Visual Features - Descriptors

Computer Vision CMP-6035B

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Visual Features

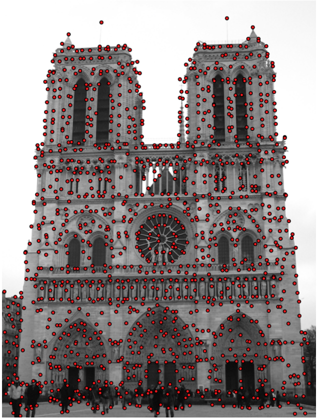

Figure 1: keypoints

Why do we want to find image features?

- Image summary.
- Classification.
- Image retrieval.
- 3D reconstruction.

How do we **describe** keypoints in a way that similar points can be matched?

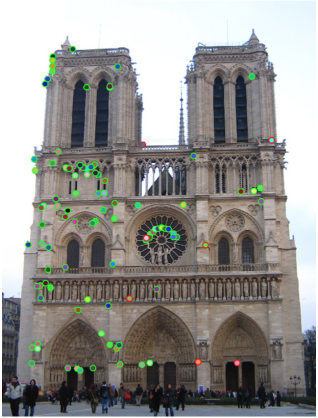

Figure 2: view 1

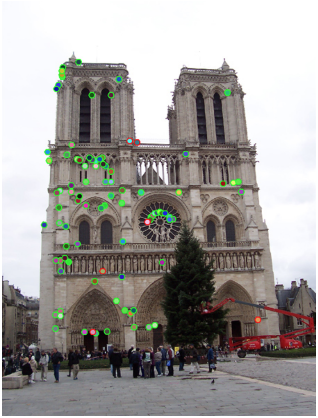

Figure 3: view 2

Keypoint and Descriptor

An important distinction:

- Keypoint is a distinct **location** in an image
- Descriptor is a summary **description** of that neighbourhood.

Keypoint and Descriptor

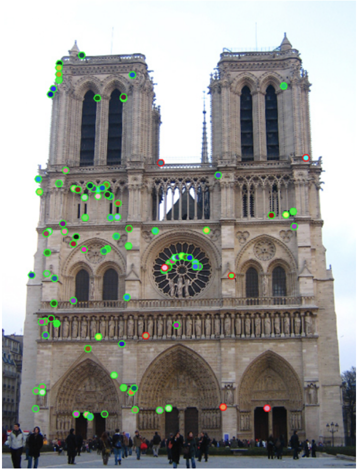

Figure 4: keypoints and descriptors

keypoint: $(x,\ y)$
descriptor *at* the keypoint:

$$\begin{bmatrix} 0.02 \\ 0.01 \\ 0.10 \\ 0.05 \\ 0.01 \\ \dots \end{bmatrix}$$

Descriptors

- HOG: Histogram of Oriented Gradients
- SIFT: Scale Invariant Feature Transform
- SURF: Speeded-Up Robust Features
- GLOH: Gradient Location and Orientation Histogram
- BRIEF: Binary Robust Independent Elementary Features
- ORB: Oriented FAST and rotated BRIEF
- BRISK: Binary Robust Invariant Scalable Keypoints
- FREAK: Fast REtinA Keypoint

... and many more

Descriptors

Describing a keypoint.

- SIFT : Scale-Invariant Feature Transform
- BRIEF : Binary Robust Independent Elementary Features
- ORB : Oriented FAST and Rotated BRIEF

SIFT

Scale-Invariant Feature Transform

SIFT Features

Image content is transformed into features that are **invariant** to:

- image translation
- image rotation
- image scale

SIFT Features

SIFT Features are *partially* invariant to:

- illumination changes
- affine transformations and 3D projections

SIFT Features

SIFT Features are *suitable* for detecting visual landmarks:

- from different angles and distances.
- with a different illumination.

DoG over Scale-Space Pyramid

Over different image pyramid levels:

1. Gaussian smoothing.
2. Difference-of-Gaussians (DoG) and find **extrema**.
3. *Maxima* suppression for edges.

SIFT Features

A SIFT feature is given by a vector computed at a local extreme point in the scale space.

$$\langle p, s, r, f \rangle$$

SIFT Features

$$\langle p, s, r, f \rangle$$

pixel location in the image

scale (extrema in scale space from DoG)

orientation from a histogram of local gradients

128D descriptor from local image gradients

Figure 5: SIFT vector

SIFT Features

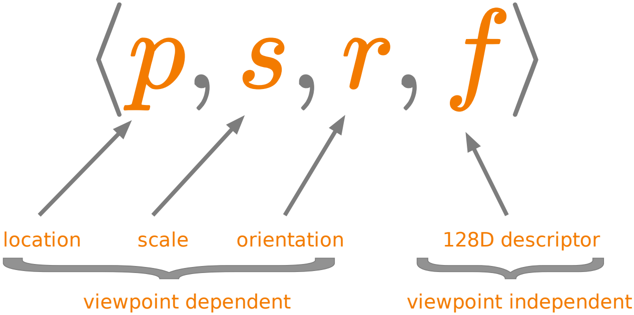

Figure 6: SIFT vector

SIFT Features

Figure 7: Input Image - Vedaldi & Fulkerson

From an input image we convert to grey scale then compute the Difference of Gaussians (DoG) and find the extrema.

SIFT Features

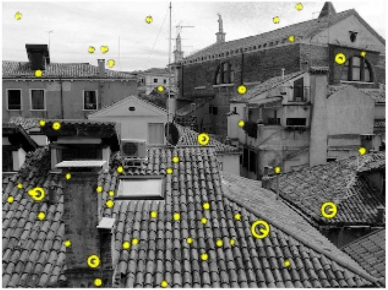

Figure 8: Keypoints, scale and orientation

We preserve the scale, and compute a peak of the histogram of orientations.

SIFT Features

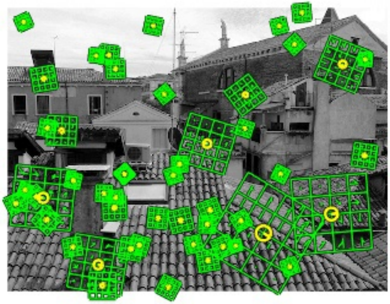

Figure 9: locally rotated patch

We compute a local patch, based on the scale and orientation.
It is from this patch we compute the 128D feature *descriptor* vector.

SIFT Descriptor

Compute image gradients in local 16x16 area at the selected scale.

- Create an array of orientation histograms
- 8 orientations x 4x4 histogram array = 128 dimensions

SIFT Descriptor

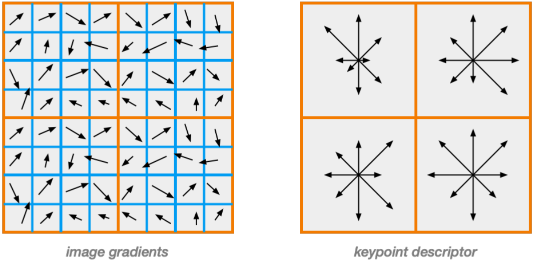

Figure 10: sift descriptor

SIFT Descriptor

Figure 11: rotate and scale to 16x16

SIFT Descriptor

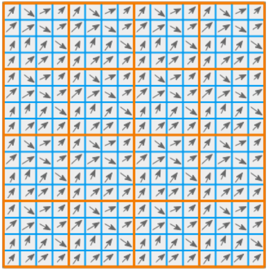

Figure 12: gradients and segregate to 16 x 4x4 regions

SIFT Descriptor

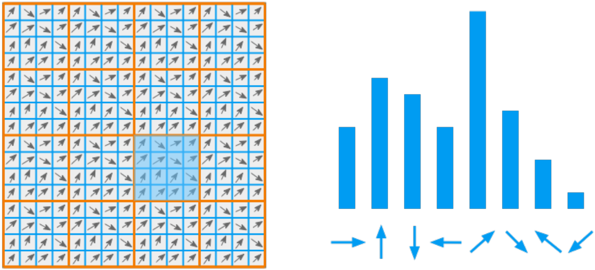

Figure 13: 4x4 region to 8 direction bins

SIFT Descriptor

Concatenate all histograms to form a 128D vector.

Figure 14: concatenate histograms

SIFT Descriptor

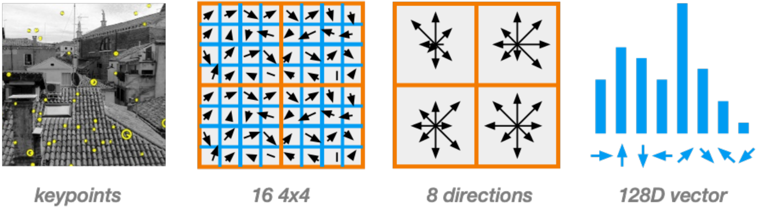

Figure 15: Descriptor Summary

SIFT Features

Keypoints : Using DoG

Descriptor : Using Gradient Histogram

Dense SIFT

Variation of the SIFT feature, where the keypoints are sampled over a uniform grid in the image domain, rather than using the sparse points from the DoG.

Dense SIFT

At each uniform grid point:

- Compute the SIFT descriptor.
- Cluster the descriptors into a vocabulary.
- K-means clustering.

Matching

How do we match features from two images?

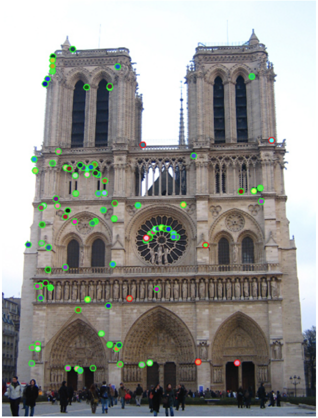

Figure 16: view 1

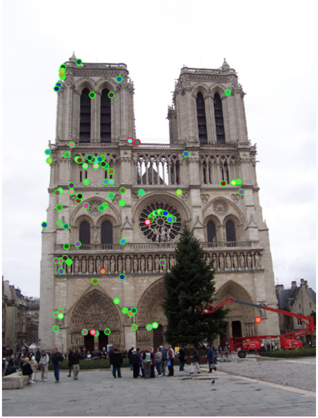

Figure 17: view 2

Distance Matching

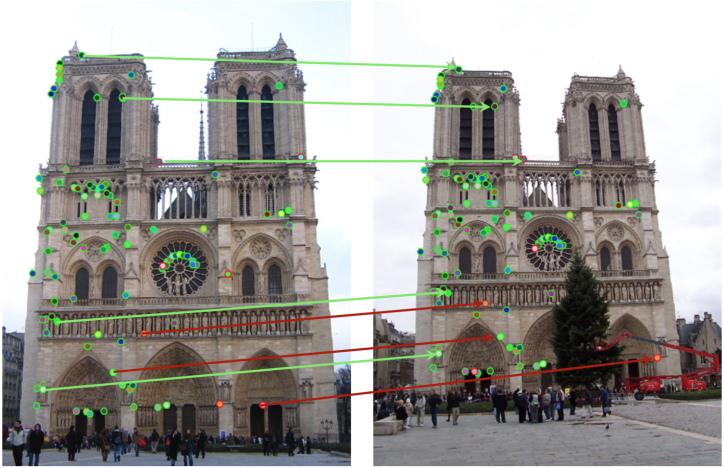

Figure 18: descriptor distance

Ratio Test

Eliminate ambiguous matches for a query feature q.

1. Find closest descriptors, p_1 and p_2 using **Euclidian** distance.
2. Test if distance to best match is smaller than a threshold:

$$d(q, p_1) < t$$

3. Accept only if the best match is substantially better than second:

$$\frac{d(q, p_1)}{d(q, p_2)} < \frac{1}{2}$$

Ratio Test

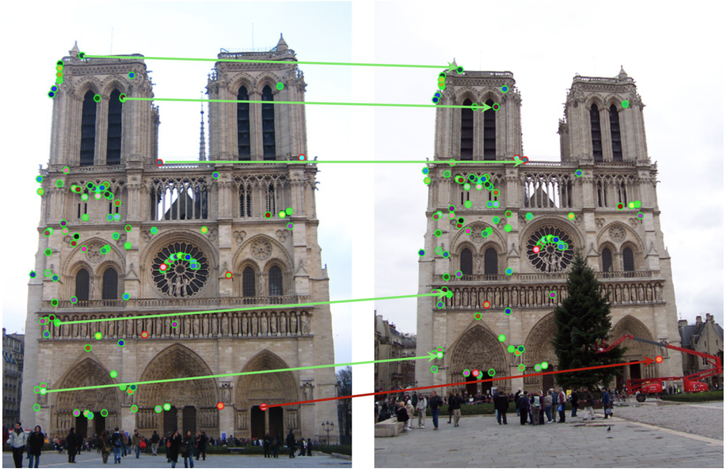

Figure 19: ratio test

Ratio Test

Lowe's Ratio test works well.

- There will still be a few outliers.
- Outliers require extra treatment.

Binary Descriptors

Computing descriptors *fast*

Why Binary Descriptors?

Complex features such as SIFT work well, but. . .

- SIFT is *expensive* to compute.
- SIFT ~~has~~ **had** patenting issues.
- Binary descriptors are easy to compute *and* compare.

Key Idea of Binary Descriptors

- Select a region around a keypoint.
- Select a *set* of pixel **pairs** in that region
- For each pair, compare the intensities.
- concatenate all b to a string.

$$b = \begin{cases} 1, & \text{if } I(s_1) > I(s_2) \\ 0, & \text{otherwise} \end{cases}$$

Example

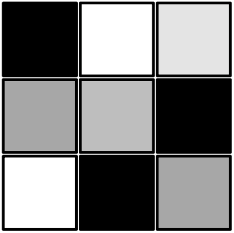

Figure 20: image region

1	2	3
4	5	6
7	8	9

Figure 21: region index

- pairs: $\{(5,1),(5,9),(4,6),(8,2),(3,7)\}$
- test: $b=0,\ b=0,\ b=0,\ b=1,\ b=1$
- result: $B = 00011$

Advantages of Binary Descriptors

Compact descriptor

- The number of pairs gives the length in bits

Advantages of Binary Descriptors

Fast to compute

- Simply intensity value comparisons

Advantages of Binary Descriptors

Trivial and fast to compare *Hamming* distance:

$$d_{Hamming}(B_1, B_2) = sum(xor(B_1, B_2))$$

Different binary descriptors differ mainly by the strategy of selecting the pairs.

Important

In order to compare descriptors we must:

- Use the same pairs
- Maintain the same order in which the pairs are tested.

BRIEF

Binary Robust Independent Elementary Features.

- BRIEF: Binary Robust Independent Elementary Features.
- Calonder, et al. 2010.

BRIEF

First binary image descriptor.

- Proposed in 2010
- 256 bit descriptor
- Provides five different sampling strategies
- Operations performed on a smoothed image to deal with noise

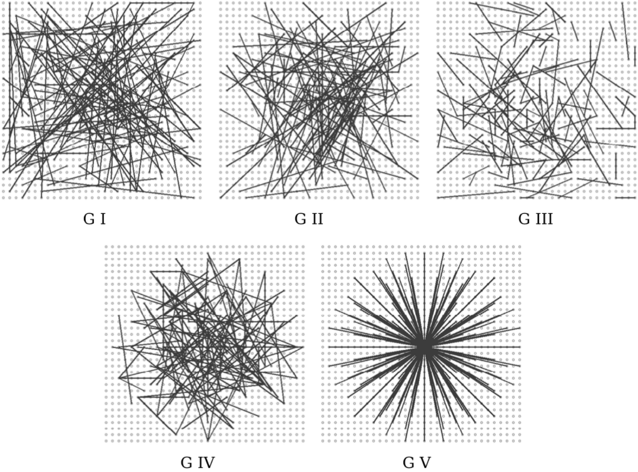

Figure 22: BRIEF sampling pairs

BRIEF sampling pairs

- G I: Uniform random sampling
- G II: Gaussian sampling
- G III: s_1 Gaussian; s_2 Gaussian centred around s_1 .
- G IV: Discrete location from a coarse polar grid.
- G V: $s_1 = (0, 0)$, s_2 are all locations from a coarse polar grid.

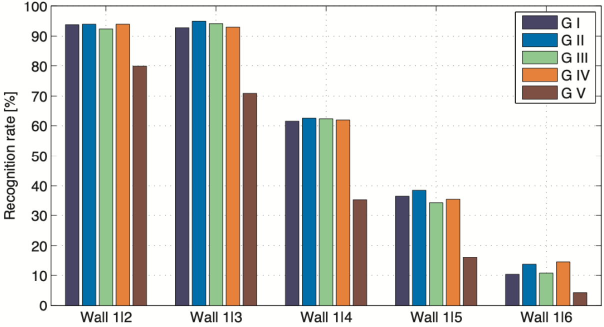

Figure 23: BRIEF sampling performance

ORB

Oriented FAST Rotated BRIEF.

- ORB: an efficient alternative to SIFT or SURF
- Rublee, et al. 2011.

ORB

An extension to BRIEF that:

- Adds rotation compensation.
- Learns the optimal sampling pairs.

ORB: Rotation Compensation

Estimates the centre of mass and the main orientation of the local area.

Image moment:

$$m_{pq} = \sum_{x,y} x^p y^q I(x, y)$$

Centre of Mass, Orientation:

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}} \right) \ , \ \theta = \operatorname{arctan2}(m_{01}, m_{10})$$

ORB: Rotation Compensation

Rotate the coordinates of all pairs by θ around C:

$$s' = T(C, \theta)s$$

- Use the transformed pixel coordinates for performing the test.
- Rotation is invariant in the image plane.

ORB: Learning Sampling Pairs

Pairs should be **uncorrelated**.

- each new pair adds new information to the descriptor

Pairs should have **high variance**.

- makes a feature more discriminative

ORB defines a strategy for selecting 256 pairs, optimising for these properties using a training database.

ORB versus SIFT

- ORB is 100x faster than SIFT
- ORB: 256 bit vs. SIFT: 4096 bit
- ORB is not scale invariant (achievable via an image pyramid)
- ORB mainly in-plane rotation invariant
- ORB has a similar matching performance as SIFT (w/o scale)
- Several modern online systems (e.g. SLAM) use binary features

Summary

- Keypoint and descriptor together define visual features
- Keypoint describes the appearance
- SIFT
- Binary descriptors

Reading:

- The papers mentioned in the lecture
- Forsyth, Ponce; Computer Vision: A modern approach, 2nd ed.
- VLFeat.org - nice tutorials.