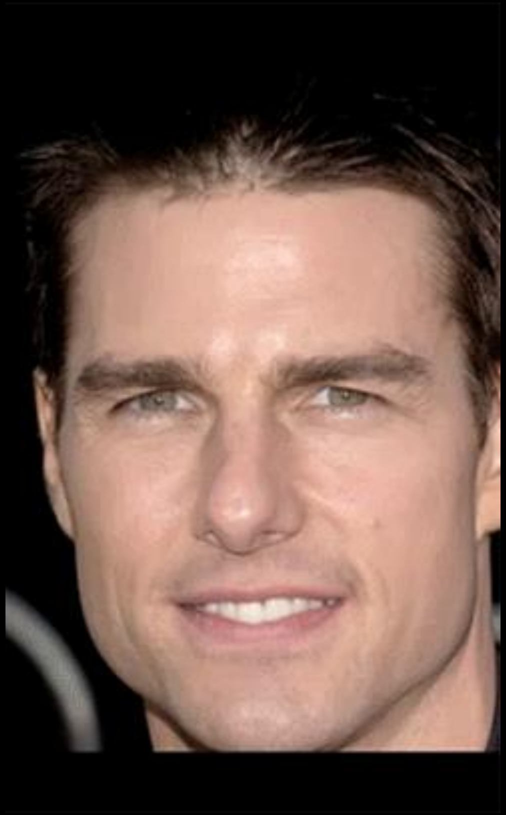
Read Szeliski 7.1.2 and 7.1.3

Local Image Features

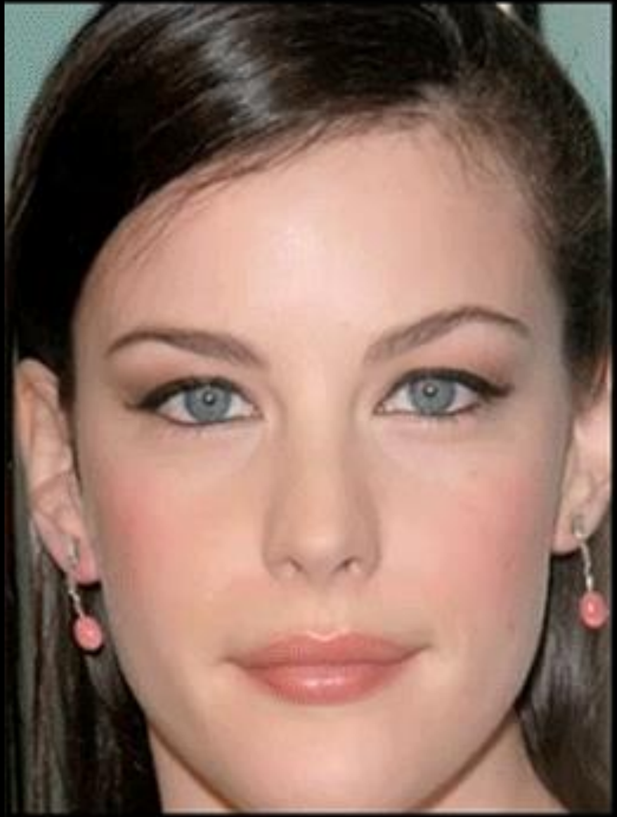
Computer Vision

James Hays

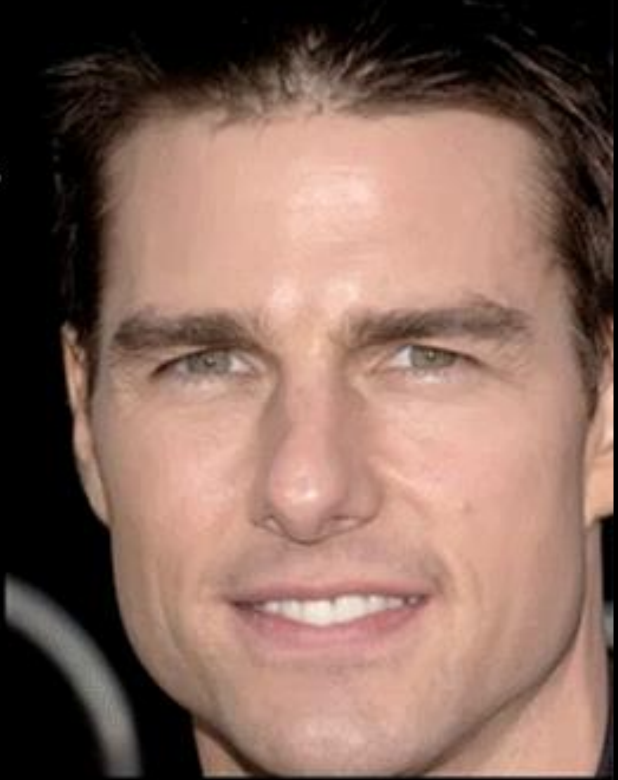
Acknowledgment: Many slides from Derek Hoiem and Grauman&Leibe 2008 AAAI Tutorial



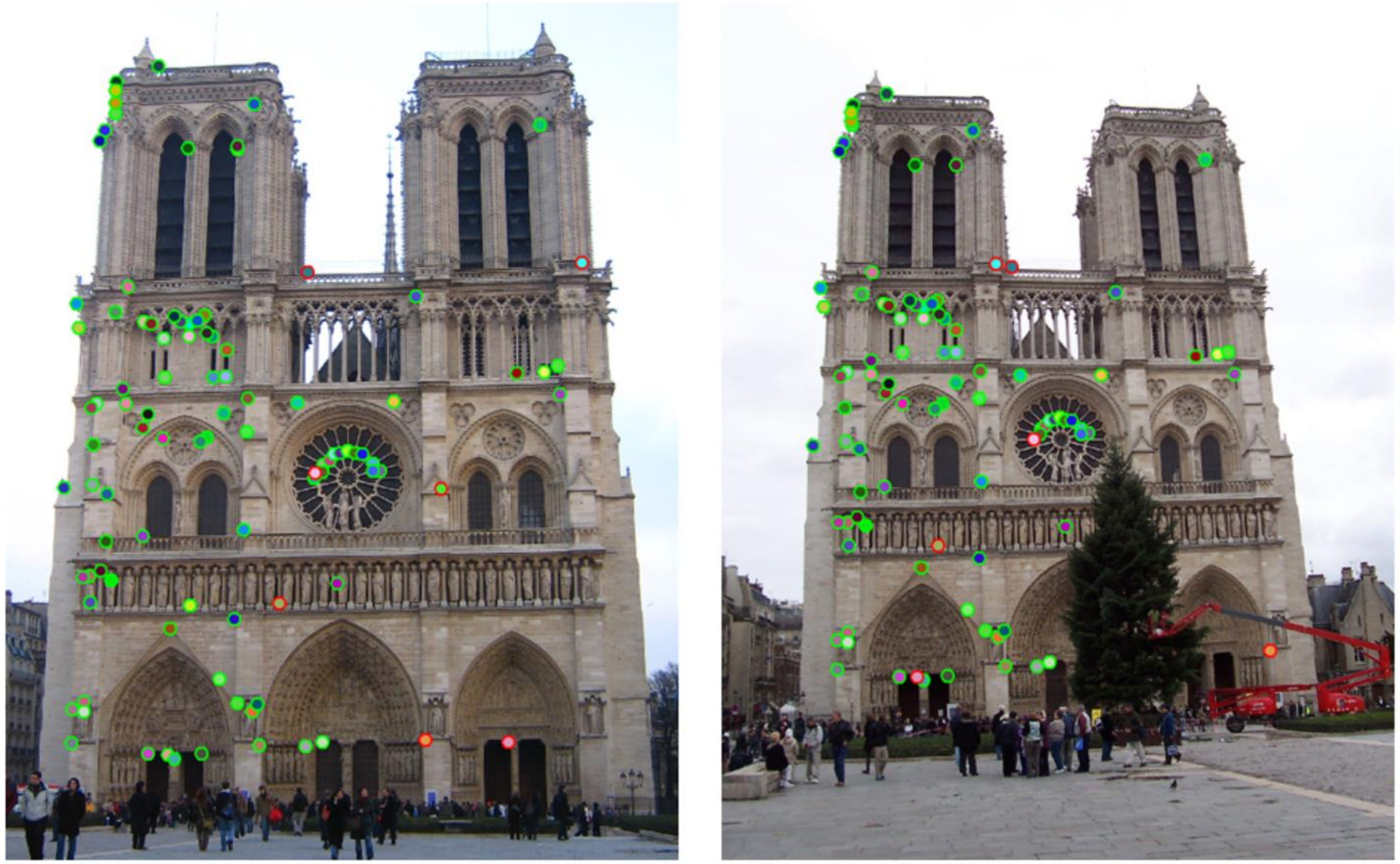
"Flashed Face Distortion"
2nd Place in the 8th Annual
Best Illusion of the Year Contest , VSS 2012



Keep your eyes
on the cross



Project 2

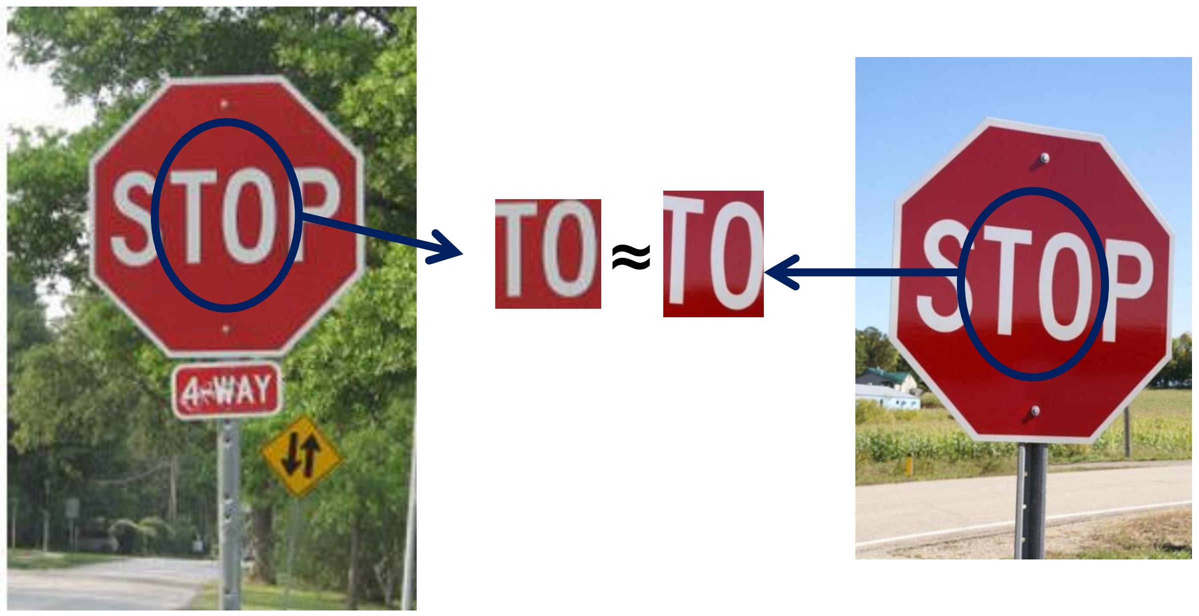


The top 100 most confident local feature matches from a baseline implementation of project 2. In this case, 93 were correct (highlighted in green) and 7 were incorrect (highlighted in red).

Project 2: Local Feature Matching

This section: correspondence and alignment

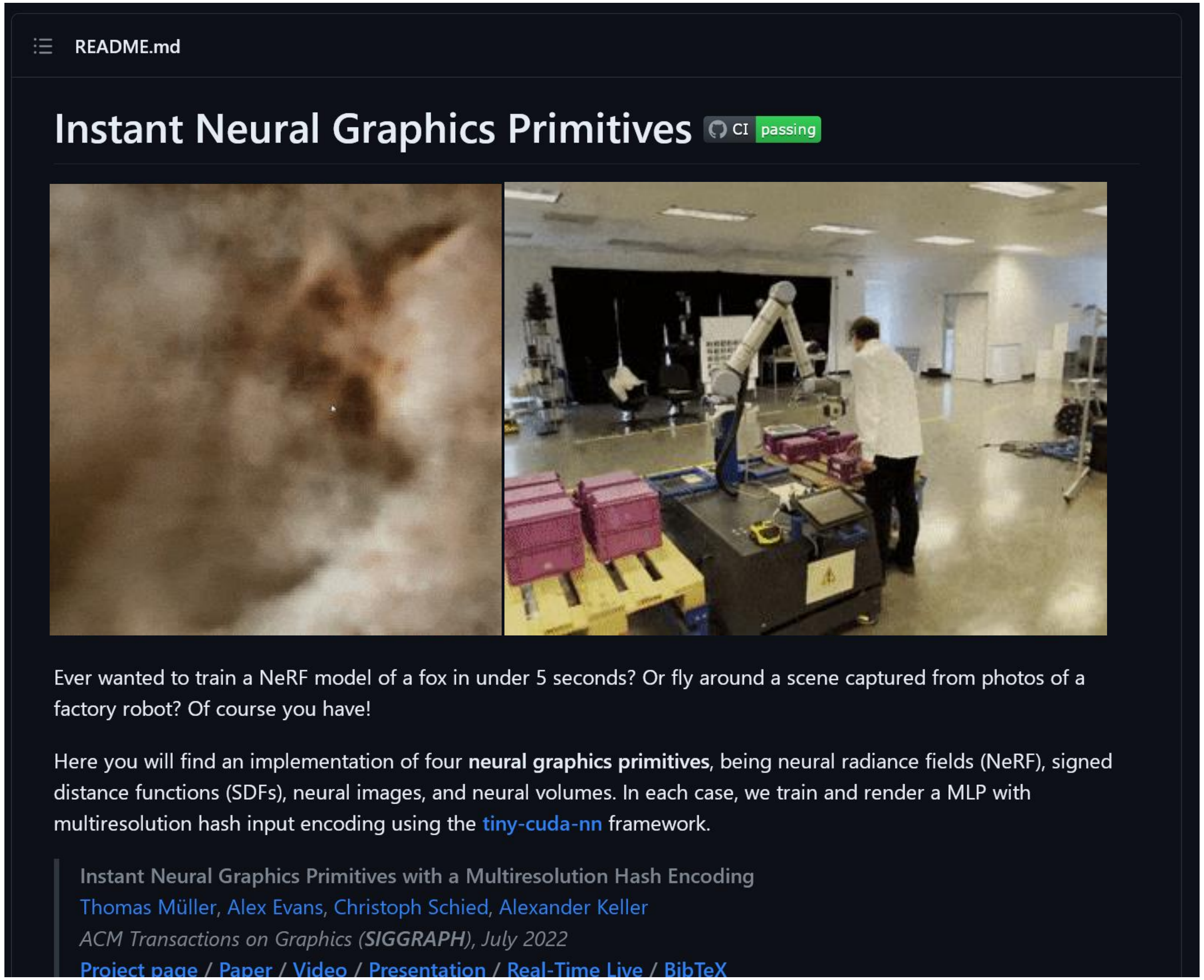
- Correspondence: matching points, patches, edges, or regions across images



SIFT is 20+ years old. Is it still useful?

SIFT is 20+ years old. Is it still useful?

- Let's look at some trendy research on Neural Radiance Fields (NERF)



README.md

Instant Neural Graphics Primitives

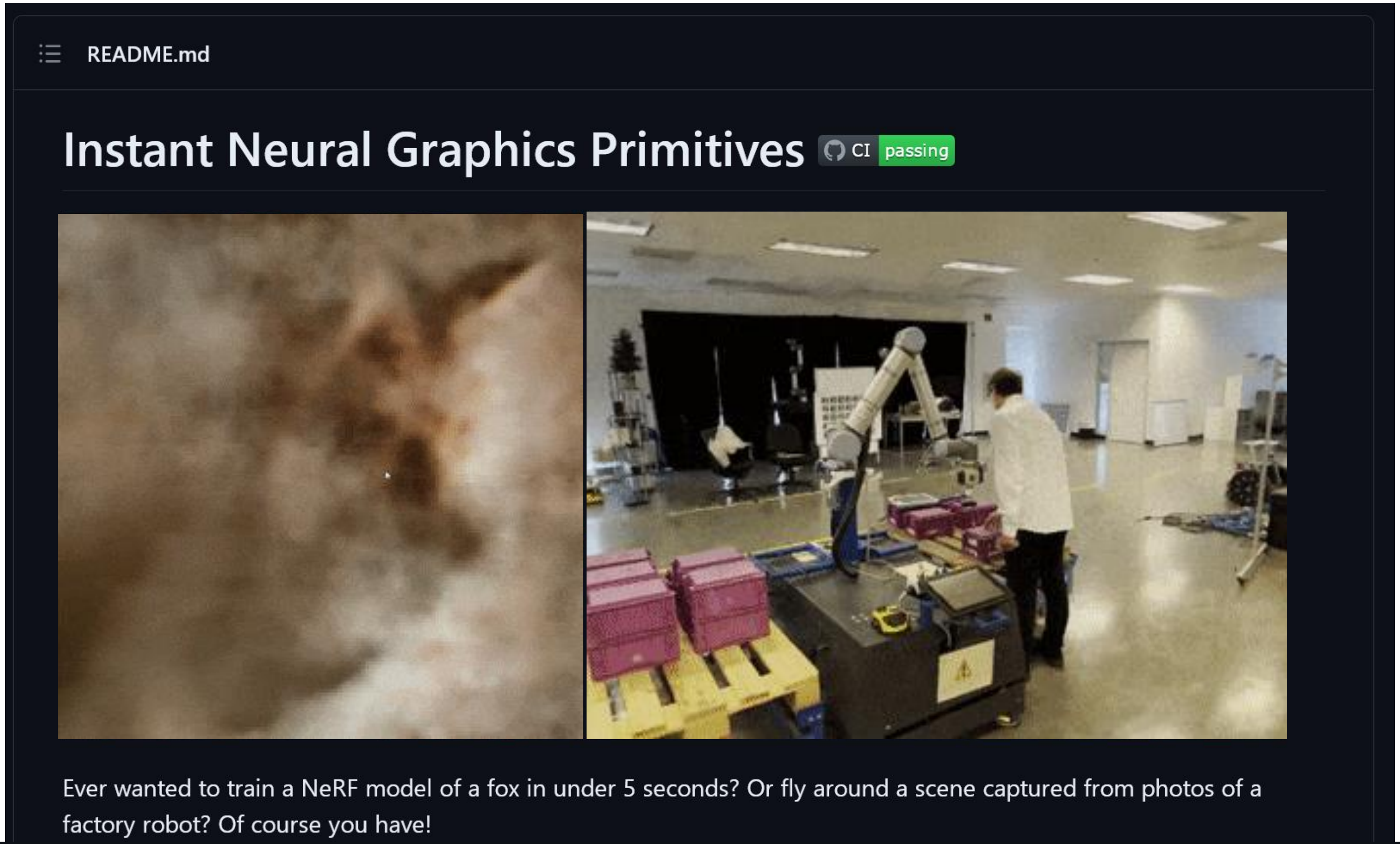
Ever wanted to train a NeRF model of a fox in under 5 seconds? Or fly around a scene captured from photos of a factory robot? Of course you have!

Here you will find an implementation of four **neural graphics primitives**, being neural radiance fields (NeRF), signed distance functions (SDFs), neural images, and neural volumes. In each case, we train and render a MLP with multiresolution hash input encoding using the tiny-cuda-nn framework.

> Instant Neural Graphics Primitives with a Multiresolution Hash Encoding
> Thomas Müller, Alex Evans, Christoph Schied, Alexander Keller
> *ACM Transactions on Graphics (**SIGGRAPH**), July 2022*
> Project page / Paper / Video / Presentation / Real-Time Live / BibTeX

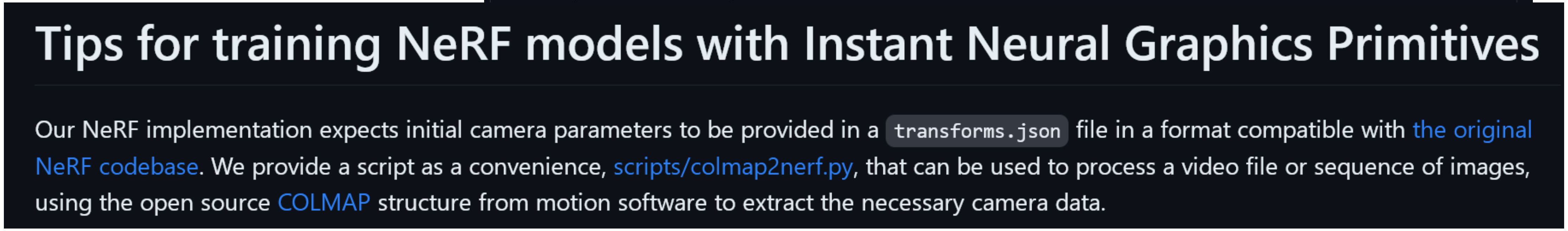
SIFT is 20+ years old. Is it still useful?

- Let’s look at some trendy research on Neural Radiance Fields (NERF)
- Let’s look under the hood


README.md

Instant Neural Graphics Primitives

Ever wanted to train a NeRF model of a fox in under 5 seconds? Or fly around a scene captured from photos of a factory robot? Of course you have!



Tips for training NeRF models with Instant Neural Graphics Primitives

Our NeRF implementation expects initial camera parameters to be provided in a `transforms.json` file in a format compatible with the original NeRF codebase. We provide a script as a convenience, scripts/colmap2nerf.py, that can be used to process a video file or sequence of images, using the open source COLMAP structure from motion software to extract the necessary camera data.

SIFT is 20+ years old. Is it still useful?

- COLMAP is the "standard" way to do structure from motion these days

COLMAP

Sparse model of central Rome using 21K photos produced by COLMAP's SfM pipeline.

Dense models of several landmarks produced by COLMAP's MVS pipeline.

"Structure-From-Motion Revisited". Johannes L. Schonberger, Jan-Michael Frahm; CVPR 2016
5k+ citations

SIFT is 20+ years old. Is it still useful?

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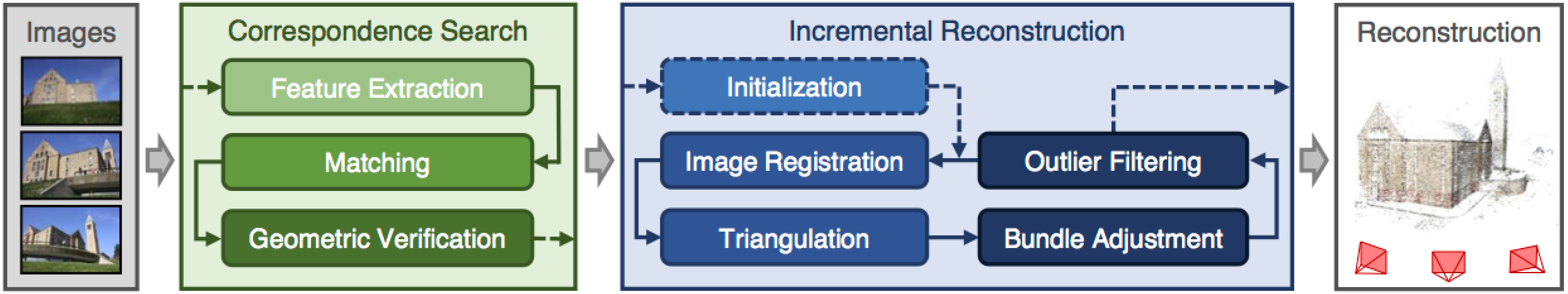
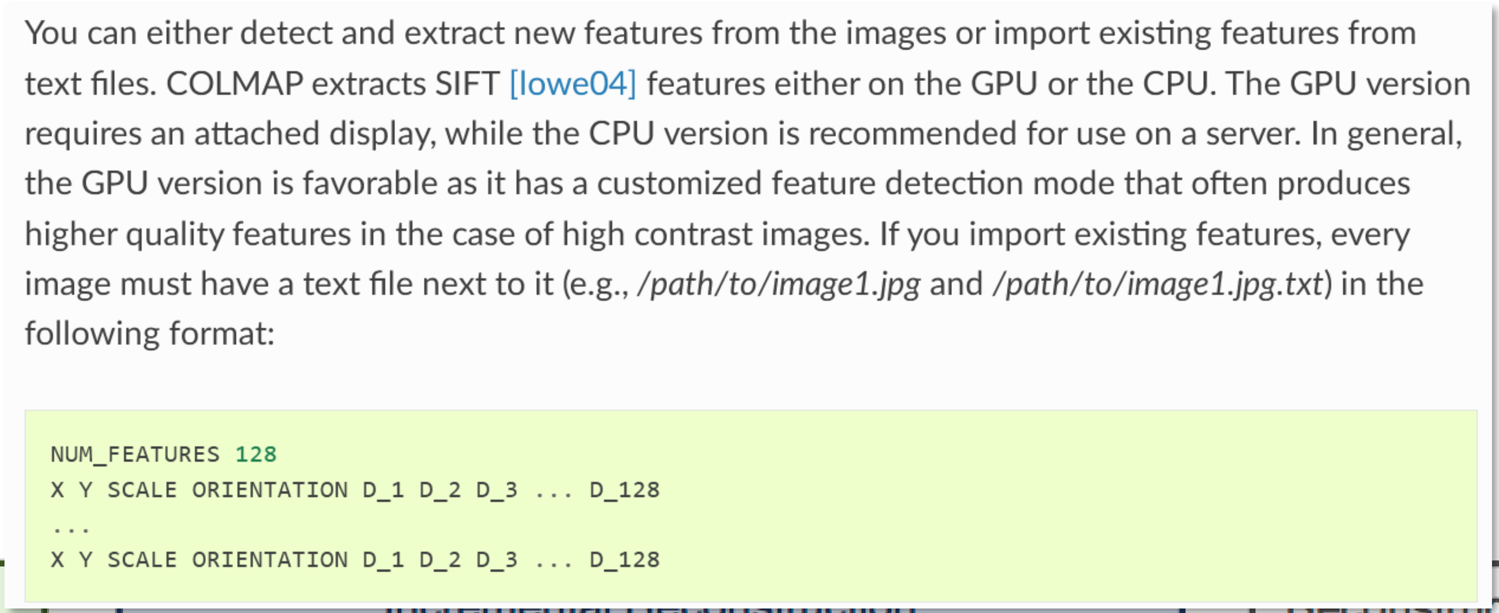


“Structure-From-Motion Revisited”. Johannes L. Schonberger, Jan-Michael Frahm; CVPR 2016
3k+ citations

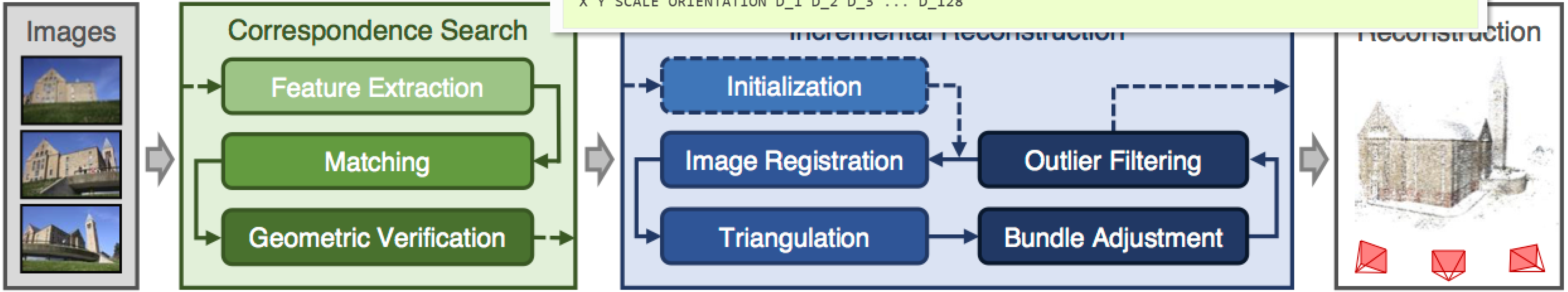
SIFT is 20+ years old. Is it still useful?

- COLMAP is the "standard" way to do structure from motion these days



You can either detect and extract new features from the images or import existing features from text files. COLMAP extracts SIFT [lowe04] features either on the GPU or the CPU. The GPU version requires an attached display, while the CPU version is recommended for use on a server. In general, the GPU version is favorable as it has a customized feature detection mode that often produces higher quality features in the case of high contrast images. If you import existing features, every image must have a text file next to it (e.g., */path/to/image1.jpg* and */path/to/image1.jpg.txt*) in the following format:

```
NUM_FEATURES 128
X Y SCALE ORIENTATION D_1 D_2 D_3 ... D_128
...
X Y SCALE ORIENTATION D_1 D_2 D_3 ... D_128
```



"Structure-From-Motion Revisited". Johannes L. Schonberger, Jan-Michael Frahm; CVPR 2016
3k+ citations

Distributed Global Structure-from-Motion with a Deep Front-End

Ayush Baid *† John Lambert*† Travis Driver* Akshay Krishnan*
Hayk Stepanyan Frank Dellaert
Georgia Tech

Abstract

While initial approaches to Structure-from-Motion (SfM) revolved around both global and incremental methods, most recent applications rely on incremental systems to estimate camera poses due to their superior robustness. Though there has been tremendous progress in SfM 'front-ends' powered by deep models learned from data, the state-of-the-art (incremental) SfM pipelines still rely on classical SIFT features, developed in 2004. In this work, we investigate whether leveraging the developments in feature extraction and matching helps global SfM perform on par with the SOTA incremental SfM approach (COLMAP). To do so, we design a modular SfM framework that allows us to easily combine developments in different stages of the SfM pipeline. Our experiments show that while developments in deep-learning based two-view correspondence estimation do translate to improvements in point density for scenes reconstructed with global SfM, none of them outperform SIFT when comparing with incremental SfM results on a range of datasets. Our SfM system is designed from the ground up to leverage distributed computation, enabling us to parallelize computation on multiple machines and scale to large scenes. Our code is publicly available at github.com/borglab/gtsfm.

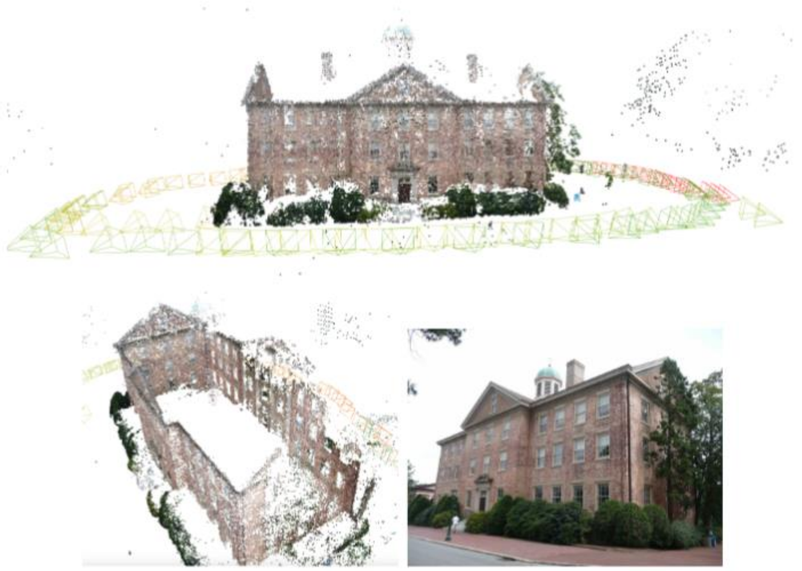


Figure 1. A sparse reconstruction of the UNC South Building using GTSfM with a deep LoFTR-based [64] front-end, with an example image input. Multi-view stereo is not used.

[53, 57], Gaussian Splatting [32], accurate monocular depth predictions for humans [39], and more.

Incremental SfM is the dominant paradigm, as global SfM suffers from a lack of accuracy, largely due to difficulty in reasoning about outliers globally in a single pass. However, to our knowledge, almost all global SfM systems

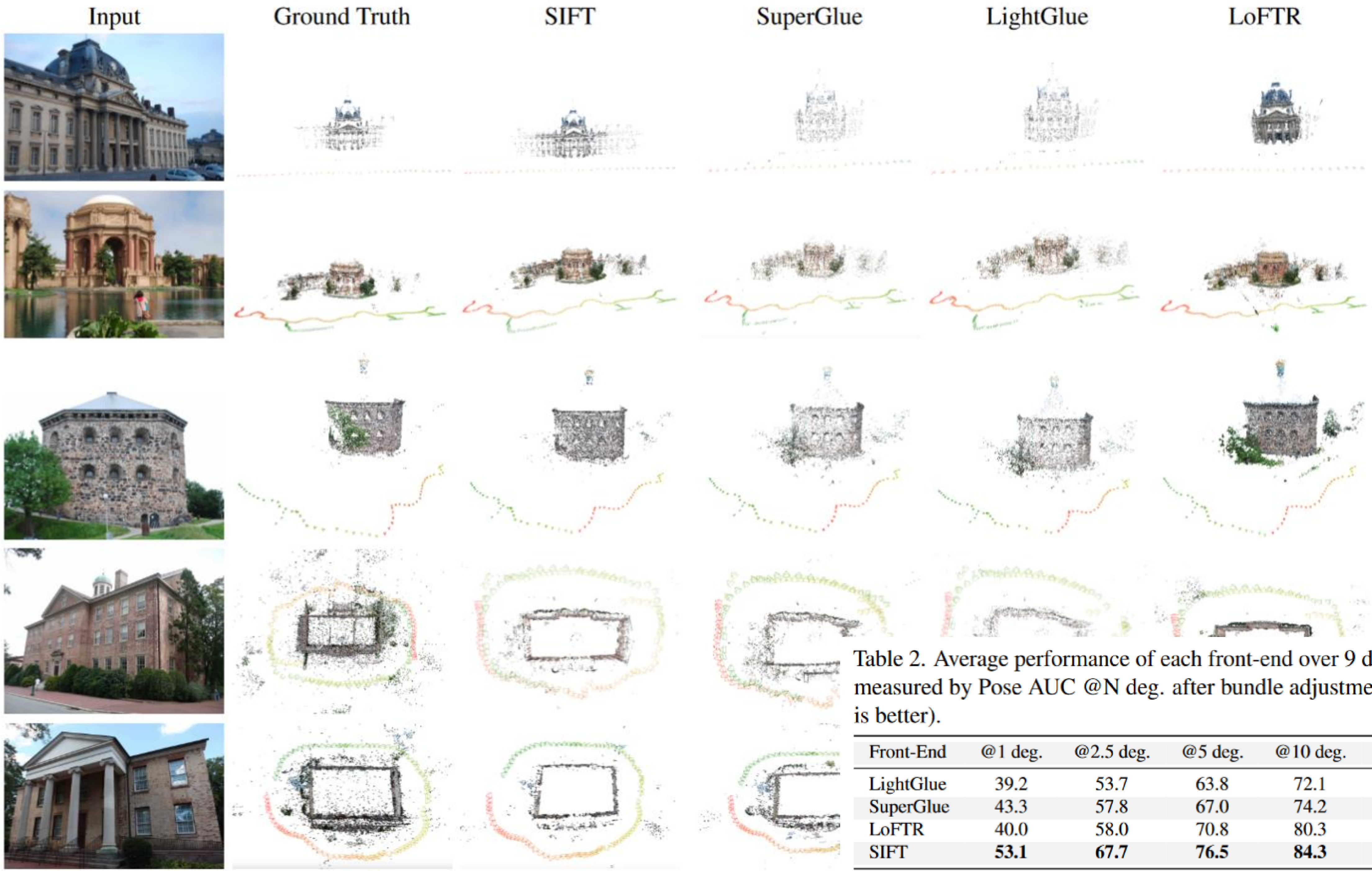
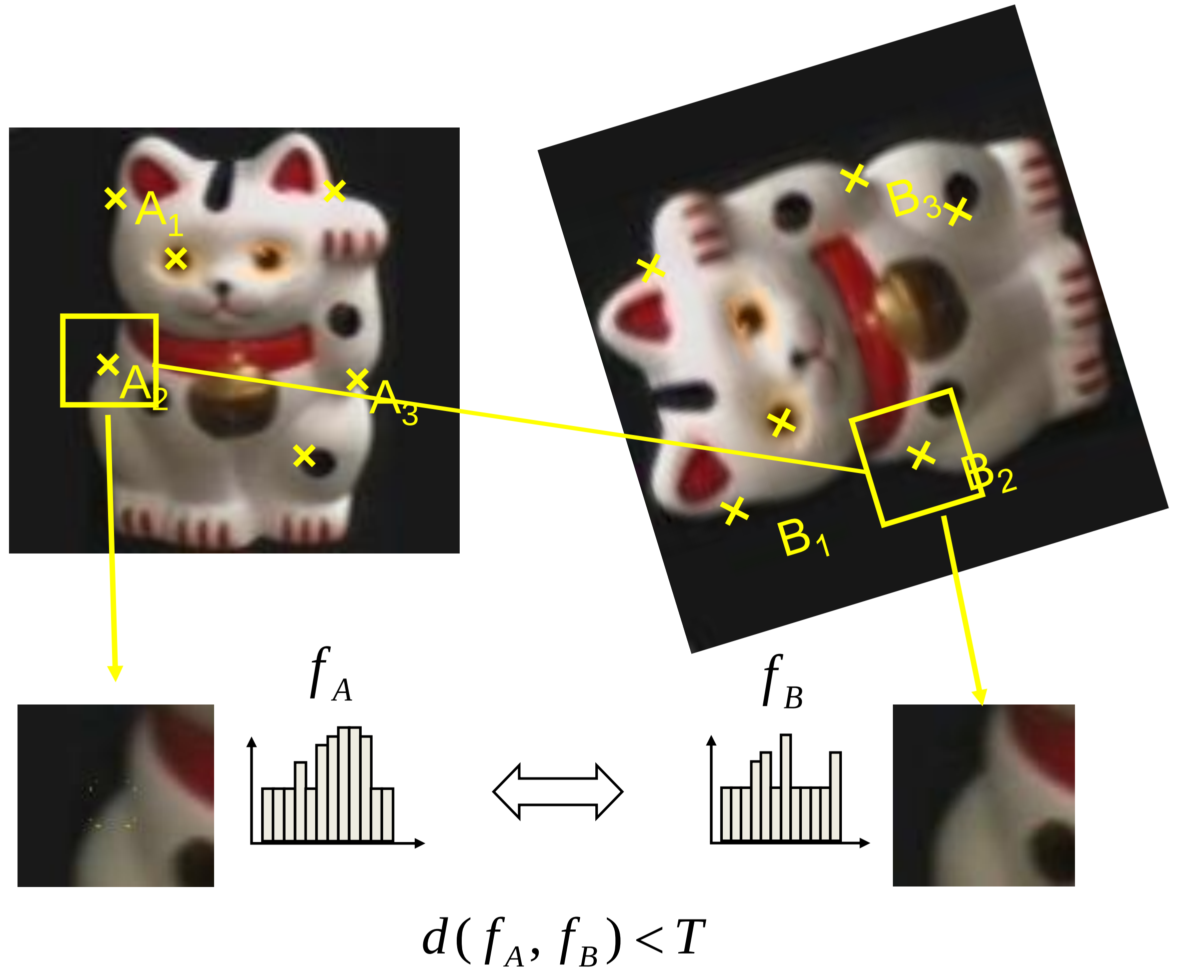


Table 2. Average performance of each front-end over 9 datasets, as measured by Pose AUC @N deg. after bundle adjustment (higher is better).

Front-End	@1 deg.	@2.5 deg.	@5 deg.	@10 deg.	@20 deg.
LightGlue	39.2	53.7	63.8	72.1	77.9
SuperGlue	43.3	57.8	67.0	74.2	79.0
LoFTR	40.0	58.0	70.8	80.3	86.2
SIFT	**53.1**	**67.7**	**76.5**	**84.3**	**90.3**

Overview of Keypoint Matching



1. Find a set of distinctive keypoints

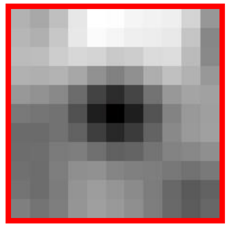
2. Compute a local descriptor from the region around each keypoint

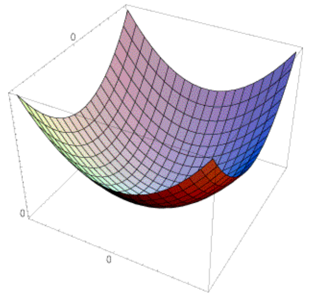
3. Match local descriptors

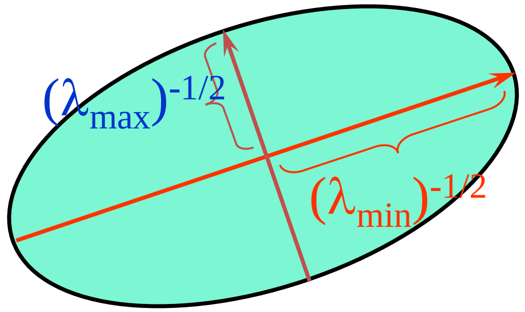
Review: Harris corner detector

- Define distinctiveness by local auto-correlation.
- Approximate local auto-correlation by second moment matrix
- Quantify distinctiveness (or cornerness) as function of the eigenvalues of the second moment matrix.
- But we don't actually need to compute the eigenvalues. Instead, we use the determinant and trace of the second moment matrix.

$E(u, v)$



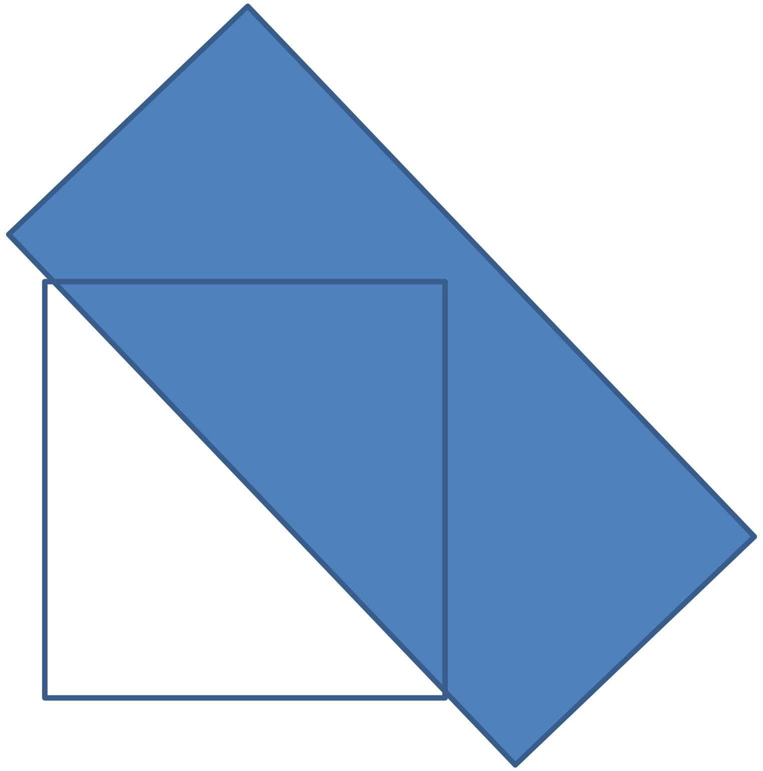




Review: Harris corner detector

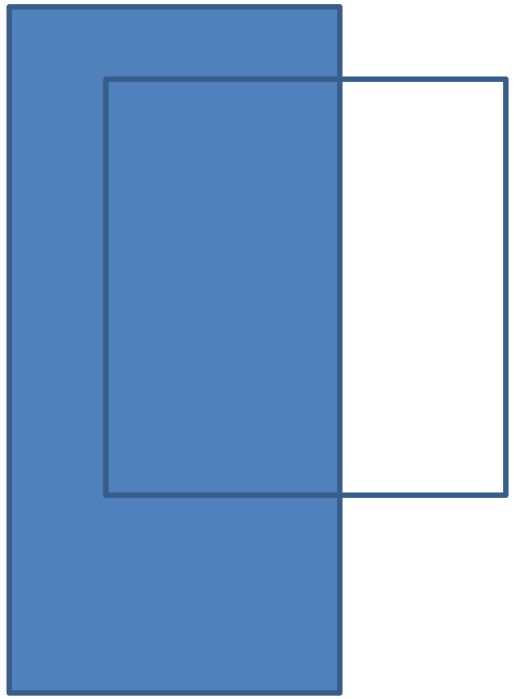
- We want to find *distinctive* patches that don't look self-similar to neighboring patches
- If there are *gradients* in a patch, those gradients indicate distinctiveness in a particular direction.
- We want to check that we have strong, independent gradients in all directions.
- The eigenvalues of a the collection of gradients in a patch tell us this.

What do the gradients / structure matrix look like?



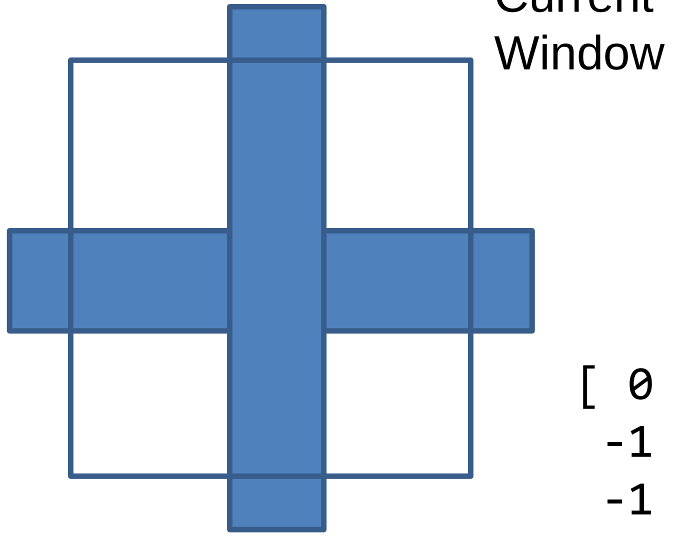
```
[ 0 0
 -1 1
 -1 1
  0 0
  0 0
 -1 1
  0 0
  …   ]
```

$$\begin{bmatrix} C & -C \\ -C & C \end{bmatrix}$$



```
[ 0 0
  1 0
  1 0
  0 0
  0 0
  0 0
  1 0
  …   ]
```

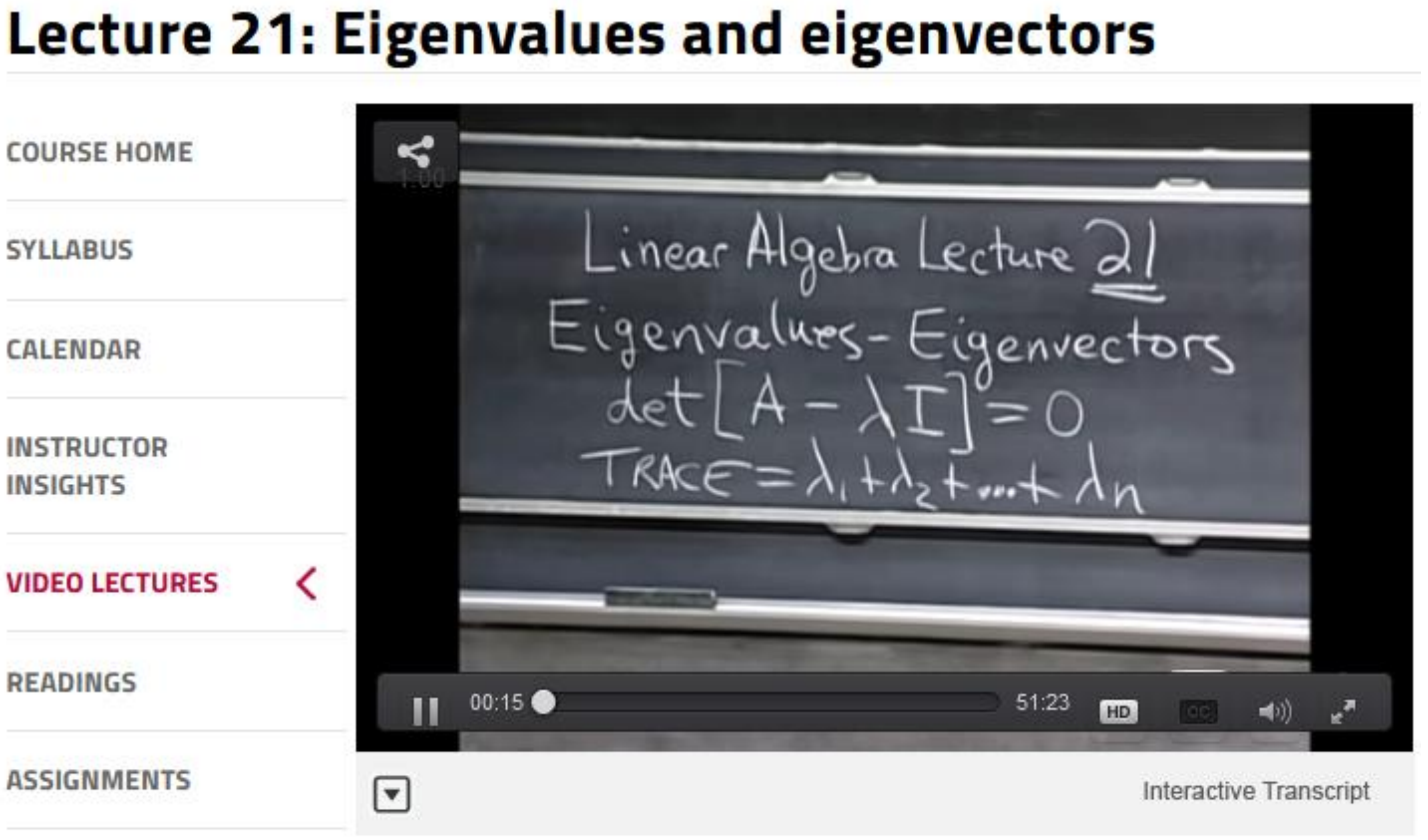
$$\begin{bmatrix} C & 0 \\ 0 & 0 \end{bmatrix}$$



```
[ 0 0
 -1 0
 -1 0
  0 0
  0 0
  0 1
  1 0
  …   ]
```

$$\begin{bmatrix} C & 0 \\ 0 & C \end{bmatrix}$$

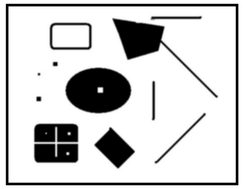
If you're not comfortable with Eigenvalues and Eigenvectors, Gilbert Strang's linear algebra lectures are linked from the course homepage



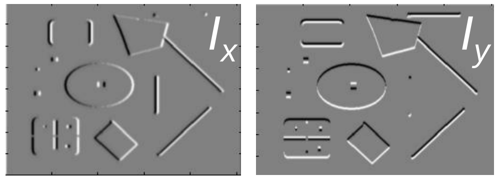
Harris Detector [Harris88]

- Second moment matrix

$$\mu(\sigma_I,\sigma_D) = g(\sigma_I) * \begin{bmatrix} I_x^2(\sigma_D) & I_x I_y(\sigma_D) \\ I_x I_y(\sigma_D) & I_y^2(\sigma_D) \end{bmatrix}$$

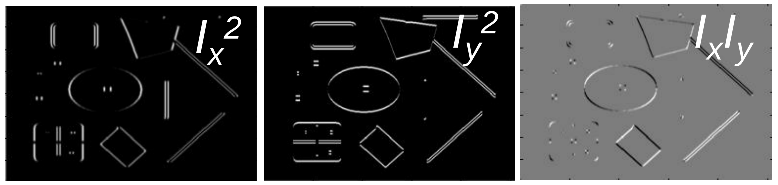


1. Image derivatives (optionally, blur first)

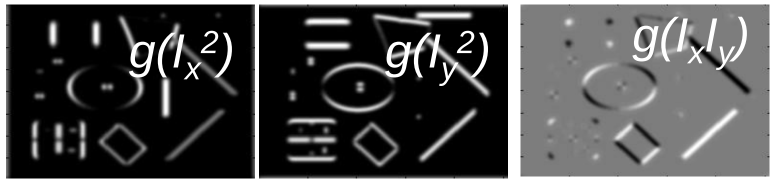


$$\det M = \lambda_1 \lambda_2$$
$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

2. Square of derivatives

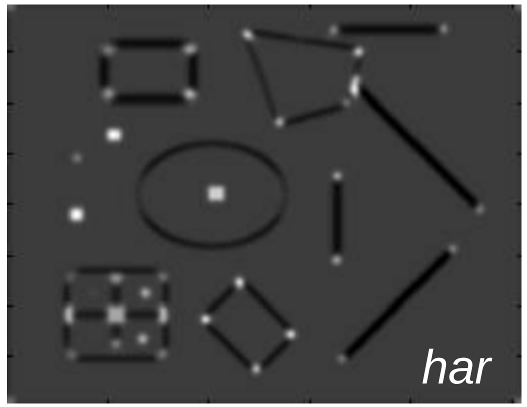


3. Gaussian filter $g(\sigma_I)$



4. Cornerness function – both eigenvalues are strong

$$har = \det[\mu(\sigma_I,\sigma_D)] - \alpha[\operatorname{trace}(\mu(\sigma_I,\sigma_D))^2] =$$
$$g(I_x^2)g(I_y^2) - [g(I_xI_y)]^2 - \alpha[g(I_x^2)+g(I_y^2)]^2$$

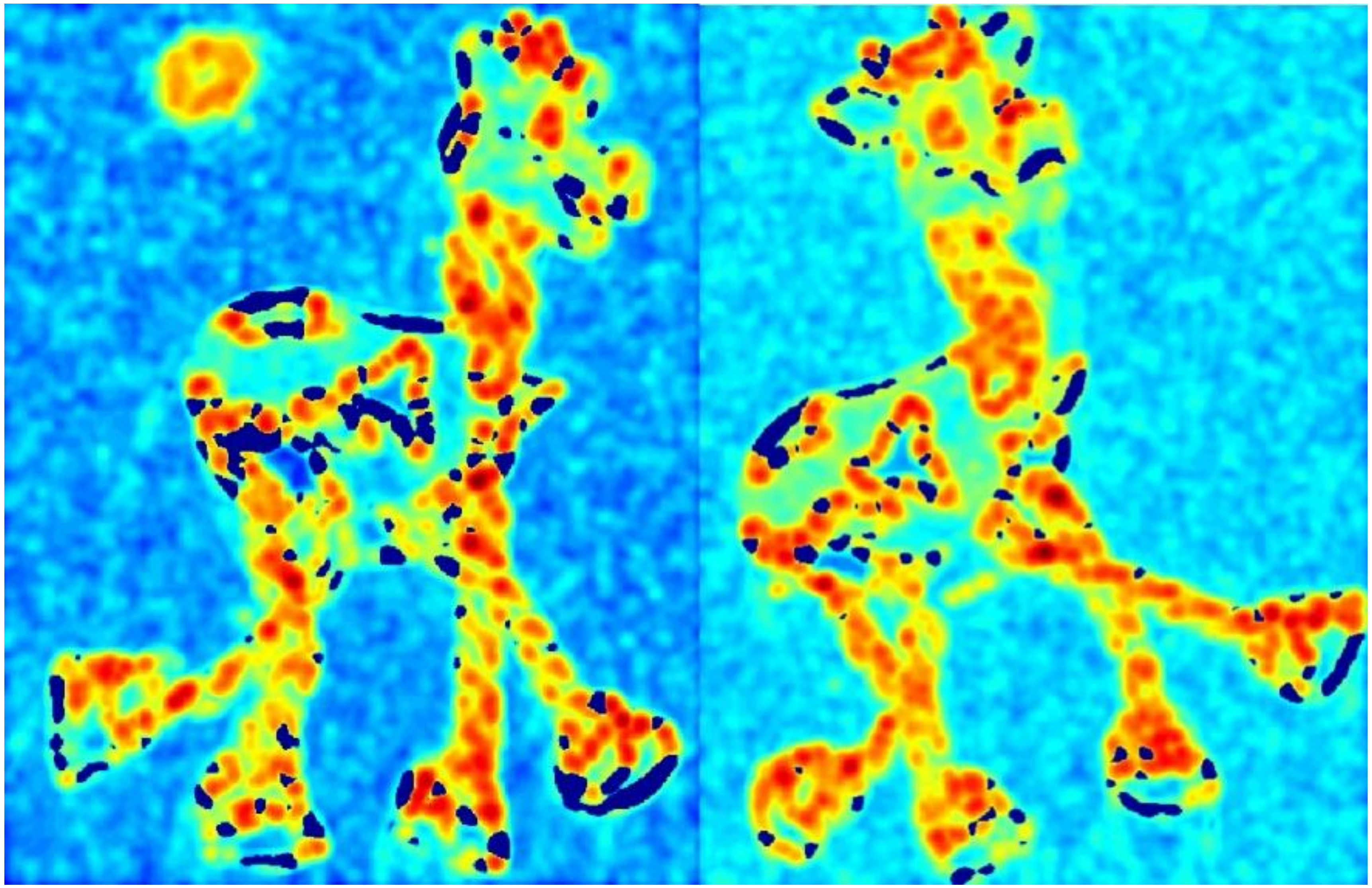


5. Non-maxima suppression

Harris Detector: Steps

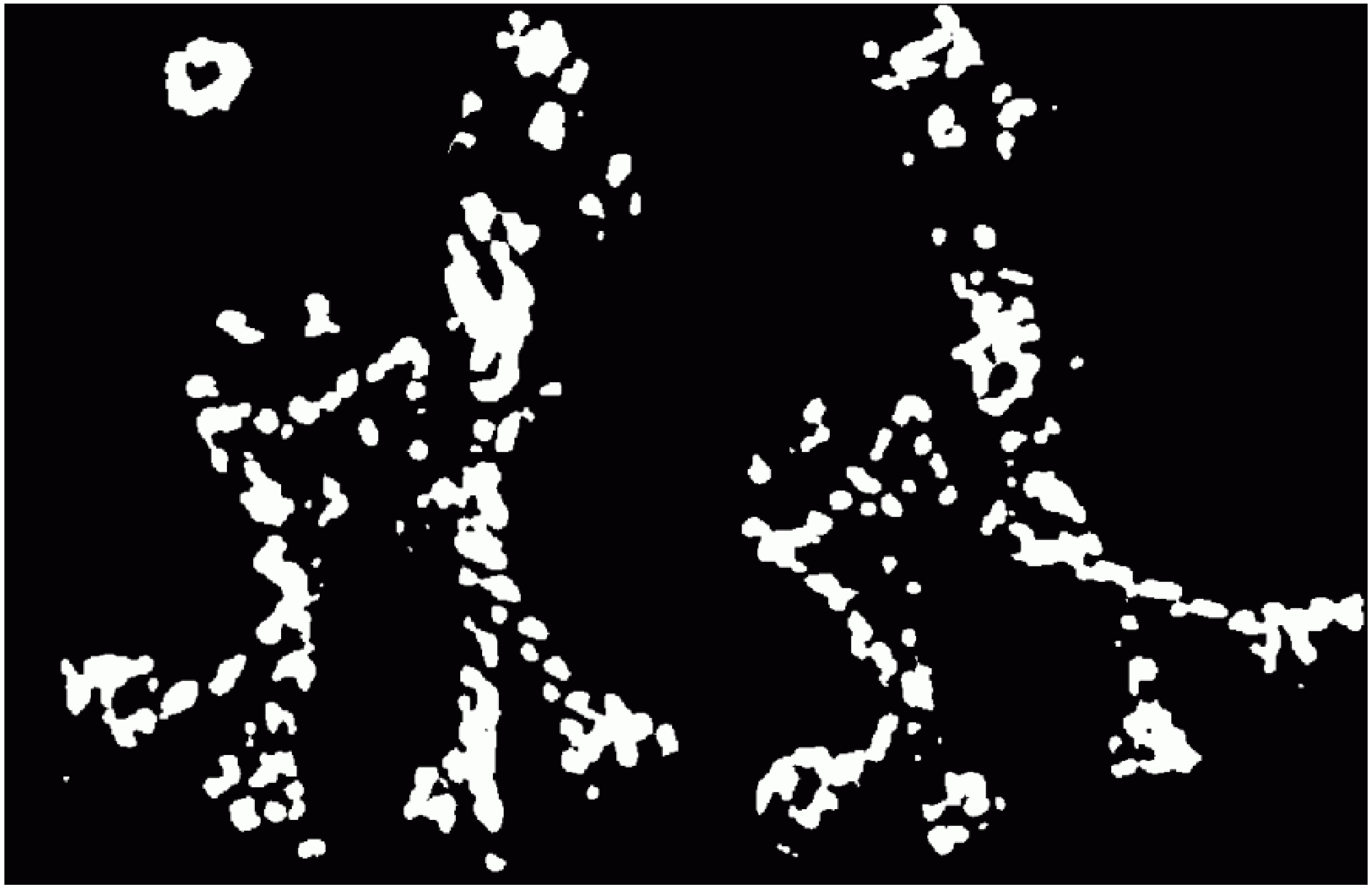
Harris Detector: Steps

Compute corner response R



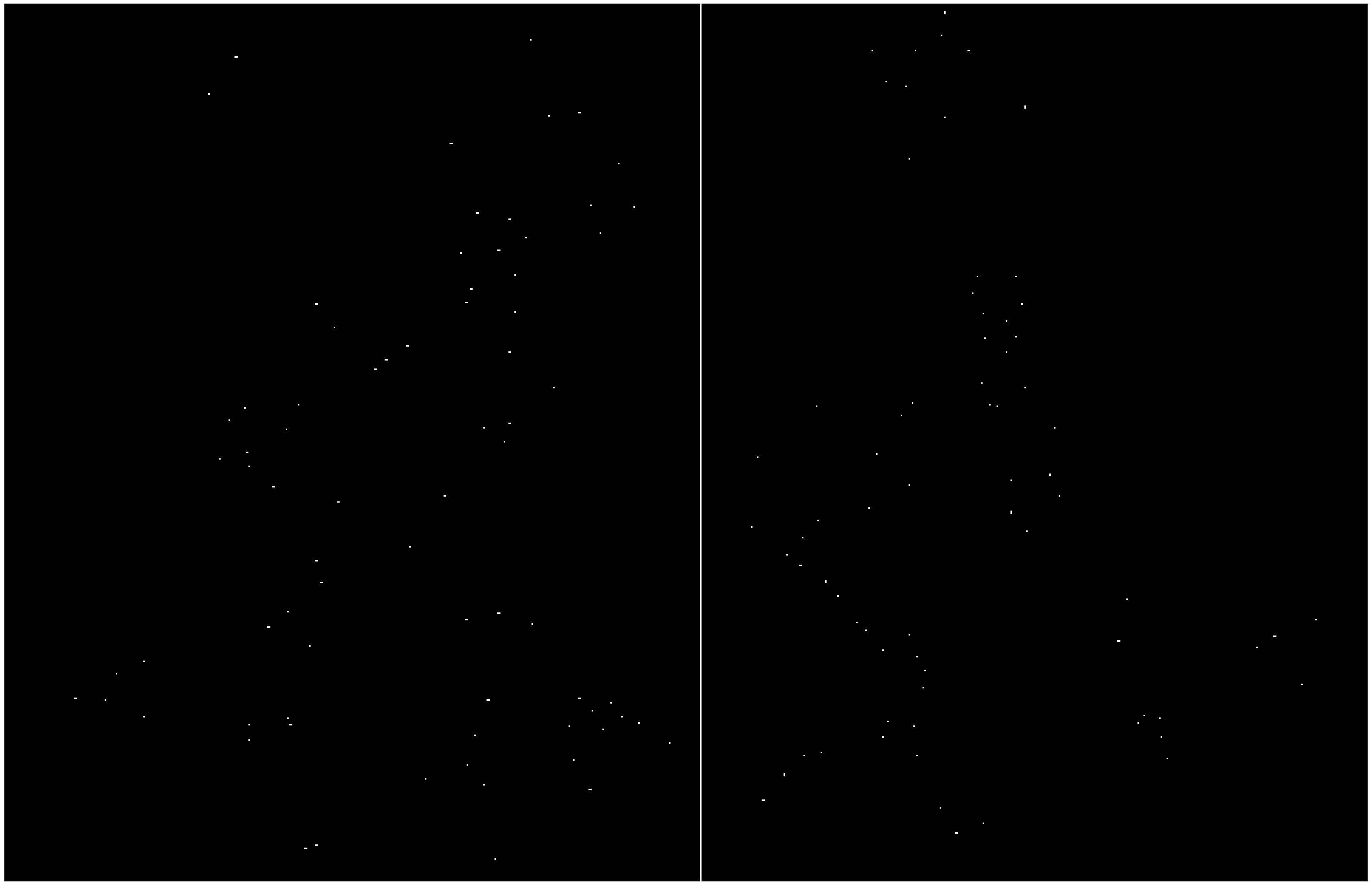
Harris Detector: Steps

Find points with large corner response: R>threshold

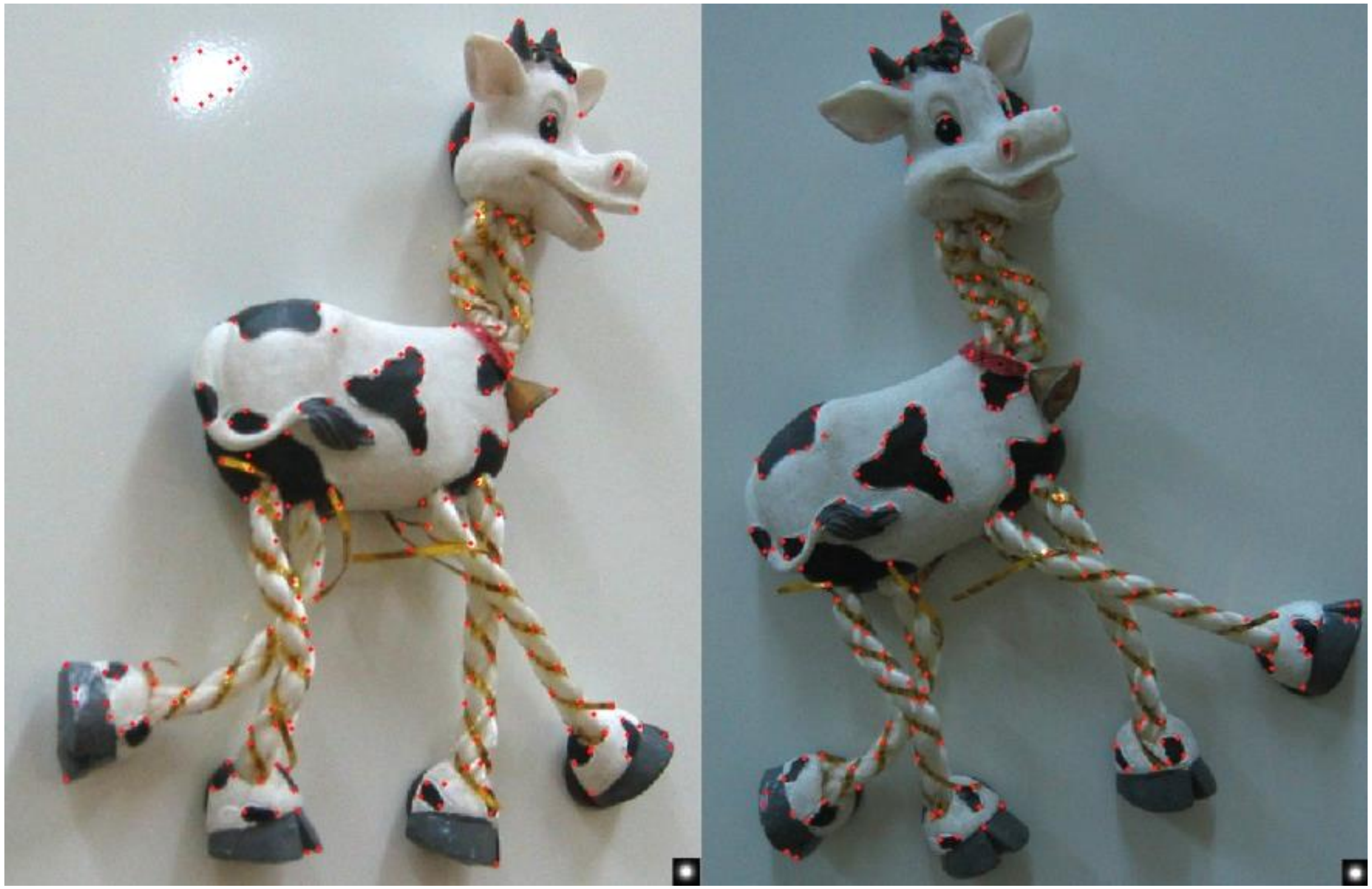


Harris Detector: Steps

Take only the points of local maxima of R

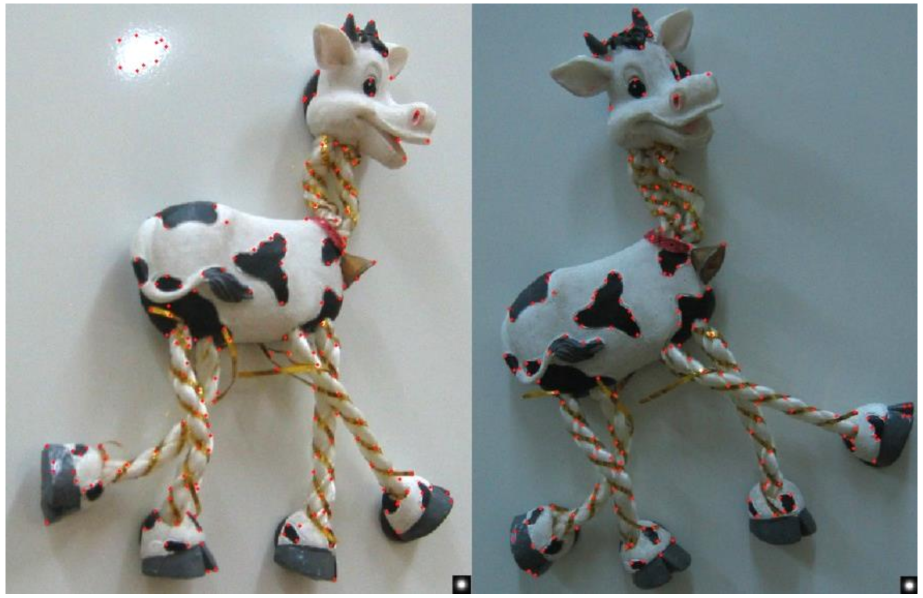


Harris Detector: Steps

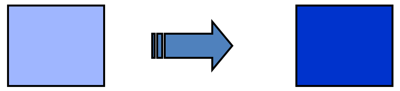


Invariance and covariance

- We want corner locations to be *invariant* to photometric transformations and *covariant* to geometric transformations
  - – **Invariance:** image is transformed and corner locations do not change
  - – **Covariance:** if we have two transformed versions of the same image, features should be detected in corresponding locations

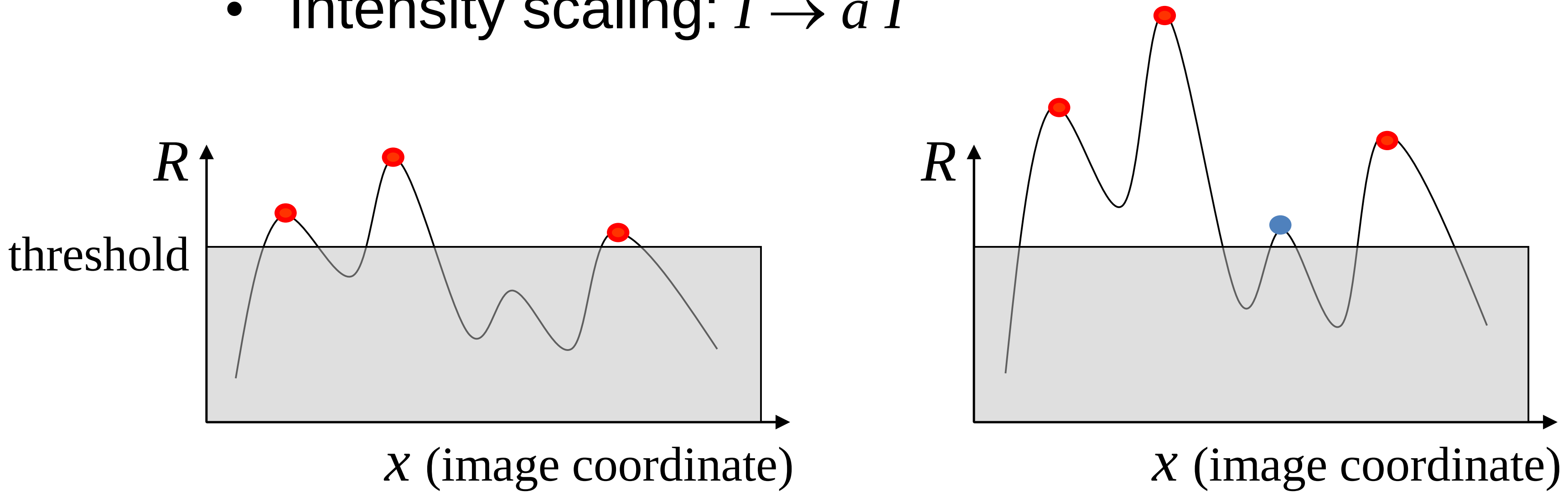


Affine intensity change



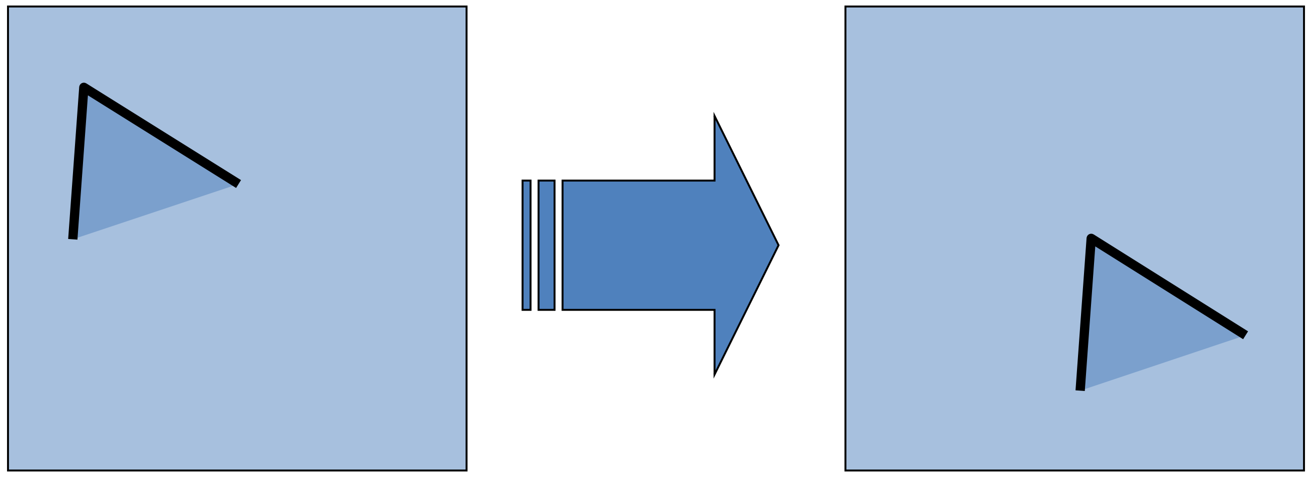
$$I \rightarrow a\,I + b$$

- Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$
- Intensity scaling: $I \rightarrow a\,I$



Partially invariant to affine intensity change

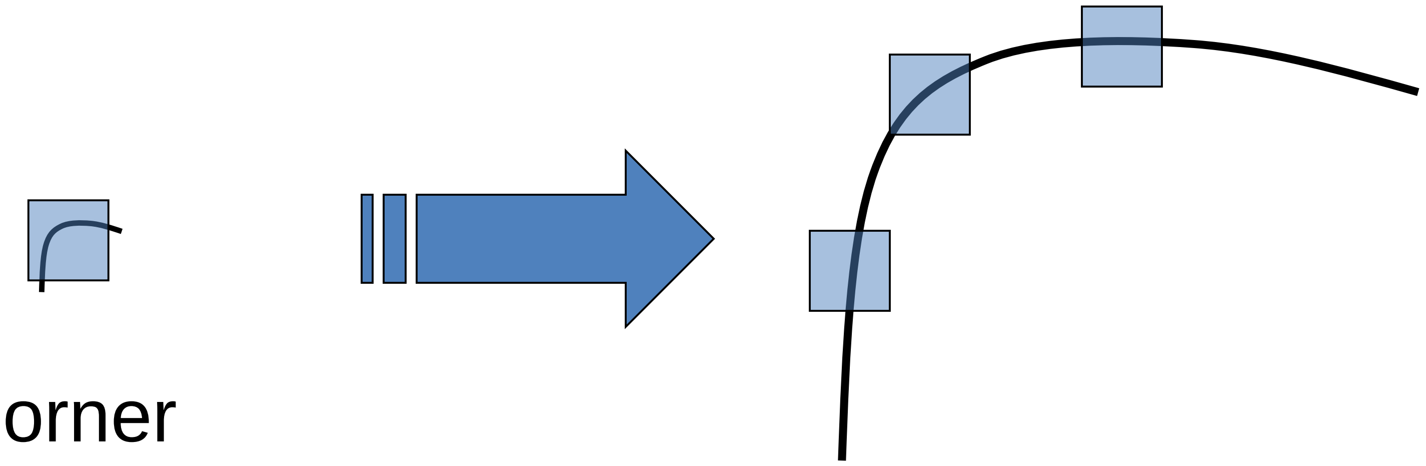
Image translation



- Derivatives and window function are shift-invariant

Corner location is covariant w.r.t. translation

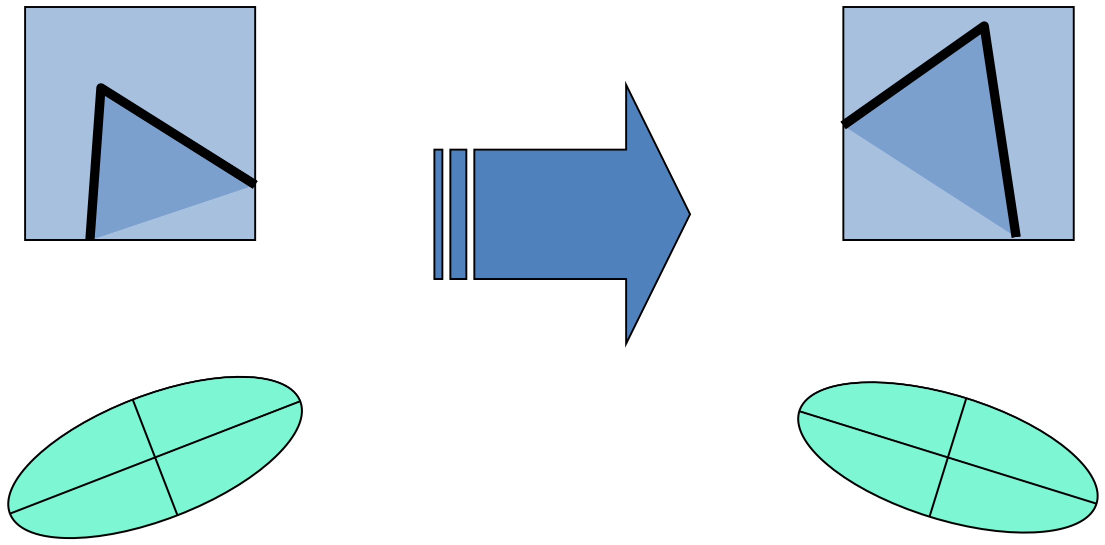
Scaling



All points will be classified as edges

Corner location is not covariant to scaling!

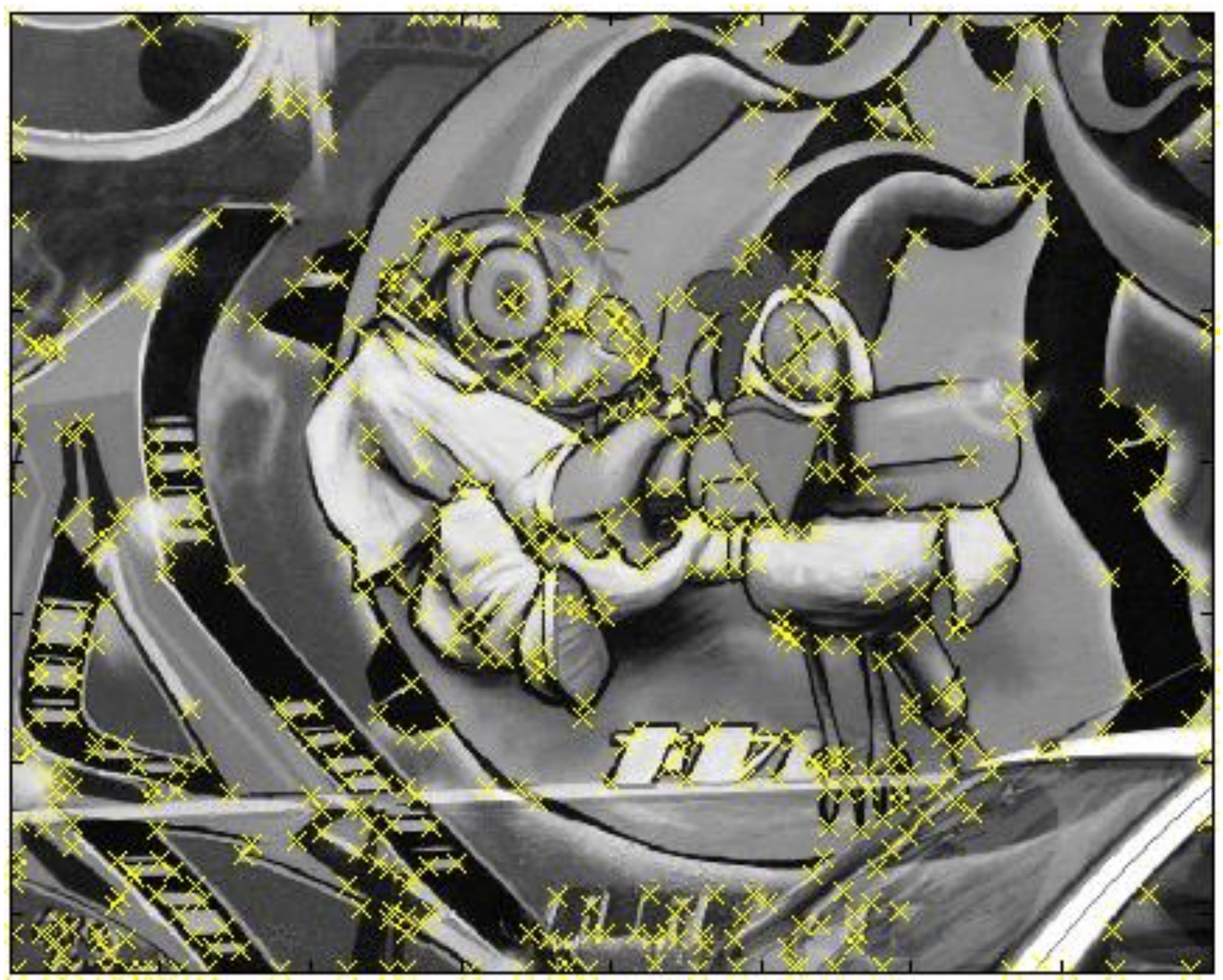
Image rotation



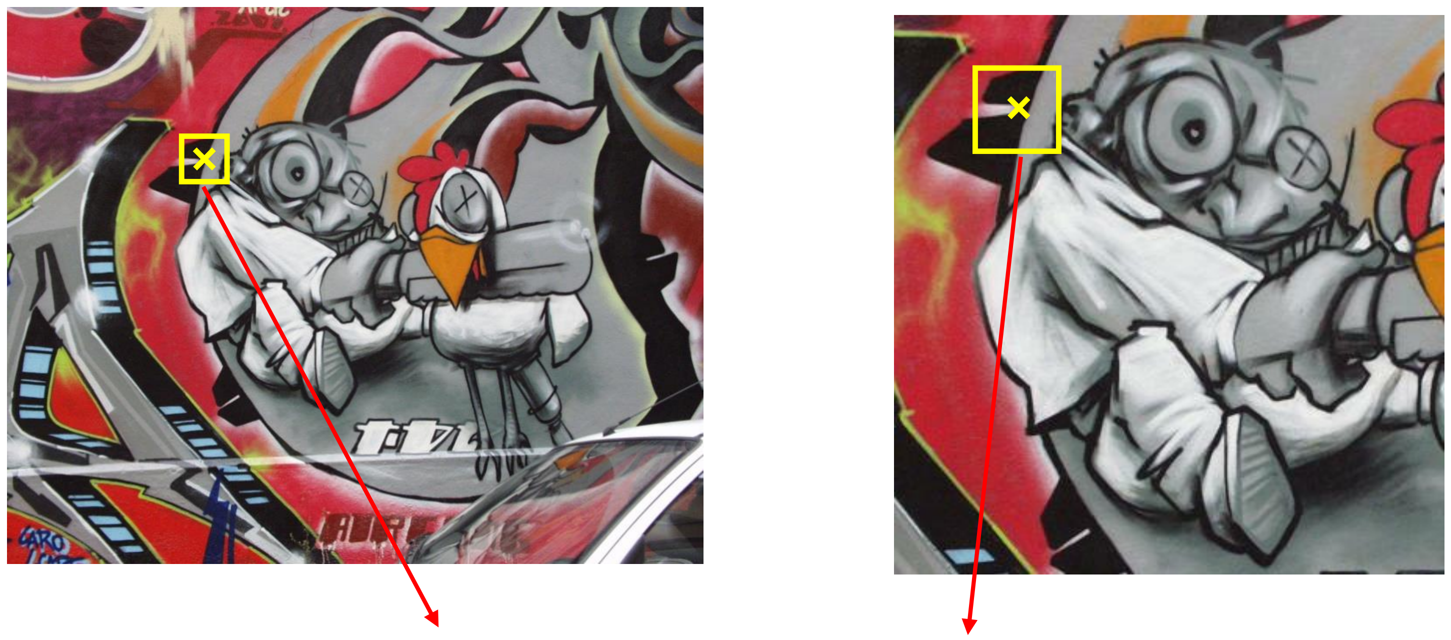
Second moment ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner location is covariant w.r.t. rotation

So far: can localize in x-y, but not scale



Automatic Scale Selection



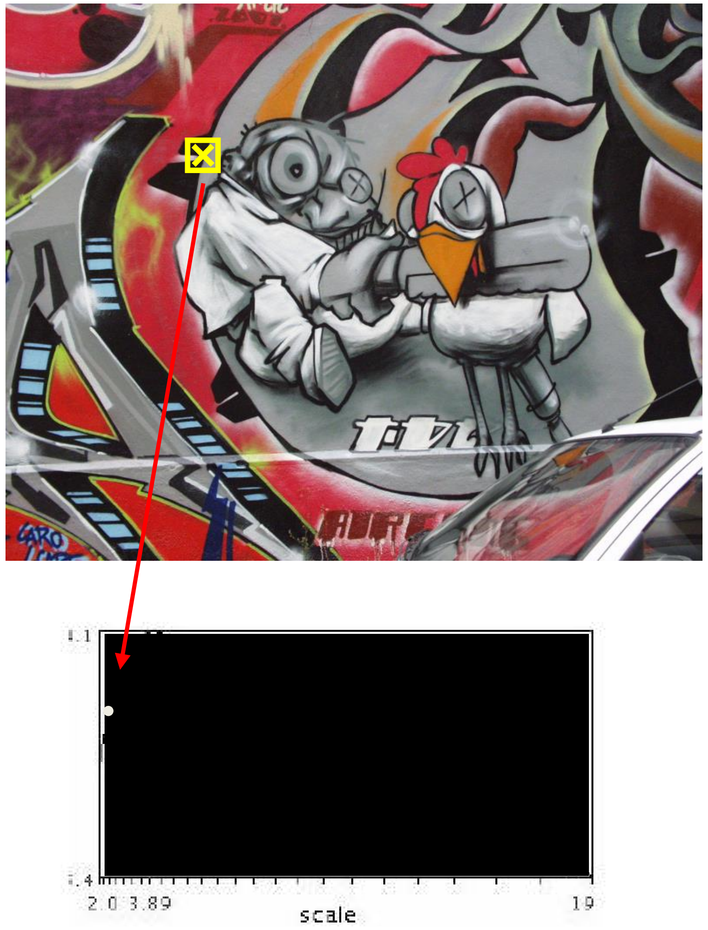
$$f(I_{i_1\ldots i_m}(x,\sigma)) = f(I_{i_1\ldots i_m}(x',\sigma'))$$

How to find corresponding patch sizes?

K. Grauman, B. Leibe

Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x, \sigma))$

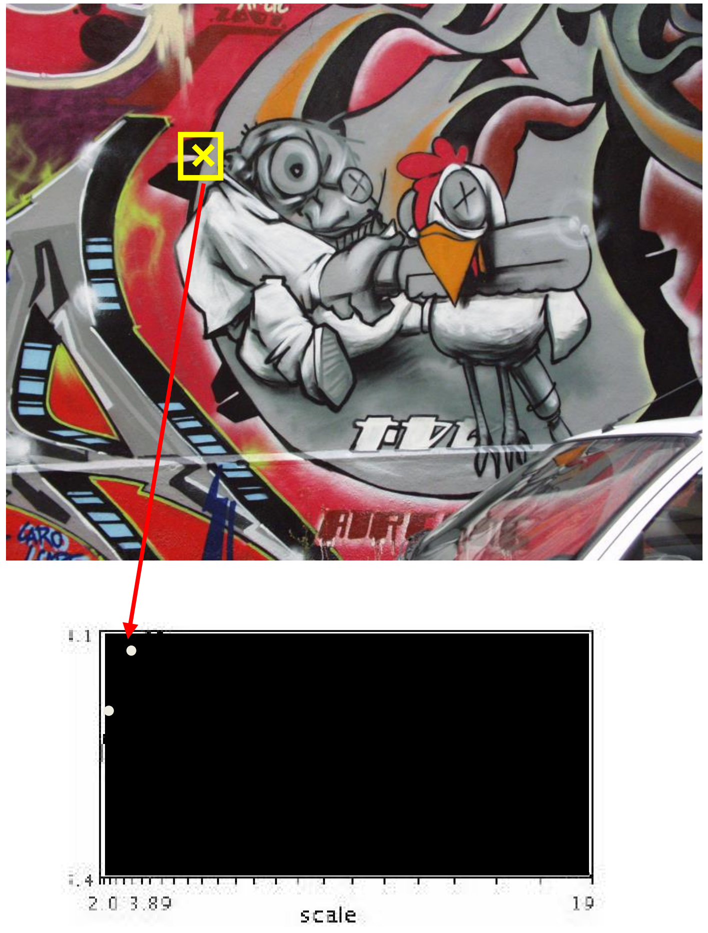
2.0
10.1
scale
19.

$f(I_{i_1 \ldots i_m}(x', \sigma))$

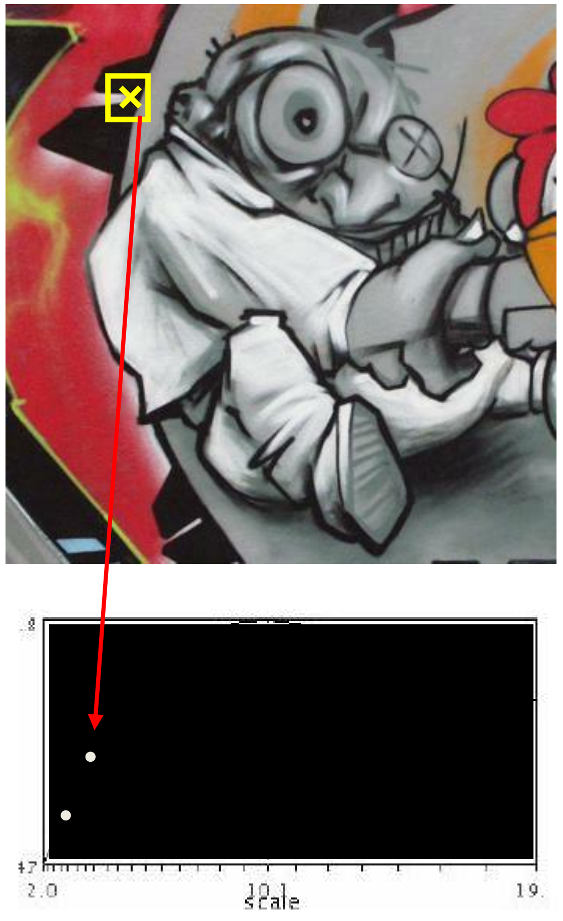
K. Grauman, B. Leibe

Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x, \sigma))$

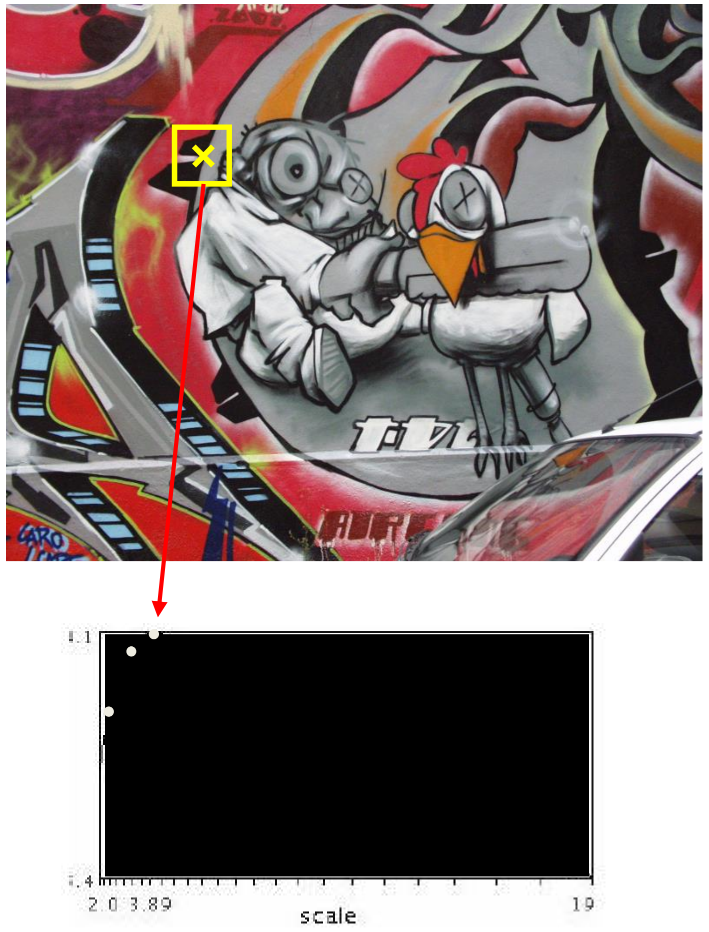


$f(I_{i_1 \dots i_m}(x', \sigma))$

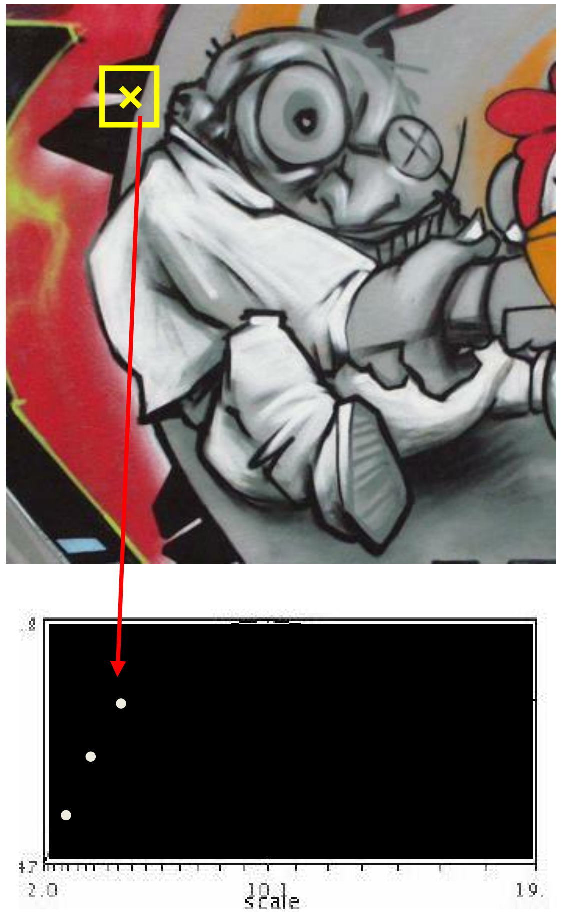
K. Grauman, B. Leibe

Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x, \sigma))$

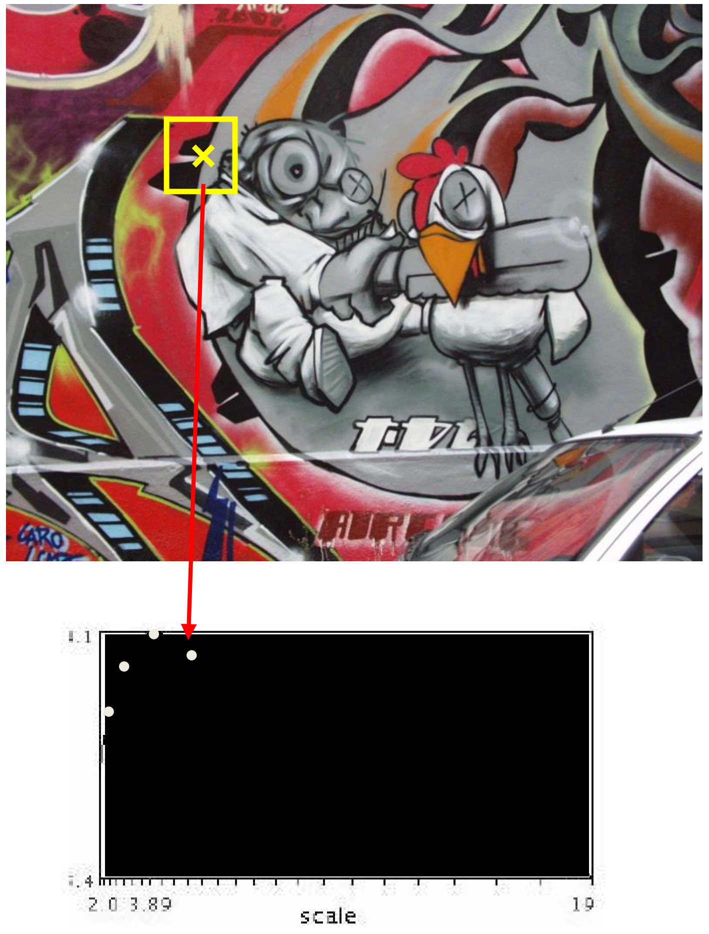


$f(I_{i_1 \ldots i_m}(x', \sigma))$

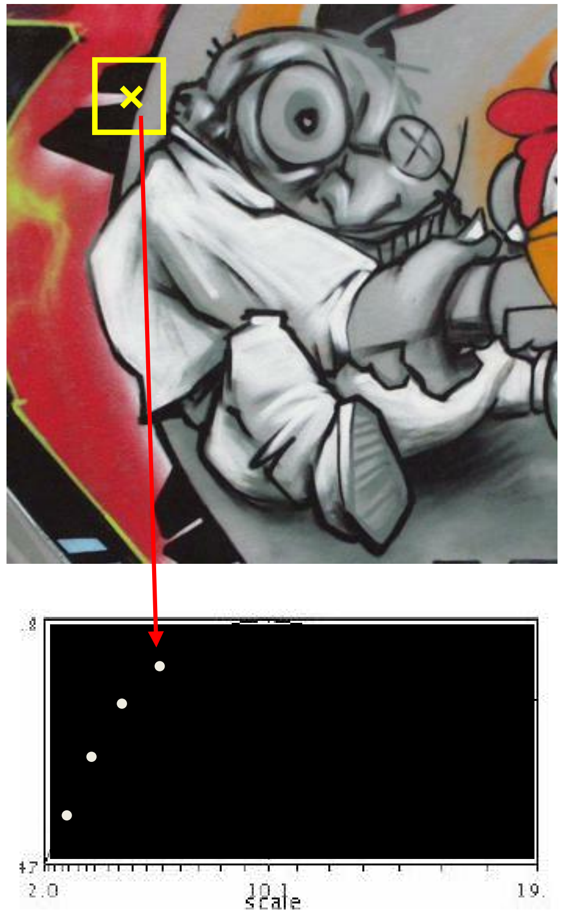
K. Grauman, B. Leibe

Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x,\sigma))$

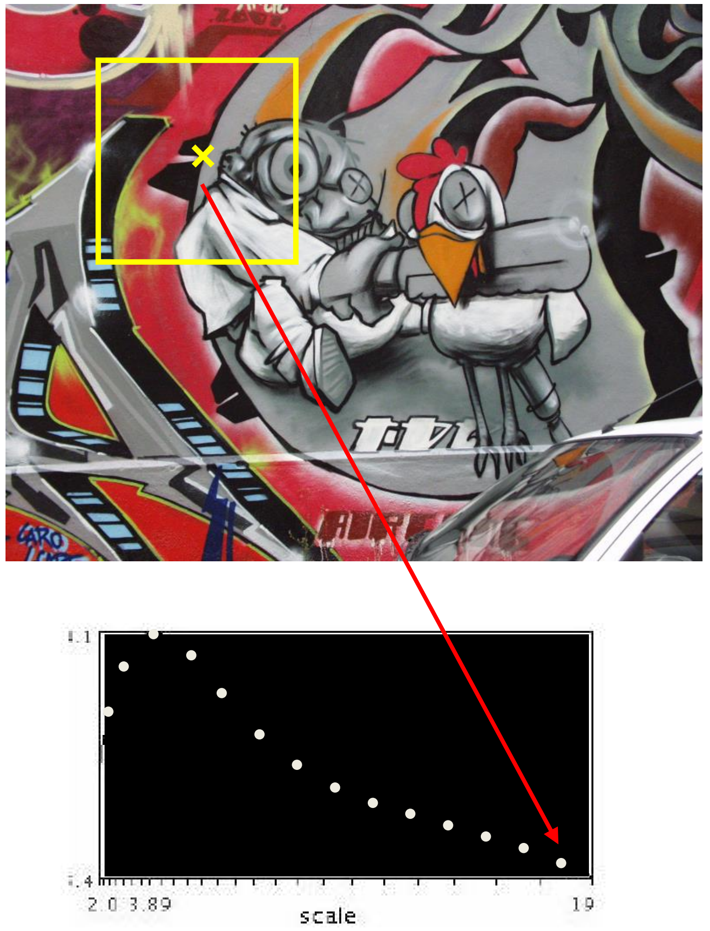


$f(I_{i_1 \ldots i_m}(x',\sigma))$

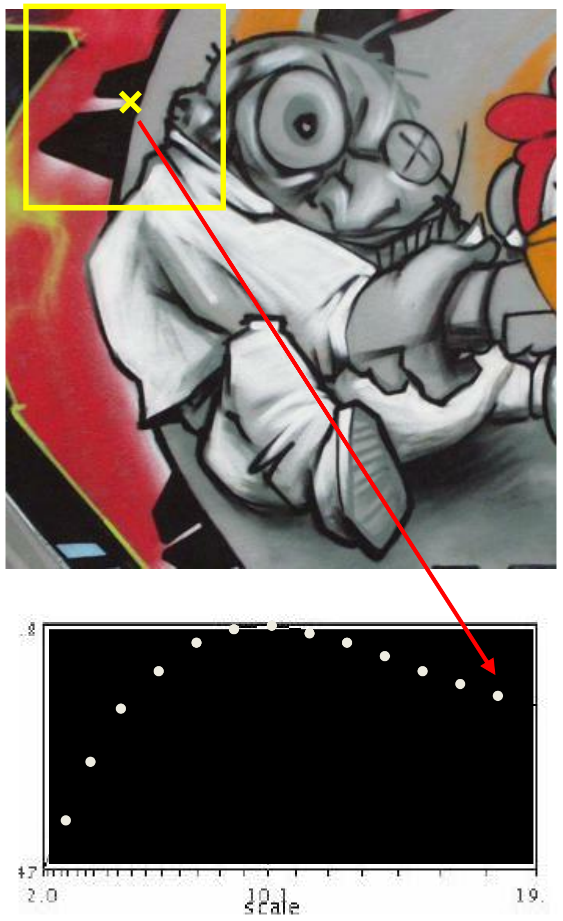
K. Grauman, B. Leibe

Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x, \sigma))$

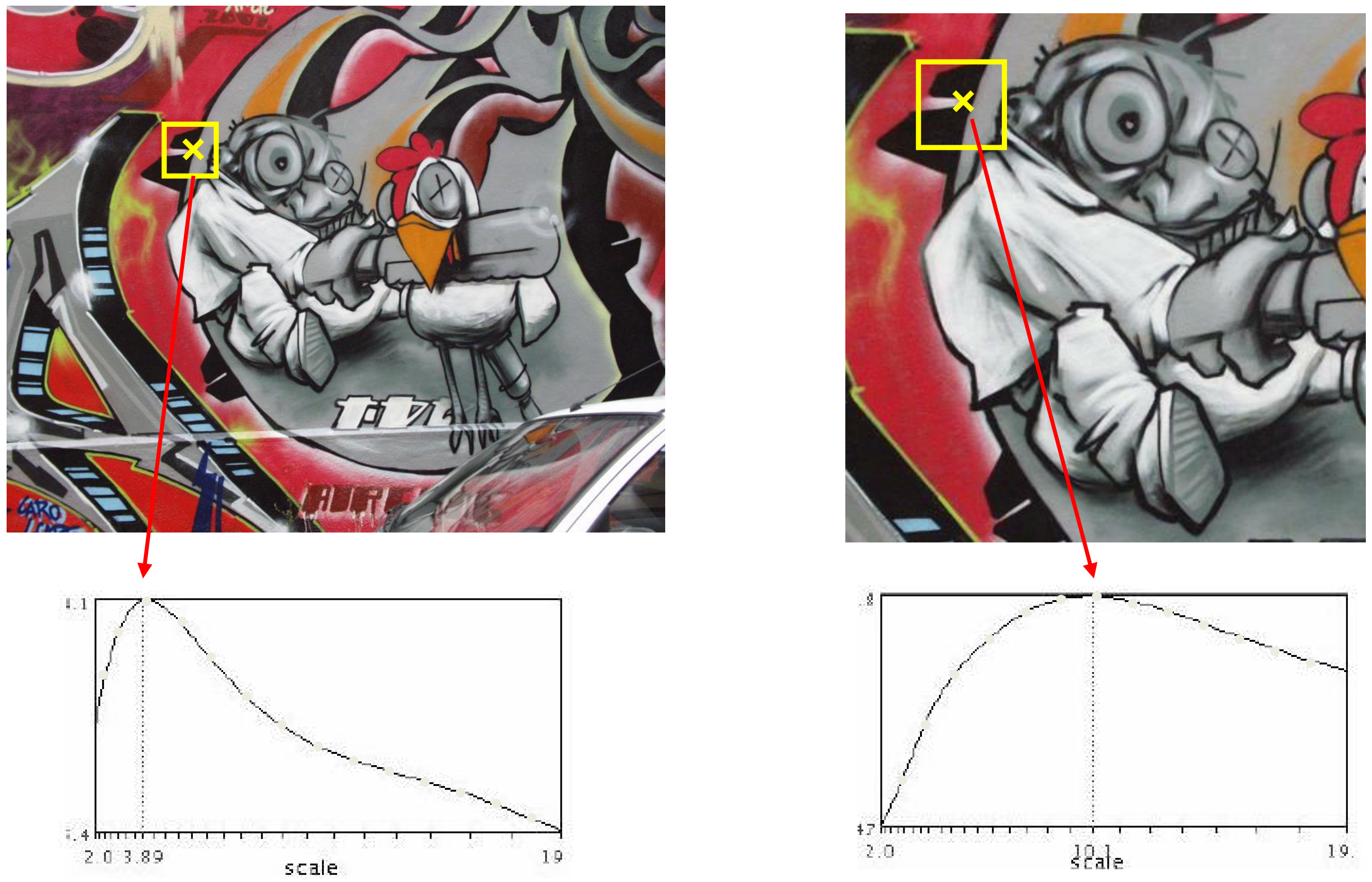


$f(I_{i_1 \ldots i_m}(x', \sigma))$

K. Grauman, B. Leibe

Automatic Scale Selection

- Function responses for increasing scale (scale signature)

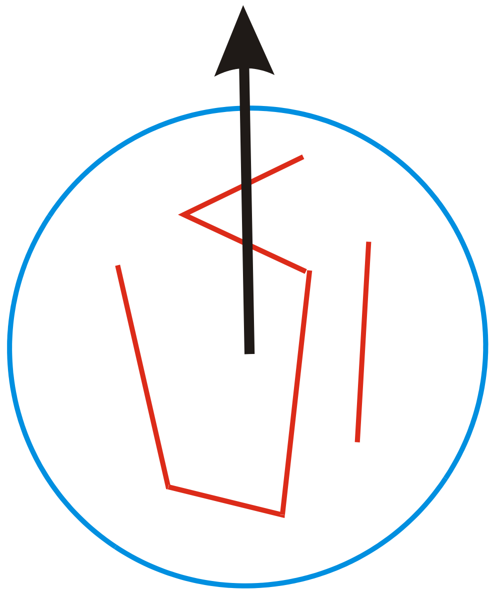


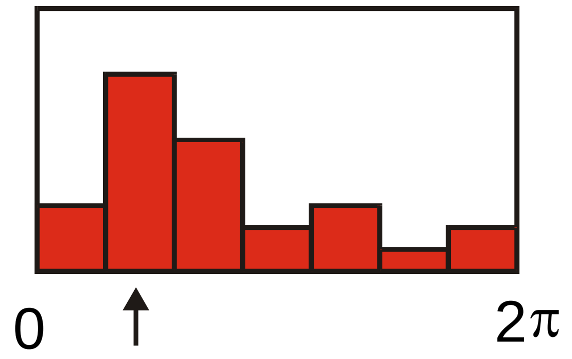
$f(I_{i_1 \dots i_m}(x, \sigma))$ $f(I_{i_1 \dots i_m}(x', \sigma'))$

Orientation Normalization

[Lowe, SIFT, 1999]

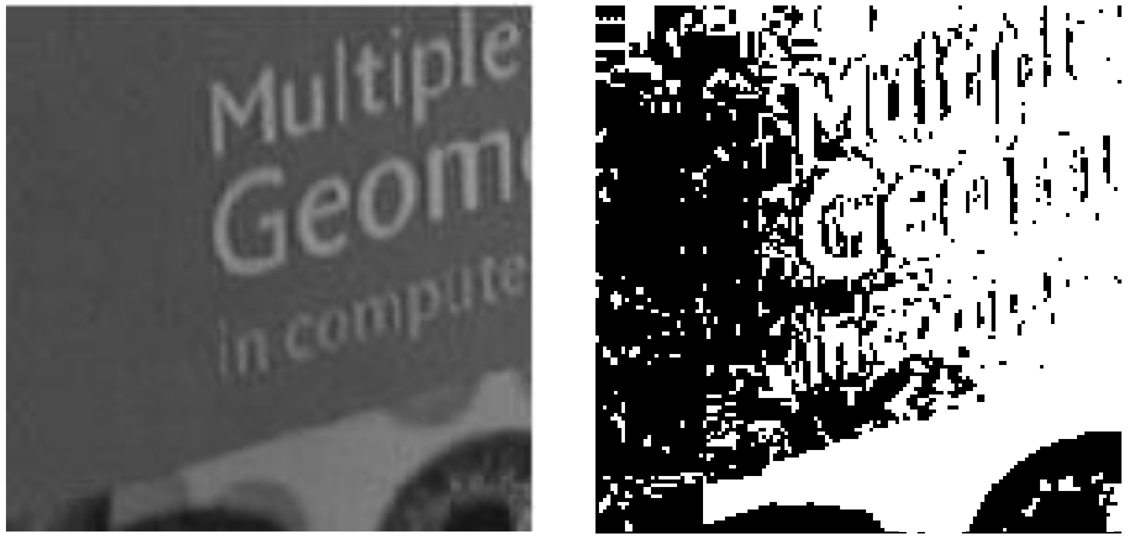
- Compute orientation histogram
- Select dominant orientation
- Normalize: rotate to fixed orientation





Maximally Stable Extremal Regions

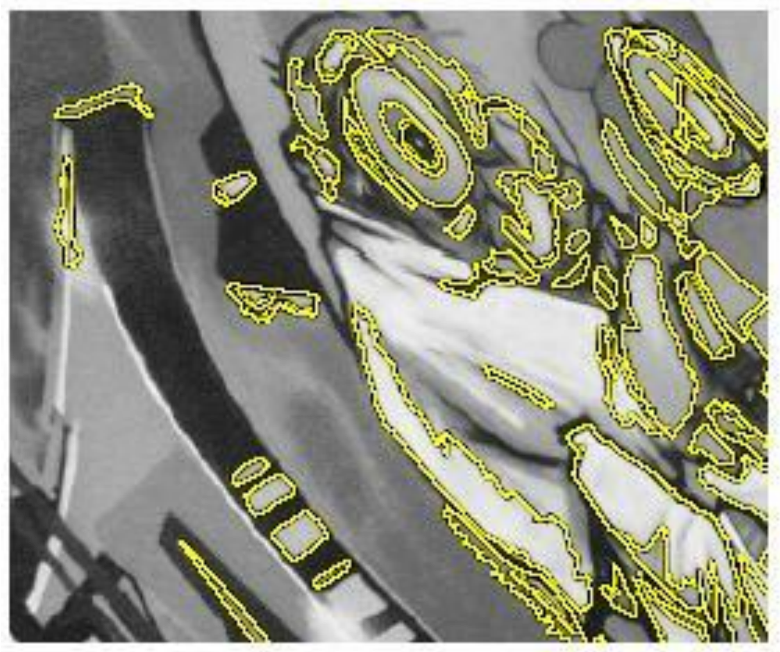
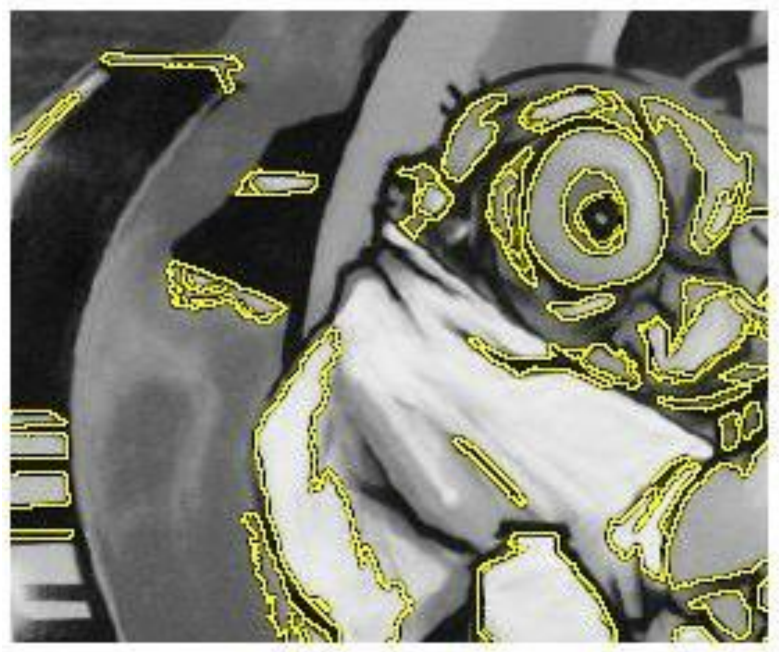
- Based on Watershed segmentation algorithm
- Select regions that stay stable over a large parameter range



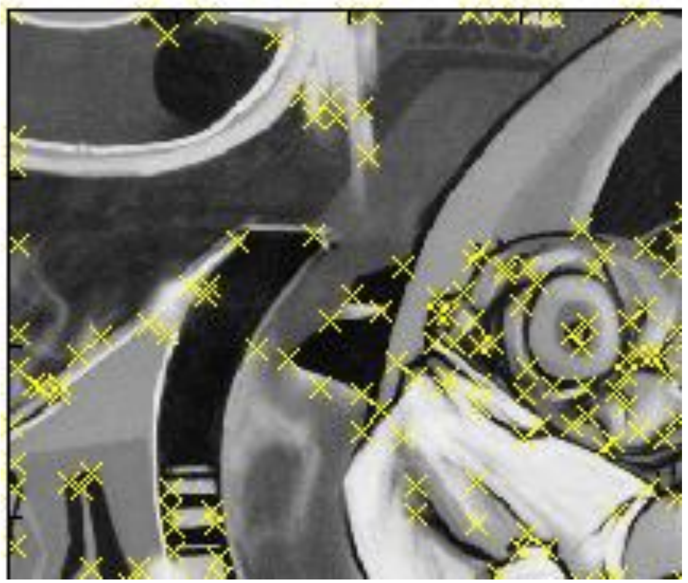
"Robust Wide Baseline Stereo from Maximally Stable Extremal Regions",
Matas, Chum, Urban, and Pajdla, BMVC 2002
6k+ citations

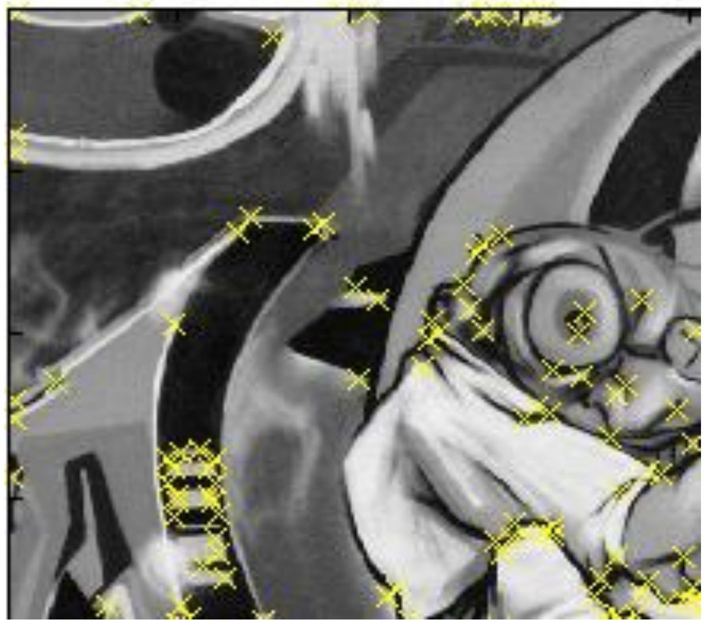
K. Grauman, B. Leibe

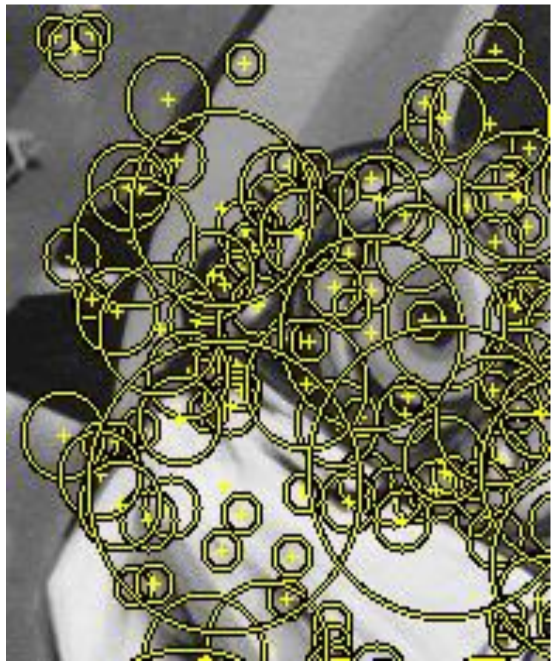
Example Results: MSER

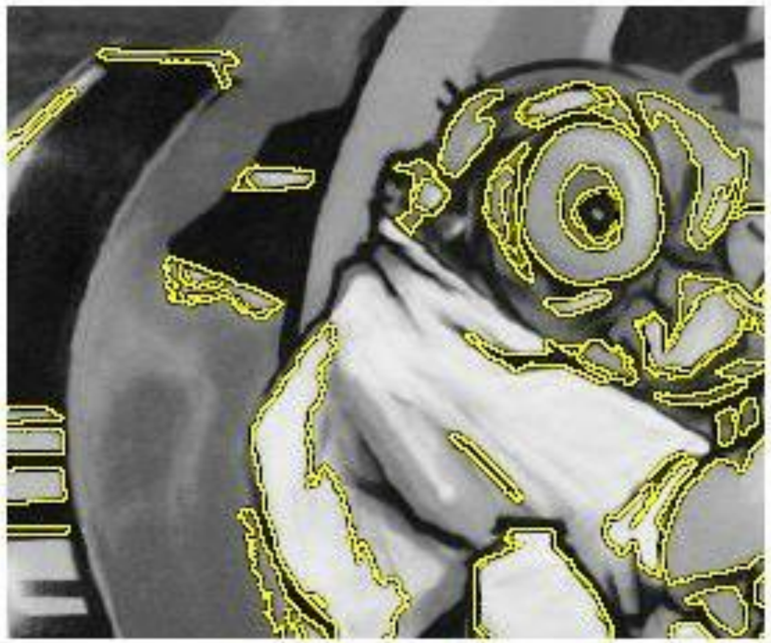



Comparison


Harris

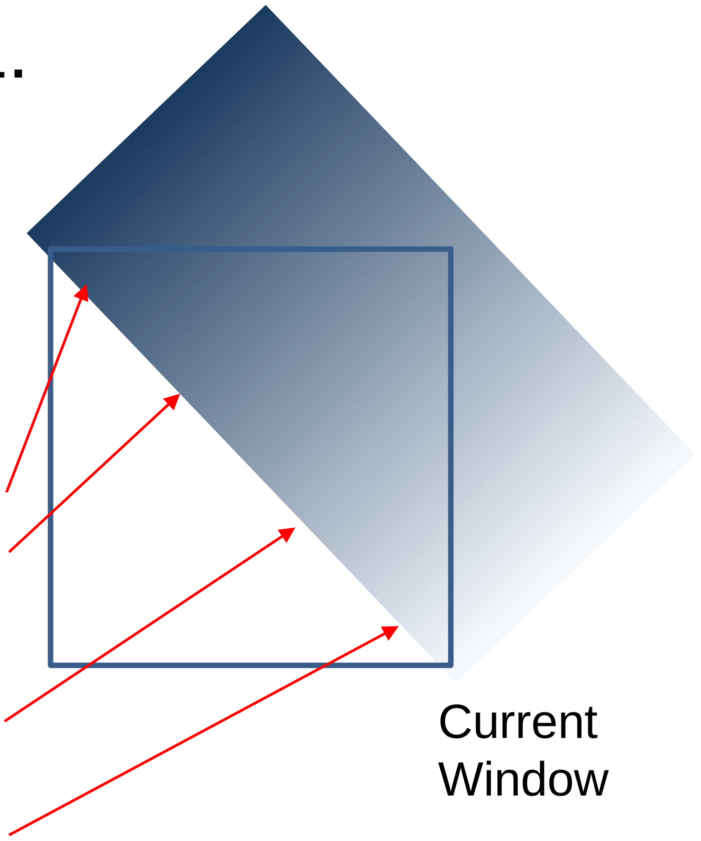
Hessian



LoG

MSER


Canvas Quiz: Are these Harris Corners?

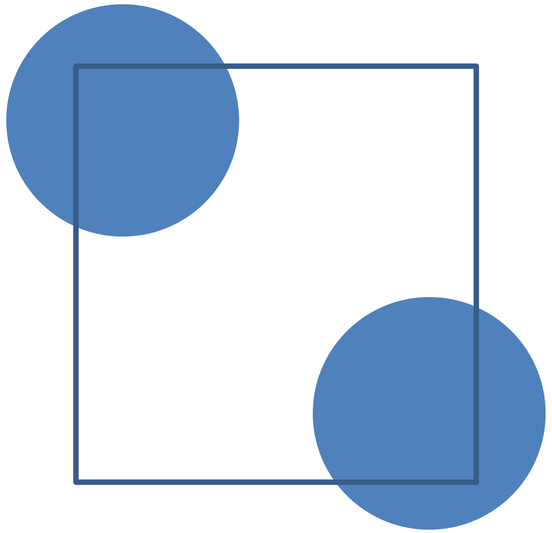
1.



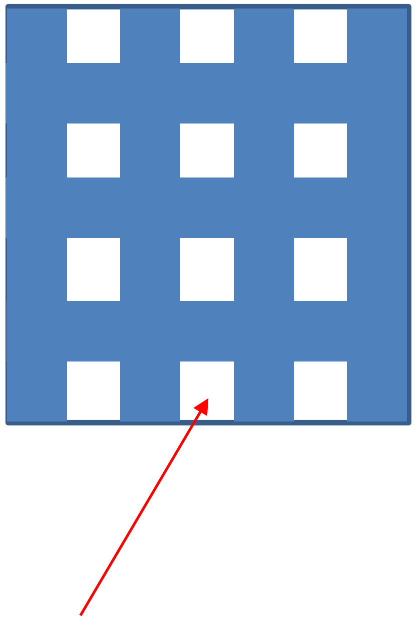
```
[   0  0
   -1  1
  -.6 .6
    0  0
    0  0
  -.3 .3
    0  0
  -.1 .1
     …   ]
```

Matrix contains pairs of (x,y) gradients at pixels in the patch

2.



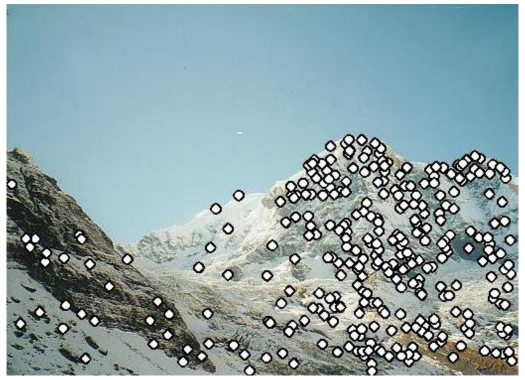
3.



Light and dark regions are a single pixel in width

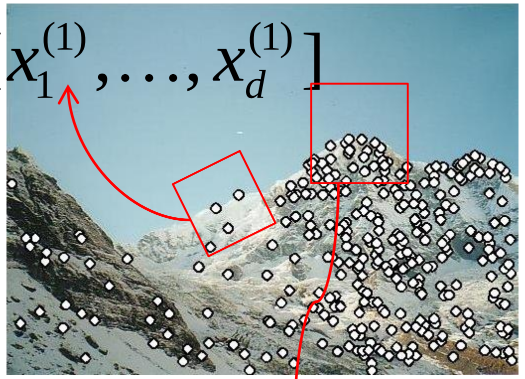
Local features: main components

1) **Detection:** Identify the interest points



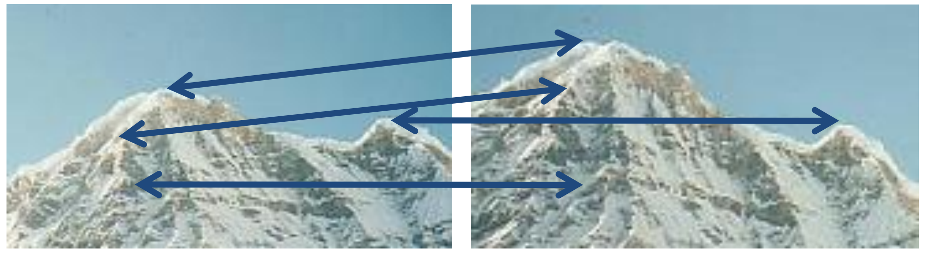
2) **Description**: Extract vector feature descriptor surrounding each interest point.

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

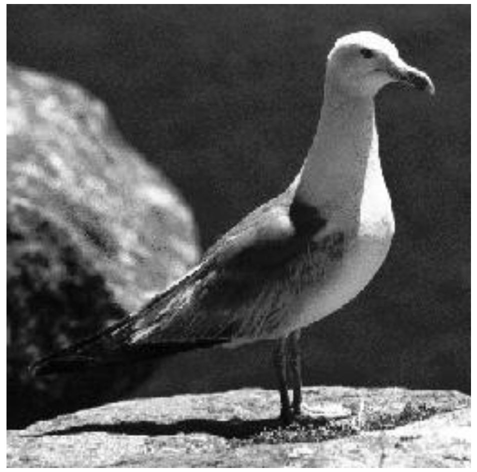
3) **Matching:** Determine correspondence between descriptors in two views

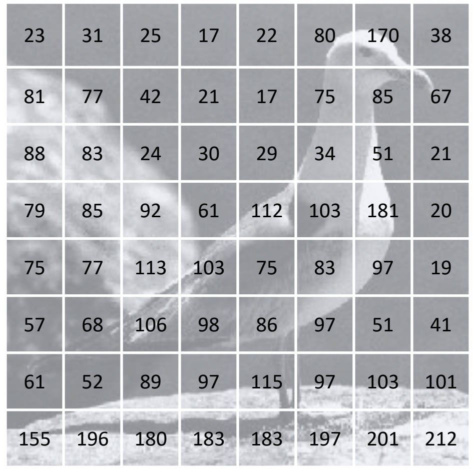


Kristen Grauman

Image representations

- Templates
  - Intensity, color, gradients, etc.
  - Keeps spatial layout





23	31	25	17	22	80	170	38
81	77	42	21	17	75	85	67
88	83	24	30	29	34	51	21
79	85	92	61	112	103	181	20
75	77	113	103	75	83	97	19
57	68	106	98	86	97	51	41
61	52	89	97	115	97	103	101
155	196	180	183	183	197	201	212

- Histograms
  - Distribution of intensity, color, texture, SIFT descriptors, etc.
  - Discards spatial layout

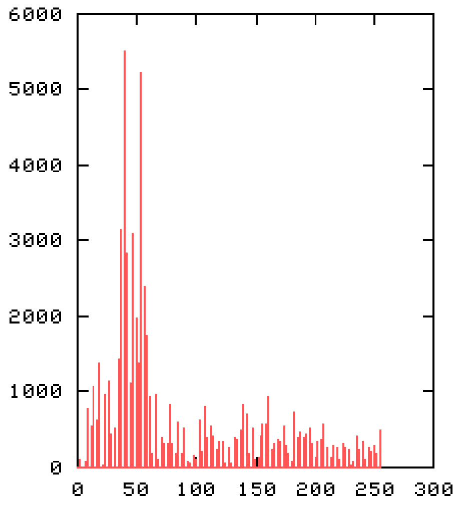
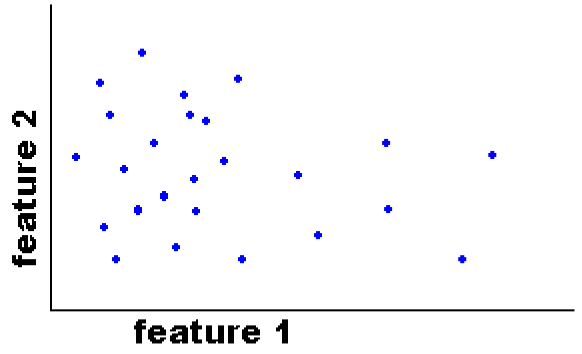
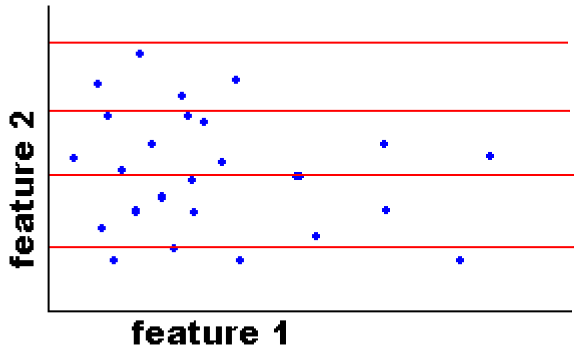
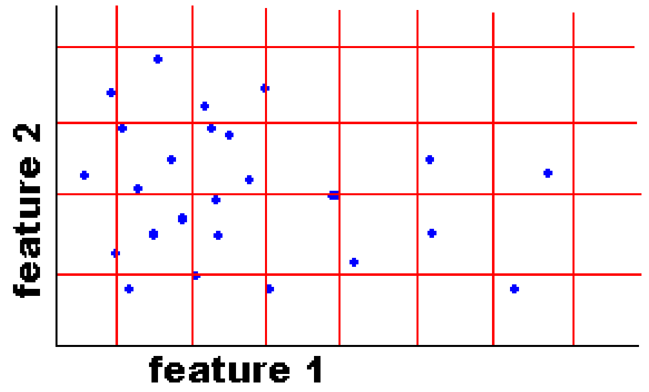


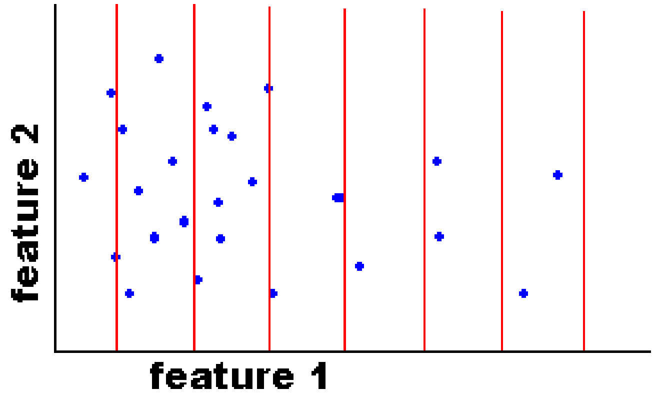
Image Representations: Histograms

Histogram: Probability or count of data in each bin









- Joint histogram
  - Requires lots of data
  - Loss of resolution to avoid empty bins

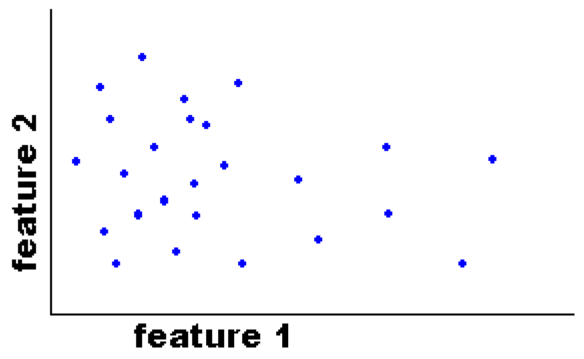
Marginal histogram

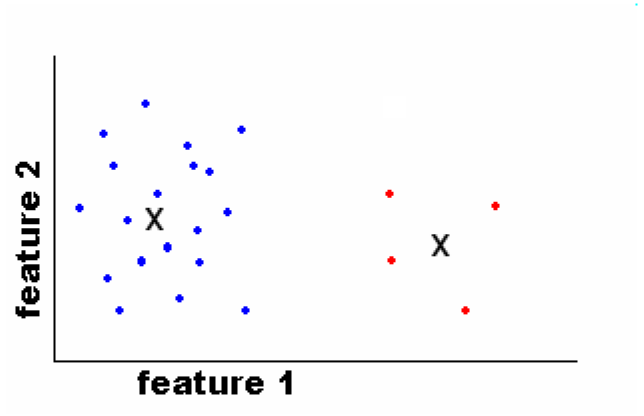
- Requires independent features
- More data/bin than joint histogram

Images from Dave Kauchak

Image Representations: Histograms

Clustering



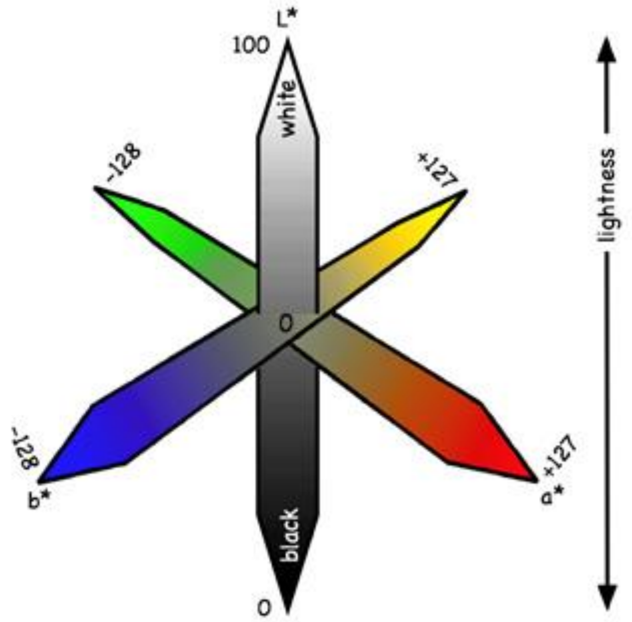


Use the same cluster centers for all images

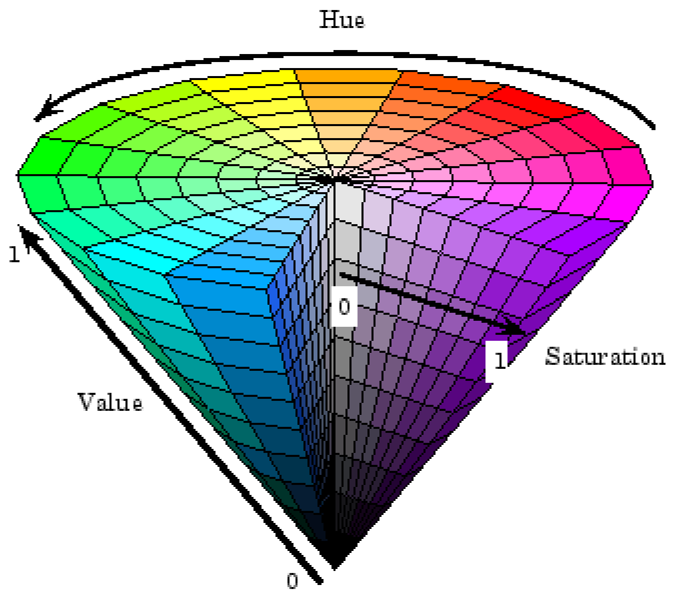
Images from Dave Kauchak

What kind of things do we compute histograms of?

- Color



L*a*b* color space

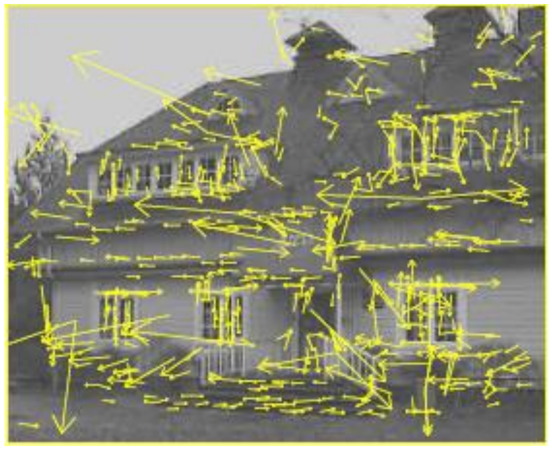


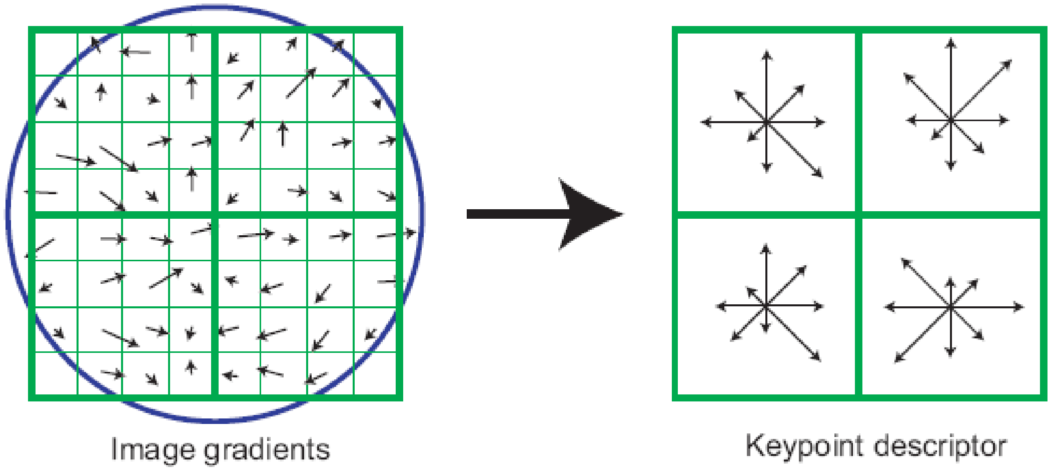
HSV color space

- Texture (filter banks or HOG over regions)

What kind of things do we compute histograms of?

- Histograms of oriented gradients

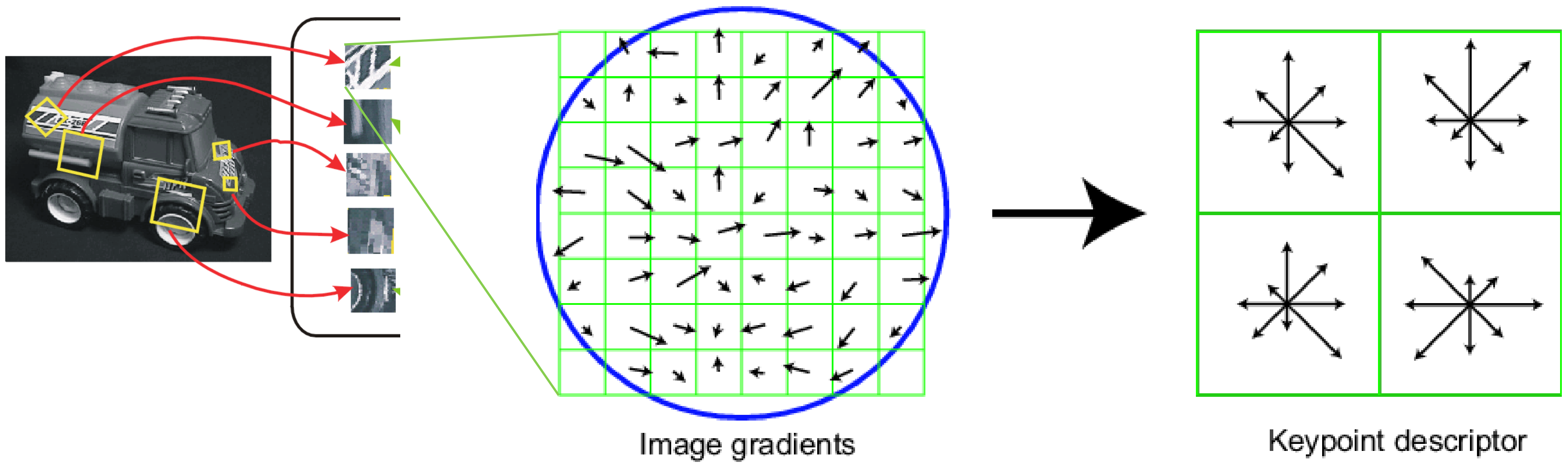




SIFT – Lowe IJCV 2004

SIFT vector formation

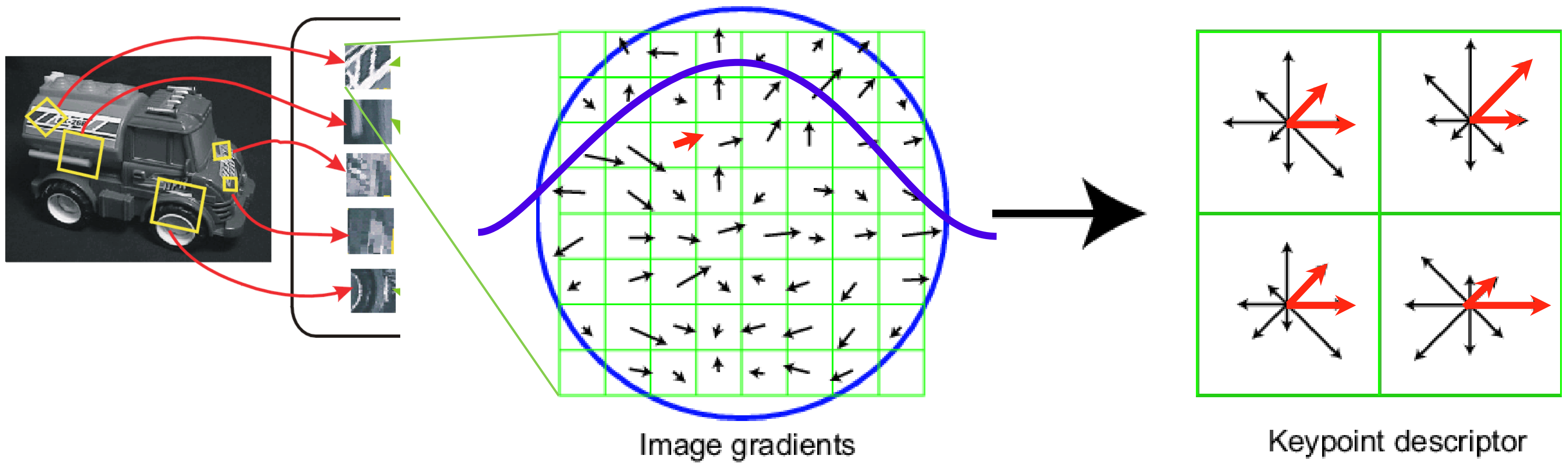
- 4x4 array of gradient orientation histogram weighted by magnitude
- 8 orientations x 4x4 array = 128 dimensions
- Motivation: some sensitivity to spatial layout, but not too much.



showing only 2x2 here, but typical feature would be 4x4

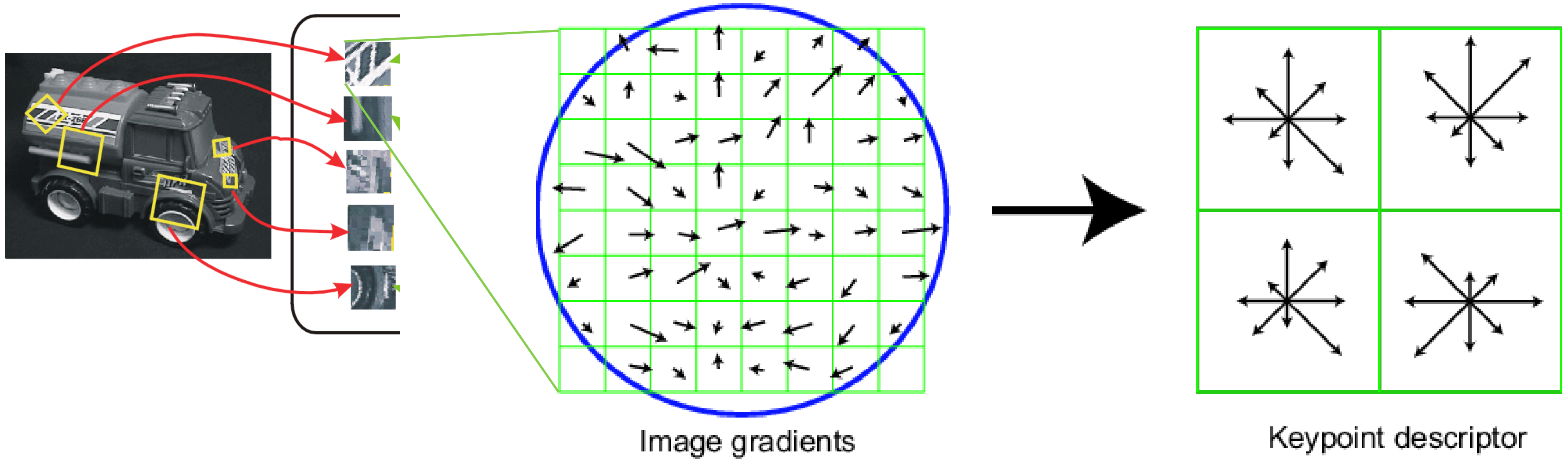
Ensure smoothness

- Gaussian weight
- Interpolation
  - a given gradient contributes to 8 bins: 4 in space times 2 in orientation

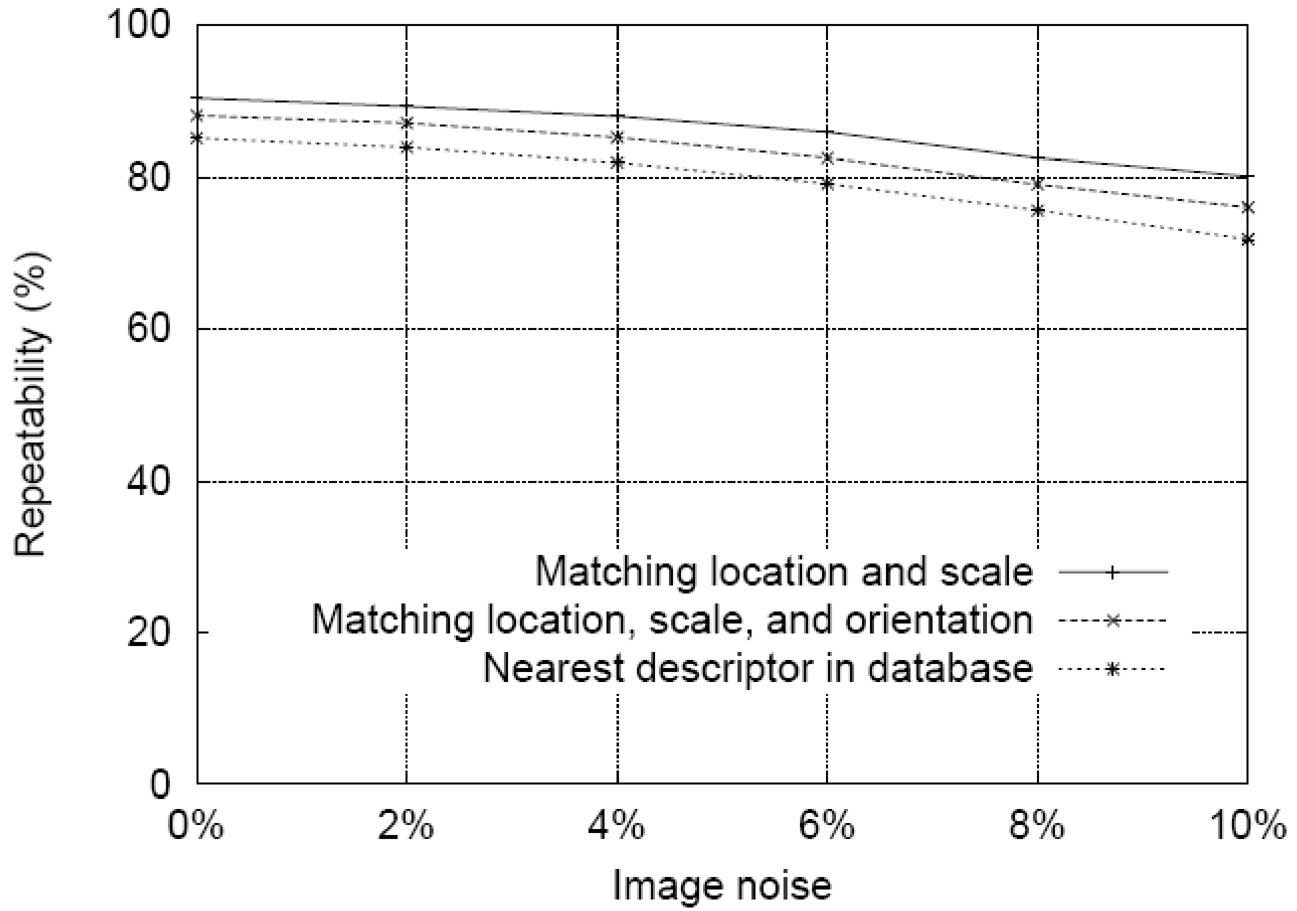


Reduce effect of illumination

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



SIFT Repeatability

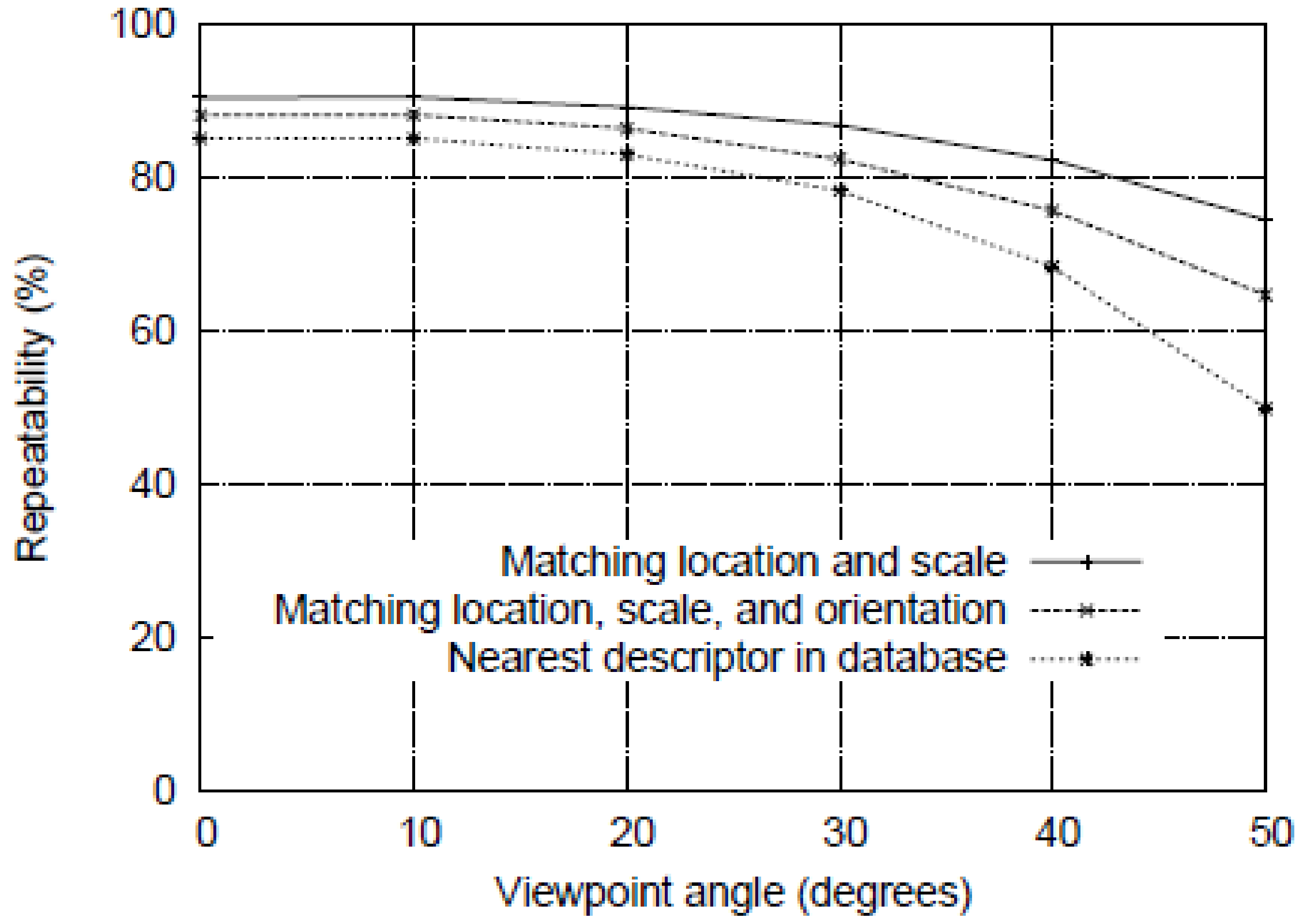


6.4 Matching to large databases

An important remaining issue for measuring the distinctiveness of features is how the reliability of matching varies as a function of the number of features in the database being matched. Most of the examples in this paper are generated using a database of 32 images with about 40,000 keypoints. Figure 10 shows how the matching reliability varies as a func-

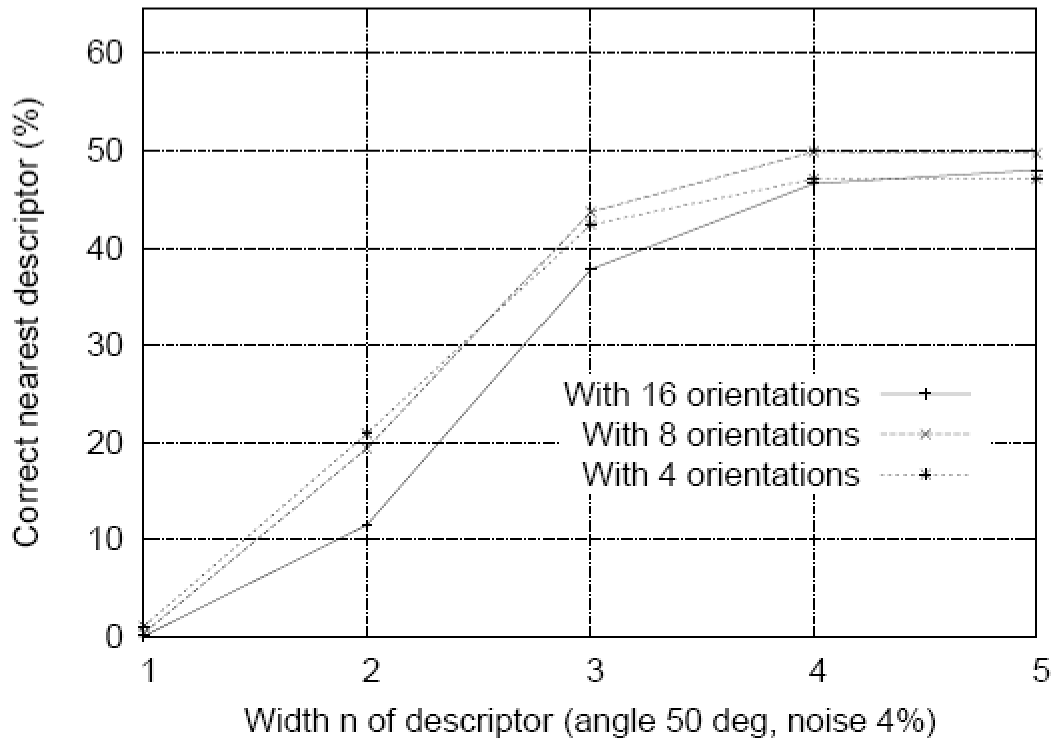
Lowe IJCV 2004

SIFT Repeatability



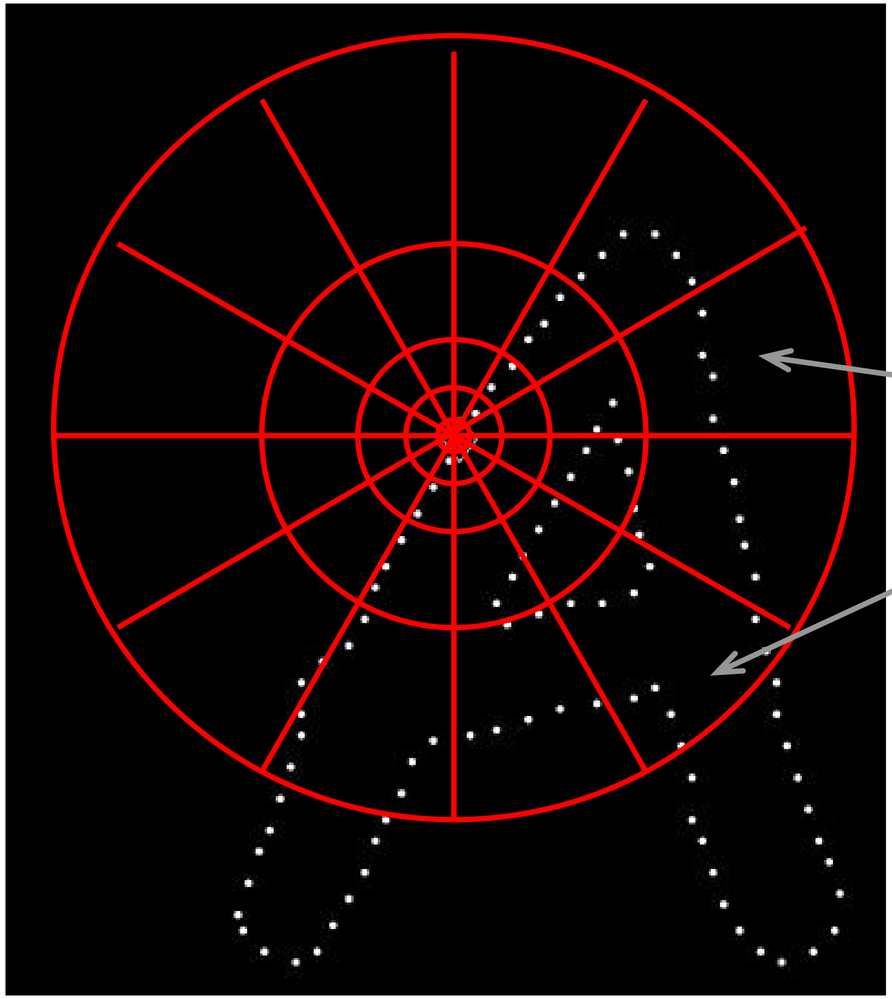
Lowe IJCV 2004

SIFT Repeatability



Lowe IJCV 2004

Local Descriptors: Shape Context



Count the number of points inside each bin, e.g.:

Count = 4

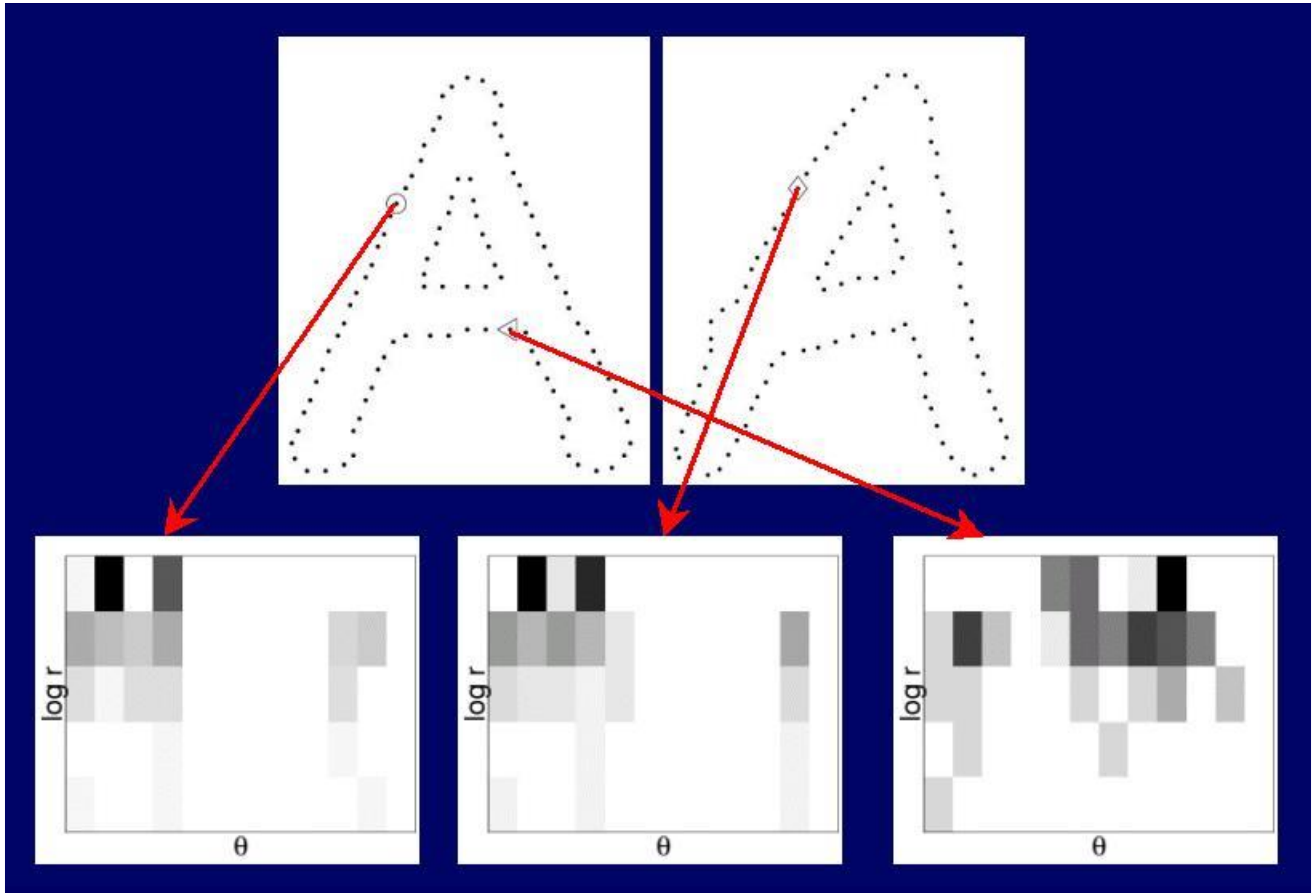
⋮

Count = 10

Log-polar binning: more precision for nearby points, more flexibility for farther points.

Belongie & Malik, ICCV 2001

Shape Context Descriptor



Self-similarity Descriptor

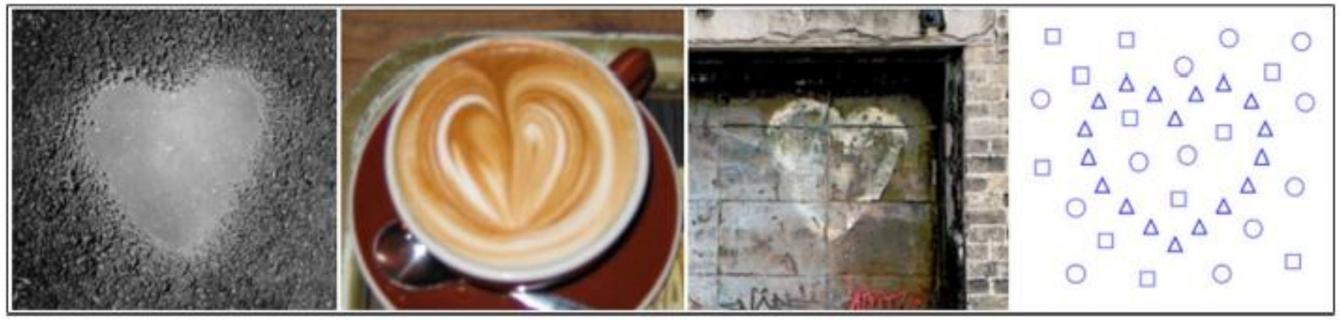
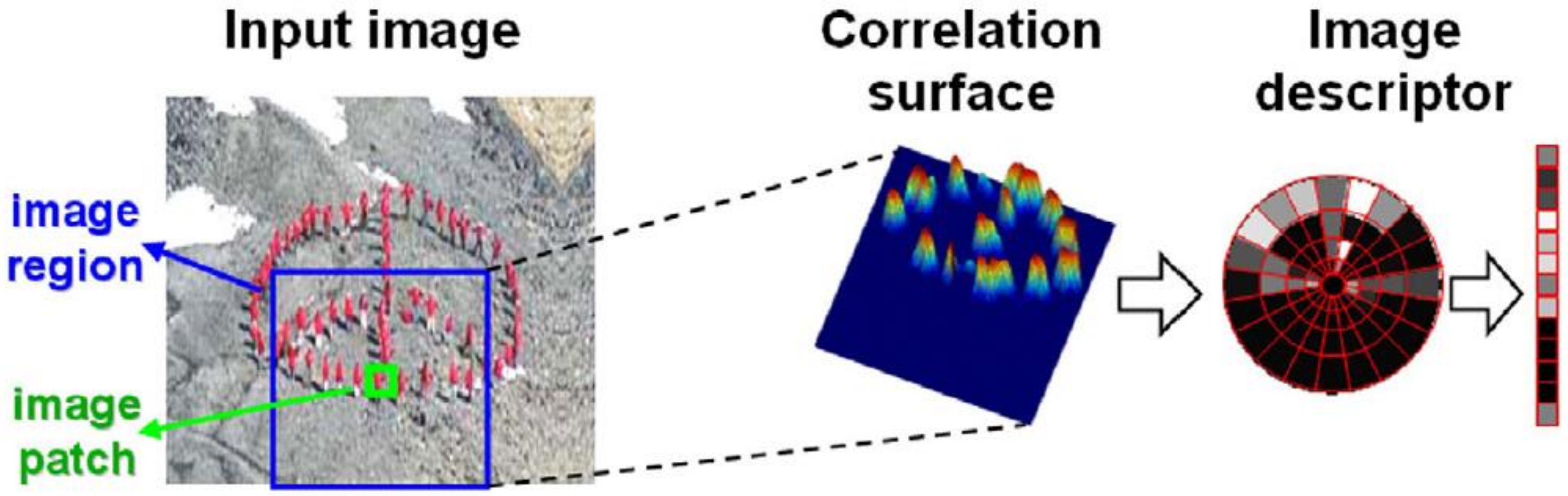


Figure 1. *These images of the same object (a heart) do NOT share common image properties (colors, textures, edges), but DO share a similar geometric layout of local internal self-similarities.*

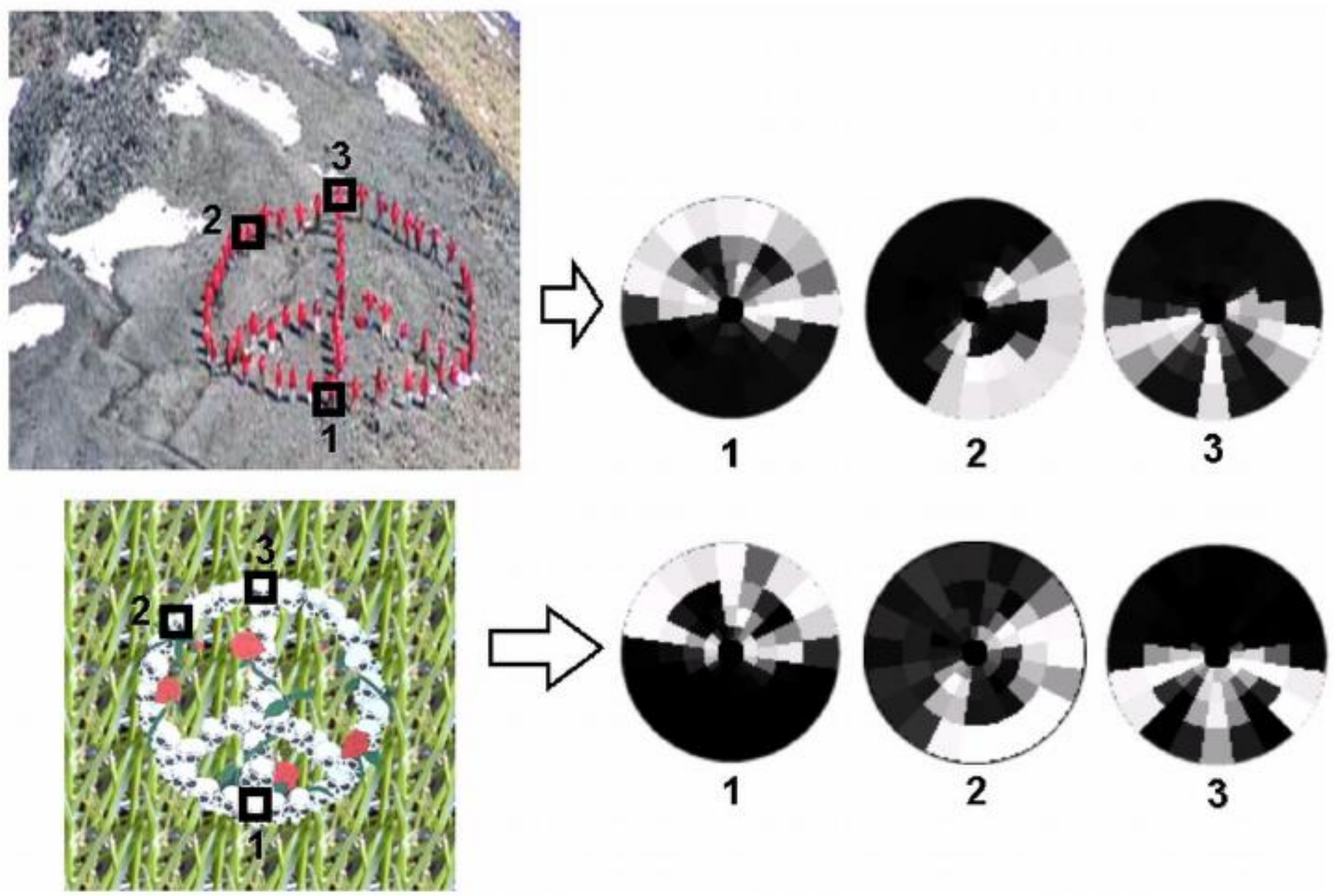
Matching Local Self-Similarities across Images and Videos, Shechtman and Irani, 2007

Self-similarity Descriptor



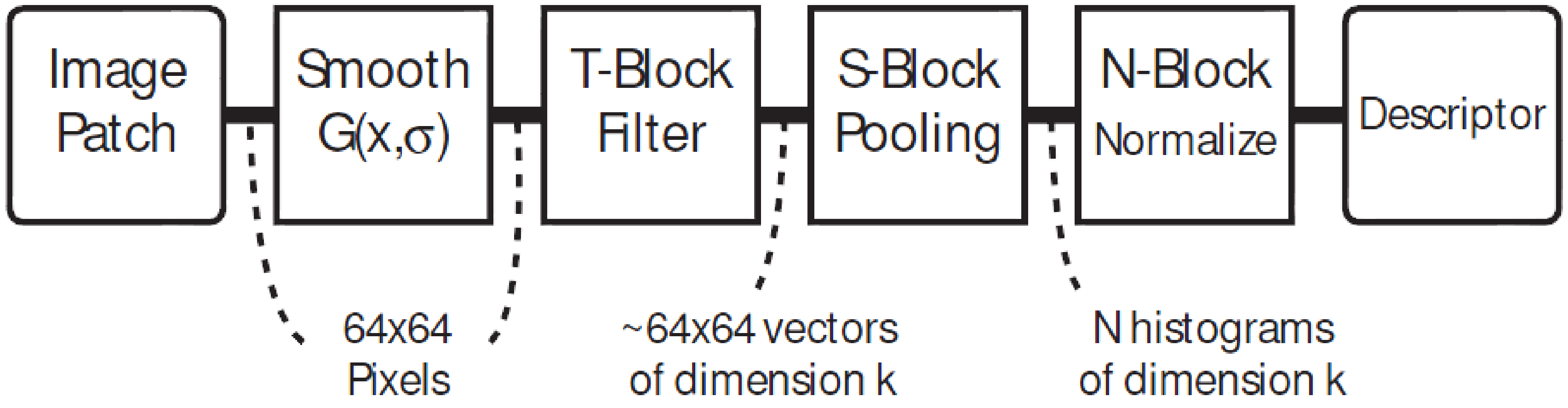
Matching Local Self-Similarities across Images and Videos, Shechtman and Irani, 2007

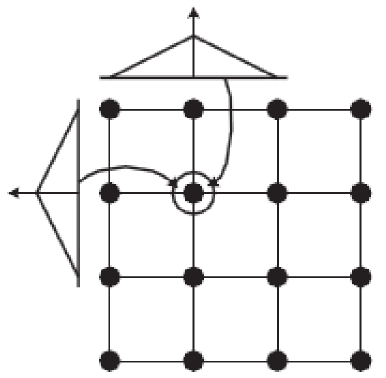
Self-similarity Descriptor

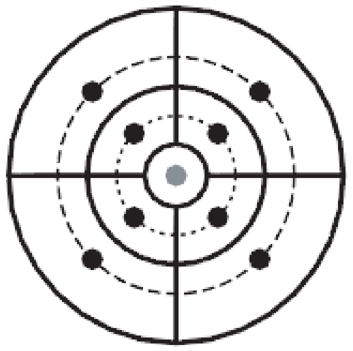


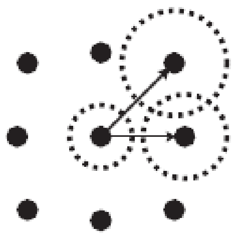
Matching Local Self-Similarities across Images and Videos, Shechtman and Irani, 2007

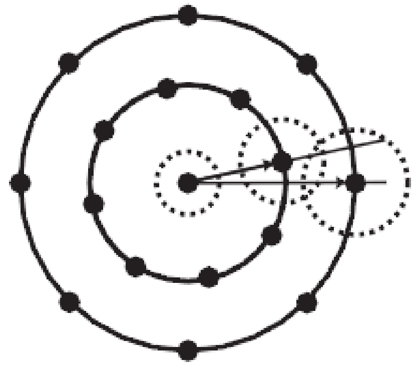
Learning Local Image Descriptors, Winder and Brown, CVPR 2007




S1: SIFT grid with bilinear weights


S2: GLOH polar grid with bilinear radial and angular weights


S3: 3x3 grid with Gaussian weights


S4: 17 polar samples with Gaussian weights

Learning Local Image Descriptors, Winder and Brown, CVPR 2007

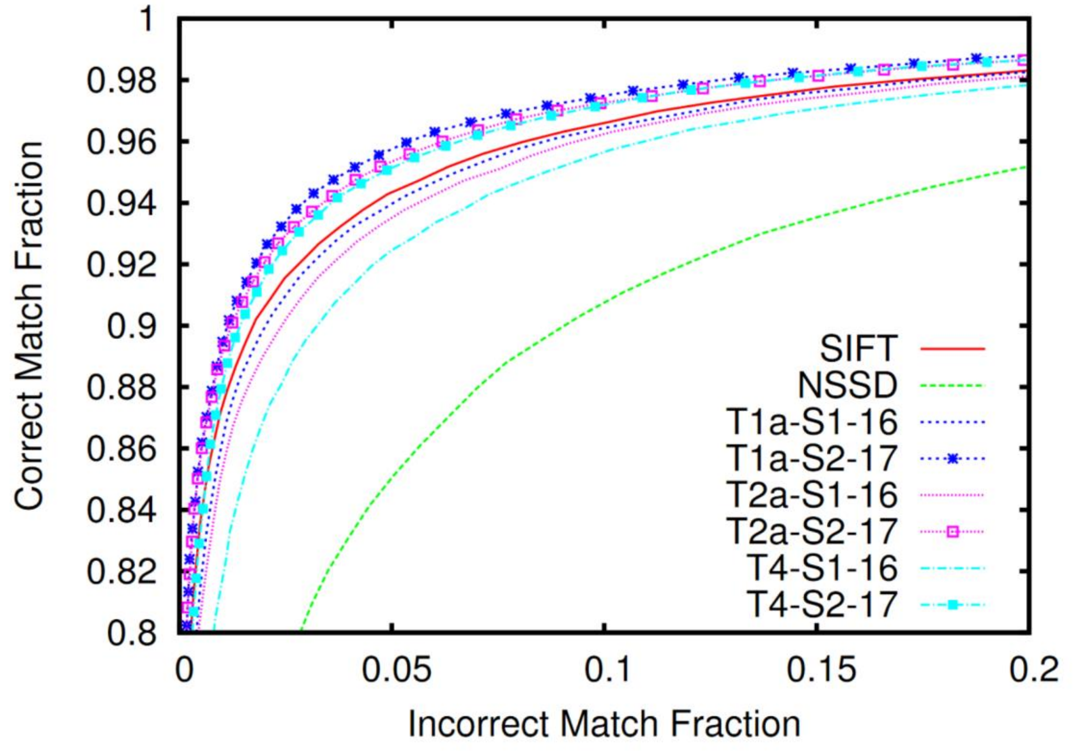


Figure 5. Selected ROC curves for the trained descriptors with four dimensional T-blocks ($k = 4$). Those that perform better than SIFT all make use of the S2 log-polar summation stage. See Table 4 for details.

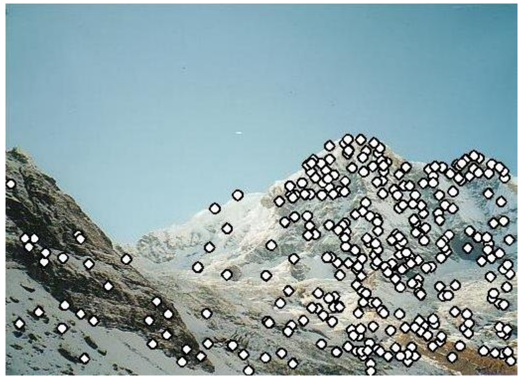
We obtained a mixed training set consisting of tourist photographs of the Trevi Fountain and of Yosemite Valley (920 images), and a test set consisting of images of Notre Dame (500 images). We extracted interest points and matched them between all of the images within a set using the SIFT detector and descriptor [9]. We culled candidate matches using a symmetry criterion and used RANSAC [5] to estimate initial fundamental matrices between image pairs. This stage was followed by bundle adjustment to reconstruct 3D points and to obtain accurate camera matrices for each source image. A similar technique has been described by [17].

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
  - Color rarely used

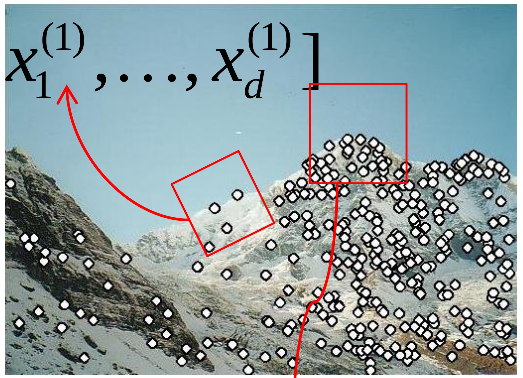
Local features: main components

1) **Detection:** Identify the interest points



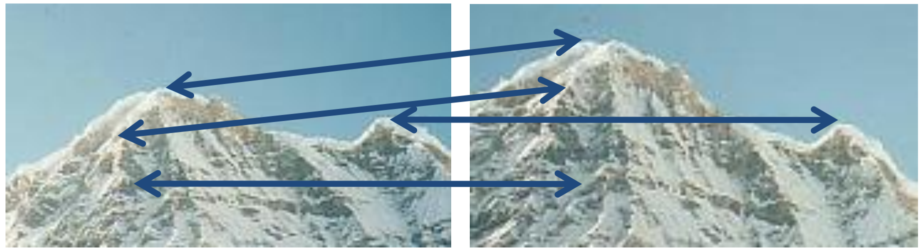
2) **Description**: Extract vector feature descriptor surrounding each interest point.

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

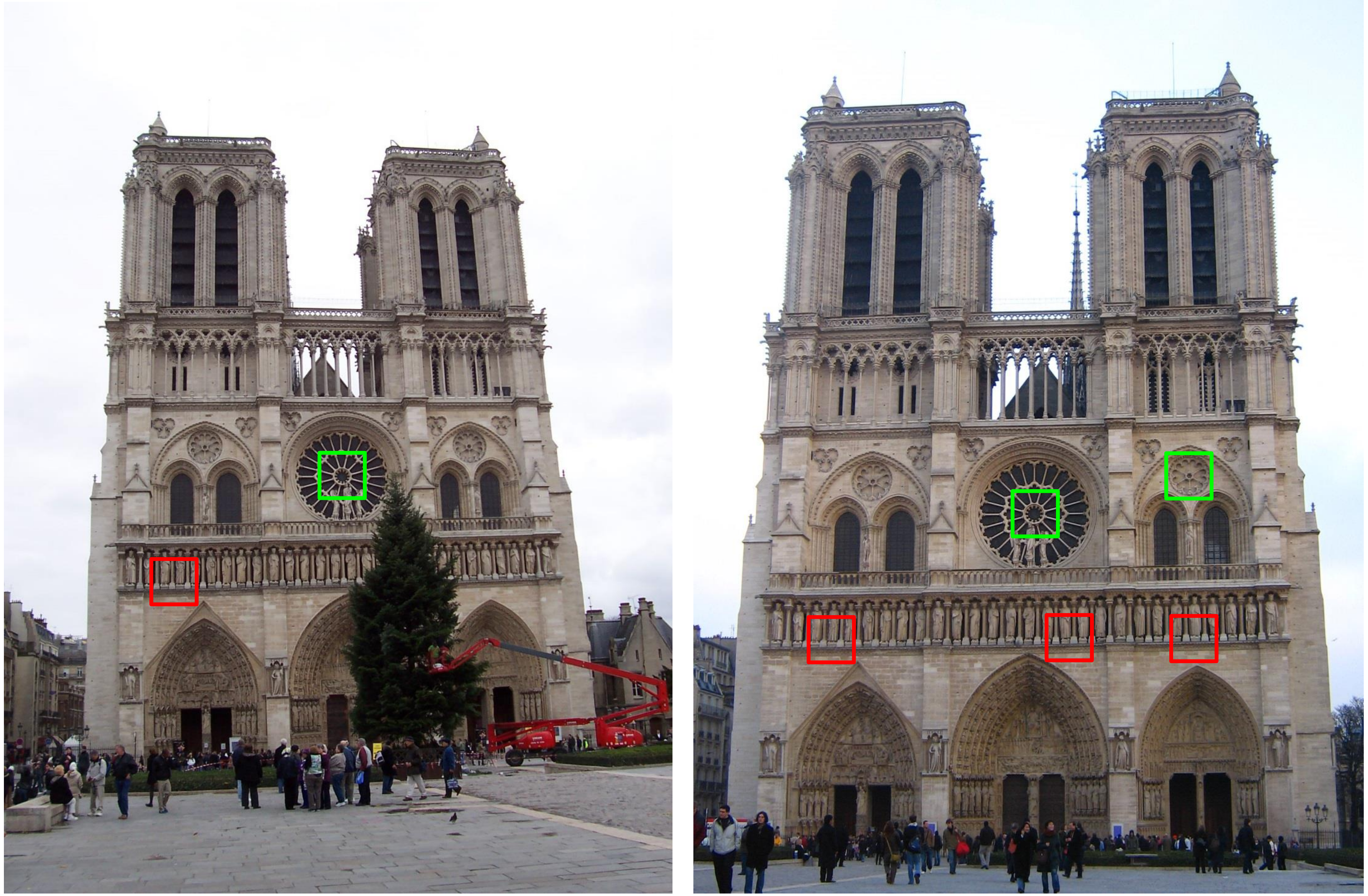
3) **Matching:** Determine correspondence between descriptors in two views



Kristen Grauman

Matching

- Simplest approach: Pick the nearest neighbor. Threshold on absolute distance
- Problem: Lots of self similarity in many photos



Distance: 0.34, 0.30, 0.40

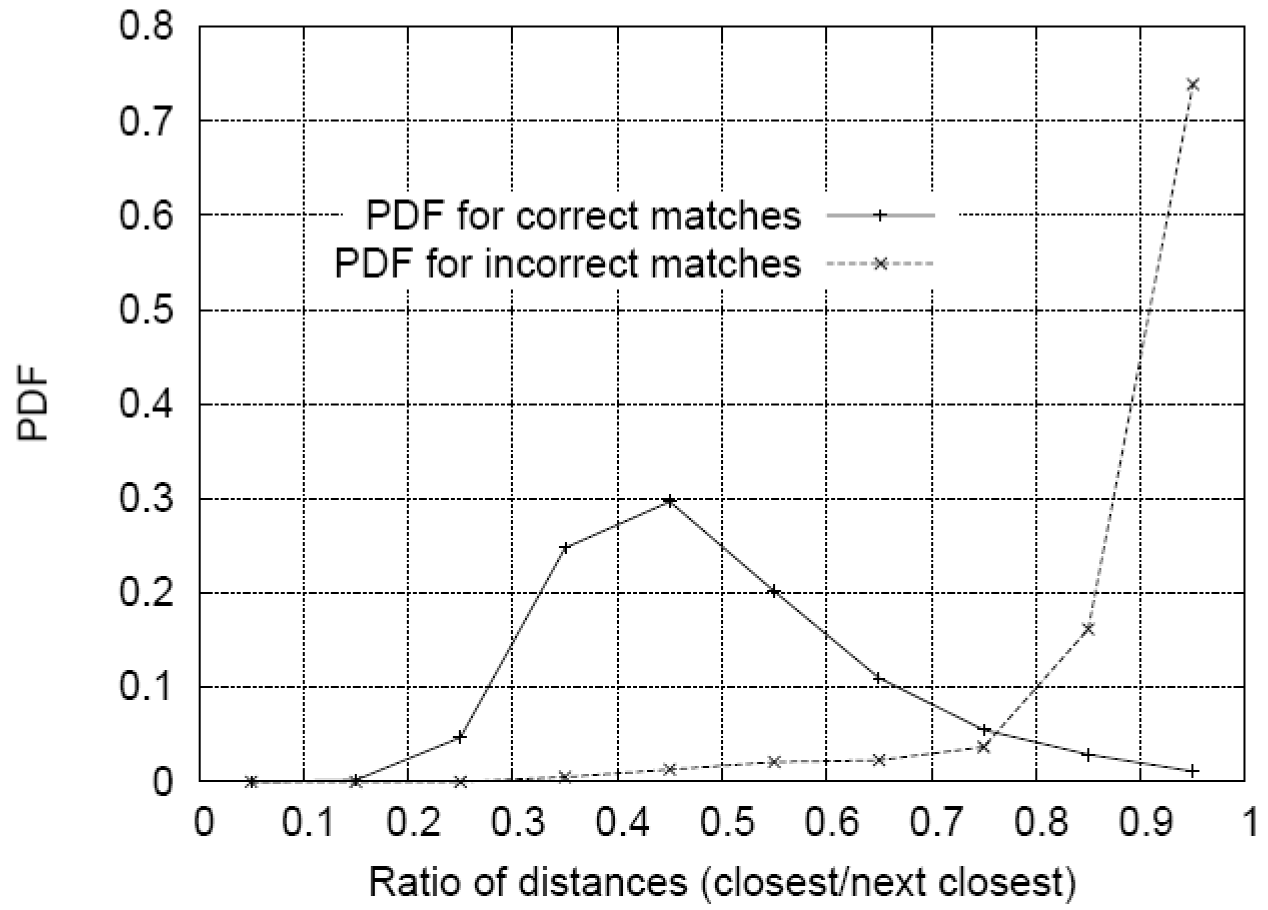
Distance: 0.61
Distance: 1.22

Nearest Neighbor Distance Ratio

- $\frac{NN1}{NN2}$ where NN1 is the distance to the first nearest neighbor and NN2 is the distance to the second nearest neighbor.
- Sorting by this ratio (into ascending order) puts matches in order of confidence (in descending order of confidence).

Matching Local Features

- Nearest neighbor (Euclidean distance)
- Threshold ratio of nearest to 2nd nearest descriptor



Lowe IJCV 2004

Comparison of Keypoint Detectors

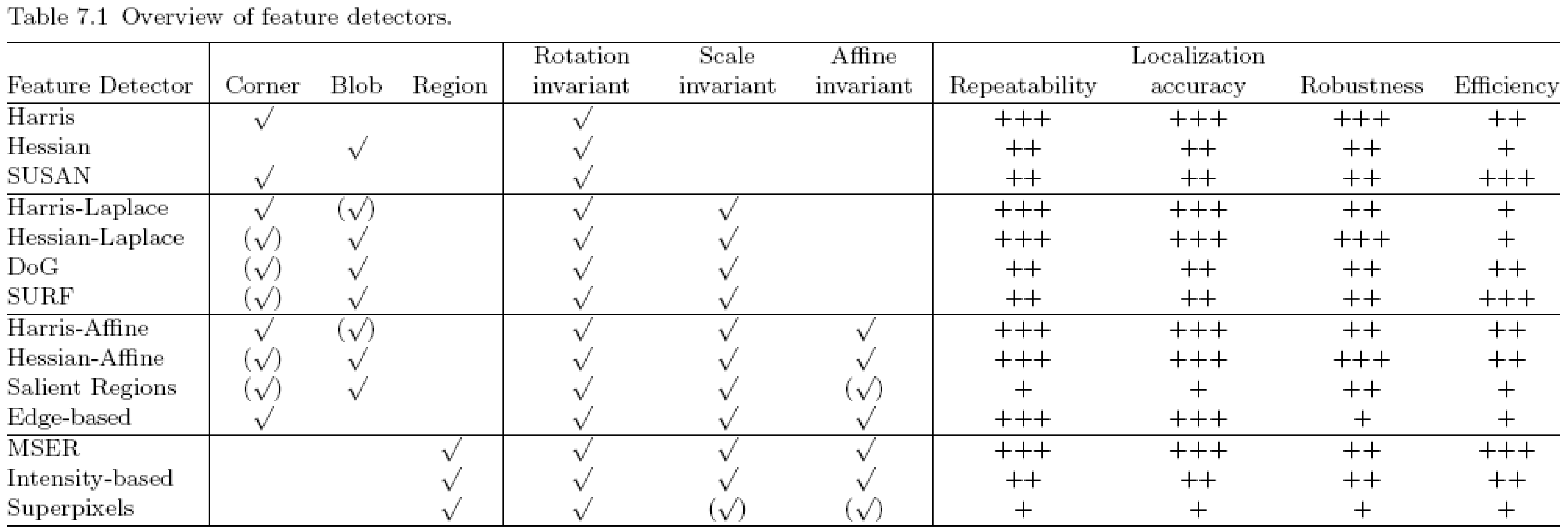


Table 7.1 Overview of feature detectors.

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			√	√	(√)	(√)	+	+	+	+

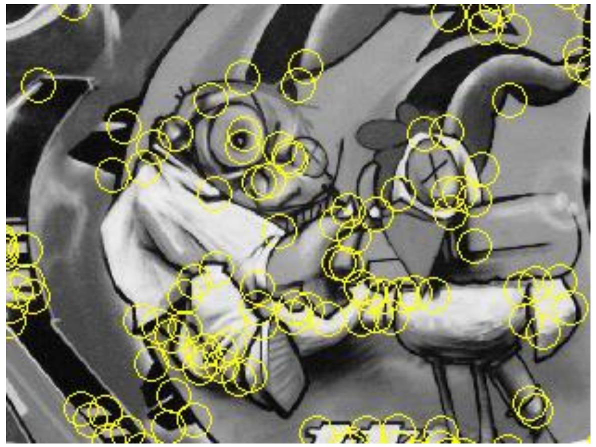
Tuytelaars Mikolajczyk 2008

Choosing a descriptor

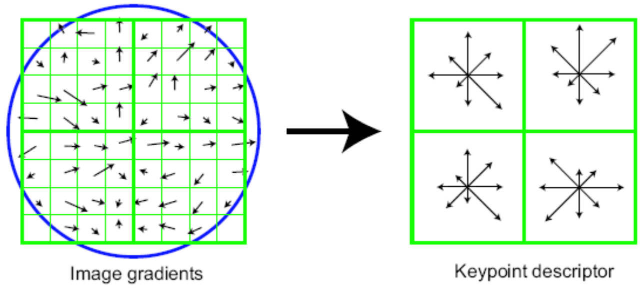
- Again, need not stick to one
- For object instance recognition or stitching, SIFT or variant is a good choice
- Learning-based methods are taking over this space, although not as quickly as one might expect.

Things to remember

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

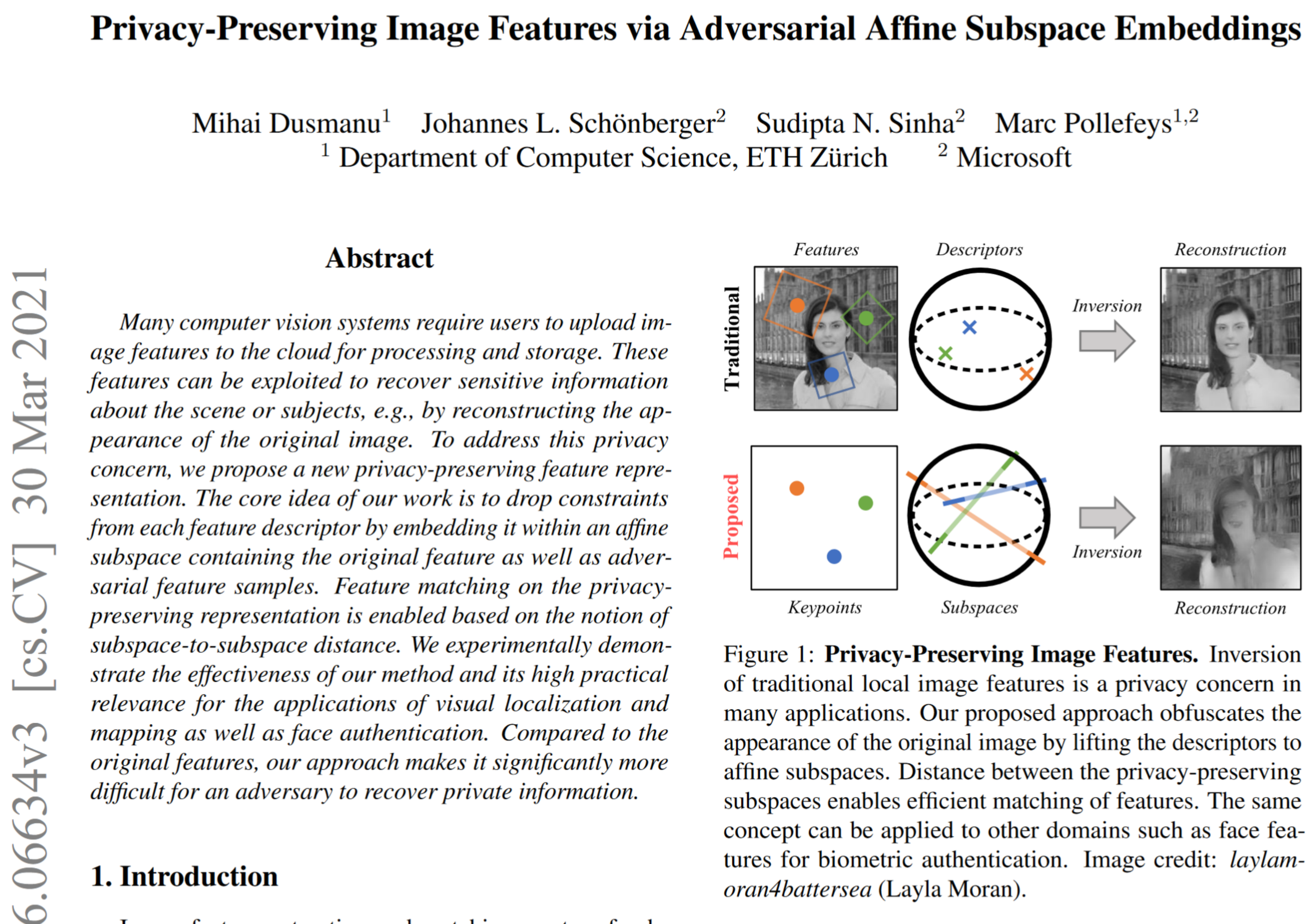


- Descriptors: robust and selective
  - spatial histograms of orientation
  - SIFT



Canvas Quizlet

Can we invert SIFT descriptors?



Privacy-Preserving Image Features via Adversarial Affine Subspace Embeddings

Mihai Dusmanu[1] Johannes L. Schönberger[2] Sudipta N. Sinha[2] Marc Pollefeys[1,2]
[1] Department of Computer Science, ETH Zürich [2] Microsoft

Abstract

Many computer vision systems require users to upload image features to the cloud for processing and storage. These features can be exploited to recover sensitive information about the scene or subjects, e.g., by reconstructing the appearance of the original image. To address this privacy concern, we propose a new privacy-preserving feature representation. The core idea of our work is to drop constraints from each feature descriptor by embedding it within an affine subspace containing the original feature as well as adversarial feature samples. Feature matching on the privacy-preserving representation is enabled based on the notion of subspace-to-subspace distance. We experimentally demonstrate the effectiveness of our method and its high practical relevance for the applications of visual localization and mapping as well as face authentication. Compared to the original features, our approach makes it significantly more difficult for an adversary to recover private information.

1. Introduction

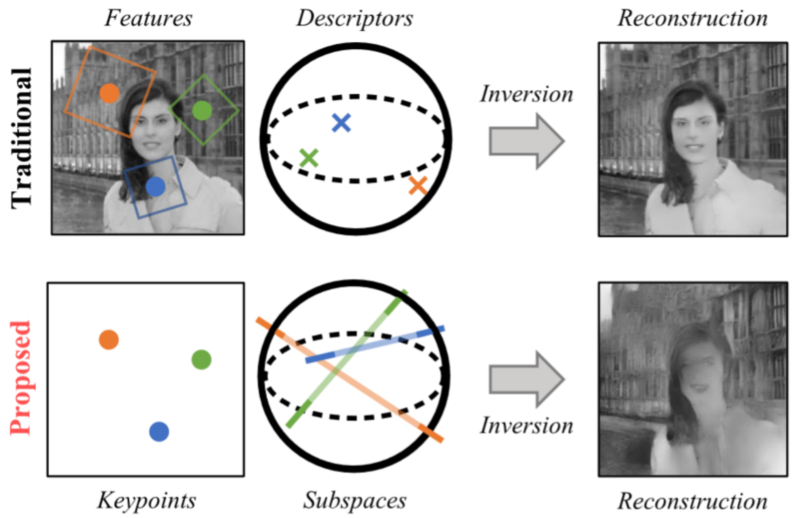


Figure 1: **Privacy-Preserving Image Features.** Inversion of traditional local image features is a privacy concern in many applications. Our proposed approach obfuscates the appearance of the original image by lifting the descriptors to affine subspaces. Distance between the privacy-preserving subspaces enables efficient matching of features. The same concept can be applied to other domains such as face features for biometric authentication. Image credit: *laylamoran4battersea* (Layla Moran).

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