# 6 - Feature-matching

## Local features

### Approach to recognition

- Detect local features, ignore spatial position
    - Example: bag of words / bag of features L6.1 P12
        - Based on the method from NLP represent a document using a histogram of word frequency
        - In an image, “words” are local features
        - Problem: in images, the same “word” can have many appearances
        - Solution: combine similar local features, e.g., with k-means clustering
        - Bag of words/features = detect local features anywhere in the image, ignore location and spatial relations
- Local features + weak spatial relations
    - Spatial pyramid models  L6.1 P17
        - Main idea: run bag of features at multiple scales -> Multiscale pooling
        - Note that there’s a difference between:
            - Detecting features at one scale and pooling at multiple scales
            - Detecting features at multiple scales
        - Spatial pyramids add weak spatial relation information to the “bag of features” approach
- The above two methods generally works well for category-level recognition and have high invariance to object translation and pose
- Detect local features and model spatial relations between them
    - Deformable parts models
    - Keypoint tracking / matching

### Feature detection

**Dense vs. sparse features L6.1 P24**

- Dense feature representation: compute local features everywhere
- Sparse feature representation : compute local features only at a few “important” points

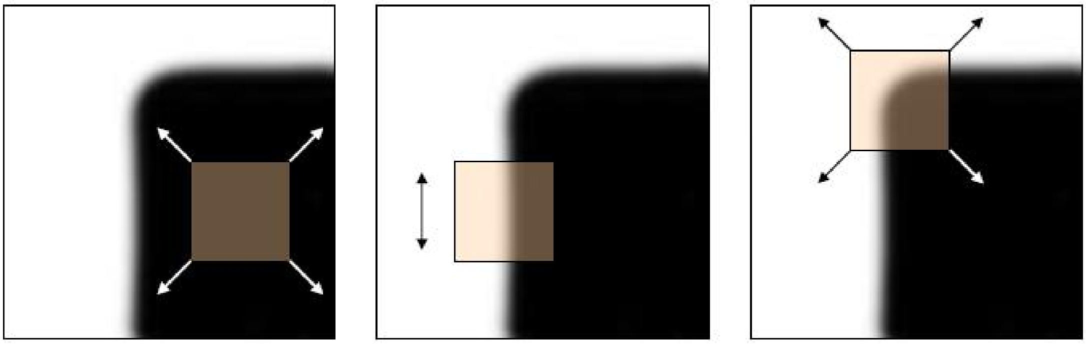
**Feature detection: finding “important” points (interest points or keypoints ) in images**

- Generally, points that can be detected reliably across image transformations

**Feature descriptor: a short code or set of numbers to represent a point in an image**

**Selecting good keypoints**

- Should be easy to recognize in a small window
- Shifting the window in any direction should produce a large change in intensity



Uniform = no change in any direction | Edge = no change along edge direction | Corner = change in all directions

## Corner detection L6.1 P30

- Change in appearance of window w(x,y) for the shift [u,v]:

$$E(u,v) = \sum_{x,y} \underbrace{w(x,y)}_{\text{Window function}} \left[ \underbrace{I(x+u, y+v)}_{\text{Shifted intensity}} - \underbrace{I(x,y)}_{\text{Intensity}} \right]^2$$

- Common window functions: square, Gaussian
- Approximate shifted intensity using Taylor series:

$$E(u,v) = \sum_{x,y} w(x,y) \left[ I(x+u, y+v) - I(x,y) \right]^2$$

$$E(u,v) \approx \sum_{x,y} w(x,y) [I(x,y) + u\underbrace{I_x}_{\frac{\partial I}{\partial x}} + v\underbrace{I_y}_{\frac{\partial I}{\partial y}} - I(x,y)]^2$$

$$= \sum_{x,y} w(x,y) [uI_x + vI_y]^2$$

$$= \sum_{x,y} w(x,y) \begin{pmatrix} u & v \end{pmatrix} \begin{bmatrix} I_x I_x & I_x I_y \\ I_x I_y & I_y I_y \end{bmatrix} \begin{pmatrix} u \\ v \end{pmatrix}$$

- Simplifies to: $E(u,v) \approx [u \ \ v] \ M \begin{bmatrix} u \\ v \end{bmatrix}$

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

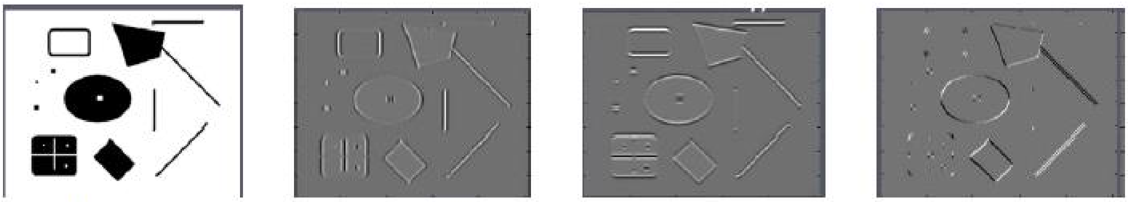
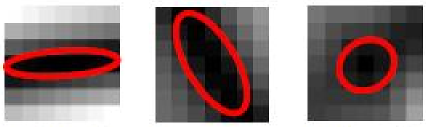


Image $\quad I_x = \frac{\partial I}{\partial x} \quad I_y = \frac{\partial I}{\partial y} \quad I_x I_y = \frac{\partial I}{\partial x}\frac{\partial I}{\partial y}$

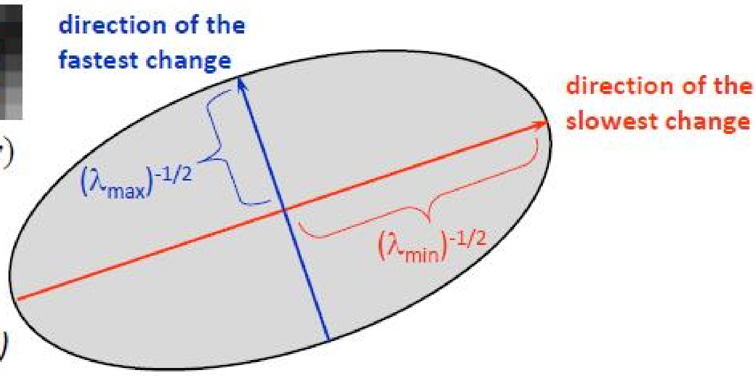
**Corner response function**

- Detect corners using eigenvalues $\lambda_1, \lambda_2$ of M

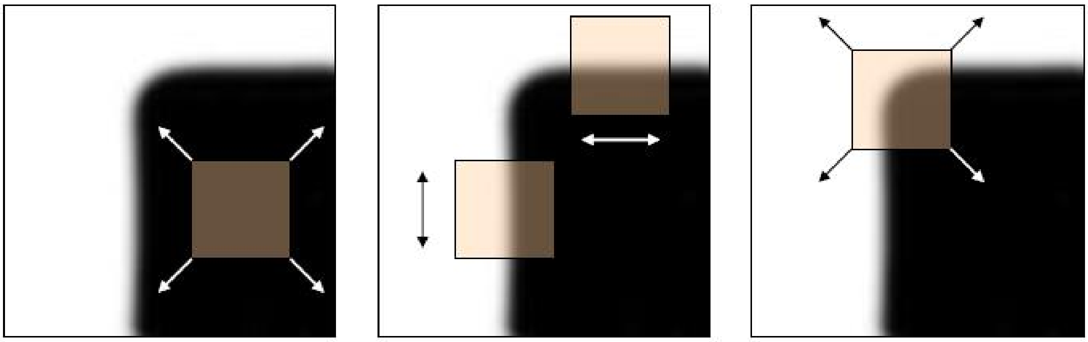
$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



$E(u,v) \quad E(u,v) \quad E(u,v)$




Iso-intensity contour of *E(u,v)*



Uniform: $\lambda_1$ and $\lambda_2$ are small

Edge: $\lambda_1 >> \lambda_2$
$\lambda_2 >> \lambda_1$

Corner: $\lambda_1$ and $\lambda_2$ are large

To find corners, look for points where $\lambda_1\lambda_2$ is high, and $\lambda_1 + \lambda_2$ is low

**Harris corners L6.1 P39**

- $\lambda_1\lambda_2$ and $\lambda_1 + \lambda_2$ are the determinant and trace of matrix M:
  - det = np.linalg.det(m) $\qquad \det(M) = \lambda_1\lambda_2$
  - trace = m.trace() $\qquad \mathrm{tr}(M) = \lambda_1 + \lambda_2$

- Harris corner response: $R = \det(M) - k(\mathrm{tr}(M))^2$

  k determined empirically, around 0.04-0.06

**Invariance / tolerance**

- Corner detection is based on the image gradient (edges), so it's
  - Invariant to translation
  - Tolerant to changes in lighting
- Because the corner response is based on eigenvalues, it is invariant to image plane rotation
- Not invariant to scale!

**Alternatives to Harris corners L6.1 P44**

**Summary - Corner detection**

- Rather than detecting local features everywhere, feature detectors can be used to find "important" points (interest points or keypoints)
- Common type of interest point = corners
- Corners can be detected from local gradients

## Feature descriptors

- Having found keypoints in an image, we need a way to represent them
- Options:
  - Image patch
  - Handcrafted descriptors

        - SIFT
        - GLOH
        - BRIEF
        - BRISK
        - ORB
    - Machine learned descriptors

**Scale-Invariant Feature Transform (SIFT) L6.1 P48**

- Compute gradient, take histograms in a grid of pixels around interest point
- Weight gradient magnitudes based on distance from centre of patch
- Normalise histograms to sum to 1
- SIFT implementation details:
    - Patch size = 16 x 16 pixels
    - Grid = 4 x 4 cells
    - Histogram bins = 8 orientations
    - Gaussian weighting from centre of patch
    - Two step normalisation: normalise to sum to 1, truncate values to 0.2, normalise to sum to 1
- Descriptor length = 4 x 4 x 8 = 128
- Interest points (blobs) are detected at multiple scales; descriptor is based on the scale with maximum response
- Histograms are encoded relative to the main orientation in the patch

**Summary - Feature descriptors**

- Feature descriptor = a code to represent a local patch or interest point in an image
- Many handcrafted feature descriptors, with different:
    - Encoding method
    - Speed
    - Descriptor size
    - Feature detection method
- Goal of feature descriptors is invariance, so points can be matched reliably across image transforms

## Summary - Local features

- Most recognition approaches are based on local features, but differ in how they represent spatial relations between features:
    - Bag of features methods: no spatial information
    - Feature detection methods: precise spatial information
- Choice of approach depends on task
    - Spatial information is probably not needed for category level recognition
    - Spatial information is useful for tasks that require matching structures across images

## Feature matching

- **Goal**
  - Simultaneously recognise object and its pose in 3D
  - Track features across multiple views
- **Challenges**
  - Features will have different appearance in each view (due to changes in pose, lighting, etc.)
  - Some features visible in one view may be missing in the other
  - Background could contain similar “matching” features

#### Feature matching as model fitting

- Not just looking for same features, but same spatial arrangement of features
- Model fitting problem:
  - Propose a model that explains correspondence between matched points
  - Find points that fit model / measure goodness of fit / find model parameters
- Problems:
  - Outliers (data not explained by model)
  - Noise in data that is explained by model

### Hough transform L6.2 P10

- Each edge point “votes” for the lines that pass through that point
- Identify lines with the most “votes”
- Identifying the parameters with most votes is easy if there is no noise in point locations
  - Usually there is some noise
  - Solution to noise: bin parameters
  - Points vote for bins
- Another problem: slope and intercept (m,b) are unbounded
  - Solution: use a polar representation of (m,b)

#### Hough transform parameters

- Bin size
- Threshold for peaks
- Number of peaks (= number of lines)
- Minimum line/segment length
- Maximum allowed gap (to treat segments as the same line)

#### Summary - Hough transform

- Hough transform is a method for detecting structure in images
- Each pixel “votes” for parameters
- Common applications:
  - Line detection
  - Circle detection
- Hough transform is basically a grid search over all possible values of each parameter

- Limit to just a few parameters for efficiency

## RANSAC

- RANSAC = Random Sample Consensus
- Like Hough transform, points "vote" for the model that explains those points
- Iteratively:
  - Sample N points at random (when N is the number of points needed to fit the model)
  - Calculate model parameters
  - Count the number of points that are explained by the model (inlier points)
- Best model = model that explains the most points

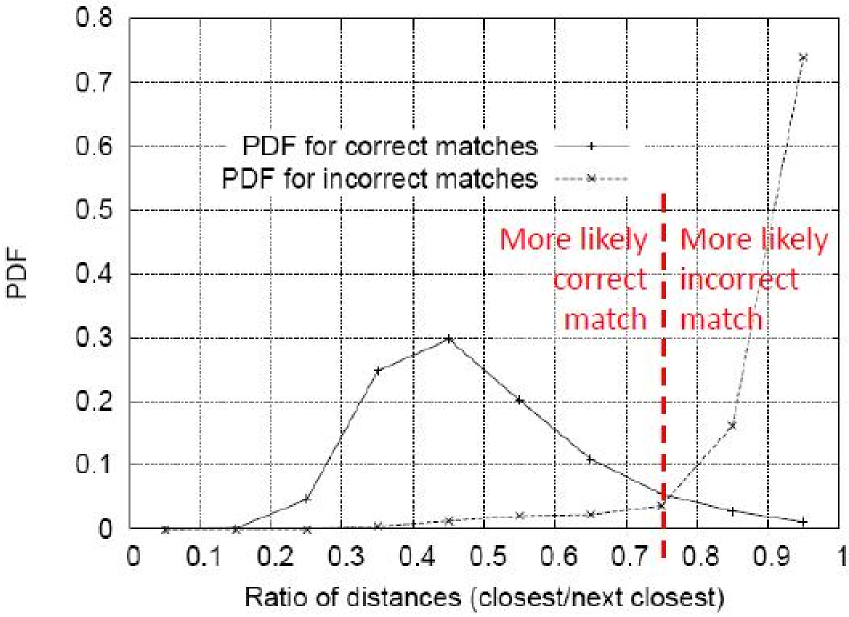
**Demo: L6.2 P29-33**

**RANSAC parameters**

- Number of iterations
  - Should be high enough that it is very likely (e.g., prob=0.99) that you will obtain at least one sample with no outliers
  - Example: Half of your data is outliers, and you want to fit a line. How many samples?
- Threshold for inliers
  - Ensure a good point with noise is likely (e.g., prob=0.95) within threshold

## Feature matching

- Step 1. Find keypoints + descriptors in each image
- Step 2. Find candidate matches: for each keypoint in image 1, find most similar match in image 2
- Problems:
  - Many keypoints, many similar features - false matches are likely
  - For more robust matching, consider ratio (similarity to best match / similarity to second best)
- Reducing false matches




- Exhaustive matching is very slow (O(m*n)), m,n = number of keypoints in each image

- More efficient option: approximate nearest neighbours
    - Faster, but may not find the closest match
- Even with ratio matching, proportion of false matches is likely to be very high
- Step 3. Use RANSAC to find subset of matches that can be explained by a transformation model

### Transformation between two camera views L6.2 P41

- Affine transformation (仿射变换): any combination of translation, scale, rotation, and shear L6.2 P43
    - Lines map to lines
    - Parallel lines remain parallel
    - Ratios are preserved
- Projective transformation combines affine transformation with a projective warp (弯曲) L6.2 P44
    - Lines map to lines
    - Parallel lines may not remain parallel
    - Ratios are not preserved
- 2D planar transformation L6.2 P45

### How many points do you need to define a projective transform? L6.2 P46

- Projective transform can include any combination of scaling, rotation, affine shift, and projective warp
- One point is insufficient to recognize any transform
- Two points - can't distinguish between different combinations of scaling, shift, and warp
- Three points sufficient to recognize an affine only transform
    - But can't distinguish between affine only and projective transforms
- Four points - unique solution

### Feature matching with RANSAC

1. Randomly sample the number of points needed to fit model (e.g., 4 for projective)
2. Compute model parameter from points
3. Count inlier points

- Repeat until max iterations, take model with most inliers

### Summary - Feature matching

- Feature matching with RANSAC finds matching keypoints across images
- Finds matching points across views, and computes the transformation that relates those points
- Applications:
    - Instance recognition
    - Video stabilisation
    - Panorama ing
    - Finding planes, vanishing points, etc. in images
    - 3D reconstruction