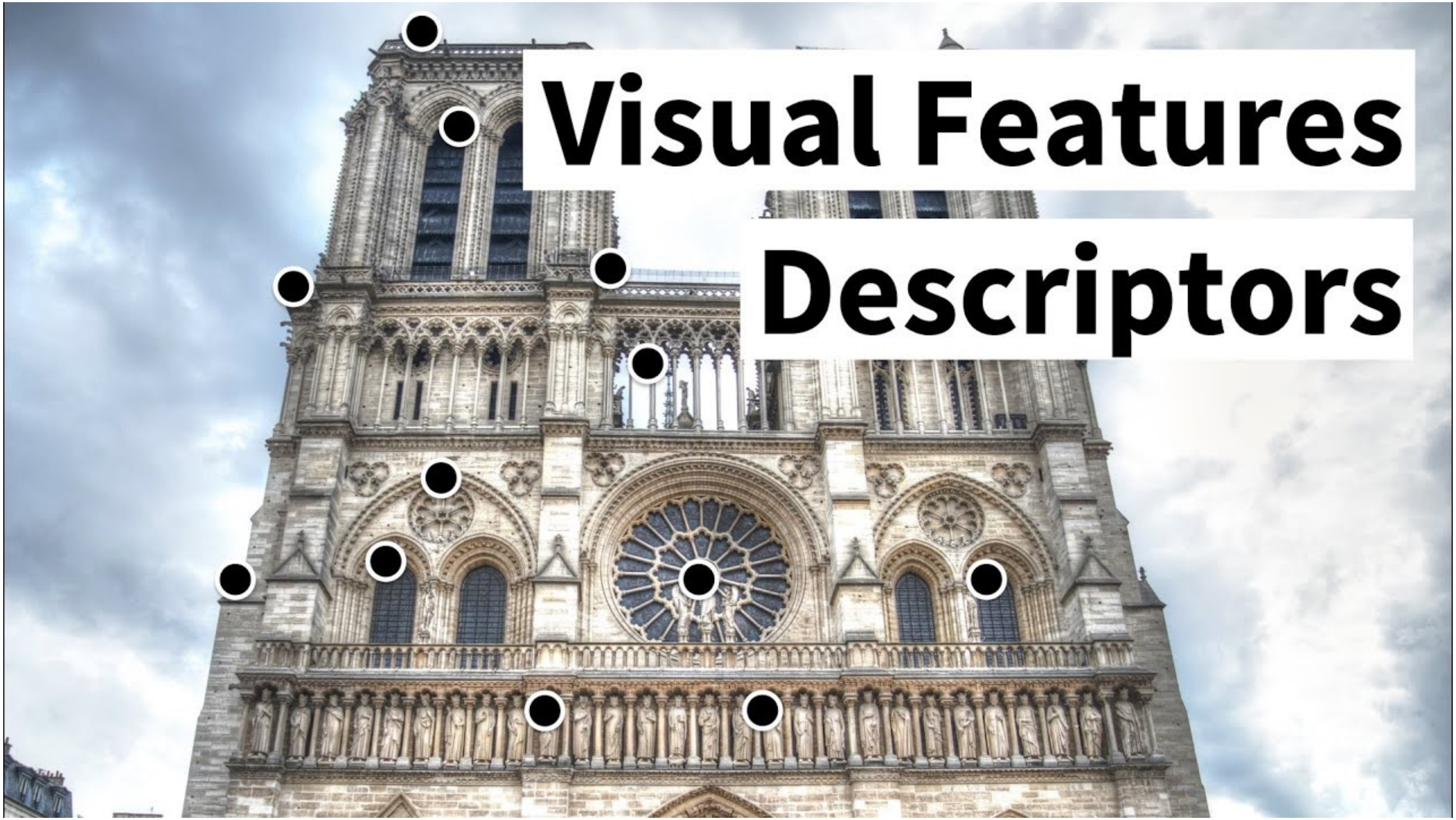


Summer term 2024 – Cyrill Stachniss

5 Minute Preparation for Today

https://www.youtube.com/watch?v=4AvTMVD9ig0

5 Minute Preparation for Today

https://www.youtube.com/watch?v=25GkgxClSaU

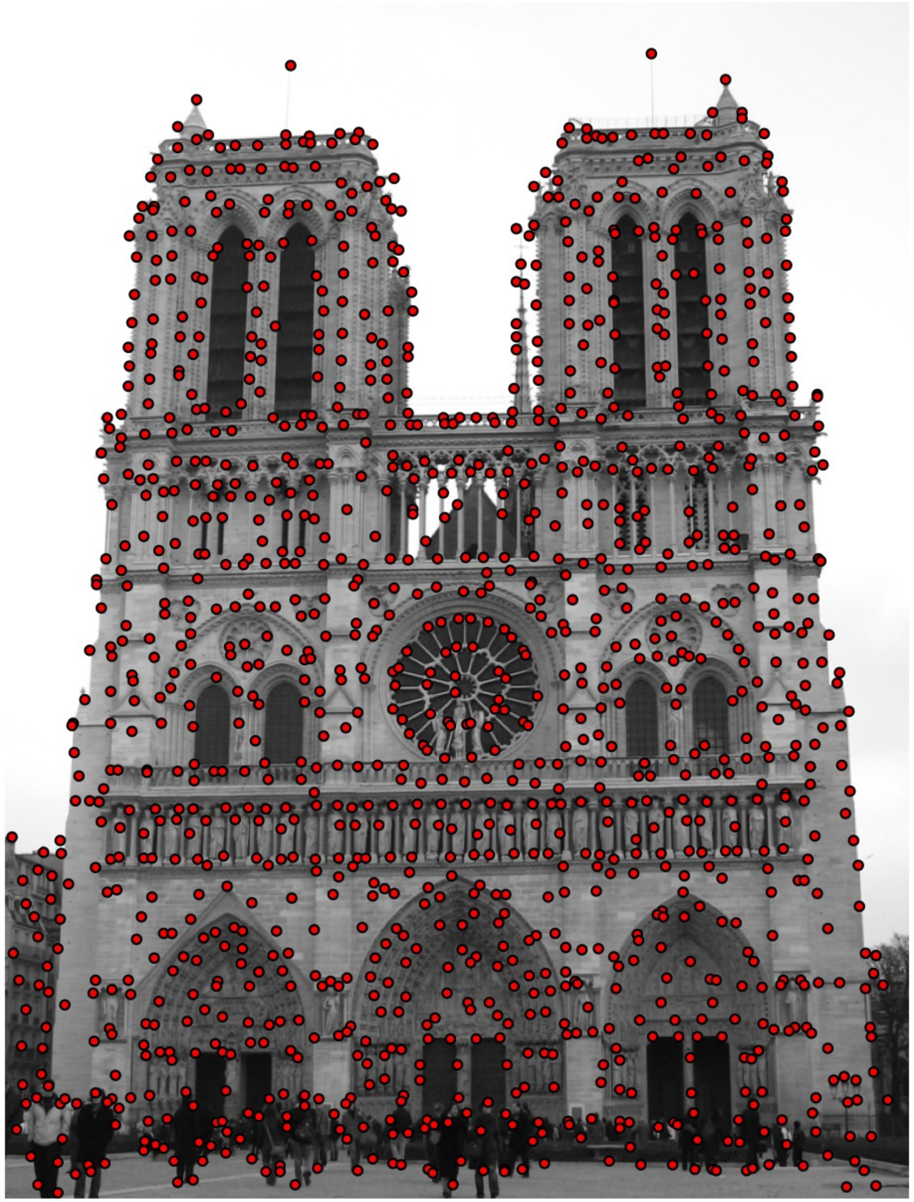
Photogrammetry & Robotics Lab

Visual Features: Descriptors (SIFT, BRIEF, and ORB)

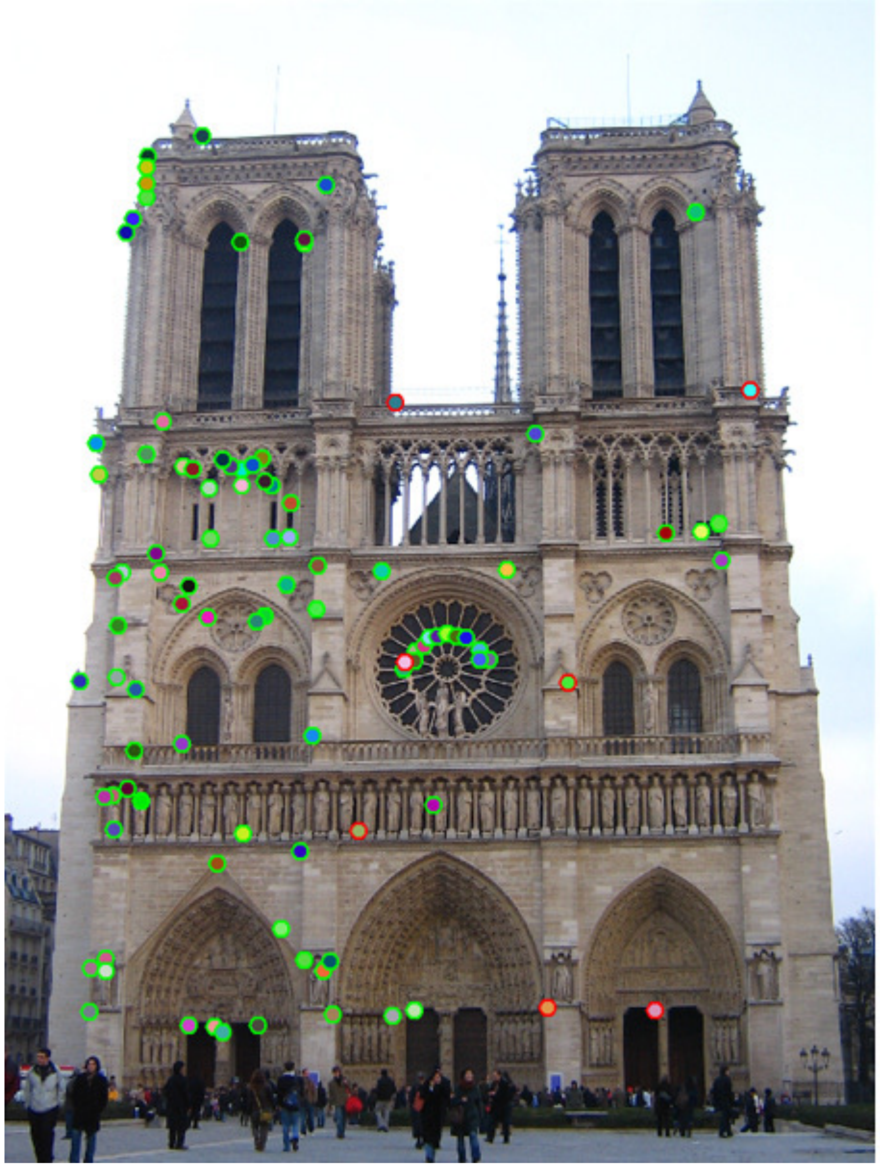
Cyrill Stachniss

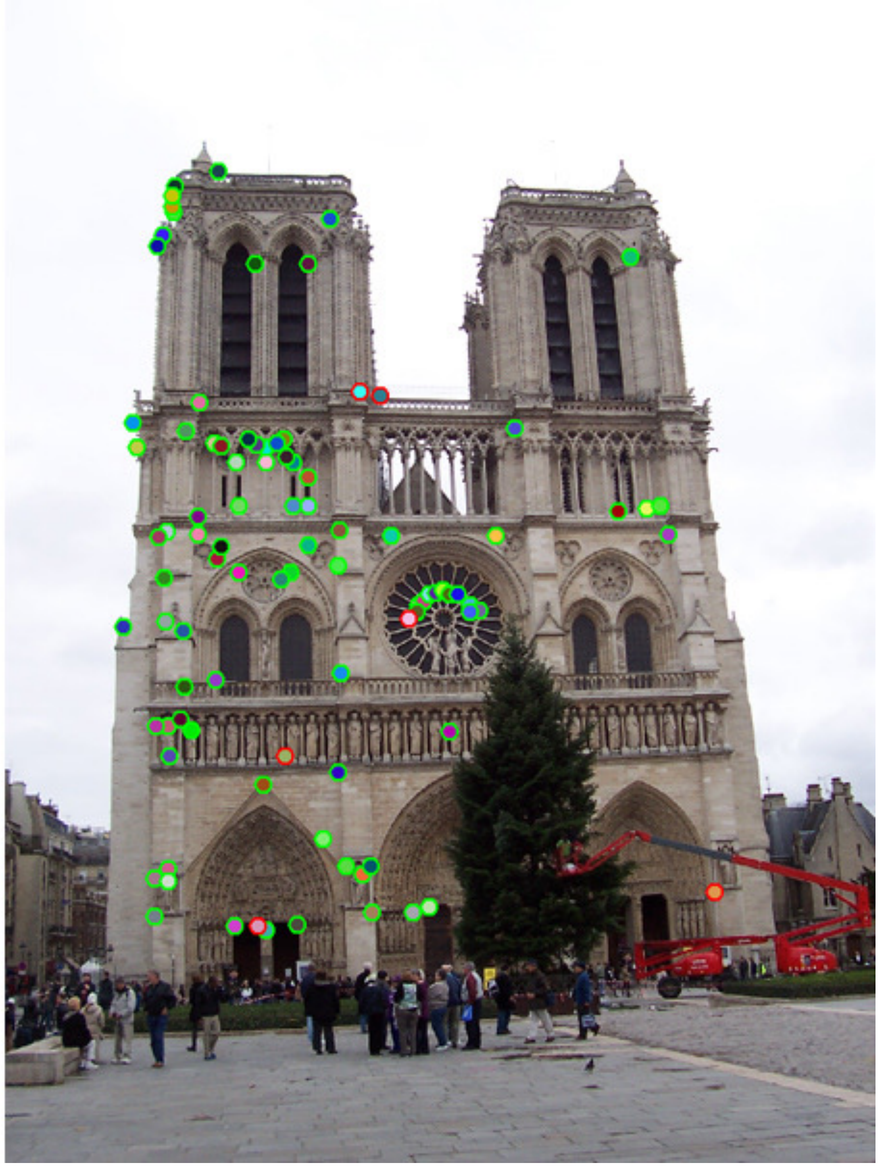
Most slides have been created by Cyrill Stachniss but for several slides courtesy by Gil Levi, A. Efros, J. Hayes, D. Lowe and S. Savarese

Motivation



Motivation

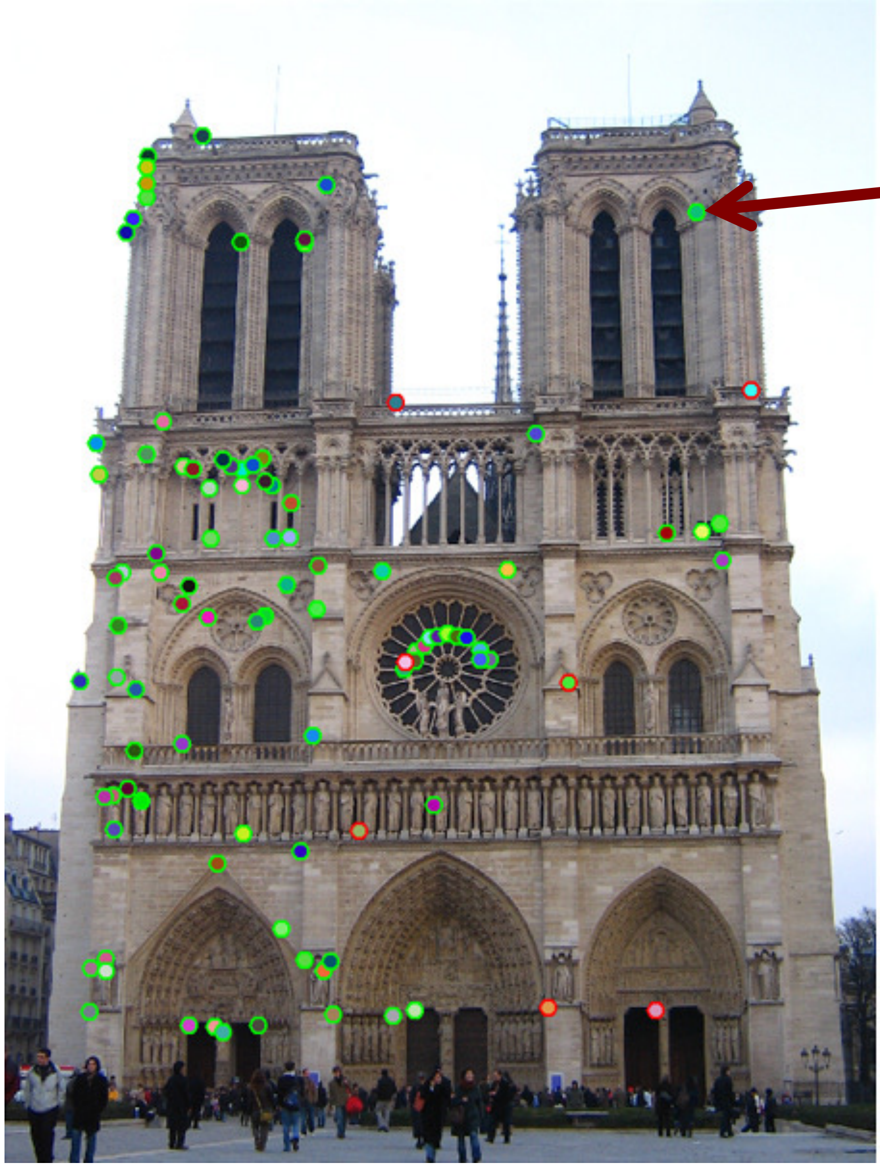




Visual Features: Keypoints and Descriptors

- **Keypoint** is a (locally) distinct location in an image
- The feature **descriptor** summarizes the local structure around the keypoint

Keypoint and Descriptor



keypoint

descriptor at the keypoint

$$f = \begin{bmatrix} 0.02 \\ 0.04 \\ 0.1 \\ 0.03 \\ 0 \\ \cdots \end{bmatrix}$$

Today’s Topics

- **Keypoints: Finding distinct points**
  - **Harris** corners
  - **Shi-Tomasi** corner detector
  - **Förstner** operator
  - **Difference of Gaussians**

- **Features: Describing a keypoint**
  - **SIFT** – Scale Invariant Feature Transform
  - **BRIEF** – Binary Robust Independent Elementary Features
  - **ORB** – Oriented FAST Rotated BRIEF

Keypoints: Difference of Gaussians Over Scale-Space Pyramid (Recap)

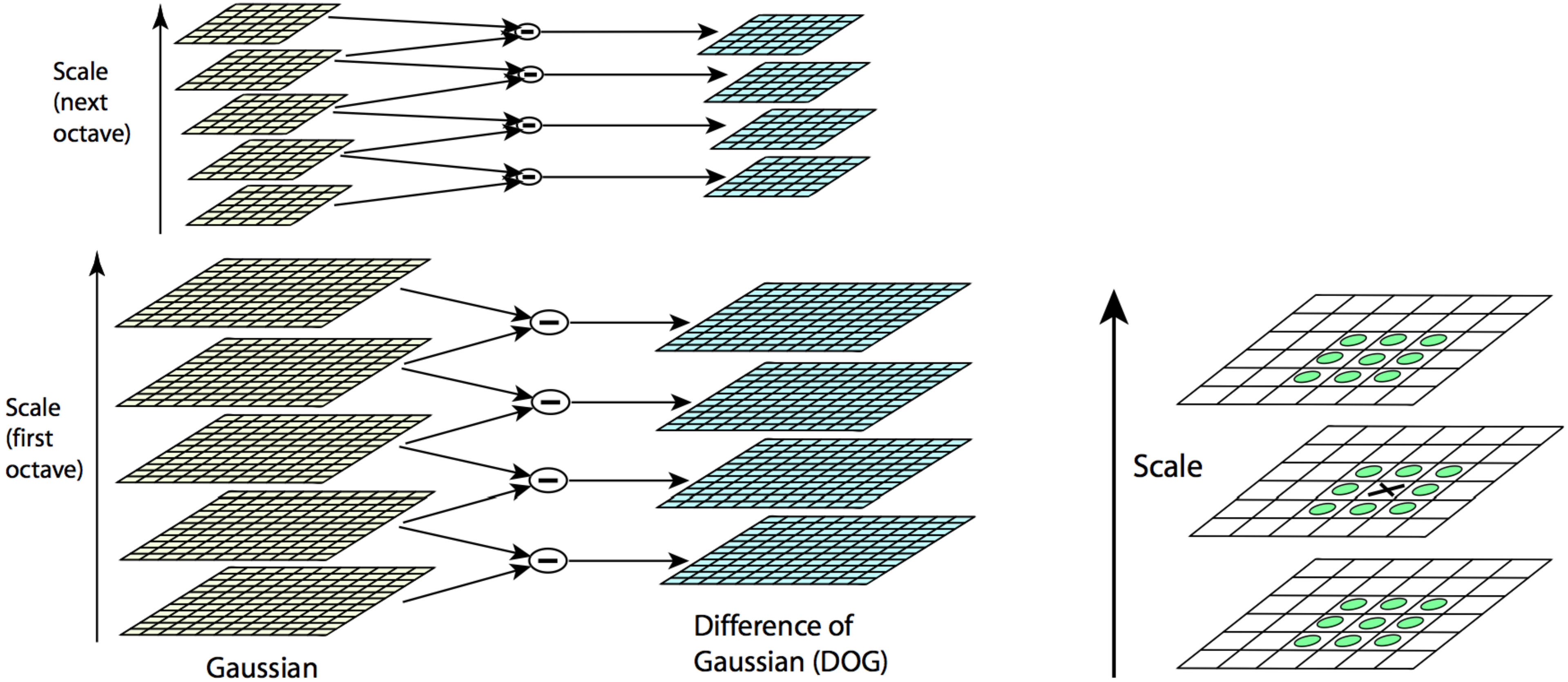
Procedure

Over different image pyramid levels

- Step 1: Gaussian smoothing
- Step 2: Difference-of-Gaussians and find extrema
- Step 3: maxima suppression for edges

Illustration (Recap)

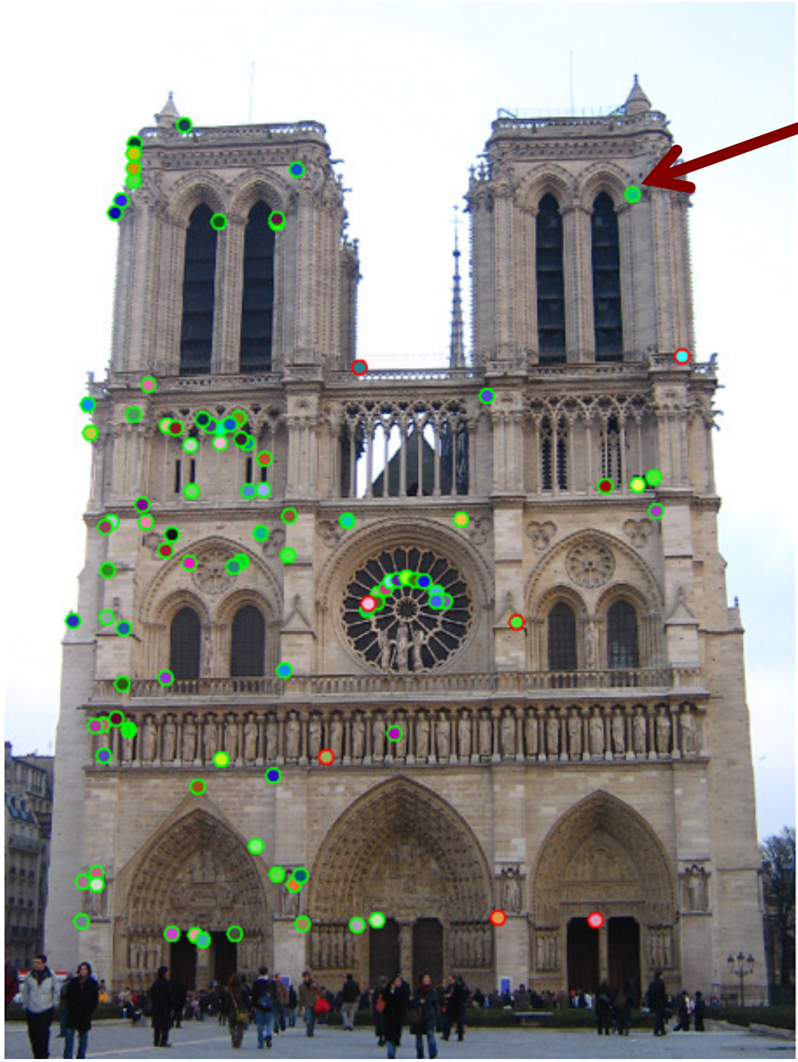
differently sized images



differently blurred images

Image courtesy: Lowe

Keypoint Done.
What about a Descriptor?

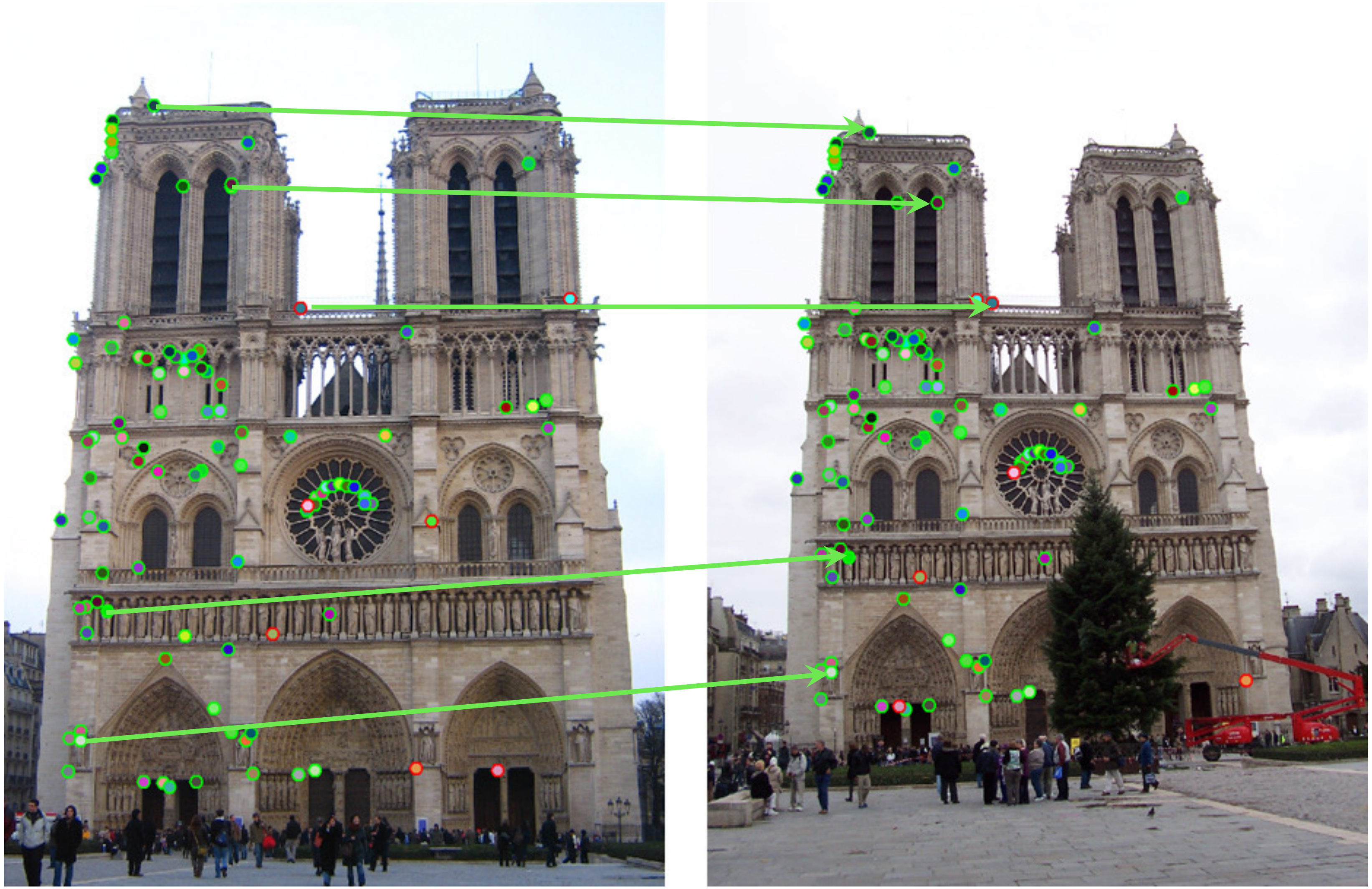


keypoint

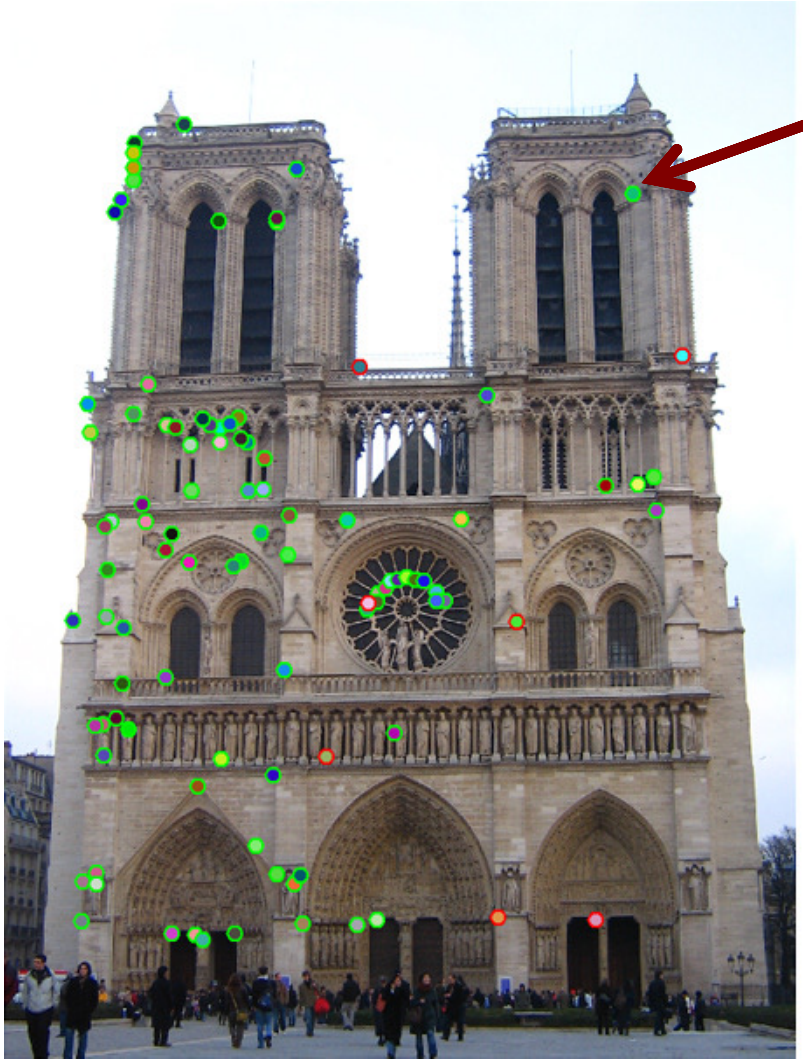
descriptor at the keypoint

$$f = \begin{bmatrix} 0.02 \\ 0.04 \\ 0.1 \\ 0.03 \\ 0 \\ \dots \end{bmatrix}$$

Can We Describe Keypoints to Enable Matching Across Images?



Is is All About the Vector f...



keypoint

descriptor at the keypoint

$$f = \begin{bmatrix} 0.02 \\ 0.04 \\ 0.1 \\ 0.03 \\ 0 \\ \cdots \end{bmatrix}$$

Popular Features 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
- ...

Popular Features Descriptors

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- ...

SIFT Descriptor

- Image content is transformed into features that are **invariant to**
  - image translation,
  - rotation, and
  - scale
- They are **partially invariant to**
  - illumination changes and
  - affine transformations and 3D projections
- Suitable for detecting visual landmarks
  - **from different angles and distances**
  - **with a different illumination**

SIFT Features

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

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

pixel **location** of the keypoint in the image

128-dim. **descriptor** generated from local image gradients

scale (extrema in scale space from DoG)

orientation: compute image gradients in a local region, build a histogram and select peak as the keypoint orietation

SIFT Features

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

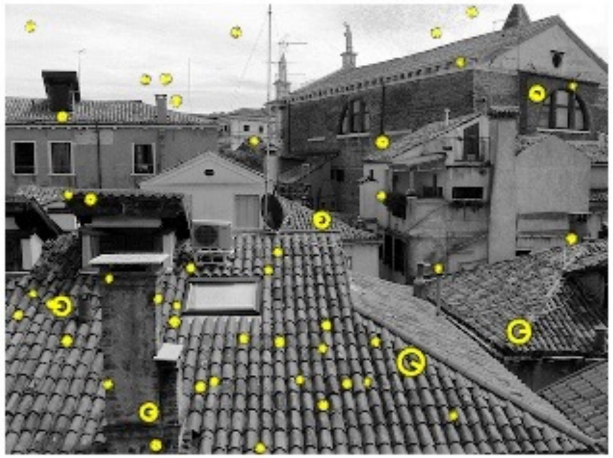
$$\langle p, s, r, f \rangle$$

location　scale　orientation　**128-dim. descriptor**

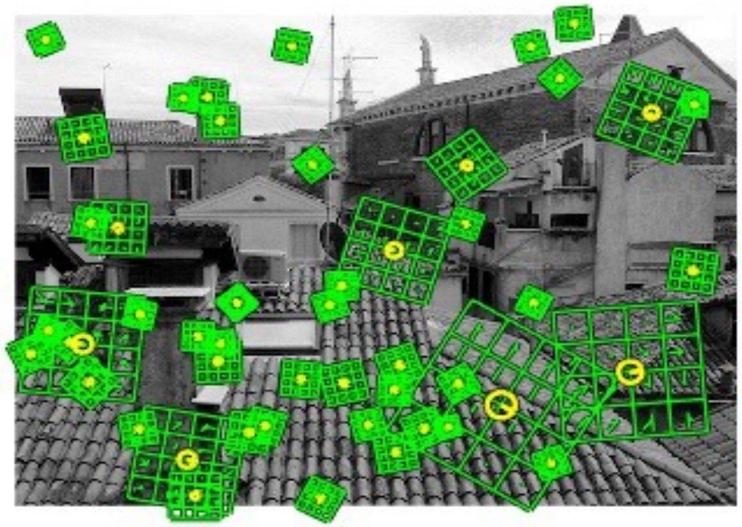
view-point dependent　mainly independent

SIFT Considers the Distribution of Gradients Around Keypoints

input



key points



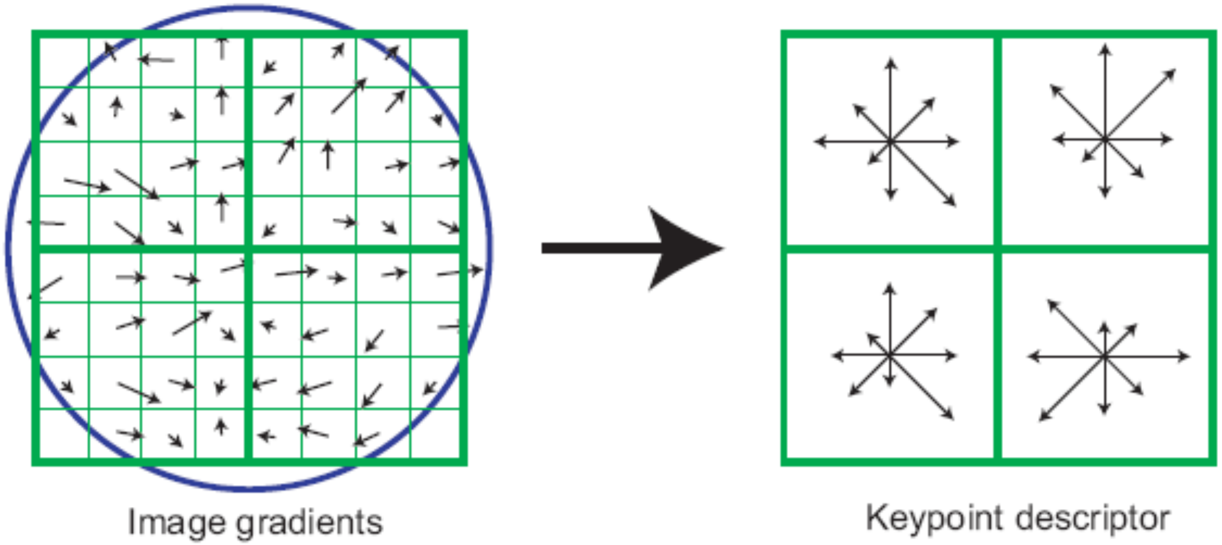
descriptor (regions)

Image courtesy: Vedaldi and Fulkerson

SIFT Descriptor in Sum

- 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 (yields best results)

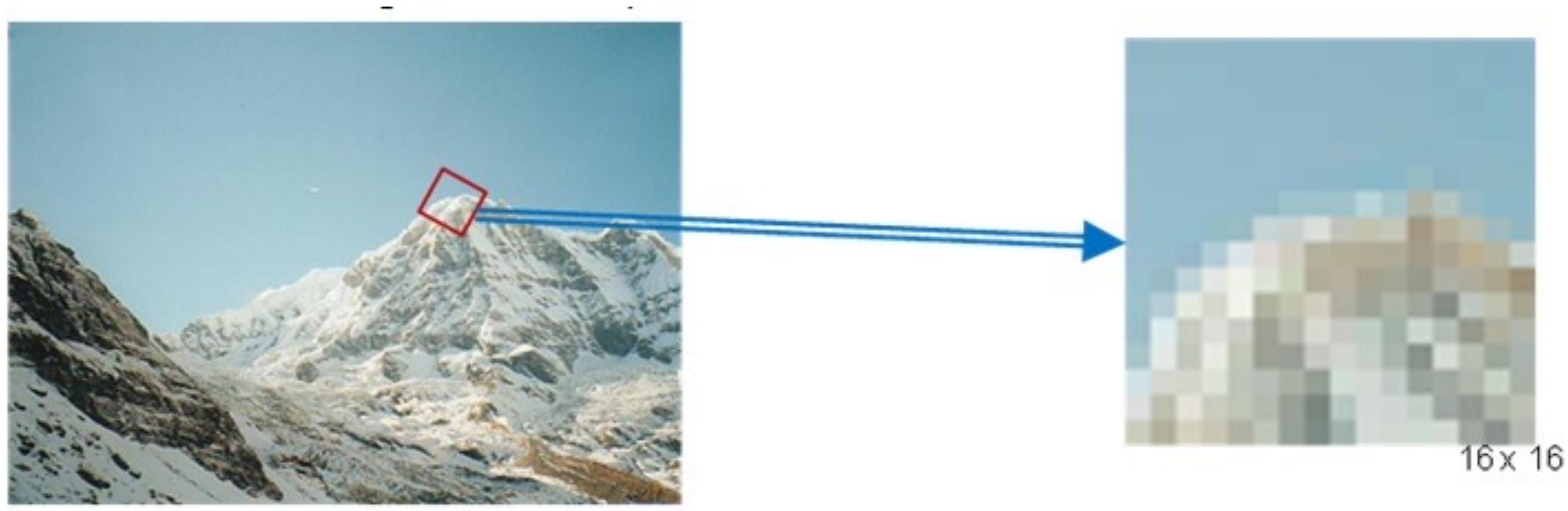
Example using a 8x8 area:



[Lowe ´04]

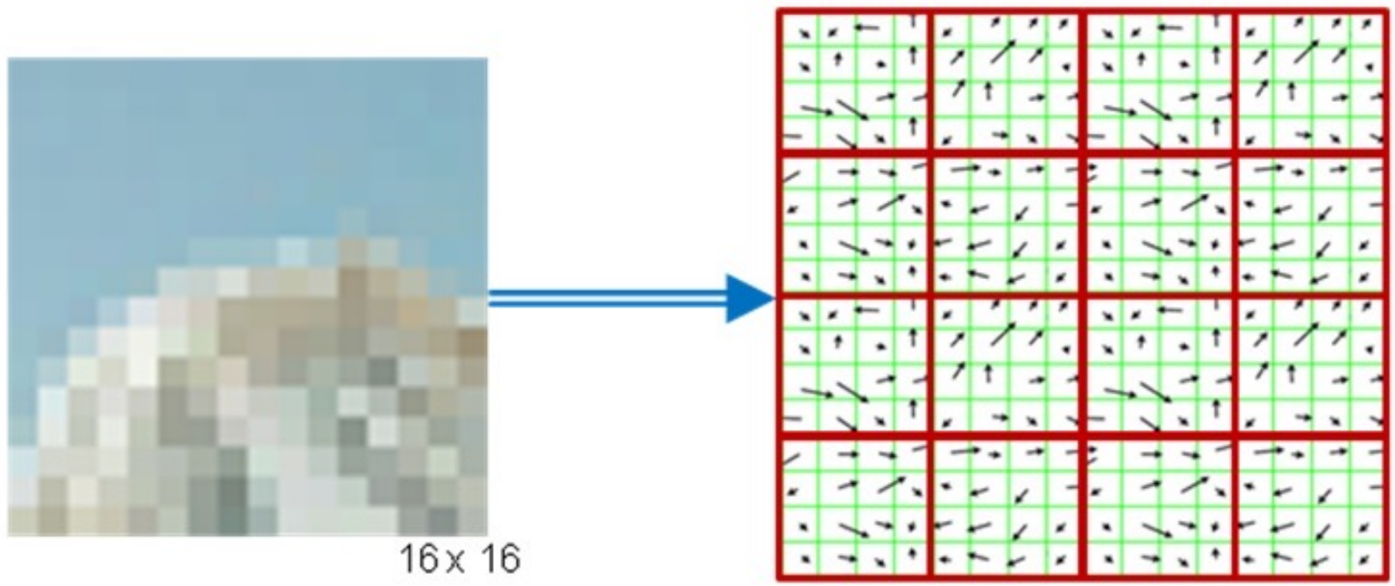
SIFT Illustration (1)

For a given keypoint, warp the region around it to orientation and scale and resize the region to 16X16 pixels.



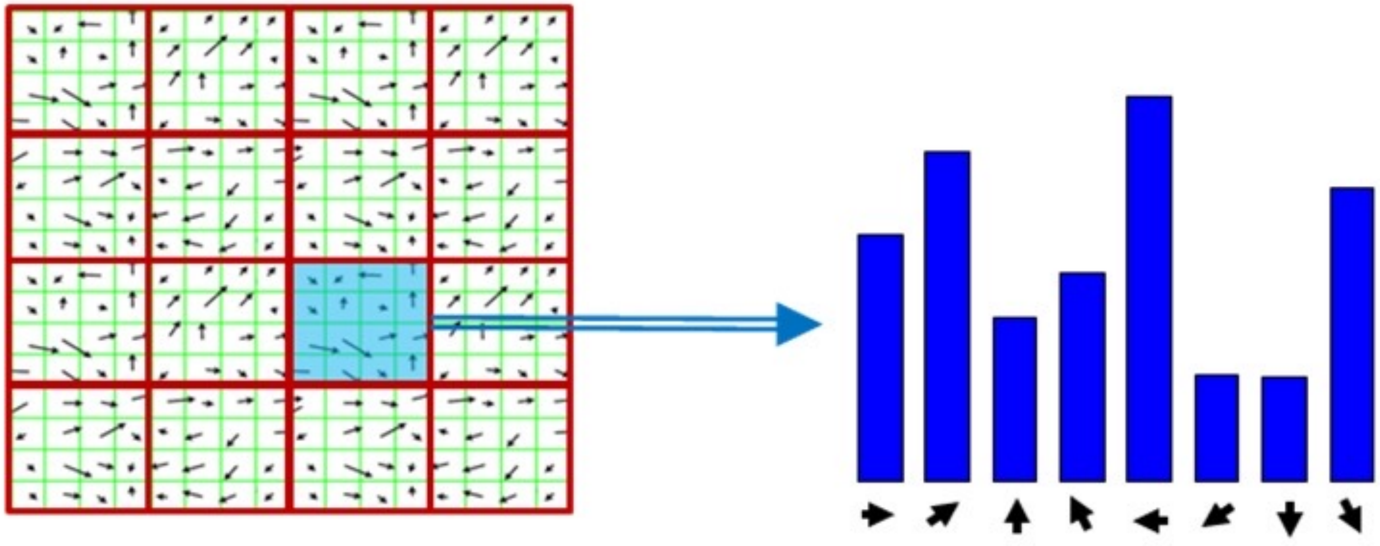
SIFT Illustration (2)

Compute the gradients for each pixels (orientation and magnitude) and divide the pixels into 16, 4X4 pixels squares



SIFT Illustration (3)

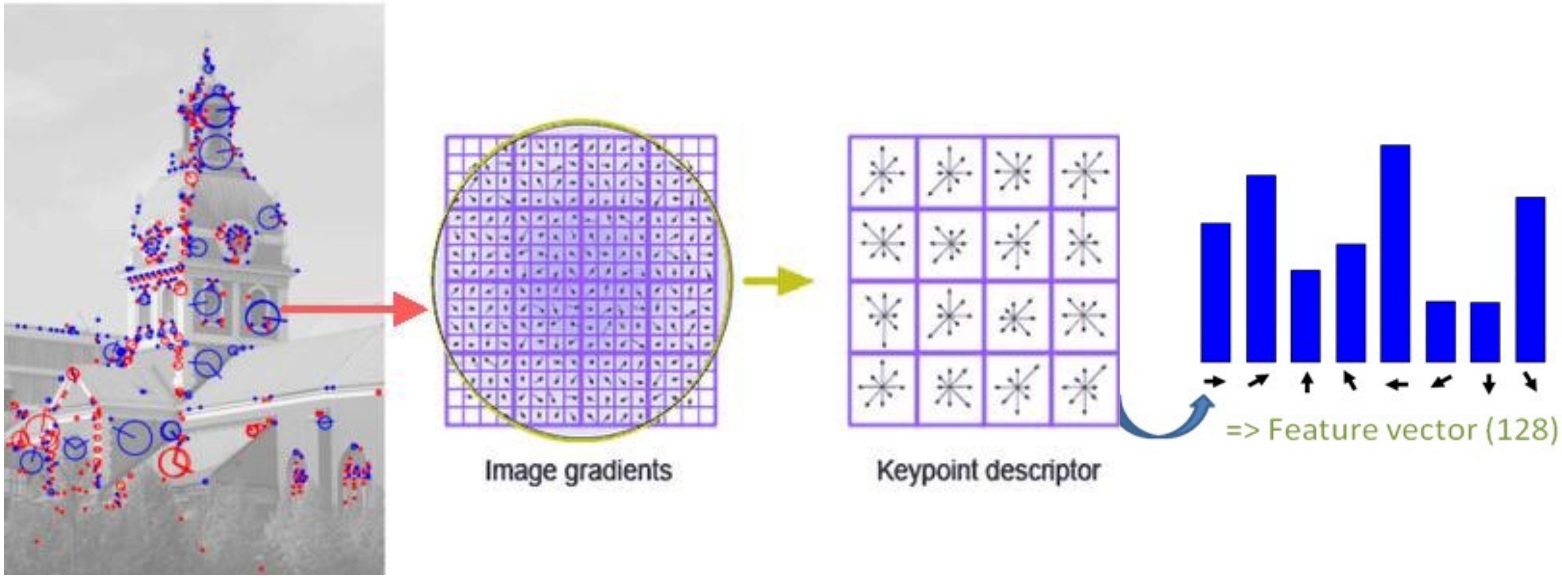
For each square, compute gradient direction histogram over 8 directions



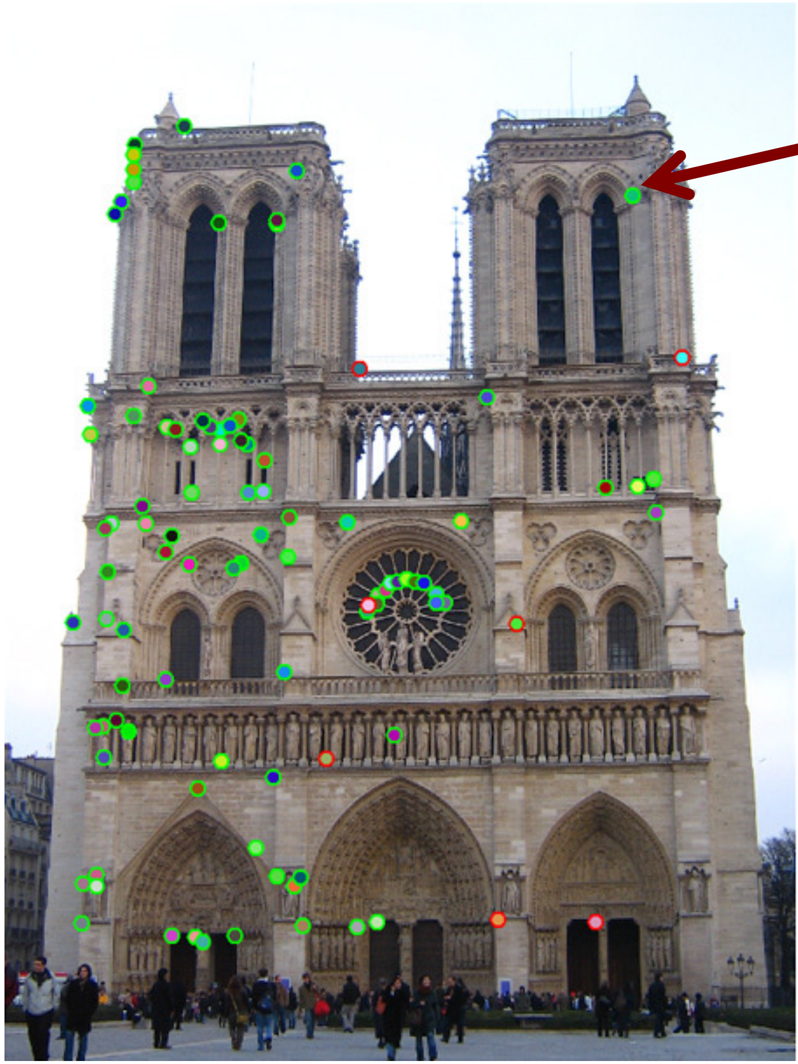
SIFT Illustration (4)

Concatenate the histograms to obtain a 128 (16*8) dimensional feature vector:

SIFT Descriptor Illustration



SIFT Approach Done!

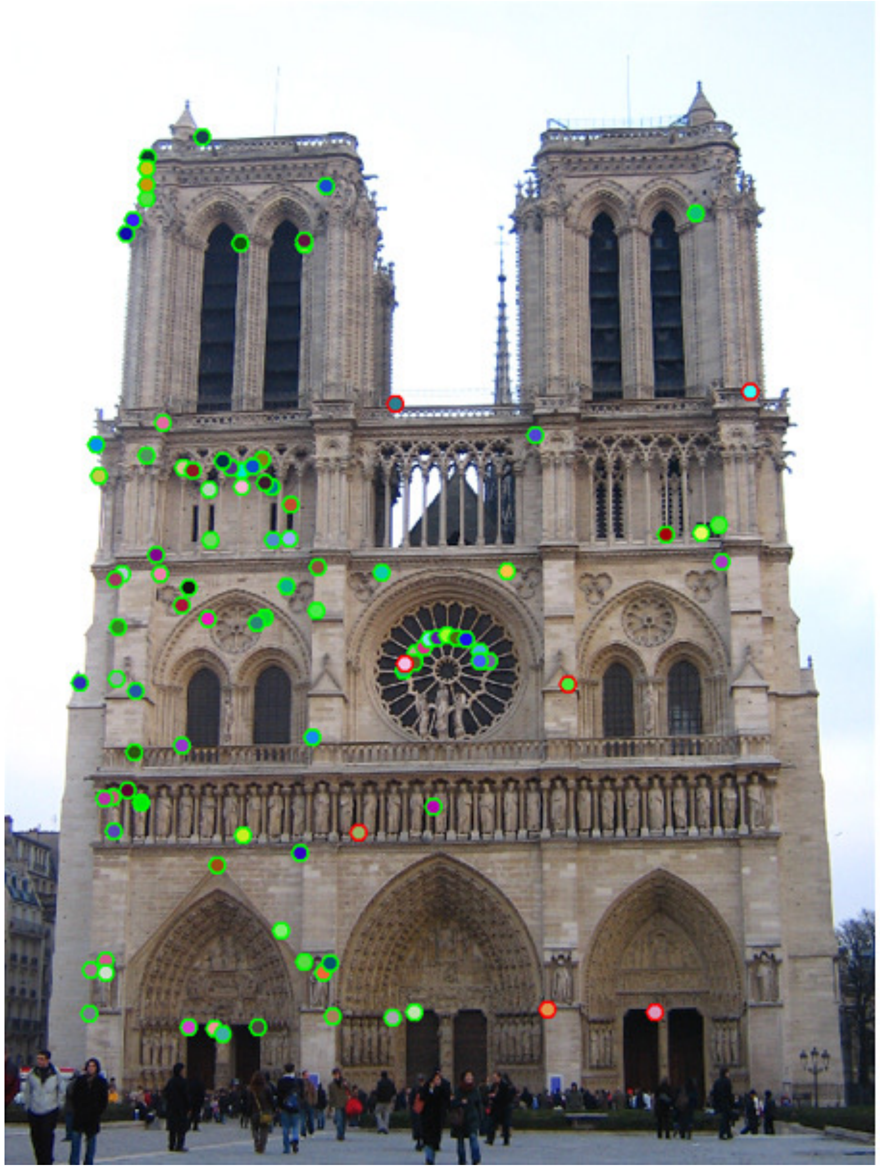


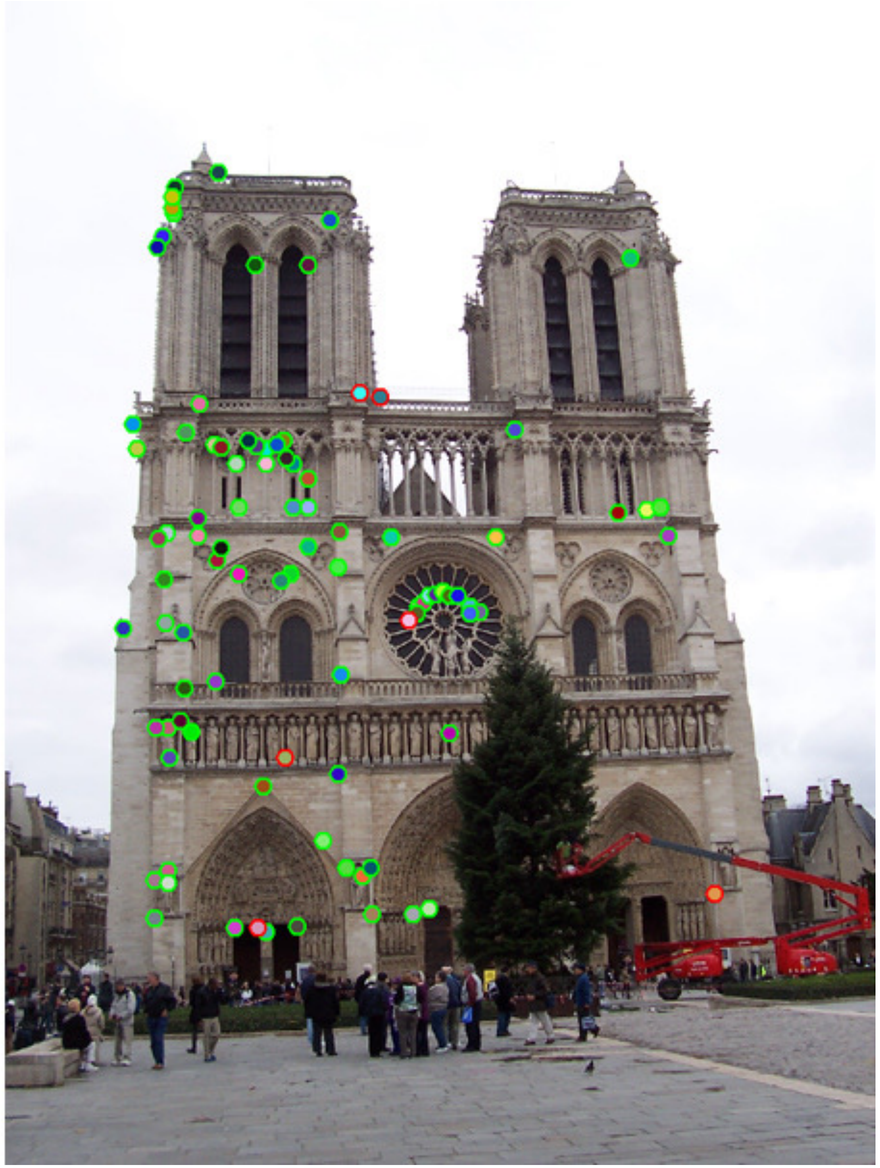
keypoint (via DoG)

descriptor (via gradient histogram)

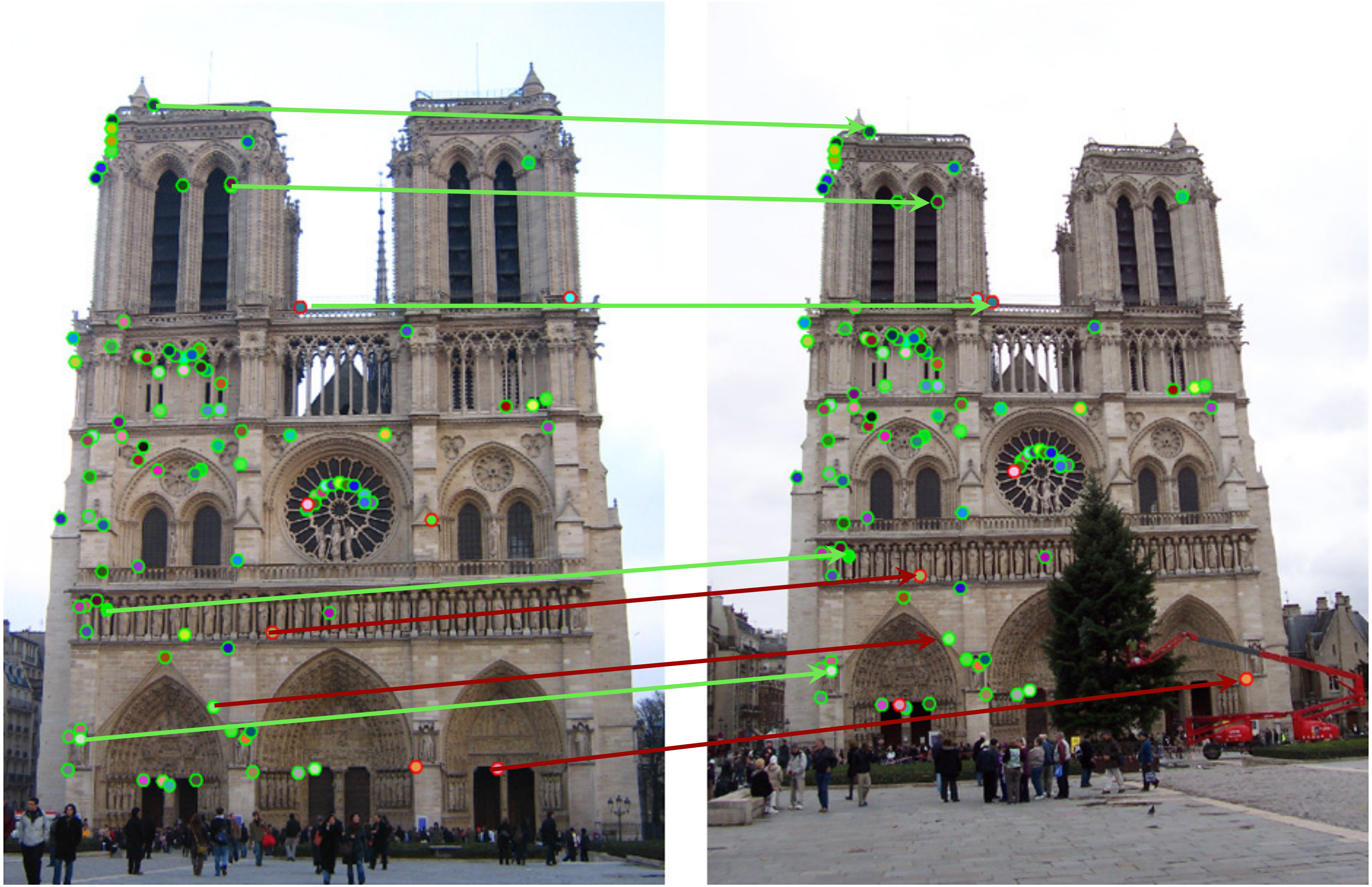
$$f = \begin{bmatrix} 0.02 \\ 0.04 \\ 0.1 \\ 0.03 \\ 0 \\ \ldots \end{bmatrix}$$

How To Match Them?





Based on Descriptor Difference

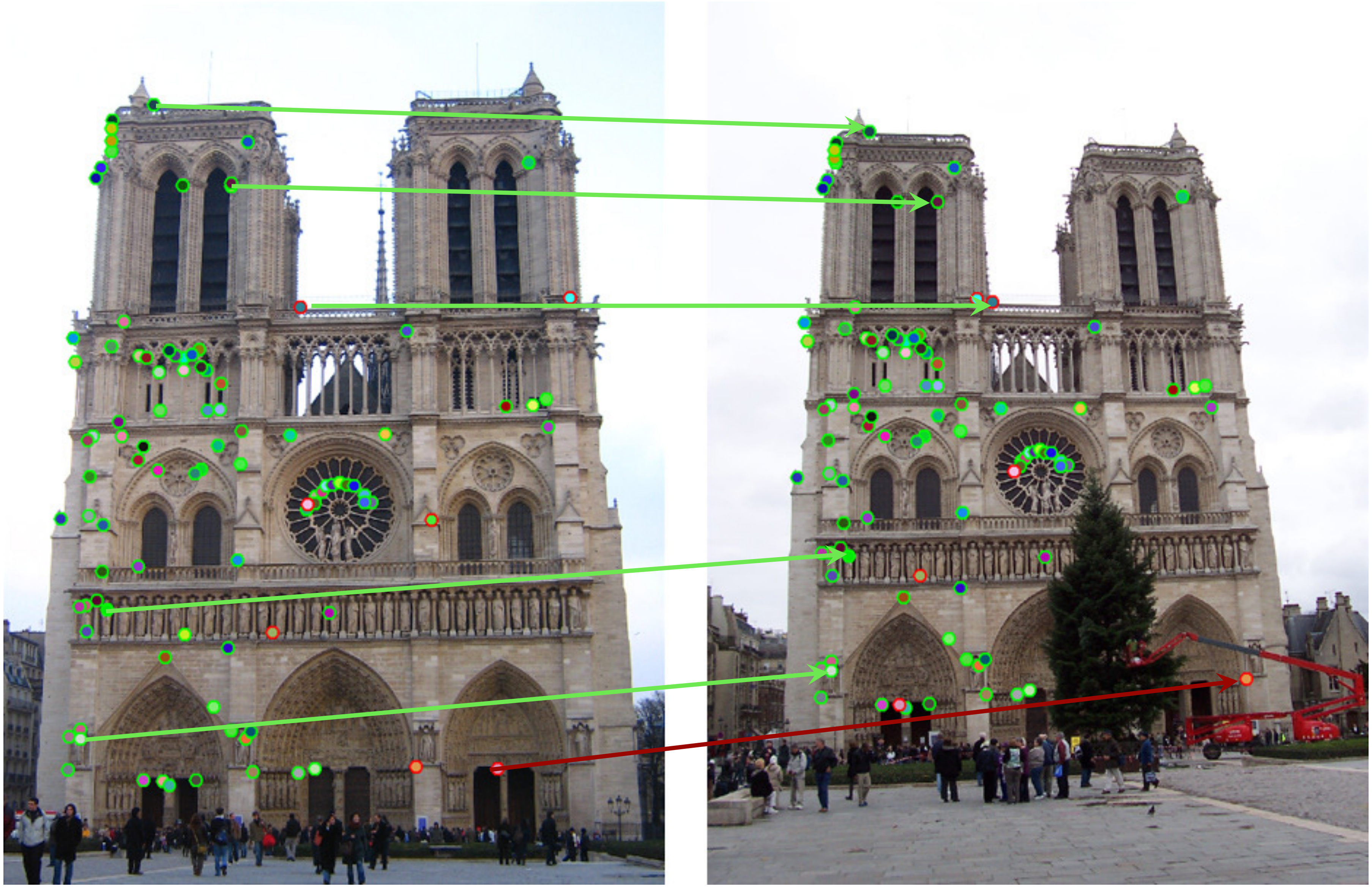


Lowe's Ratio Test

- 3 Step test to eliminate ambiguous matches for a query feature q
- 1. Step: Find closest two descriptors to q, called p_1 and p_2 based on the Euclidian distance d
- 2. Step: Test if distance to best match is smaller than a threshold: $d(q, p_1) < T$
- 3. Step: Accept match only if the best match is substantially better than second:

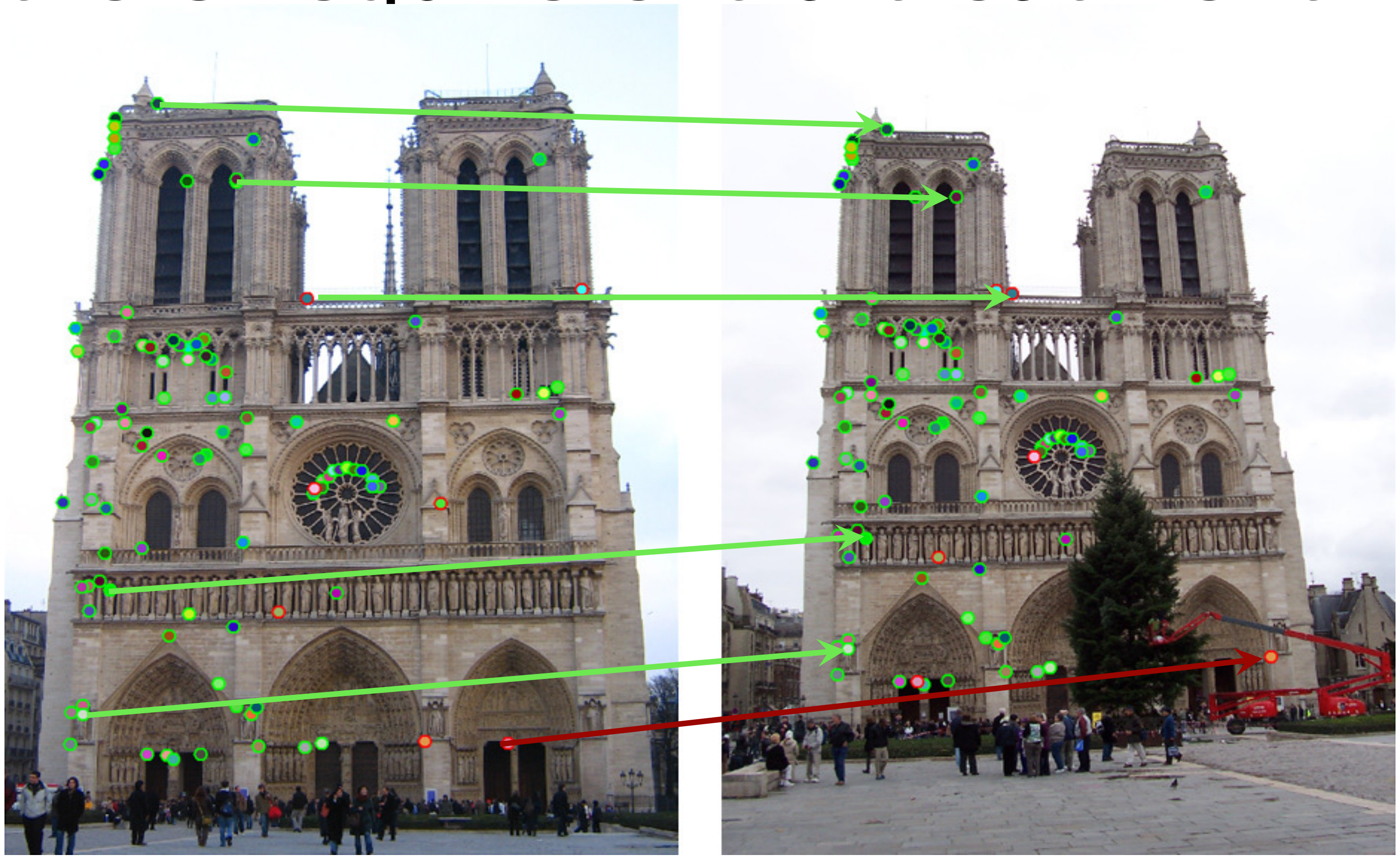
$$\frac{d(q, p_1)}{d(q, p_2)} < \frac{1}{2}$$

Based on Ratio Test



Outliers

- Lowe's Ratio test works well
- There will still remain few outliers
- Outliers require extra treatment



Binary Descriptors
or
“computing descriptor fast”

Why Binary Descriptors?

- Complex features such as SIFT work well and a a gold standard
- SIFT is expansive to compute
- SIFT has patenting issues
- Binary descriptors aim at generating **small binary strings** that are **easy to compute and compare**

Key Idea of Binary Descriptors

Fairly simple strategy

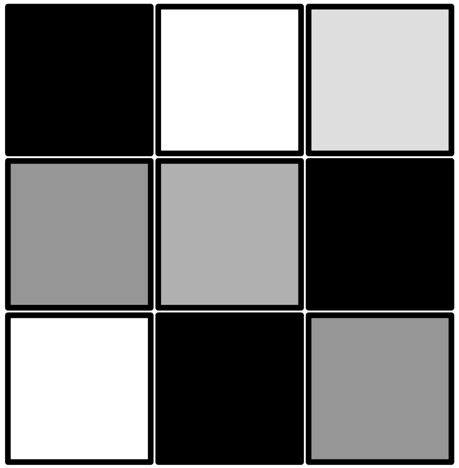
- Select a patch around a keypoint
- Select a set of pixel pairs in that patch
- For each pair, compare the intensities

$$b = \left\{ \begin{array}{ll} 1 & \text{if } I(s_1) < I(s_2) \\ 0 & \text{otherwise} \end{array} \right\}$$

- Concatenate all b`s to a bit string

Example

image area



index (for pairs)

1	2	3
4	5	6
7	8	9

pairs: $\{(5,1),\ (5,9),\ (4,6),\ (8,2),\ (3,7)\}$

tests: $b=0 \quad b=0 \quad b=0 \quad b=1 \quad b=1$

result: $B = 00011$

Key Advantages of Binary Descriptors

- **Compact descriptor**
  The number of pairs gives the length in bits

- **Fast to compute**
  Simply intensity value comparisons

- **Trivial and fast to compare**
  Hamming distance

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

Different Binary Descriptors Differ Mainly by the Strategy of Selecting the Pairs

Important Remark – Pairs

In order to compare descriptors among images, we must:

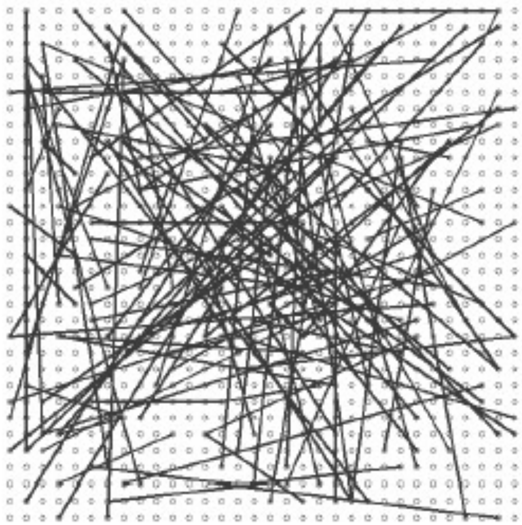
- Use the same pairs
- Maintain the same order in which the pairs are tested

Different descriptors once determine the way the pairs are chosen and fix it!

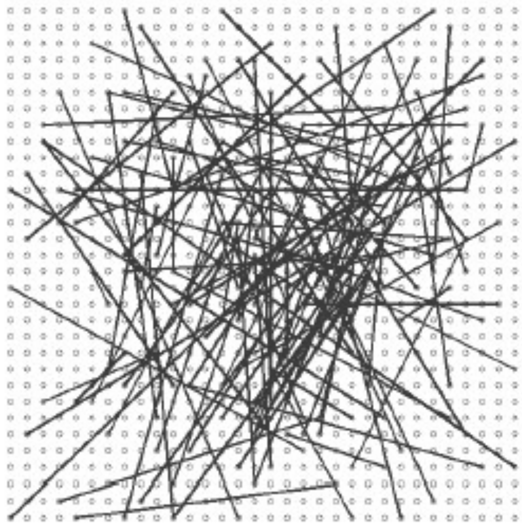
BRIEF :
Binary robust independent elementary features

- First binary image descriptor
- Proposed in 2010
- 256 bit descriptor
- Provides five different geometries as sampling strategies
- Noise: operations performed on a **smoothed** image to deal with noise

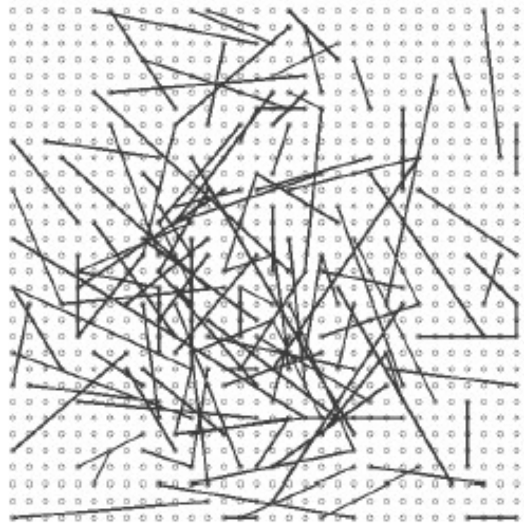
BRIEF Sampling Pairs



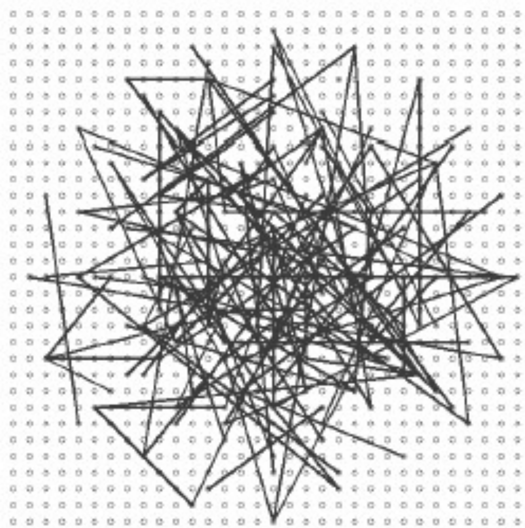
G I



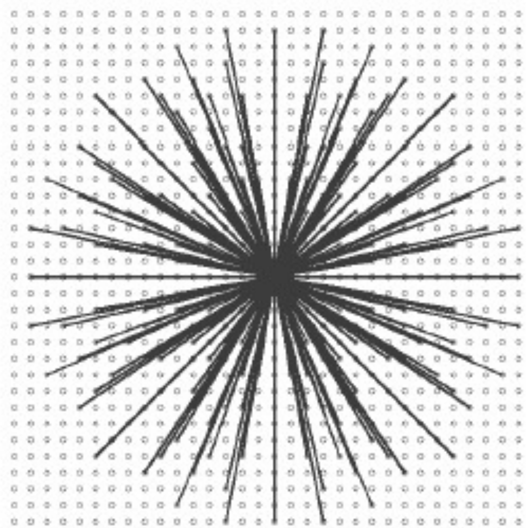
G II



G III



G IV

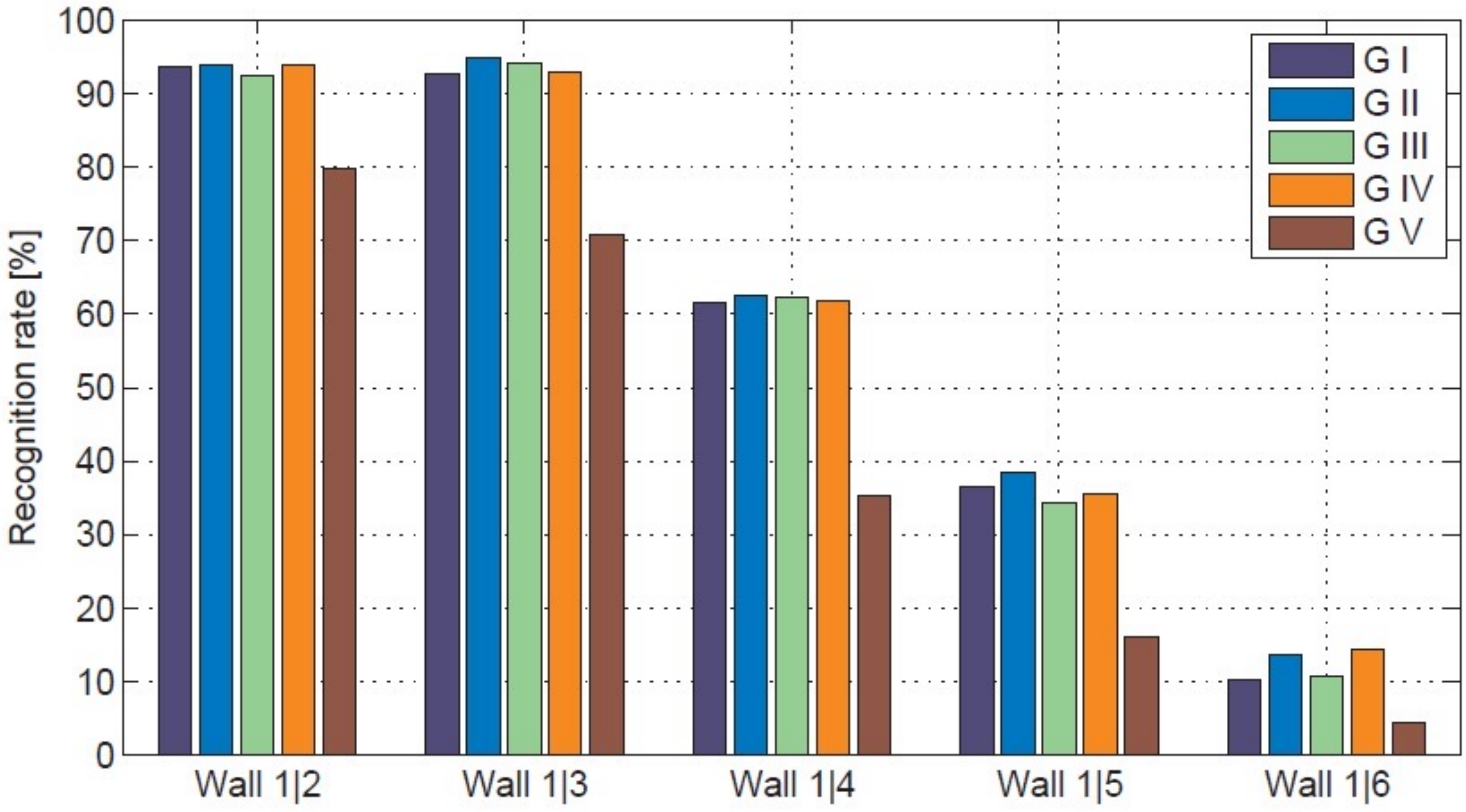


G V

BRIEF Sampling Pairs

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

Performance: G I – G IV are all good, G V less useful



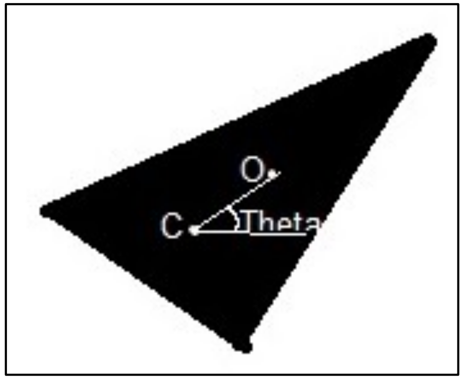
ORB: Oriented FAST Rotated BRIEF

An extension to BRIEF that

- Adds rotation compensation
- Learns the optimal sampling pairs

ORB: Rotation Compensation

- Estimates the center of mass and the main orientation of the area/patch
- Image moment



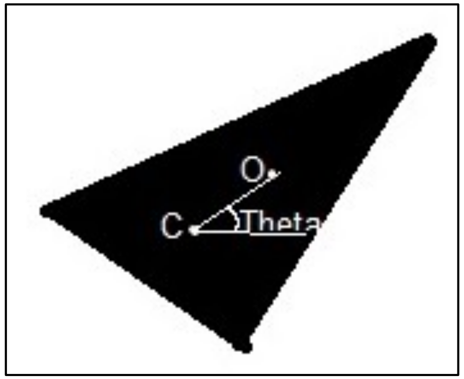
$$m_{pq} = \sum_{x,y} x^p \, y^q \, I(x, y)$$

- Center of mass $C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}} \right)$
- Orientation $\theta = \operatorname{atan2}(m_{01}, m_{10})$

ORB: Rotation Compensation

- Given CoM and orientation C, θ, we can rotate the coordinates of all pairs by θ around C:

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



- Use the transformed pixel coordinates for performing the test
- Invariance to rotation in the plane

ORB: Learning Sampling Pairs

Pairs should be / have

- **uncorrelated** – so that each new pair adds new information to the descriptor
- **high variance** – it makes a feature more discriminative

- ORB defines a strategy for selection 256 pairs optimizing for both properties using a training database

ORB vs. 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

- Keypoints and descriptor together define common visual features
- Keypoint defines the location
- Descriptor describes the appearance
- Several descriptors operating on gradient histograms (SIFT, SURF, …)
- Binary descriptors for efficiency (BRIEF, ORB, …)

Slide Information

- These slides have been created by Cyrill Stachniss as part of the Photogrammetry II course taught in 2014 and 2019
- The slides *heavily* reply on material by Gil Levi, Alexai Efros, James Hayes, David Lowe, and Silvio Savarese
- I tried to acknowledge all people from whom I used images or videos. In case I made a mistake or missed someone, please let me know.
- If you are a university lecturer, feel free to use the course material. If you adapt the course material, please make sure that you keep the acknowledgements to others and please acknowledge me as well. To satisfy my own curiosity, please send me email notice if you use my slides.

Cyrill Stachniss, 2014
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