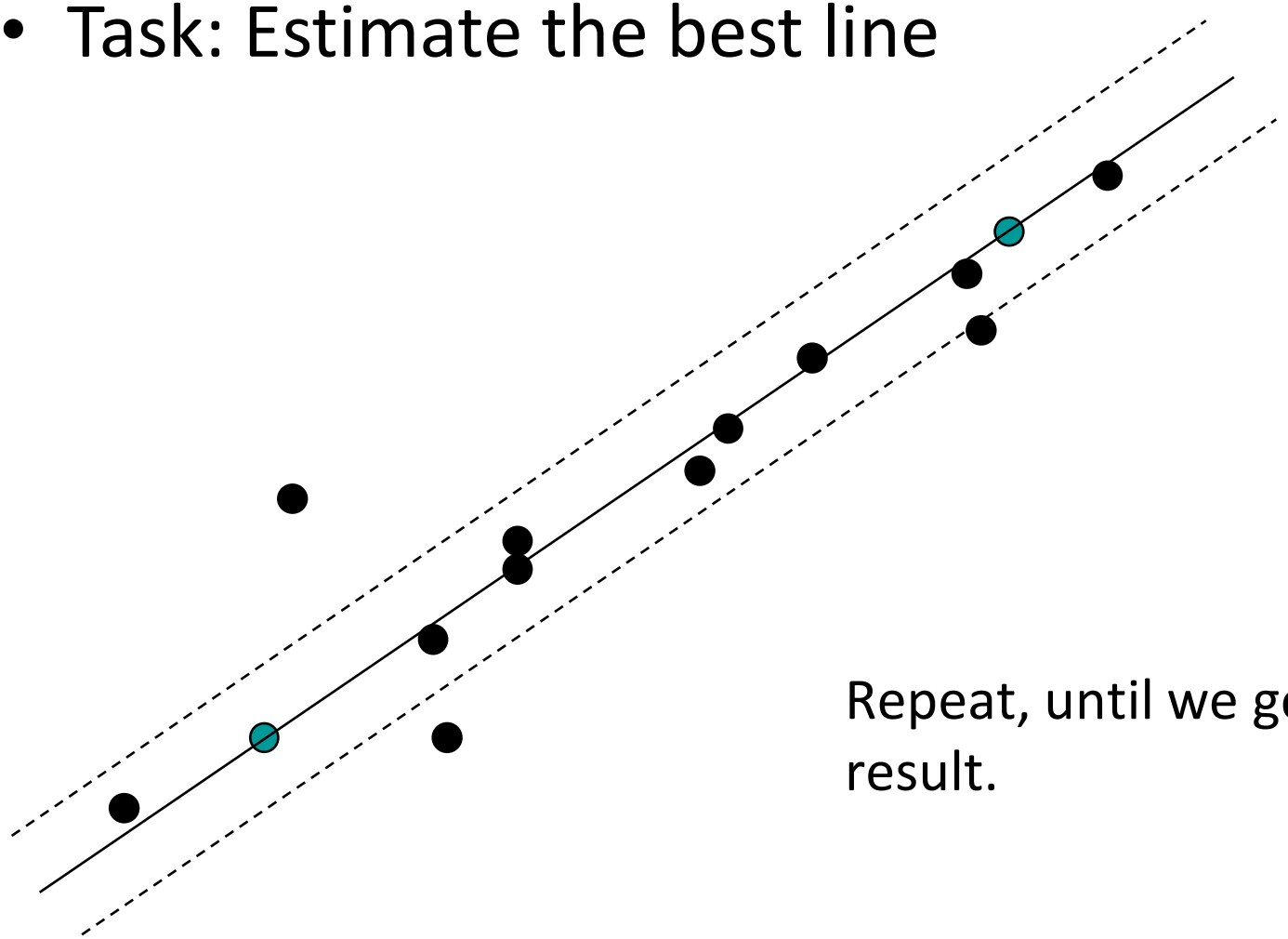
“7 inlier points”

Total number of points within a threshold of line.

Slide credit: Jinxiang Chai

RANSAC Line Fitting Example

- Task: Estimate the best line

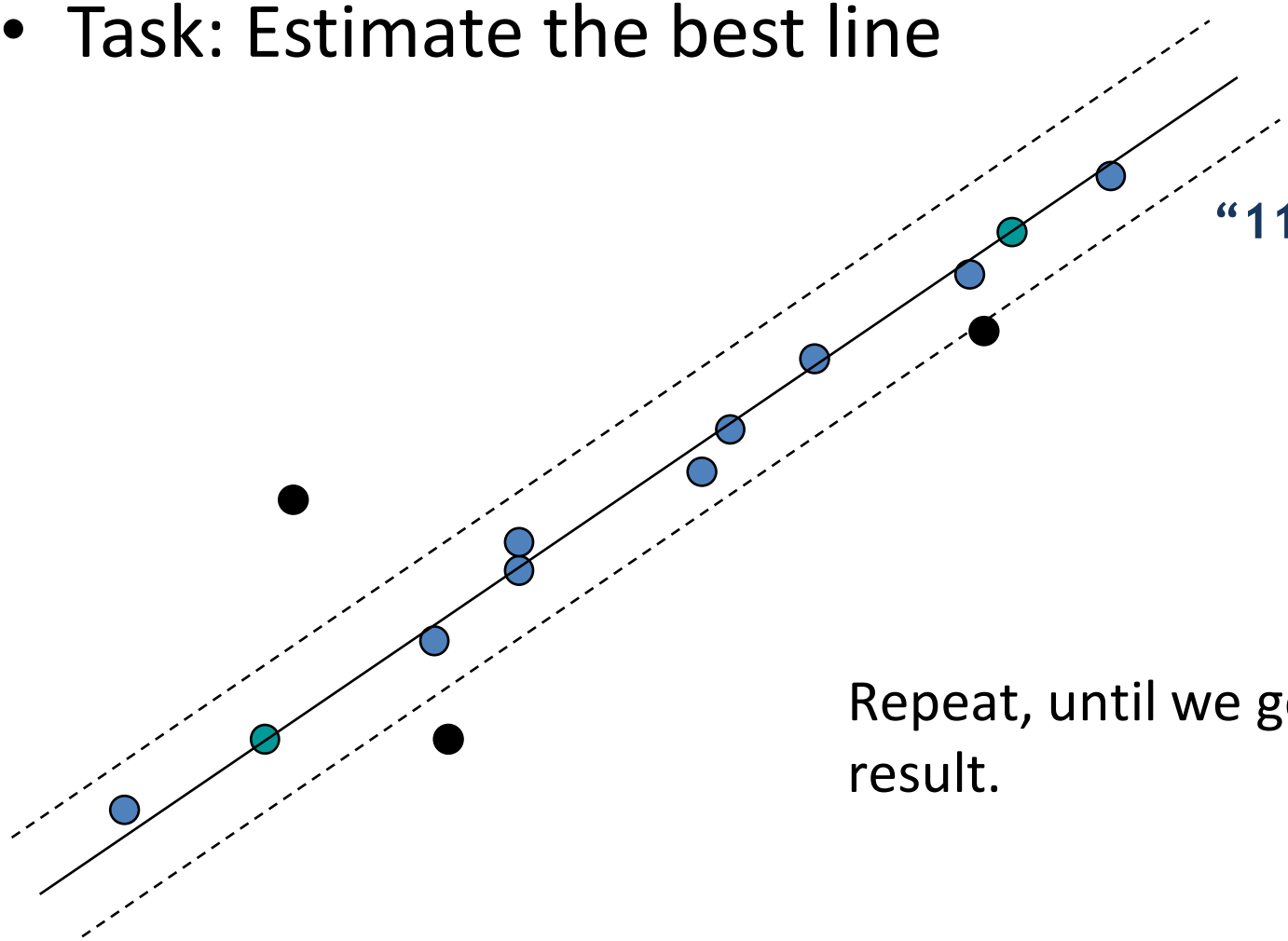


Repeat, until we get a good result.

Slide credit: Jinxiang Chai

RANSAC Line Fitting Example

- Task: Estimate the best line



"11 inlier points"

Repeat, until we get a good result.

Slide credit: Jinxiang Chai

Algorithm 15.4: RANSAC: fitting lines using random sample consensus

Determine:
    n — the smallest number of points required
    k — the number of iterations required
    t — the threshold used to identify a point that fits well
    d — the number of nearby points required
      to assert a model fits well
Until k iterations have occurred
    Draw a sample of n points from the data
      uniformly and at random
    Fit to that set of n points
    For each data point outside the sample
      Test the distance from the point to the line
        against t; if the distance from the point to the line
        is less than t, the point is close
    end
    If there are d or more points close to the line
      then there is a good fit. Refit the line using all
      these points.
end
Use the best fit from this collection, using the
  fitting error as a criterion

RANSAC: How many samples?

- How many samples are needed?
  - Suppose w is fraction of inliers (points from line).
  - n points needed to define hypothesis (2 for lines)
  - k samples chosen.
- Prob. that a single sample of n points is correct: w^n
- Prob. that all k samples fail is: $(1-w^n)^k$

$\Rightarrow$ Choose k high enough to keep this below desired failure rate.

Slide credit: David Lowe

RANSAC: Computed k (p=0.99)

Sample size n	Proportion of outliers						
	5%	10%	20%	25%	30%	40%	50%
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

Slide credit: David Lowe

RANSAC: Pros and Cons

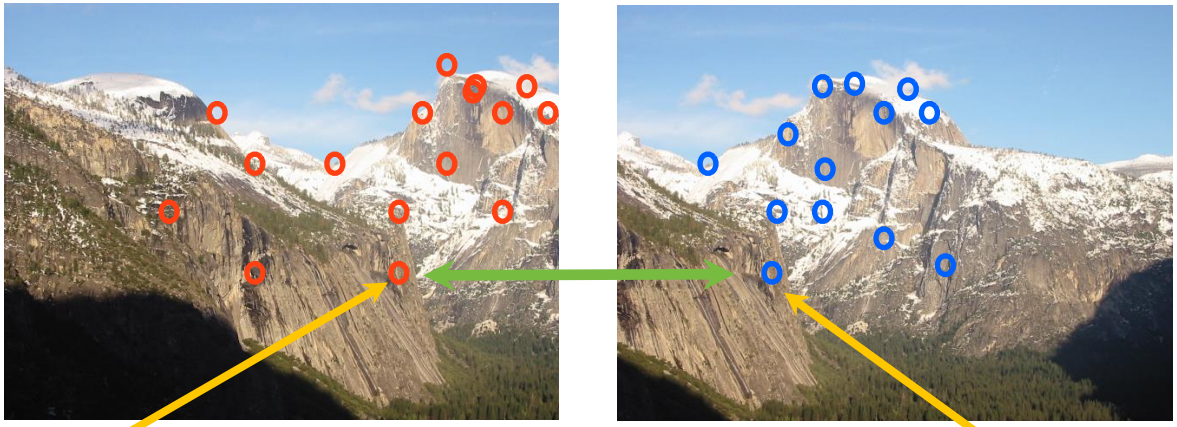
- **Pros:**
  - General method suited for a wide range of model fitting problems
  - Easy to implement and easy to calculate its failure rate
- **Cons:**
  - Only handles a moderate percentage of outliers without cost blowing up
  - Many real problems have high rate of outliers (but sometimes selective choice of random subsets can help)
- The Hough transform can handle high percentage of outliers

Skeleton Code

- RANSAC
  - ComputeError

$$\left\| \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} - H \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} \right\|_2$$

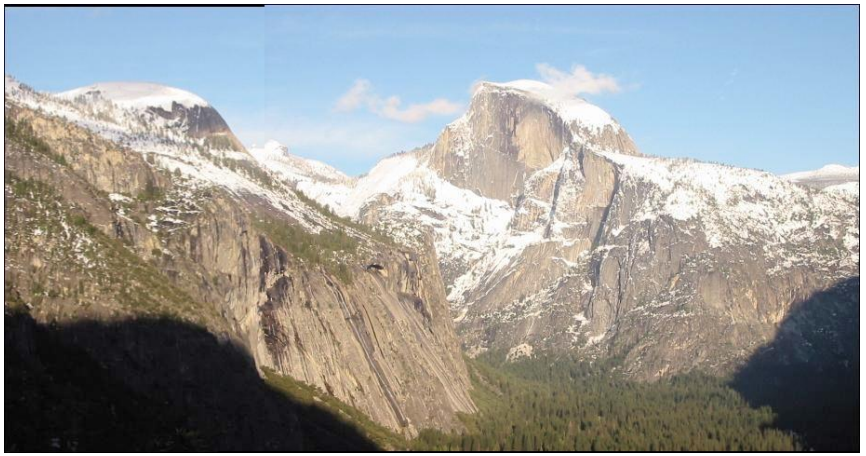
Main Flow



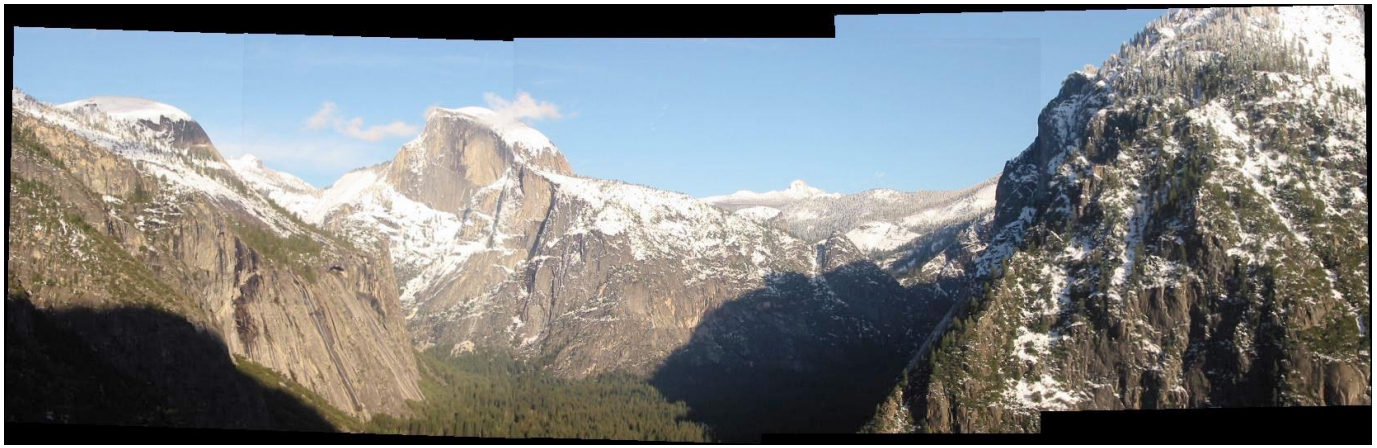
$(u_1, u_2, \ldots, u_{128})$

$(v_1, v_2, \ldots, v_{128})$

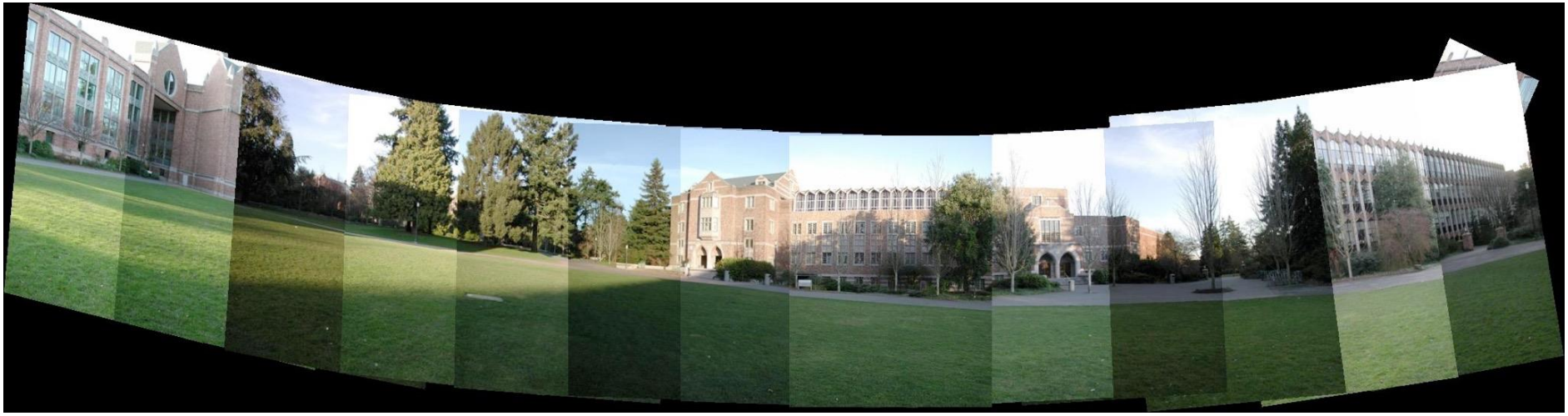
- Detect key points
- Build the SIFT descriptors
- Match SIFT descriptors
- Fitting the transformation
- RANSAC



Results

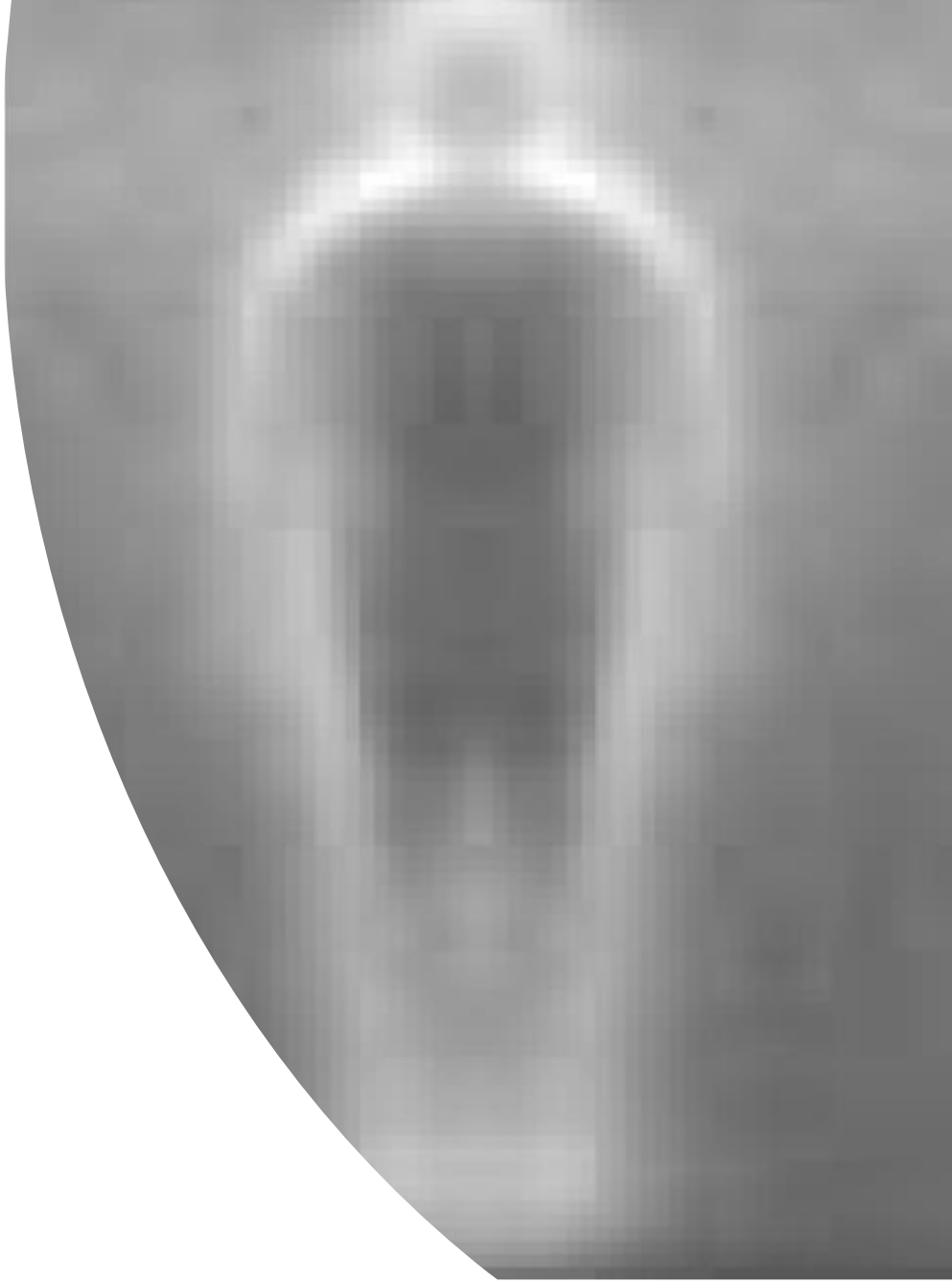


Results



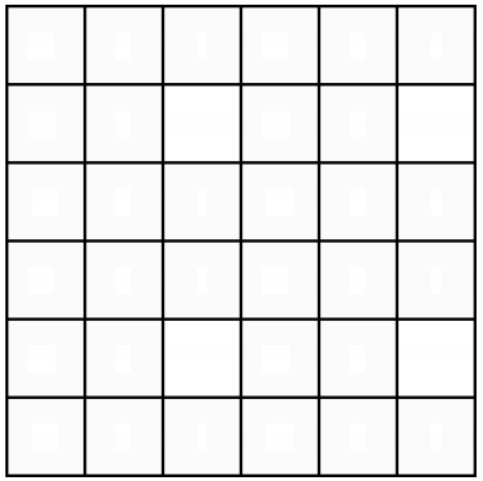
Histogram of Oriented Gradients

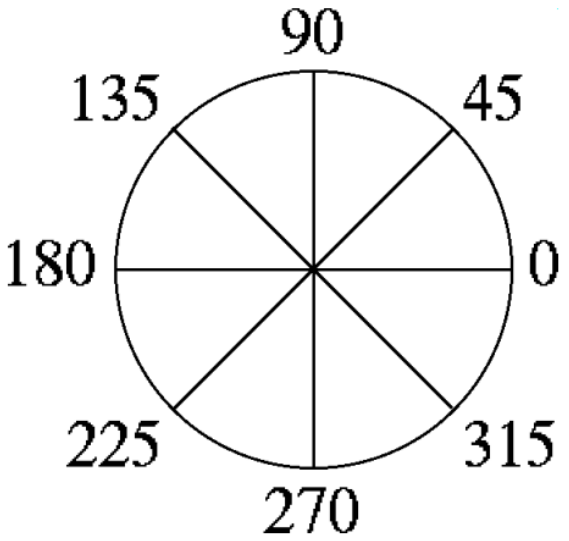
- Local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients or edge directions.



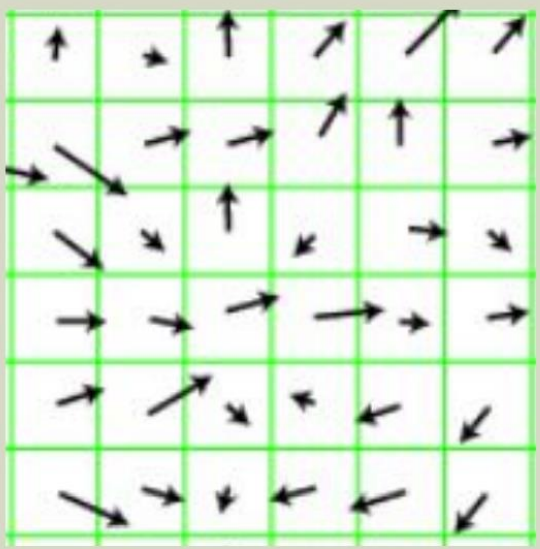
Histogram of Oriented Gradients

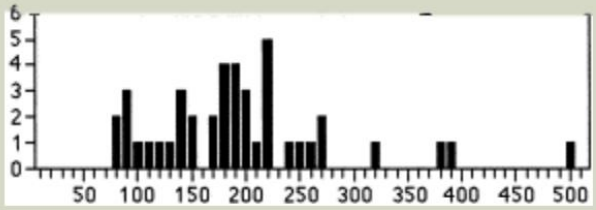
- Dividing the image window into small spatial regions (cells)
- Cells can be either rectangle or radial.
- Each cell accumulating a weighted local 1-D histogram of gradient directions over the pixels of the cell.



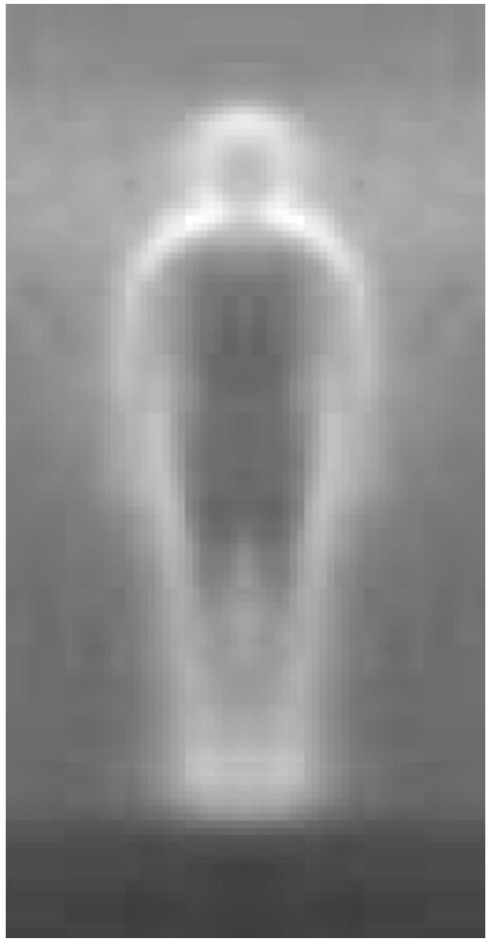


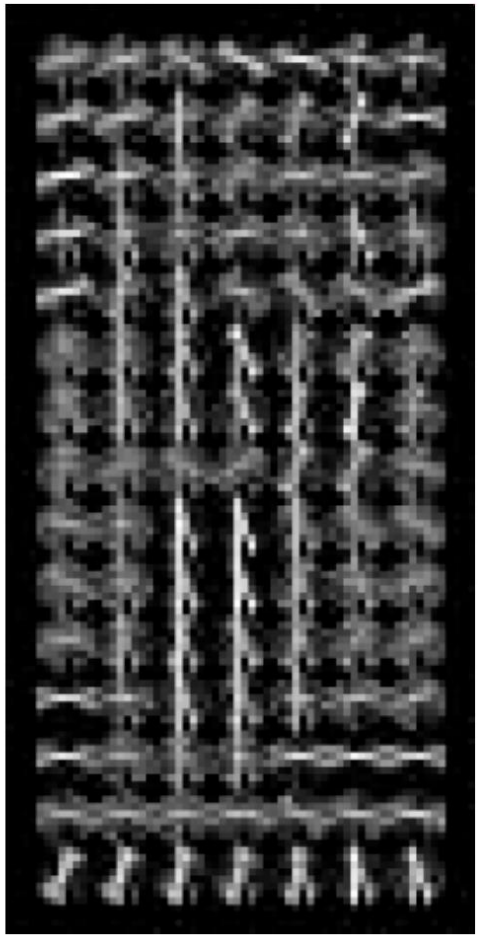
Histogram of Oriented Gradients





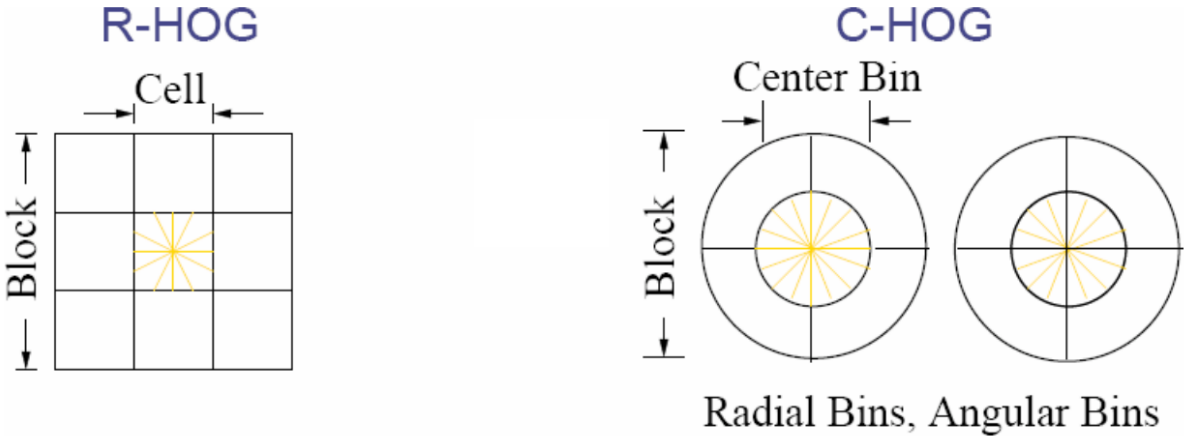
Histogram of Oriented Gradients



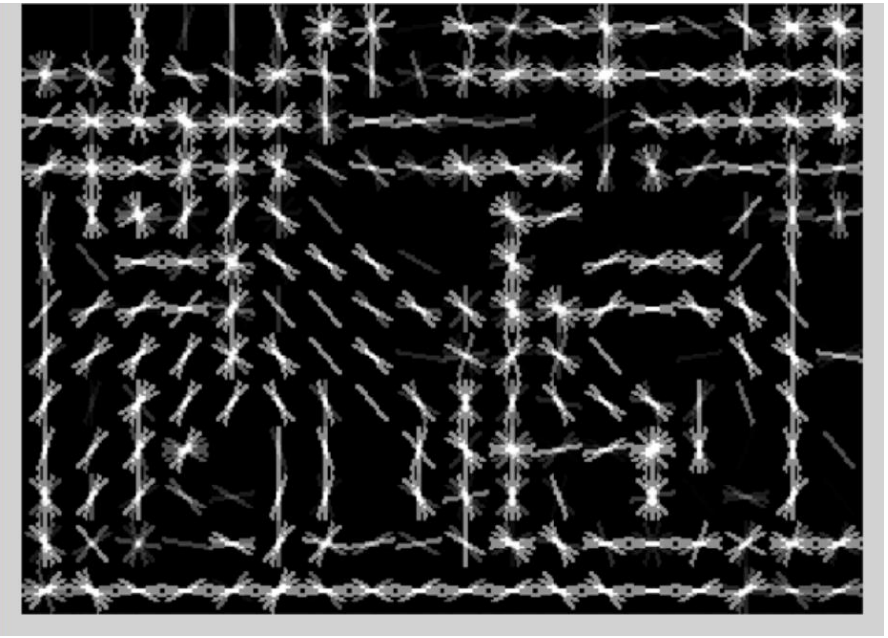


Normalization

- For better invariance to illumination and shadowing. it is useful to contrast-normalize the local responses before using them.
- Accumulate local histogram “energy” over a larger regions (“blocks”) to normalize all of the cells in the block.

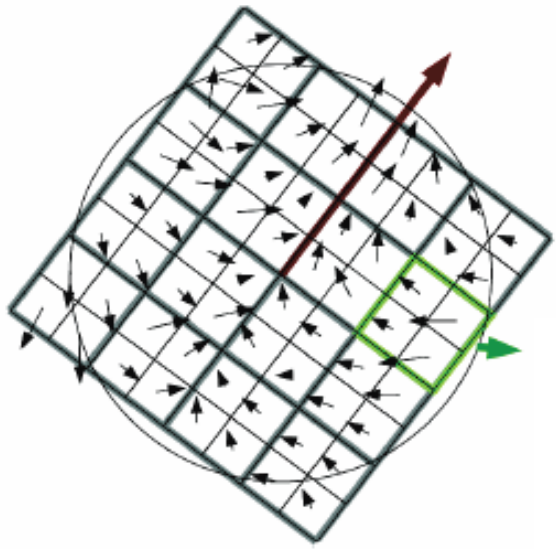


Visualizing HoG



SURF descriptor

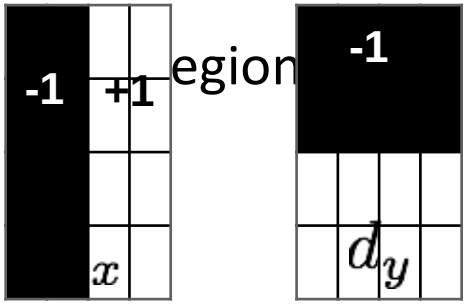
- Once interest point has been found
  - Place window around point
  - Divide into 4x4 sub-regions
  - In each sub-regions:
    - measure at 25 (5x5) places: dx and dy
    - sum over all 25 places to get 4 values:



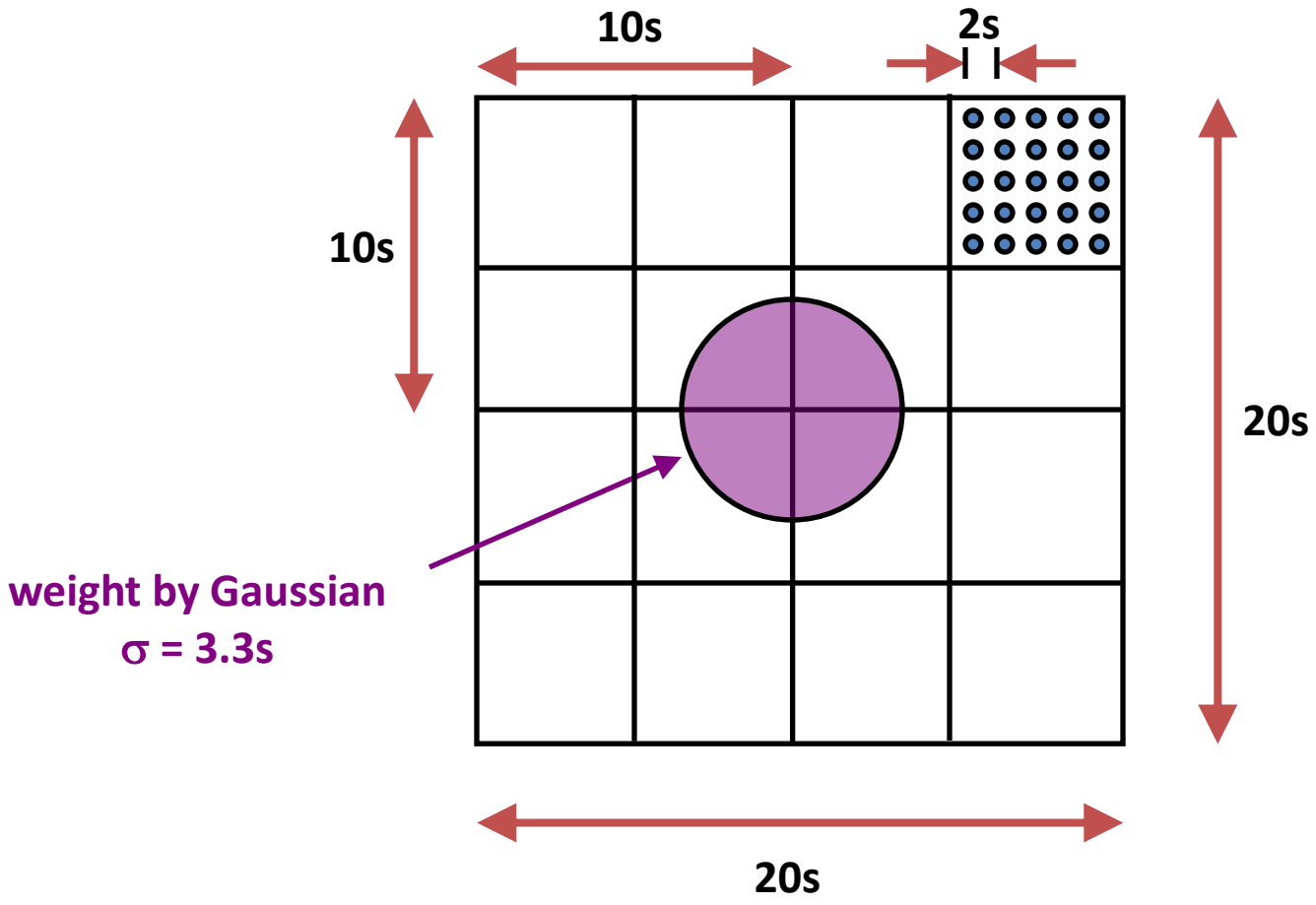
Haar wavelets filters

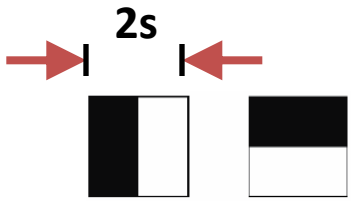
- Compute Haar wavelet response at each place in region

$$\left[\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right]$$

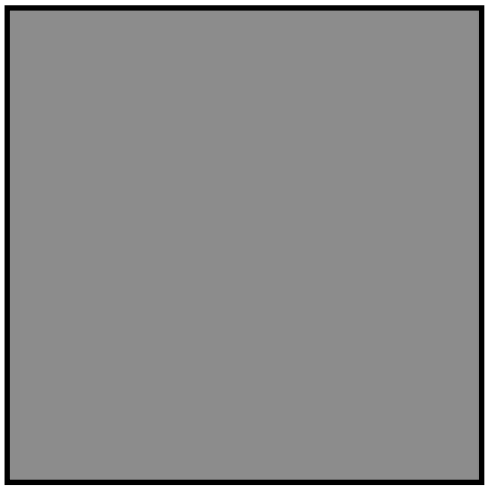


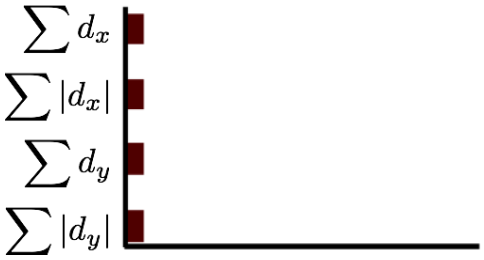
Details

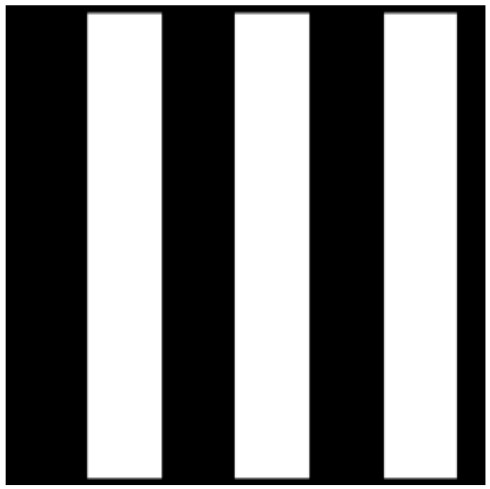


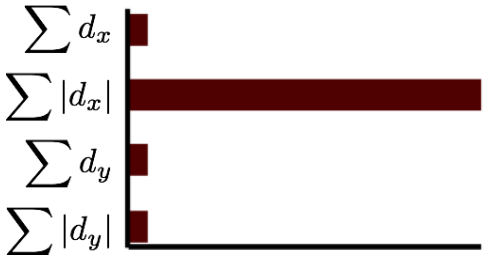


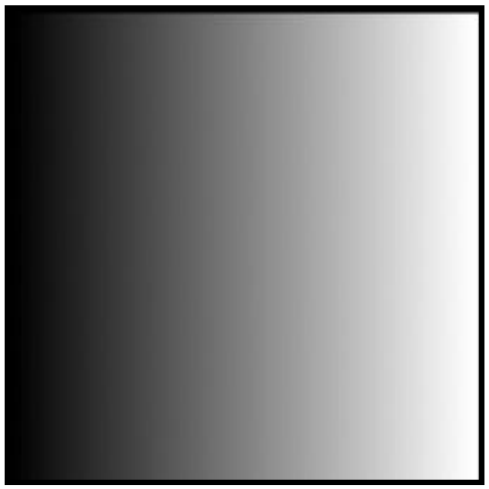
→ 65 values per interest point (16 x 4 + 1)

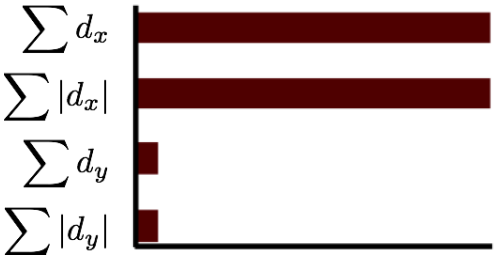



$\sum d_x$
$\sum |d_x|$
$\sum d_y$
$\sum |d_y|$




$\sum d_x$
$\sum |d_x|$
$\sum d_y$
$\sum |d_y|$




$\sum d_x$
$\sum |d_x|$
$\sum d_y$
$\sum |d_y|$