Features detectors and descriptors

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Outline

Section 1

Introduction: objectives

Applications

- Recognition, classification, database retrieval
- Image registration
- Scale detection
- Motion estimation, tracking
- Video stabilization
- Stereovision / 3D reconstruction

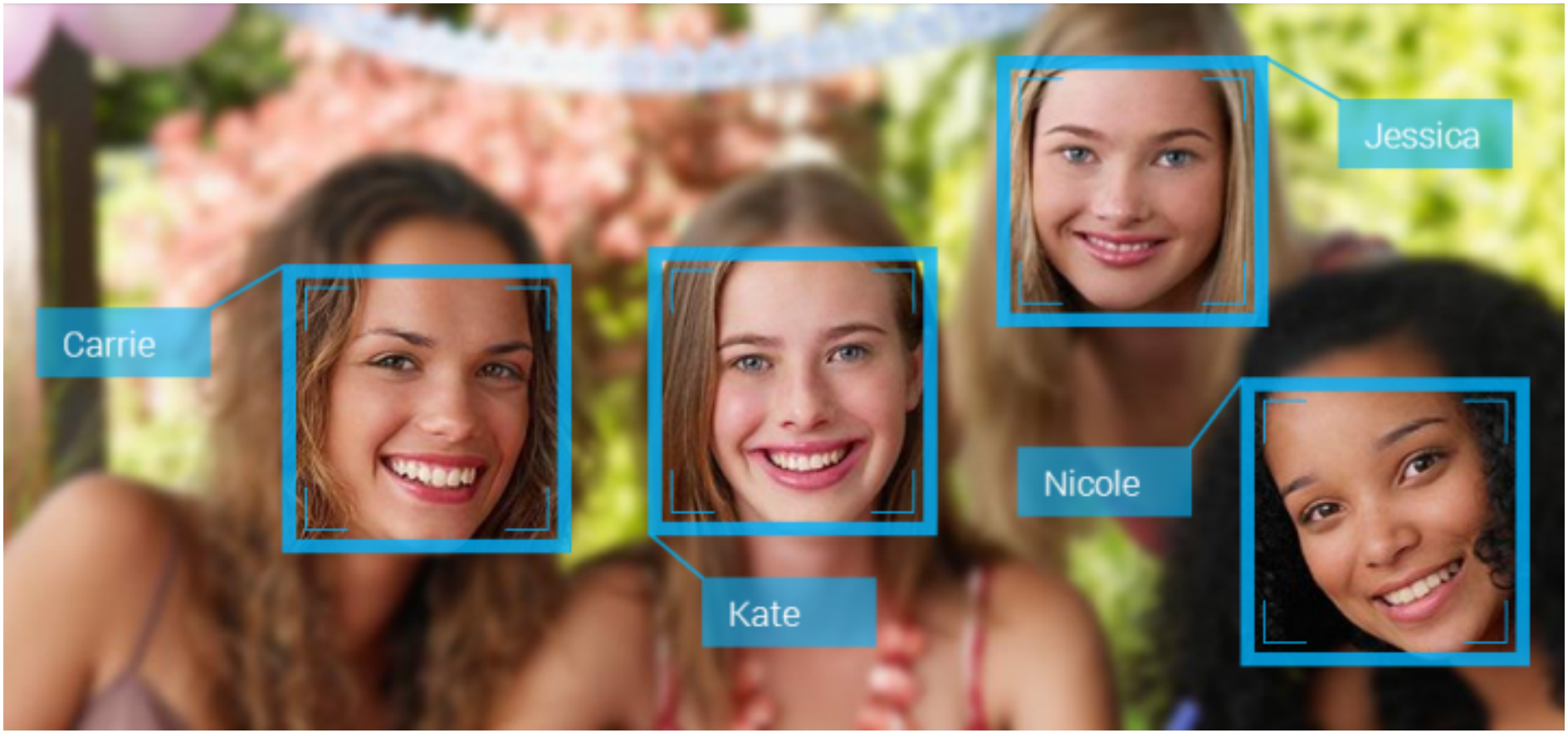
Summary

- Detect keypoints
- Look at neighborhood
- Try to find similarities
- Deduce movement

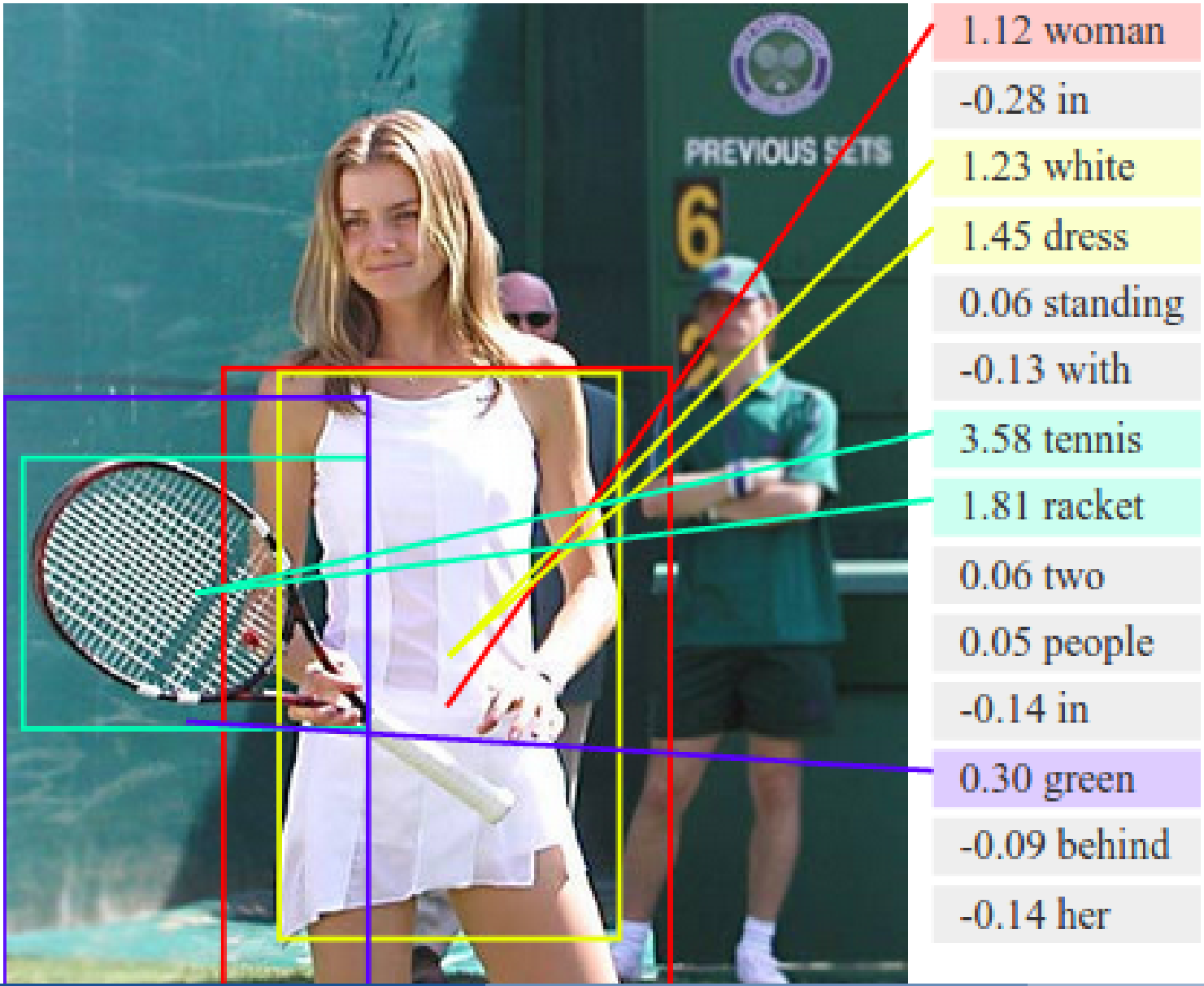
Tracking and motion estimation

Tracking and motion estimation

(Face) recognition



Classification



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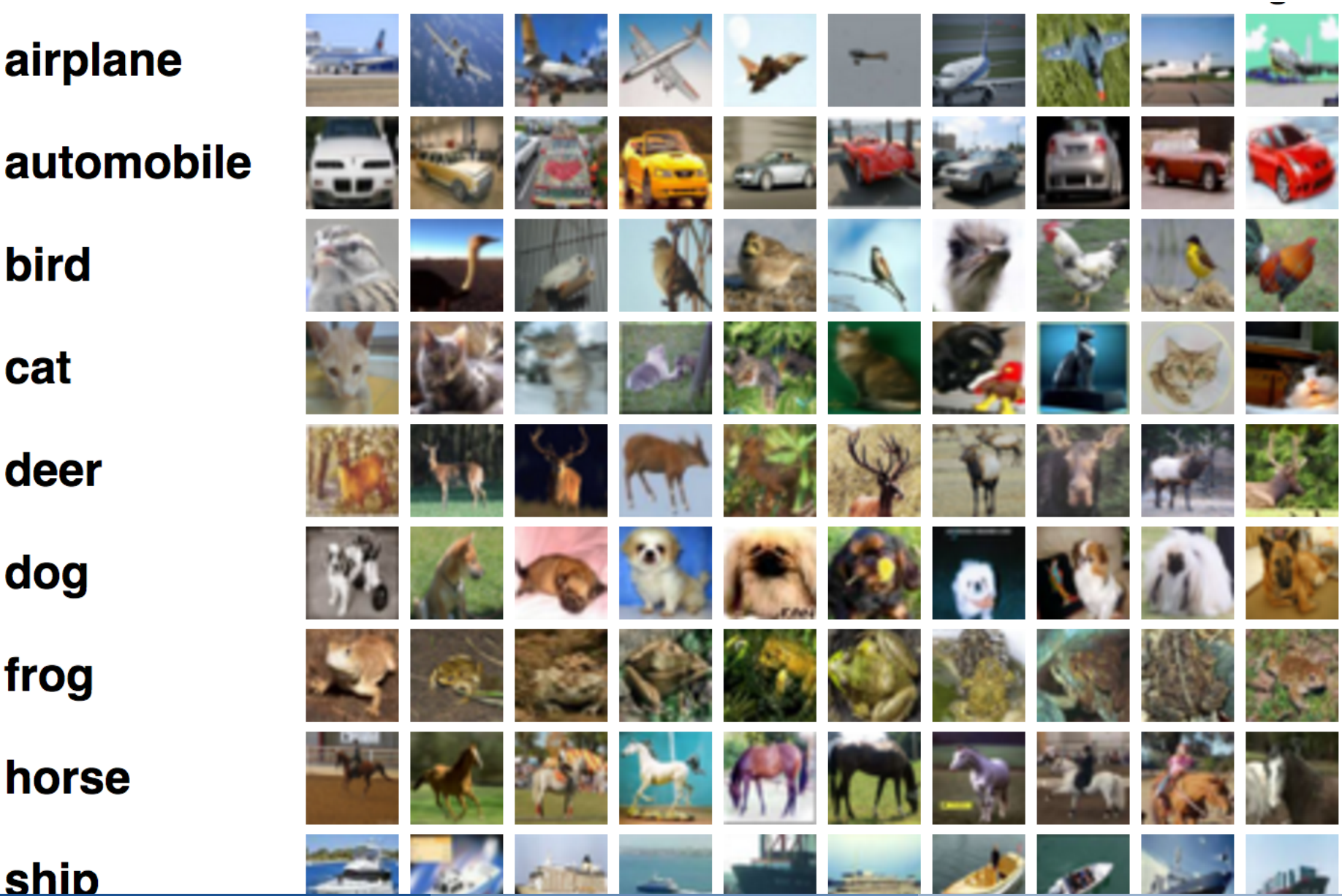
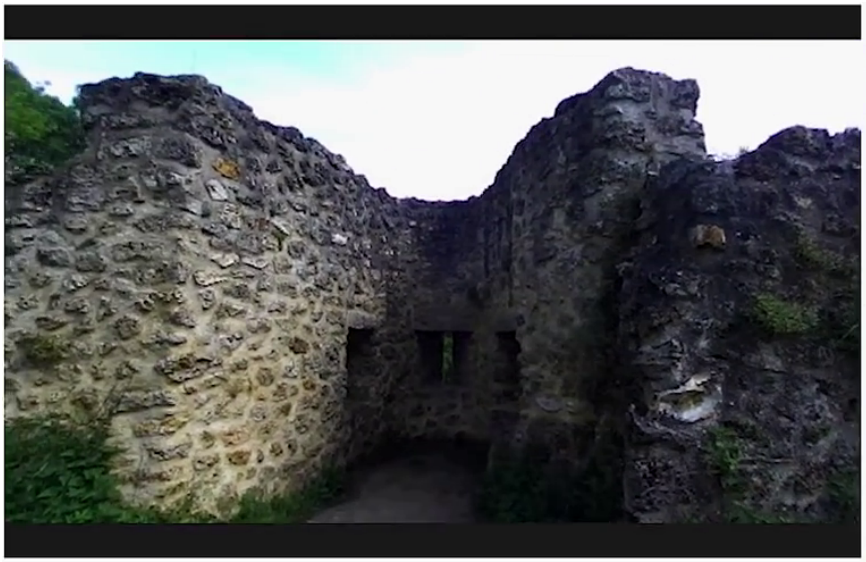
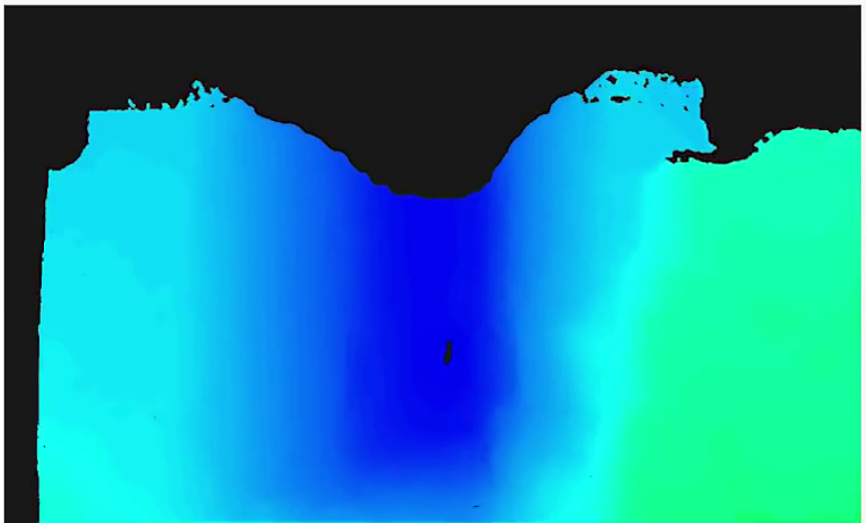


Stereovision, 3D reconstruction





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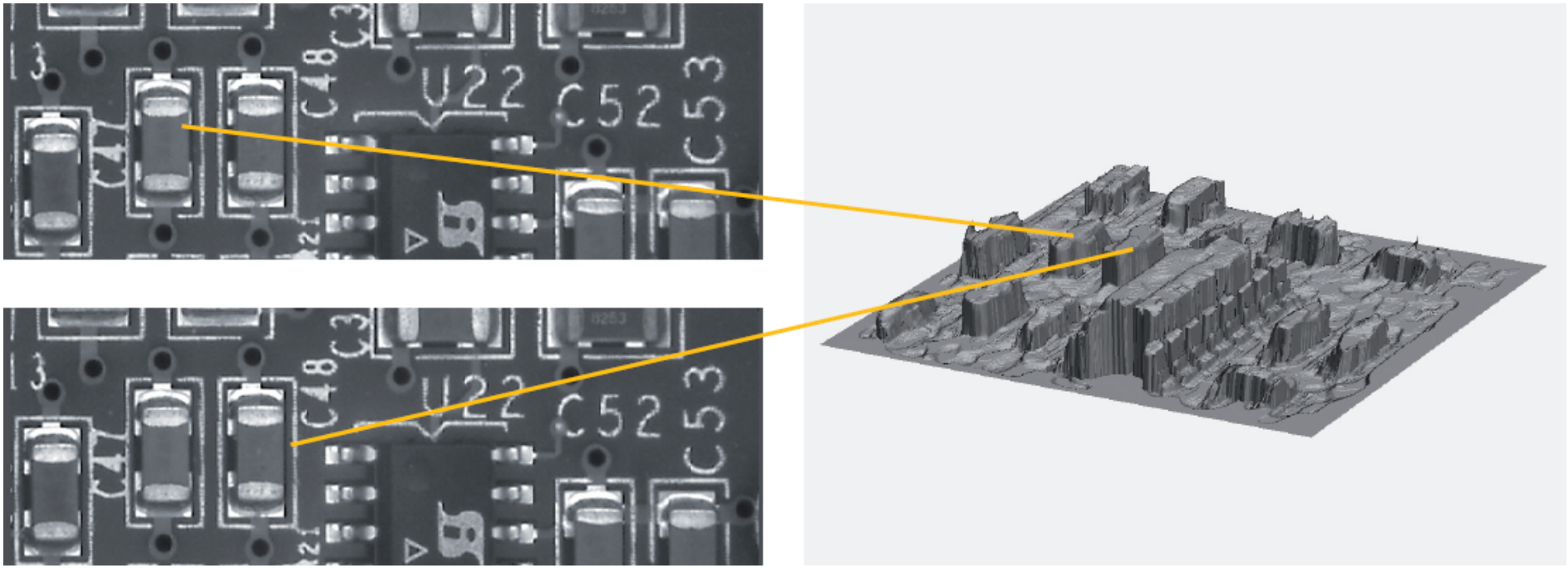
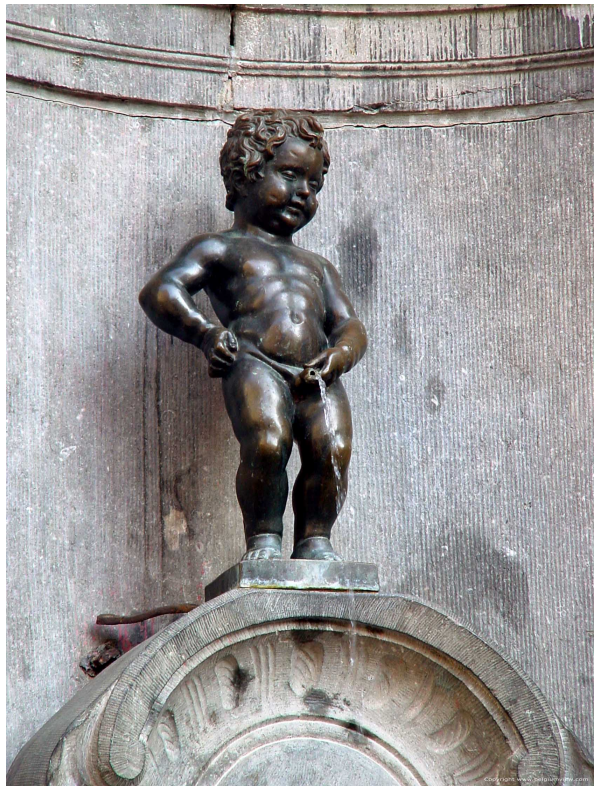


Matching: difficulties

- Illumination, color changes
- orientation, viewpoint
- scale
- occlusion...



Constructing alignment

- salient points detection
- corresponding pairs
- alignment

Problems

- detect the same points
- make the correspondance
- rotation, scale, geometry

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Method

1. Feature points detection
2. Feature descriptors
3. Matching two sets of points
4. Transformation evaluation

Objective: robustness

Ensure invariances by:

- rotation, translation, scale
- illumination, color changes
- viewpoint change

Automatic scale detection

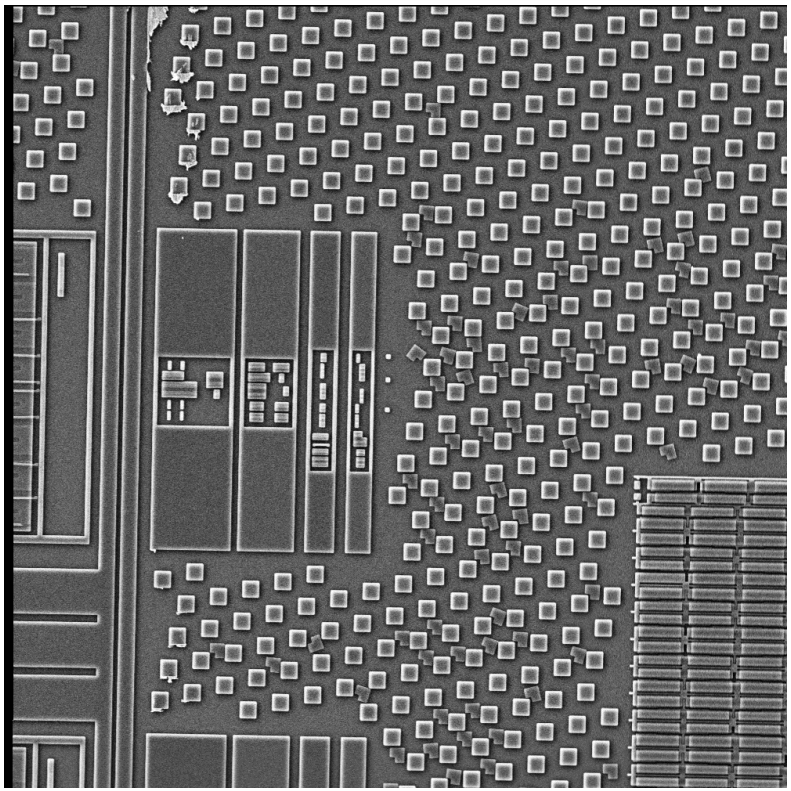
Detect scale between two different images of the same scene.

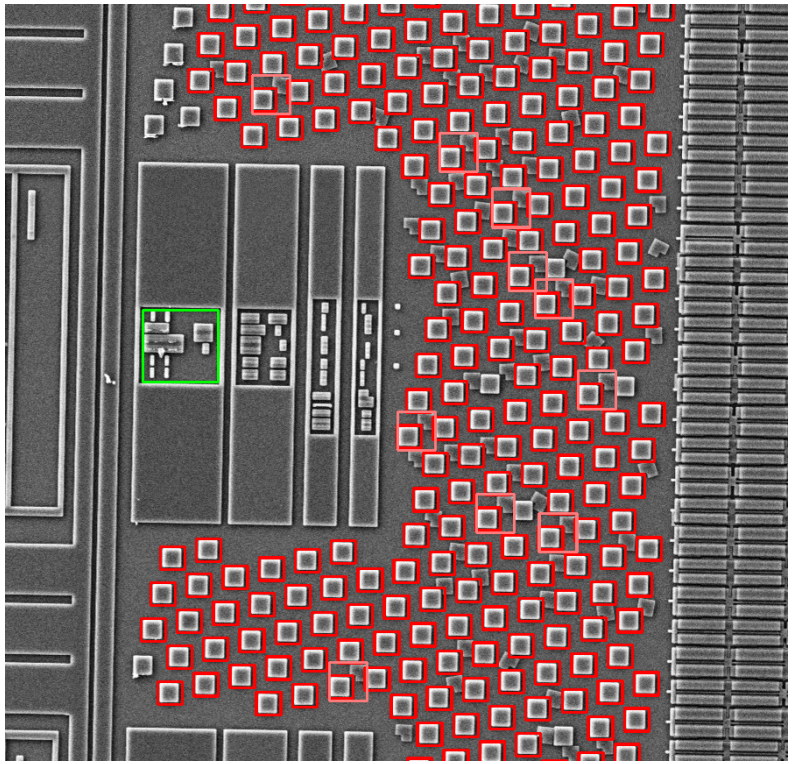
- Choose a scale invariant function
- Apply it to the same areas of the two images
- Locate the peaks in the function

Template matching

Objectives

Find areas that look like the template image ■





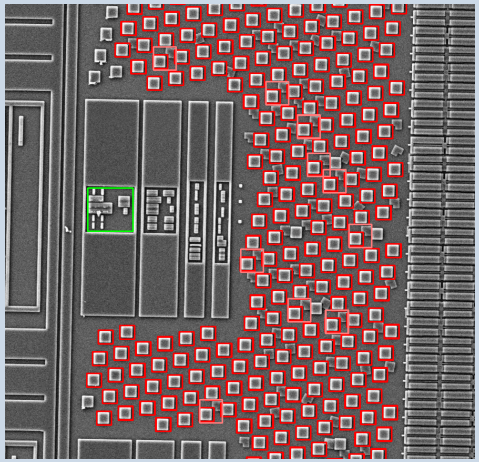
Template matching

Solution

- Use a correlation map.
- Take the maxima
- Definition:

$$(f \star g)(\tau) = \int_{-\infty}^{\infty} f^*(t)\, g(t+\tau)\, dt$$

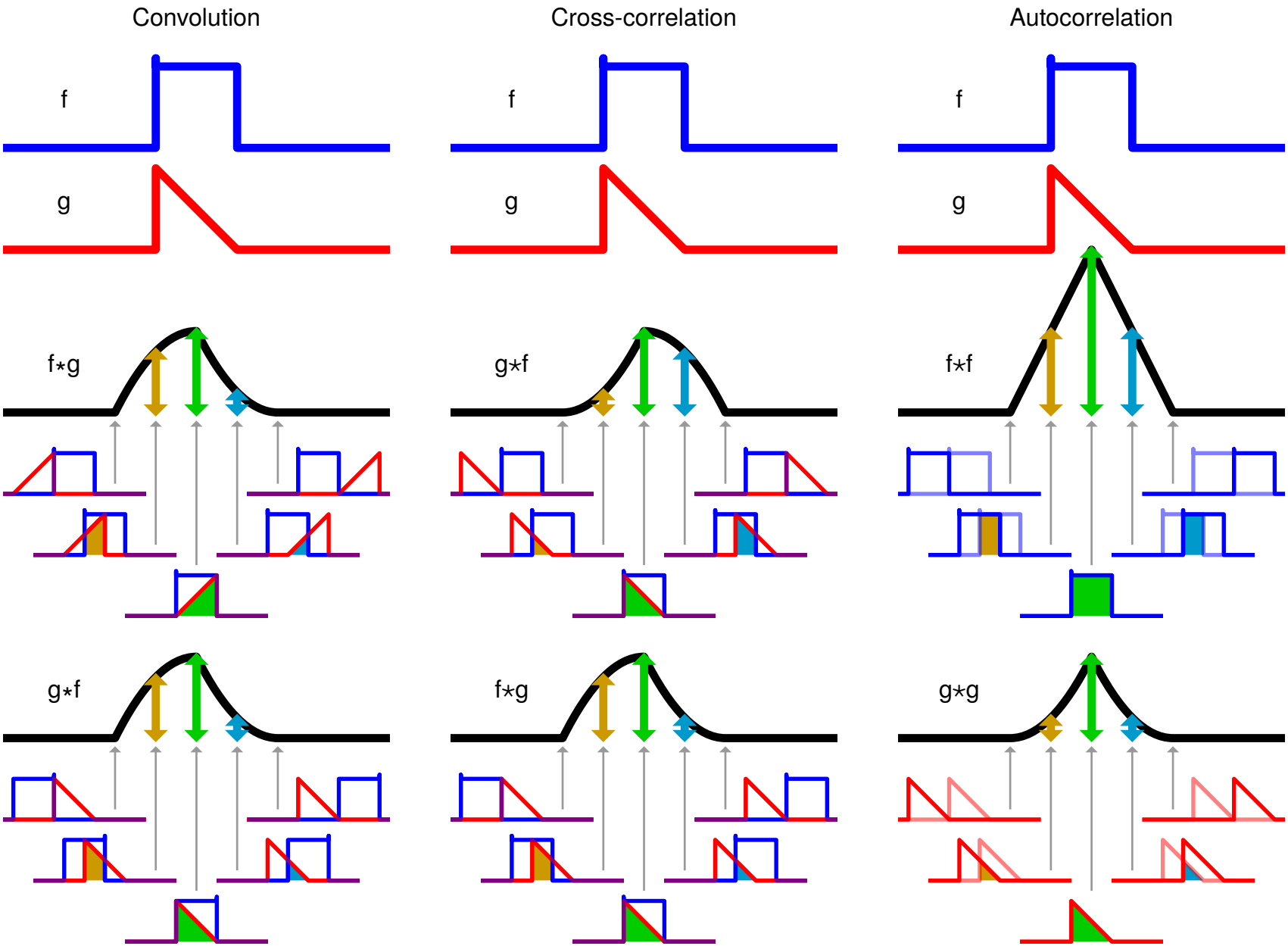
f^* is the complex conjugate.



Limitations

Intolerant to small variations:

- illumination,
- scale changes,
- rotation,
- more generally: shape variations.


Convolution
Cross-correlation
Autocorrelation
f
g
f
g
f
g
f⋆g
g⋆f
f⋆f
g⋆f
f⋆g
g⋆g

Algorithms

- Like convolution.
- Use FFT for speed

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Other measures

- SAD: Sum of Absolute Differences
- SSD: Sum of Squared Differences

Algorithms

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- Use FFT for speed

Other measures

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- SSD: Sum of Squared Differences

Efficiency

- Might be slow
- Value is sensitive to contrast and illumination changes
- Use ZNCC or NCC (Zero-Normalized Cross Correlation)
  - uses integral image
  - parallel version
  - FPGA friendly

- ZSAD
- ZSSD

To go further:
Census Transform

Section 2

Feature detectors

Point features: Corner vs Blob detectors

Corners:

- Harris,
- Shi-Tomasi,
- SUSAN
- FAST

Blob:

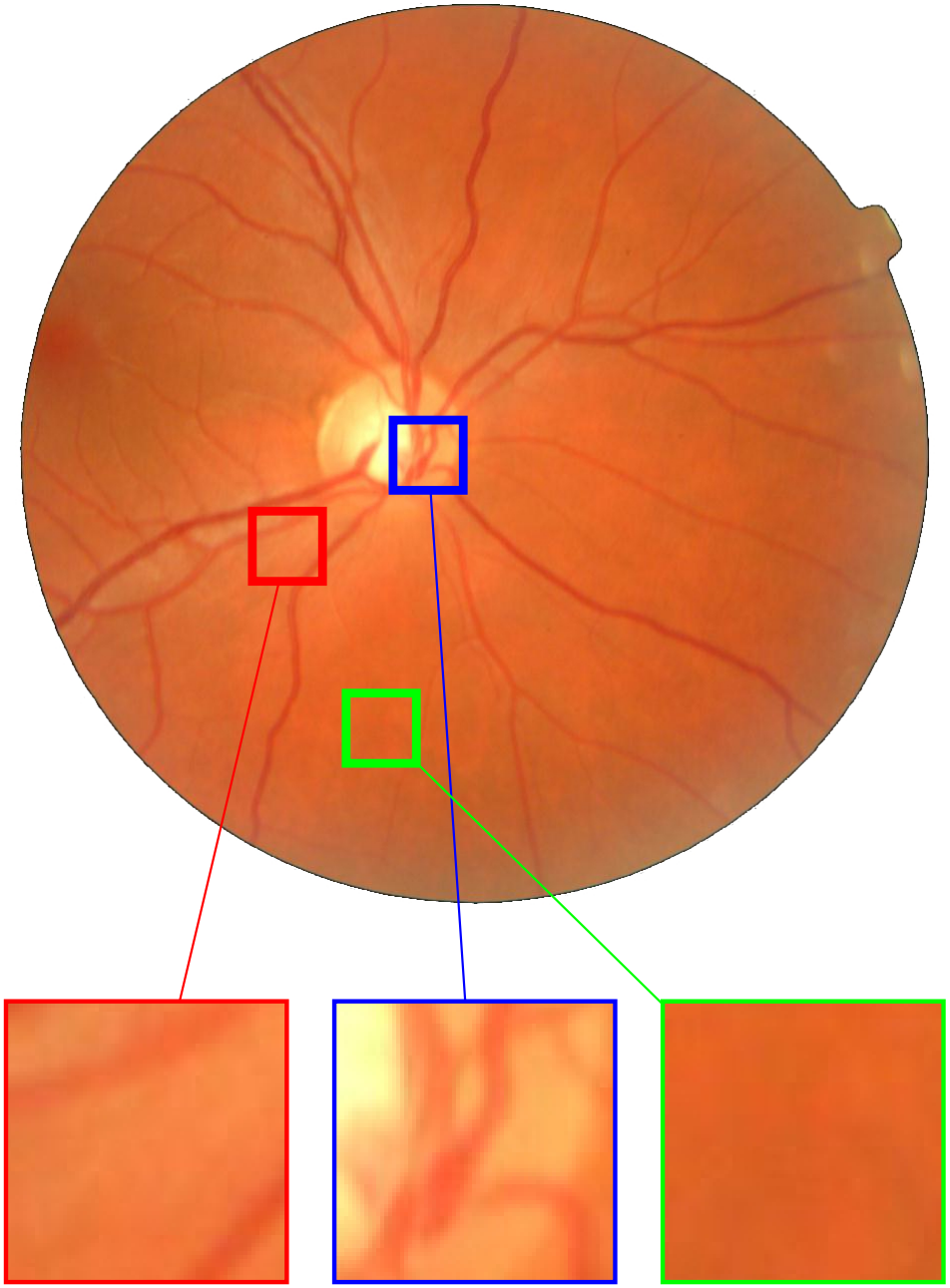
- MSER
- DoG (SIFT), LoG
- SURF
- CenSurE

Vocabulary

- Edges: contours
- Points
- Blobs: regions
- Ridges: medial axis

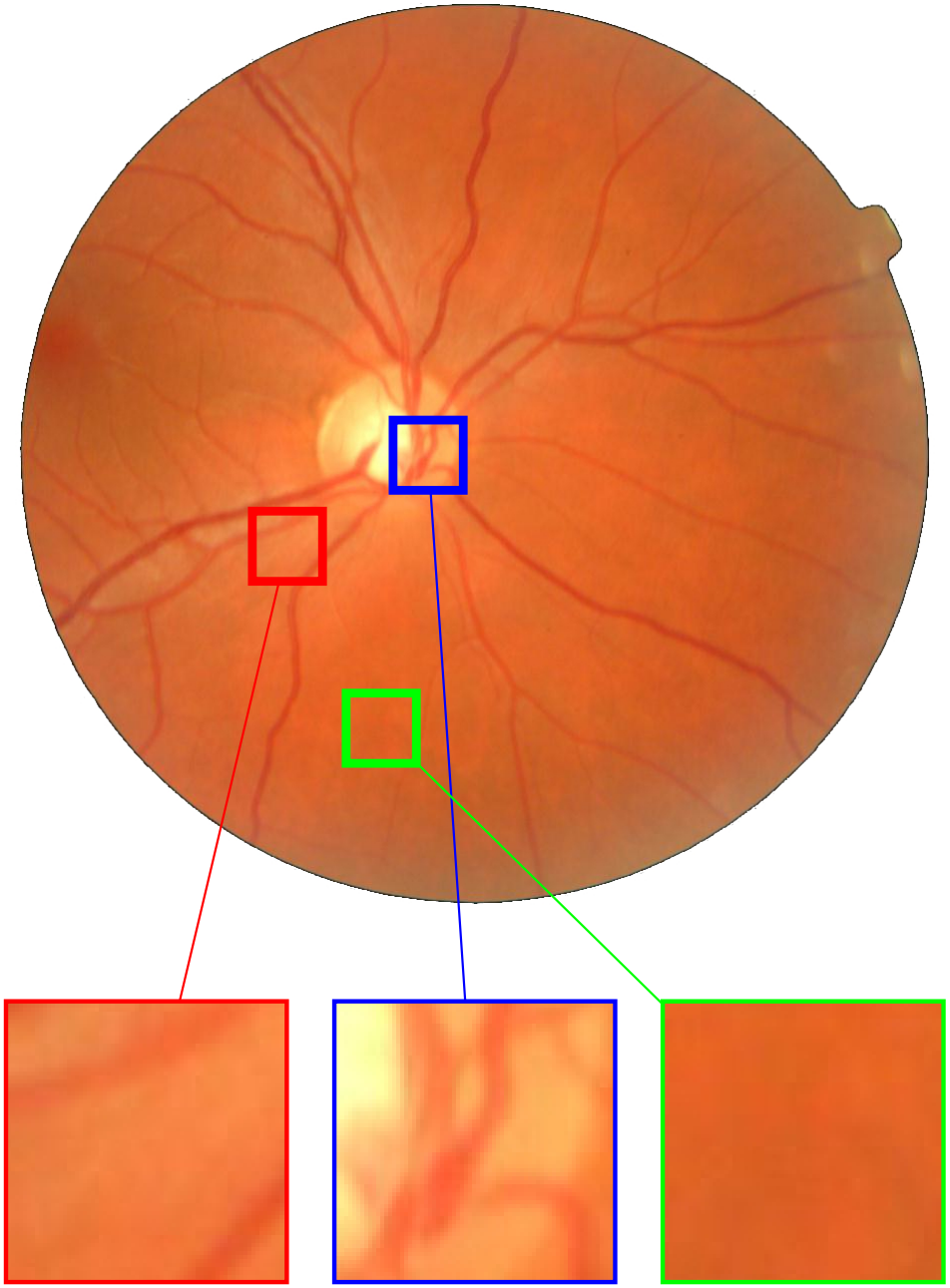
Properties

- Robustness (scales, deformations...)
- Repeatability (different conditions)
- Accuracy (spatial precision)
- Generality of applications
- Efficiency (speed)
- Quantity (all features detected)



Goal

- Find and match patches
- What is a good patch?



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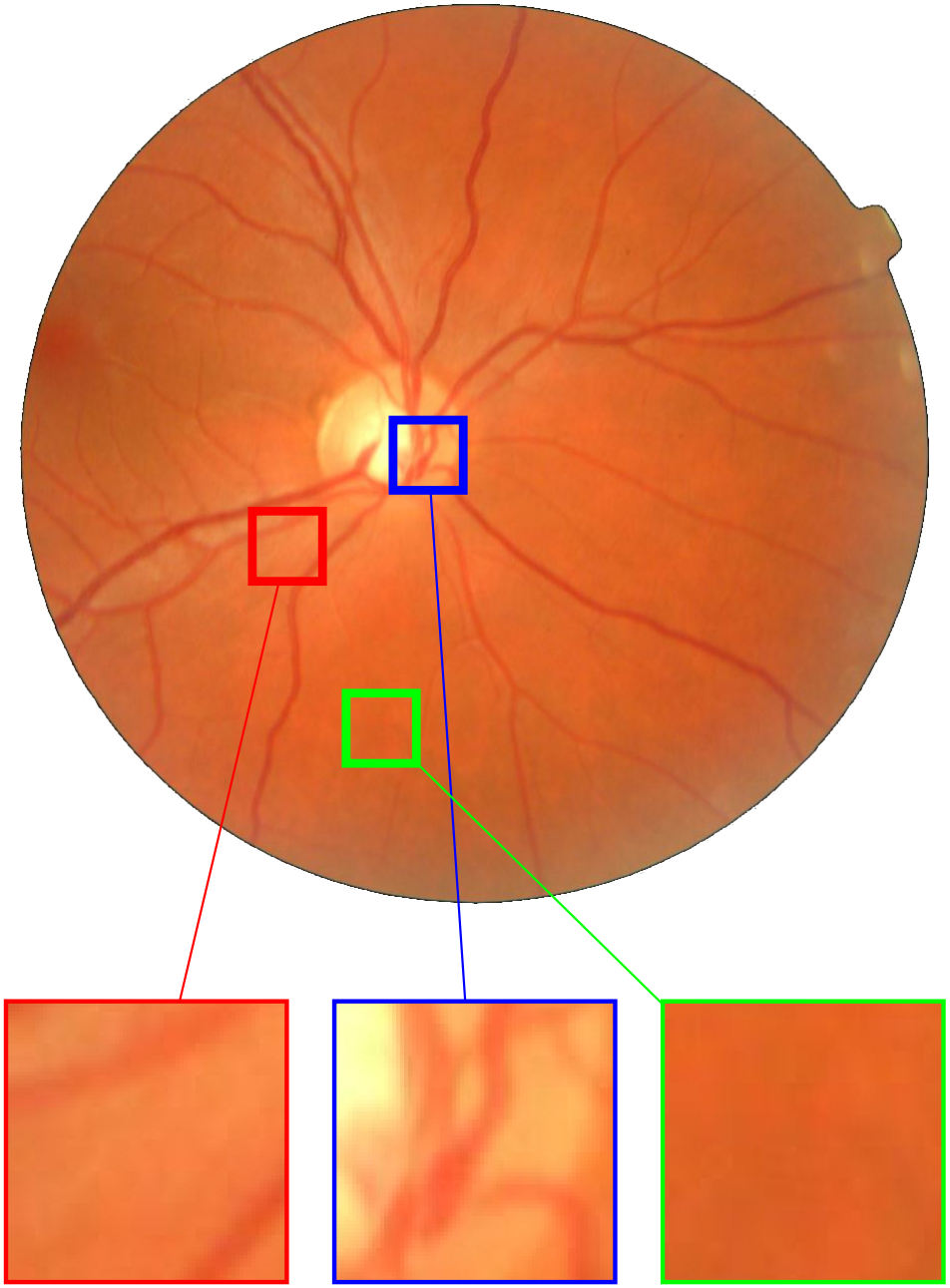
- What is a good patch?

- can see differences
- corners ?
- non flat areas



Goal

- Find and match patches
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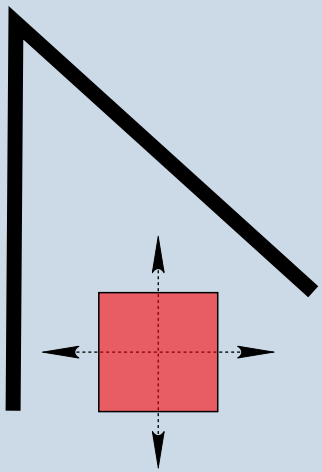
What is a corner?

- junctions of contours/edges
- intensity variations in neighborhood

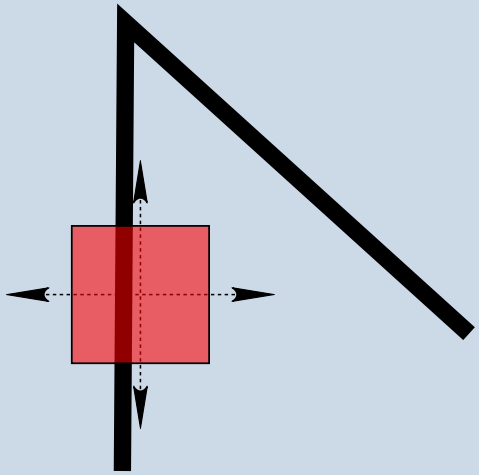
Corner detection

Basic idea

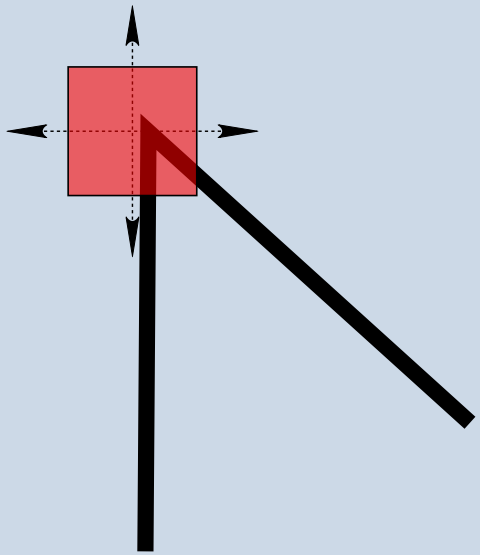
- Look at neighborhood
- Evaluate intensity change
- For all directions



No change



No change along edge

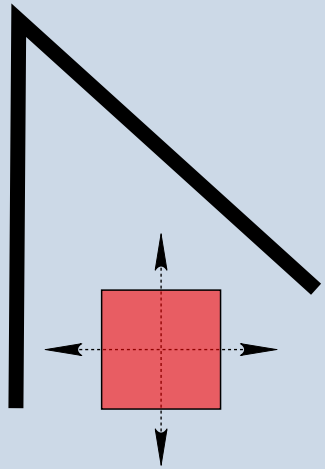


Big changes

Moravec's detector

Intensity variation evaluation

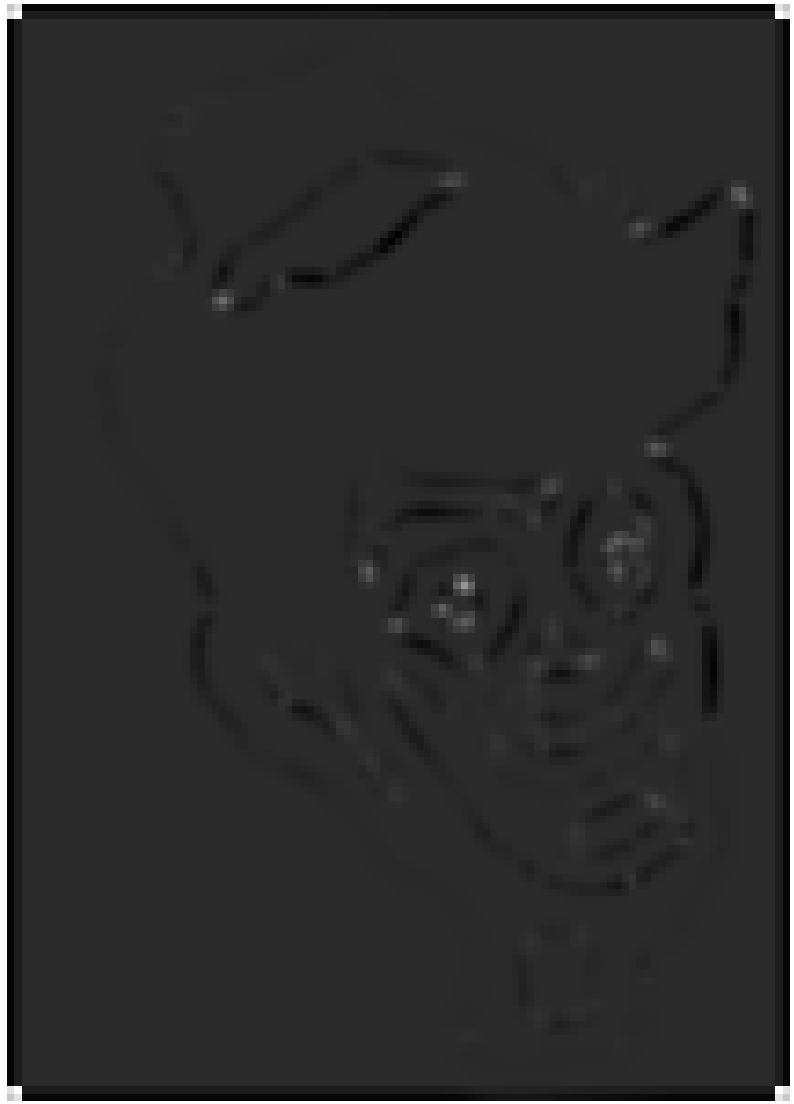
- Mathematical formulation of the "changes".
- Let I be a grayscale image
- W is a window (rectangular, gaussian...)
- $\Delta x, \Delta y$ is the shift



Intensity Variation : V

We want to maximize V

Intensity variation



Moravec's detector

$$V_{\Delta x,\Delta y}(x,y) = \sum_{(u,v)\in W(x,y)} \left(I(u,v) - I(u+\Delta x, v+\Delta y)\right)^2$$

Cornerness map

$\Delta x, \Delta y$ vary in a neighborhood.

$$C(x,y) = \min\left(V_{\Delta x,\Delta y}(x,y)\right)$$

Treshold value T

Keep local maxima that are higher than threshold value T.
Remaining points are corners.

Pros

- Detect the majority of the corners.

Cons

- Anisotropic: thus, not invariant by rotation.

Harris Corner detector

Taylor series expansion

$$I(x + \Delta x, y + \Delta y) \approx I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y$$

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

Harris Corner detector

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Approximation of intensity Variation V

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Approximation of intensity Variation V

$$V_{\Delta x,\Delta y}(x,y) \approx \begin{pmatrix}\Delta x & \Delta y\end{pmatrix} M \begin{pmatrix}\Delta x \\ \Delta y\end{pmatrix}$$

$$M = \sum_{(u,v)\in W} \omega(u,v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

ω is a weight function (Gaussian filter)

Harris corner detector

M is the structure tensor.

- second-moment matrix (symmetric)
- predominant directions of the gradient
- depend on neighborhood and point
- 2×2 matrix

I_x and I_y are the gradients in x and y directions for the considered point.

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

Harris corner detector

$$M = \begin{bmatrix} \sum_{(u,v)\in W} \omega(u,v) I_x(u,v)^2 & \sum_{(u,v)\in W} \omega(u,v) I_x(u,v) I_y(u,v) \\ \sum_{(u,v)\in W} \omega(u,v) I_x(u,v) I_y(u,v) & \sum_{(u,v)\in W} \omega(u,v) I_y(u,v)^2 \end{bmatrix}$$

Only pointwise operations are used!

- ω introduces isotropy
- use uniform filter or Gaussian filter

Harris corner detector

Eigenvalues of M

- M is symmetric, it can be diagonalized, with eigenvalues λ_1, λ_2
- Interpretation
  - Distribution of gradient vectors
  - an ellipse with axis lengths λ_1 and λ_2

Shi and Tomasi detector

$$C(x, y) = \min(\lambda_1, \lambda_2)$$

Harris corner detector

Eigenvalues of M

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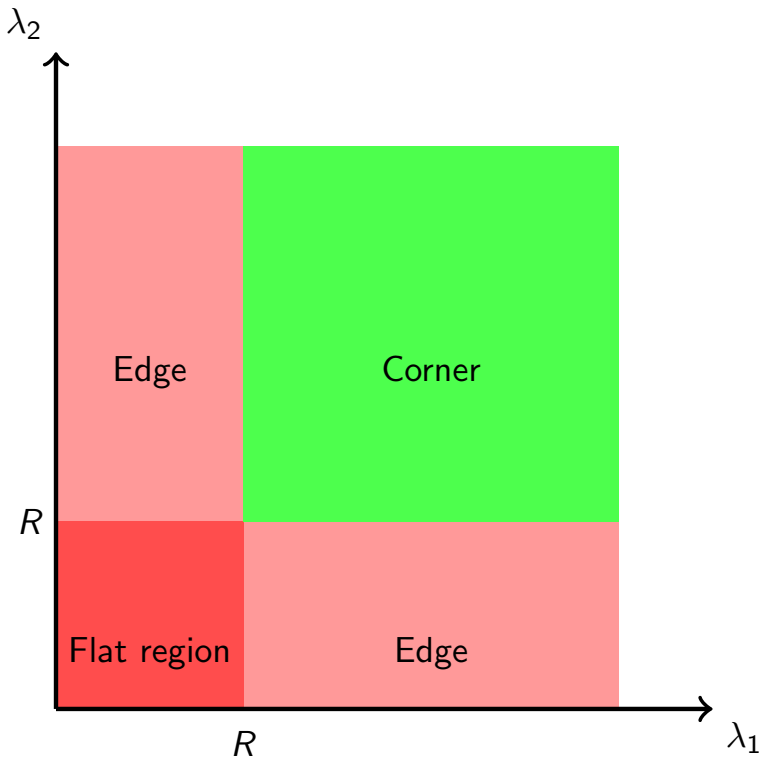
Cornerness measure (Harris and Stephens)

- $\det(M) = \lambda_1 \cdot \lambda_2$
- $\mathrm{trace}(M) = \lambda_1 + \lambda_2$
- λ_1, λ_2 not computed in practice, for efficiency reasons
- K is the *magic number*, between 0.04 and 0.15.

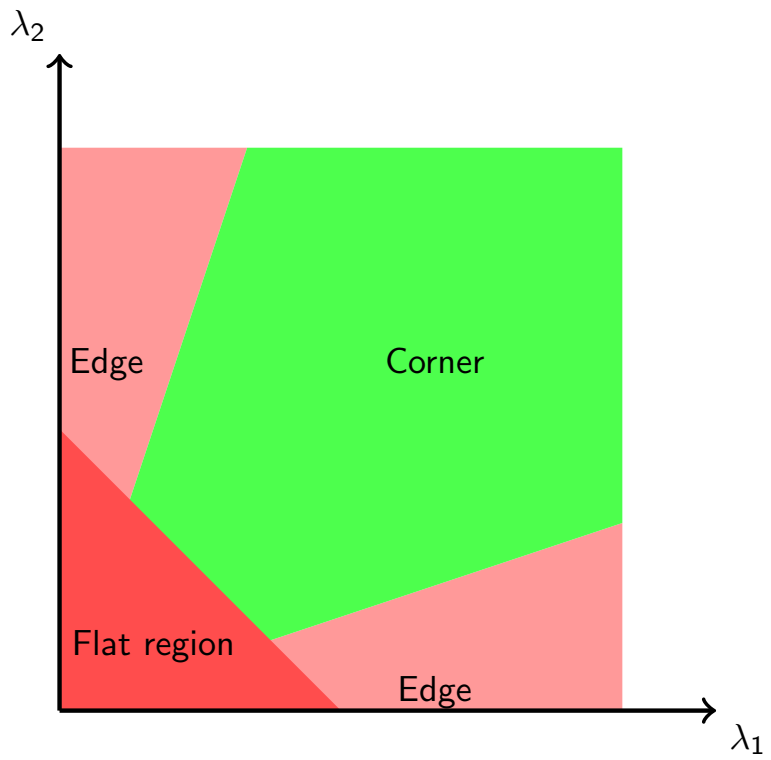
$$C(x, y) = \det(M) - K\mathrm{trace}(M)^2$$

Shi/Tomasi vs Harris corner detector

- $C(x, y) = \min(\lambda_1, \lambda_2)$
- R: threshold value



- $C(x, y) = \det(M) - K\mathrm{trace}(M)^2$
- $\lambda_1 \cdot \lambda_2 - K \cdot (\lambda_1 + \lambda_2)^2$



Harris corner detector

Algorithm

- Compute gradients in x and y directions (Sobel, prewitt...),
- Compute I_x^2, $I_x \cdot I_y$, I_y^2 (pointwise operations),
- Convolve them with ω (uniform/Gaussian filter),
- Compute the cornerness measure C,
- Keep local maxima that are above a threshold value.

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Practical problems

- Sub-pixels computation (discretization)
- Border effects
- Treshold value: keep strongest values?

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Extension

- Multiscale (Gaussian pyramid...)

SUSAN detector

- Consider a mask M (here, a disk)
- Its center: nucleus p_0
- Look at pixels $p \in M$
- Treshold value t

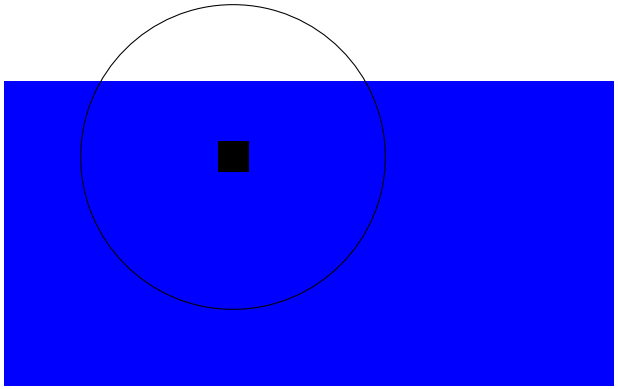
Principle

- Evaluates part of the mask that recovers the object

$$C(p, p_0) = \begin{cases} 1 \text{ if } |I(p) - I(p_0)| \leq t \\ 0 \text{ otherwise} \end{cases}$$

$$n(M) = \sum_{p \in M} C(p, p_0)$$

SUSAN detector



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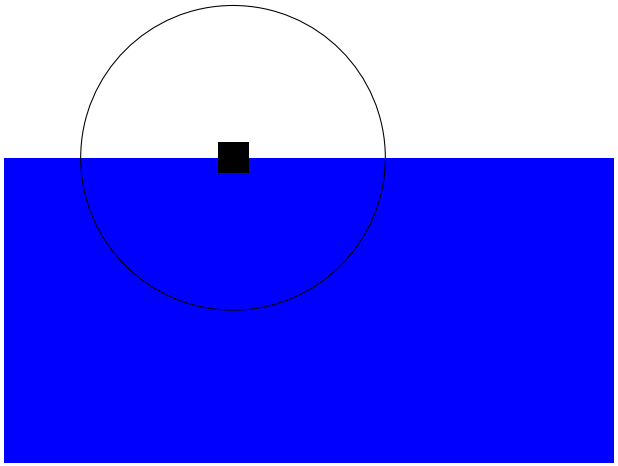

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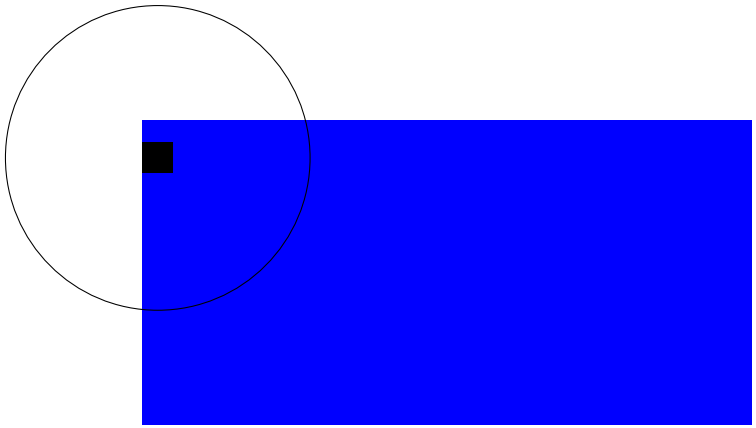

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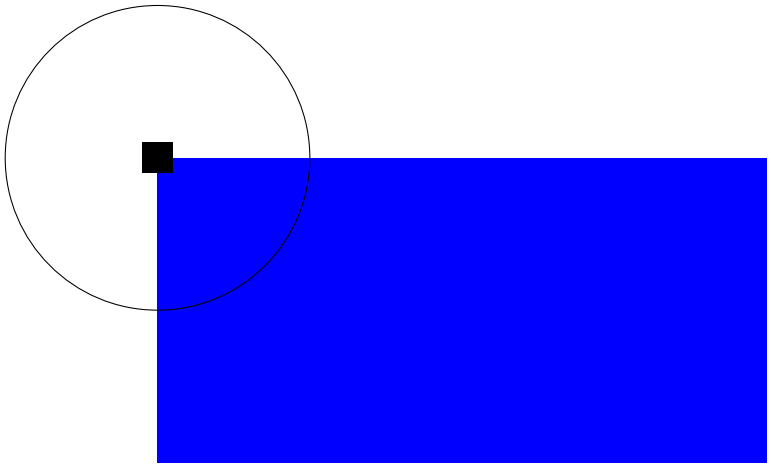

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g: geometric threshold, $R(M)) = \begin{cases} g - n(M) \text{ if } n(M) \leq g \\ 0 \text{ otherwise} \end{cases}$

- corner: n must be less than half its maximum possible value
- $g = \frac{1}{2} n_{\max}$
- threshold R, detect local maxima
- can be used as edge detector
- other distances C can be used

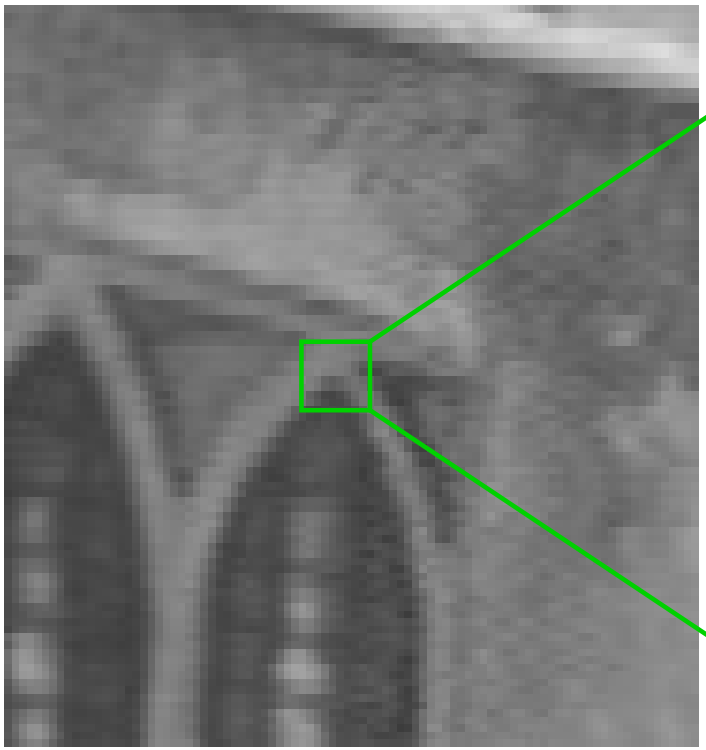
Pros and cons

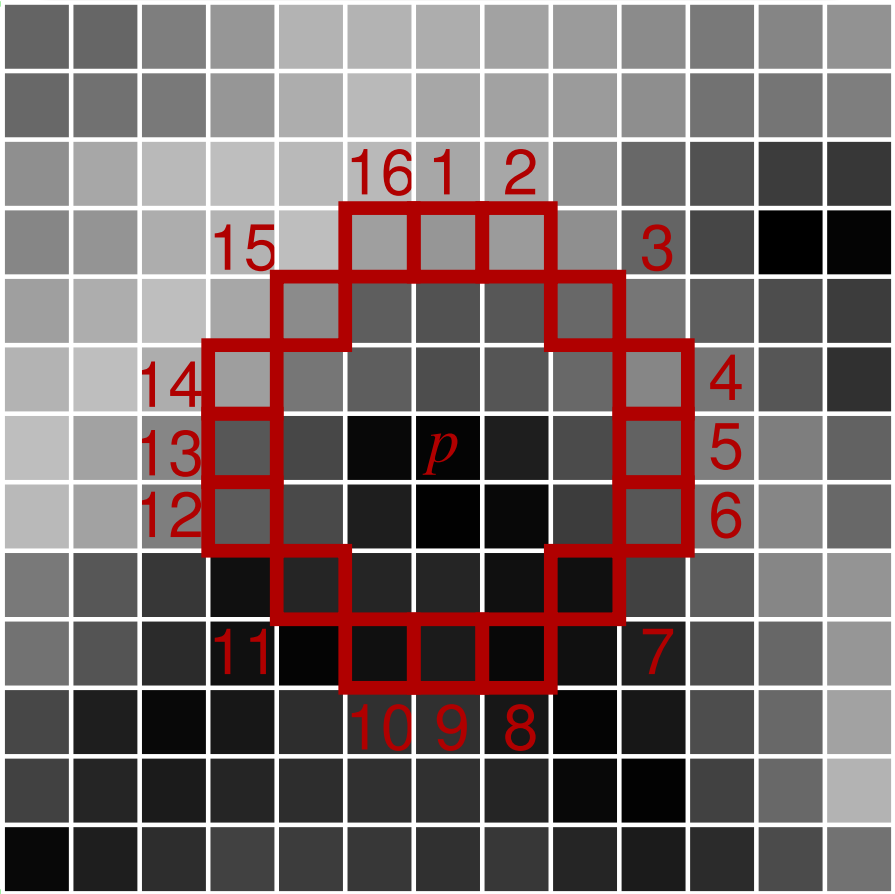
- Invariant by translation and rotation (depends on M)
- Sensitive to scaling
- Fixed global threshold g not always adapted

FAST: Feature from Accelerated Segment Test [2]

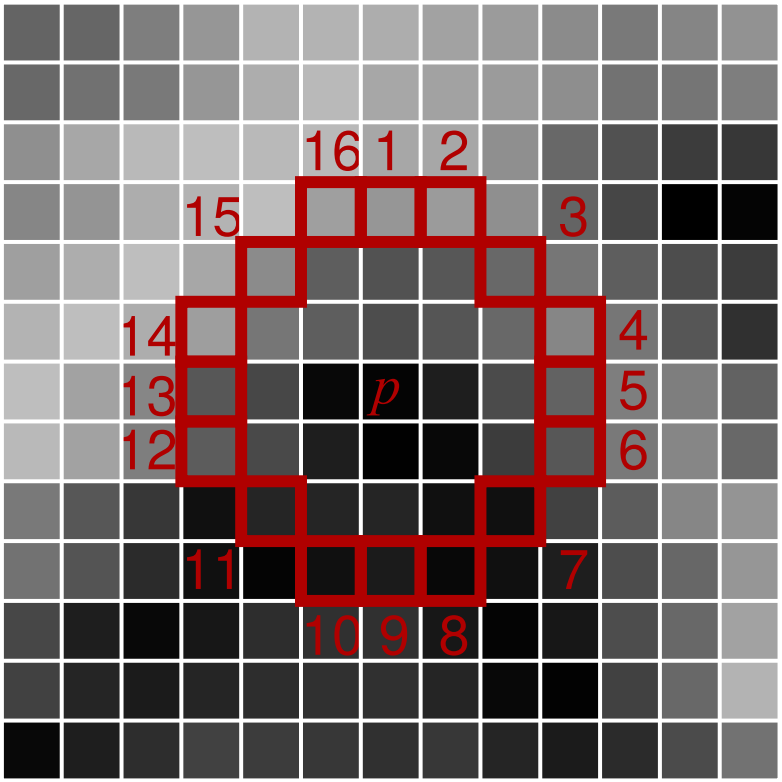
- evolution from SUSAN
- real-time operator

- Bresenham circle instead of a mask M
- 16 pixels to test



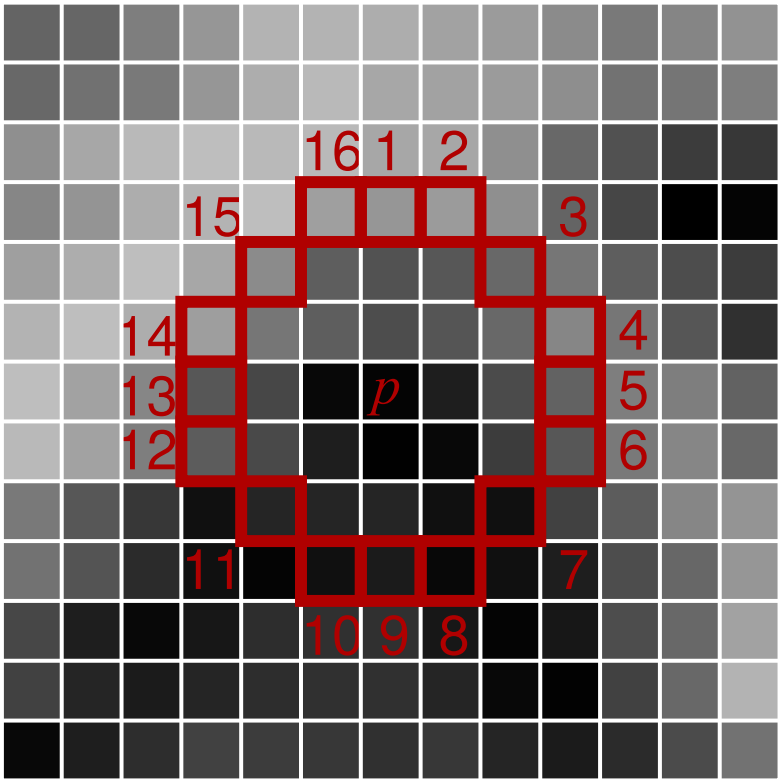


FAST



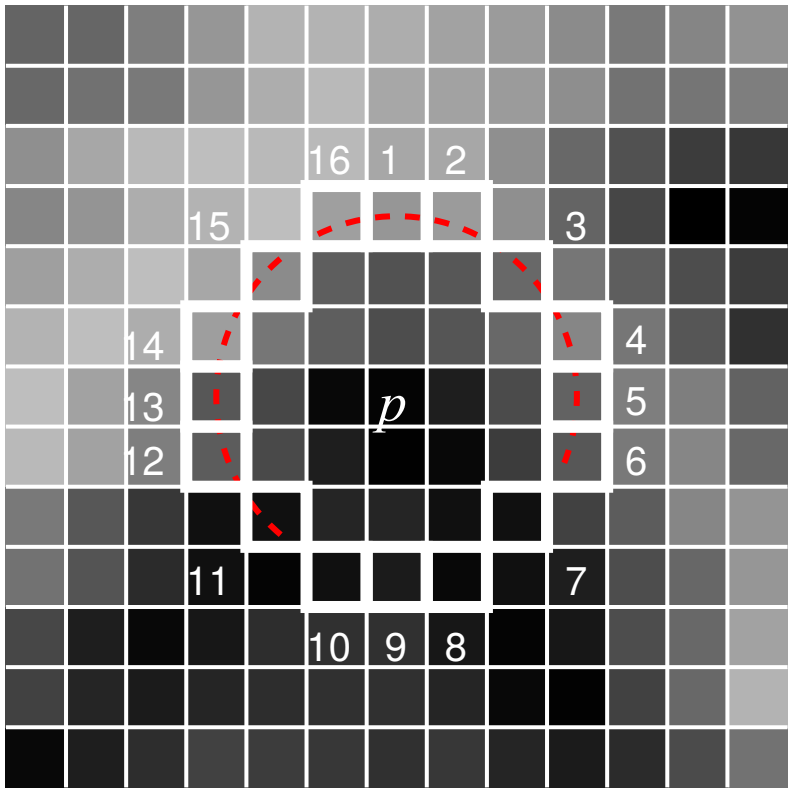
- Consider pixel p on image I

FAST



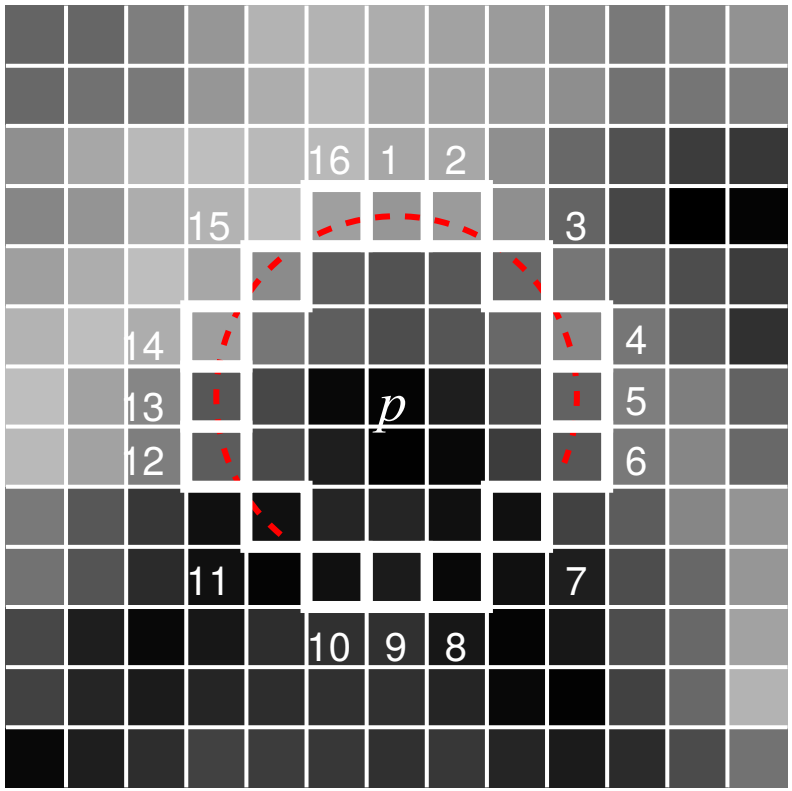
- Consider pixel p on image I
- Threshold value t

FAST



- Consider pixel p on image I
- Threshold value t
- Search for $n = 12$ contiguous pixels
  - brighter that $I_p - t$
  - or darker than $I_p + t$

FAST

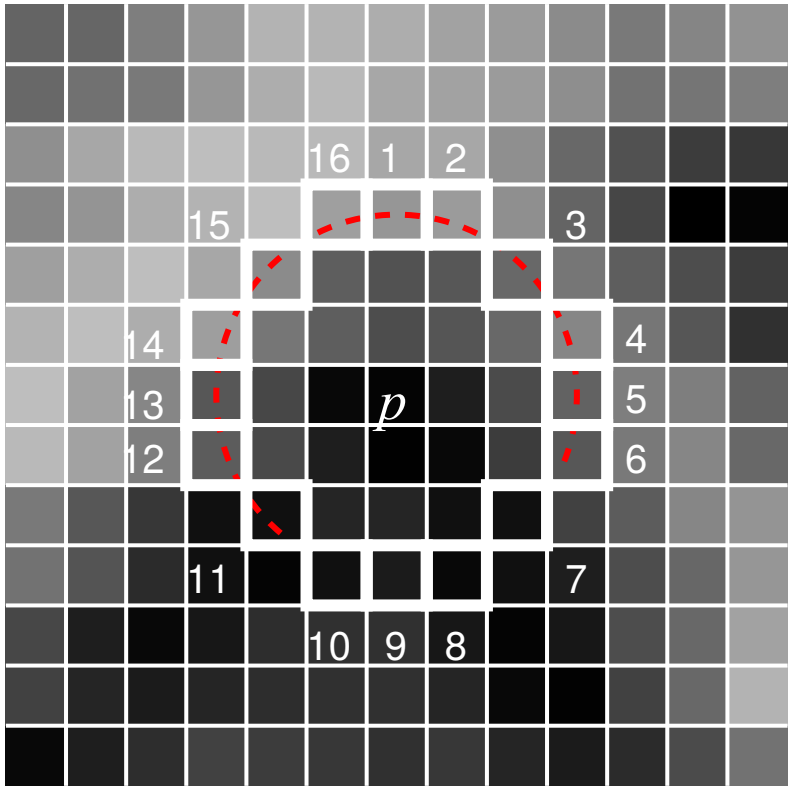


- Consider pixel p on image I
- Threshold value t
- Search for $n = 12$ contiguous pixels
  - brighter that $I_p - t$
  - or darker than $I_p + t$

High-speed test

- Test 1 and 9
- Test 5 and 13
- Test full segment

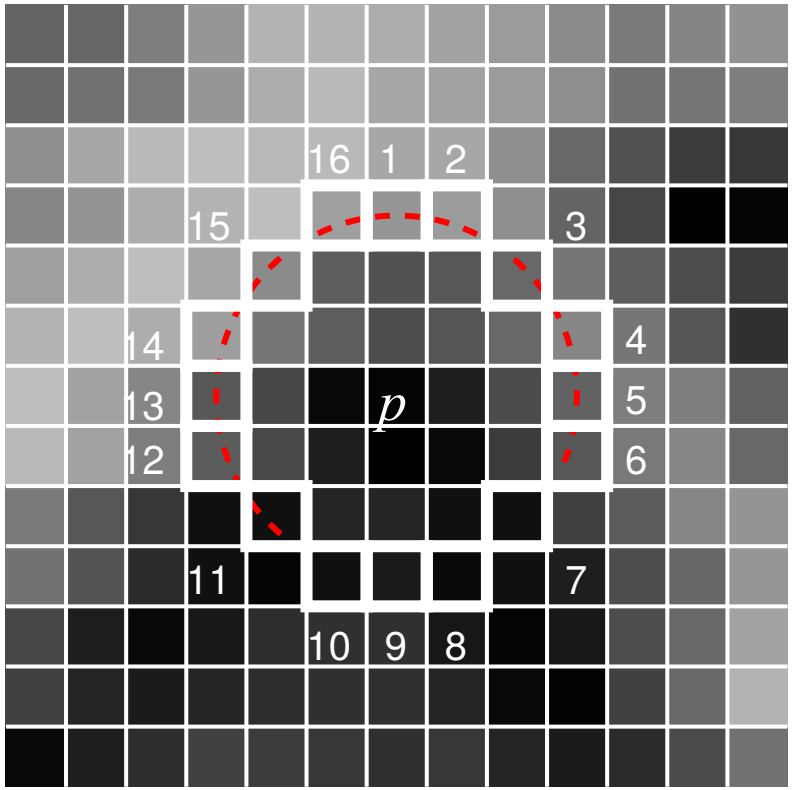
FAST-ER: machine learning enhancement [3]



Drawbacks

- It does not reject as many candidates for $n < 12$.
- choice of pixels not optimal
  - its efficiency depends on ordering of the tests
  - and distribution of corner appearances.
- No memory in the tests.
- Multiple features are detected adjacent to one another.

FAST-ER: machine learning enhancement [3]



Summary

- Suitable for real-time video processing
- NOT invariant to scales changes
- sensitive to noise
- selecting threshold is not trivial

Hessian blob detector

Hessian Matrix

$$H(p,\sigma) = \begin{pmatrix} L_{xx}(p,\sigma) & L_{xy}(p,\sigma) \\ L_{yx}(p,\sigma) & L_{yy}(p,\sigma) \end{pmatrix}$$

Gaussian function

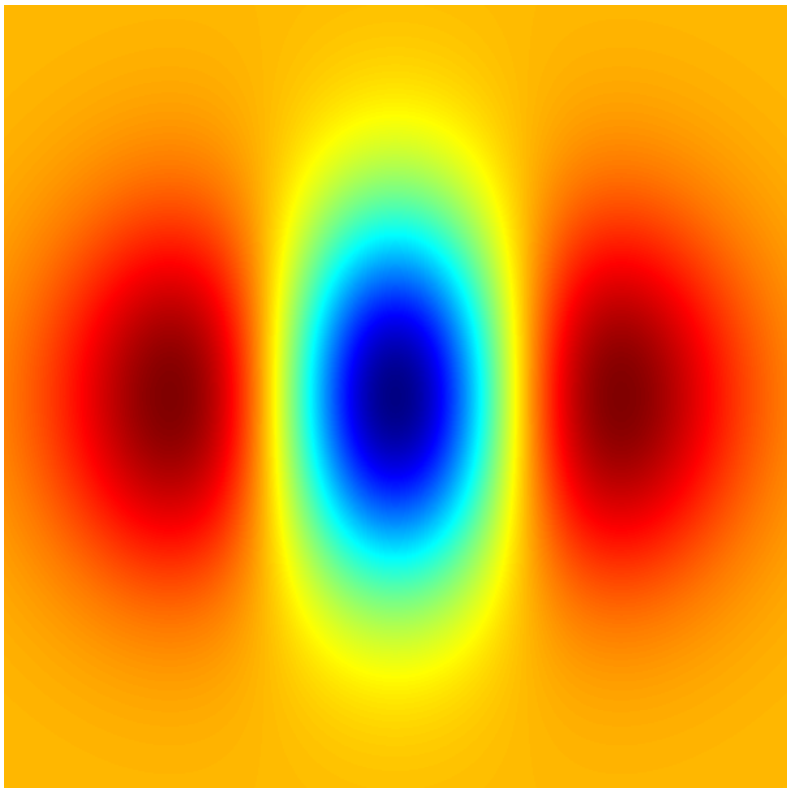
$$g(p,\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{\|p\|^2}{2\sigma^2}}$$

$$L_{xx} = \frac{\partial^2 g}{\partial x^2} * I \qquad L_{xy} = L_{yx} = \frac{\partial^2 g}{\partial x \partial y} * I$$

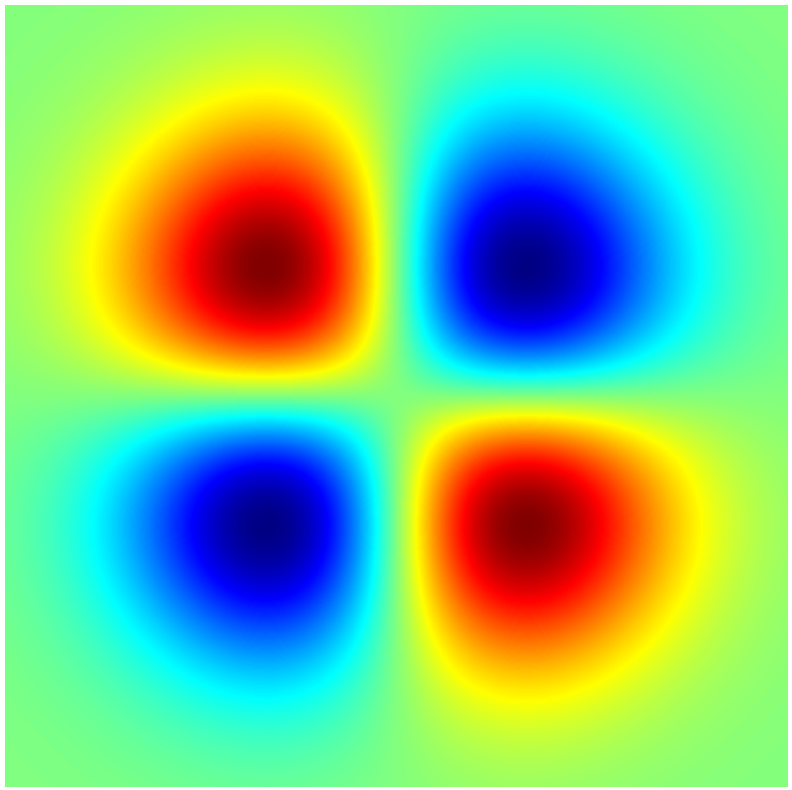
Convolution of second derivative of Gaussian function with the image.

Hessian blob detector: Gaussian derivatives

$$\frac{\partial^2 g}{\partial x^2}$$



$$\frac{\partial^2 g}{\partial x \partial y}$$



Hessian blob detector

Detector: determinant of Hessian matrix

$$\det(H) = I_{xx} I_{yy} - I_{xy}^2$$

Determine local maxima:

- global threshold
- regional maximum

- Sensitive to noise
- Scale-space approach

Laplacian of Gaussian LoG

Gaussian function

$$g(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Scale-space representation

$$L(x, y; \sigma) = g(x, y, \sigma) * f(x, y)$$

Laplacian operator

Second derivatives L_{xx}, L_{yy}

$$\nabla^2 L = L_{xx} + L_{yy}$$

Feature detector

Scale-normalized Laplacian operator:

$$\nabla^2_{\text{norm}} L = \sigma^2 (L_{xx} + L_{yy})$$

Detect min and max according to (x, y, σ)

- Scale invariance
- Rotation invariance
- less noise-sensitve than Hessian detector

LoG: automatic scale detection [1]

Property of LoG

- (x_0, y_0, σ_0) is a max/min
- s scale parameter
- $(s \cdot x_0, s \cdot y_0, s \cdot \sigma_0)$ is also a max/min

Evolution

- Harris-Laplace
- Harris: rotation/illumination invariant
- adds scale

DoG: Difference of Gaussians

Definition

$$L(x, y; \sigma) = g(x, y, \sigma) * f(x, y)$$

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$

- scale-space decomposition
- minima/maxima extraction

- High computation time for all scales
- also detects edges (not only corners)

Useful concepts

- octave: doubling the value of σ
- k: limits the number of scales per octave

Section 3

Feature descriptors

Feature descriptors: introduction

- Detection of points of interest
- objective: matching, pairing
- NEED for a comparison

Key question

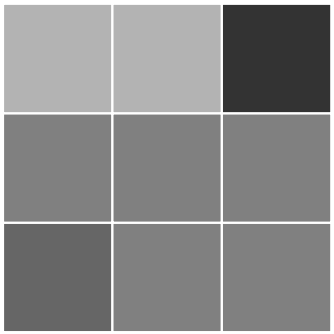
How to compare neighborhoods of keypoints?

Descriptor

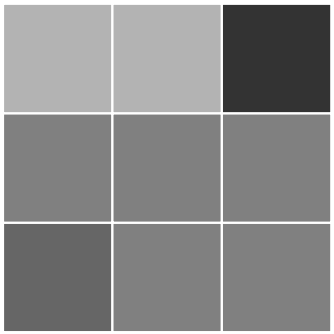
- signature
- distance between descriptors
- invariance to:
  - scale,
  - transformation,
  - noise,
  - viewing conditions...

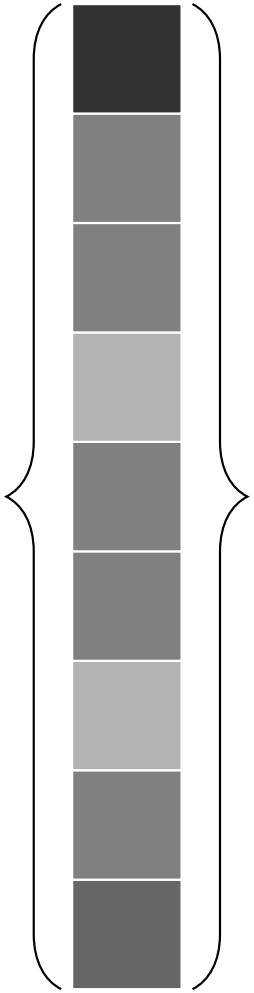
Feature descriptor: naive approach

- 3×3 neighborhood



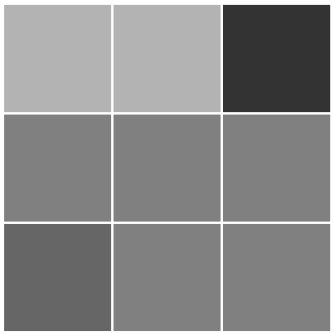
Feature descriptor: naive approach

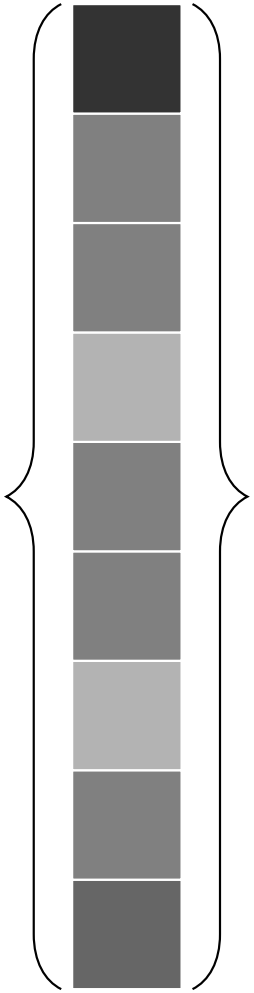




- 3×3 neighborhood
- Vector of intensities

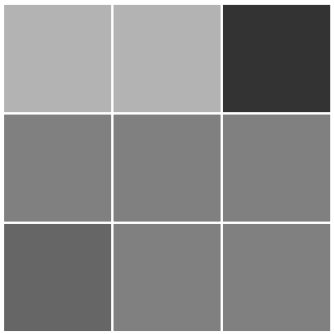
Feature descriptor: naive approach

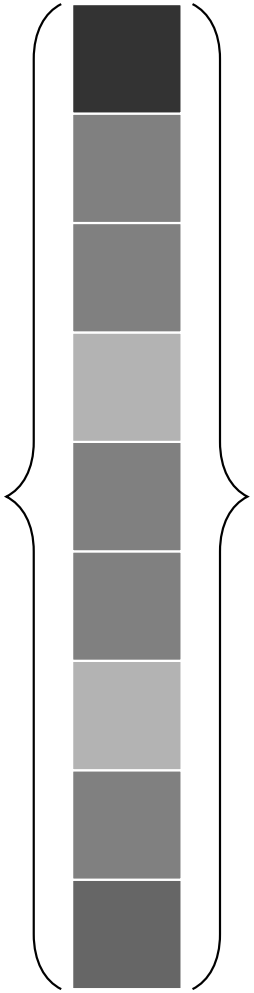




- 3×3 neighborhood
- Vector of intensities
- Euclidean distance

Feature descriptor: naive approach



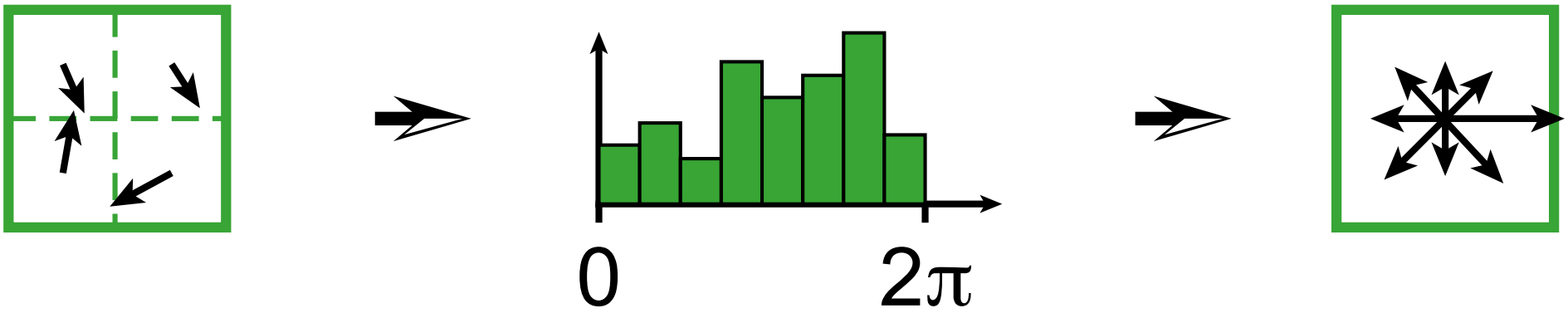


- 3×3 neighborhood
- Vector of intensities
- Euclidean distance

Problems

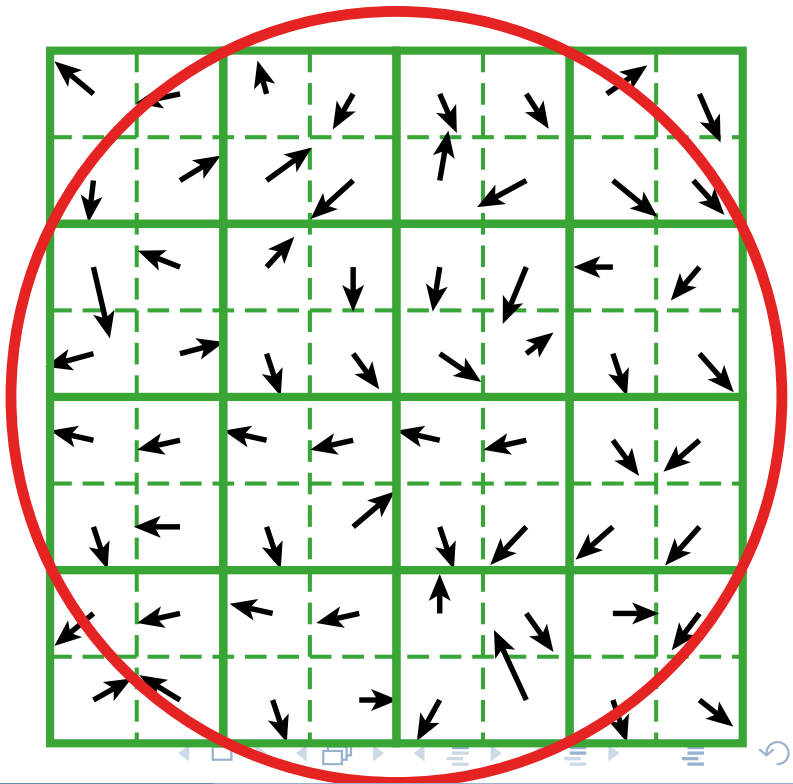
- Rotation?
- Scale?
- Noise?
- Performance?

HOG Histogram of Oriented Gradients

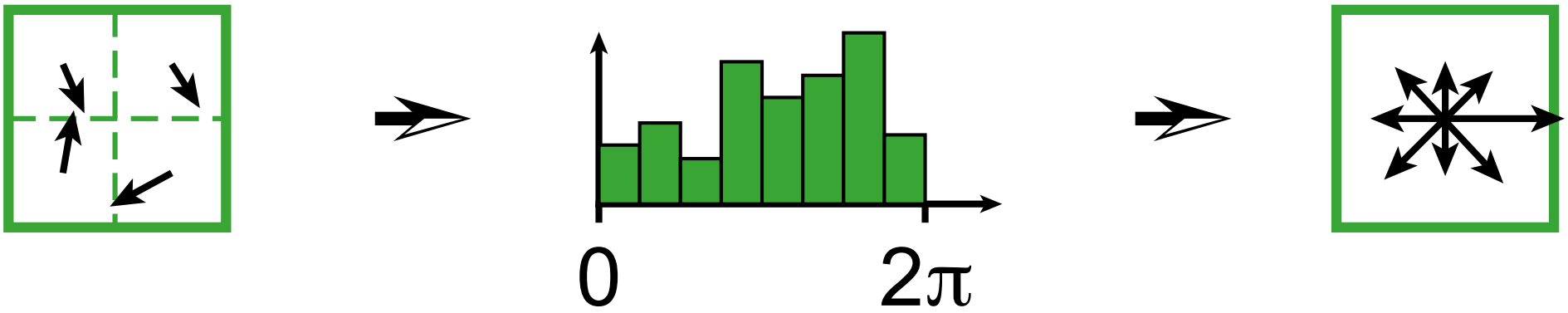


Principle

- Compute gradients (neighborhood of detected keypoints)
- Construct histogram (weighted by Gaussian function and amplitude)
- Concatenate all histograms in 1 vector



HOG Histogram of Oriented Gradients



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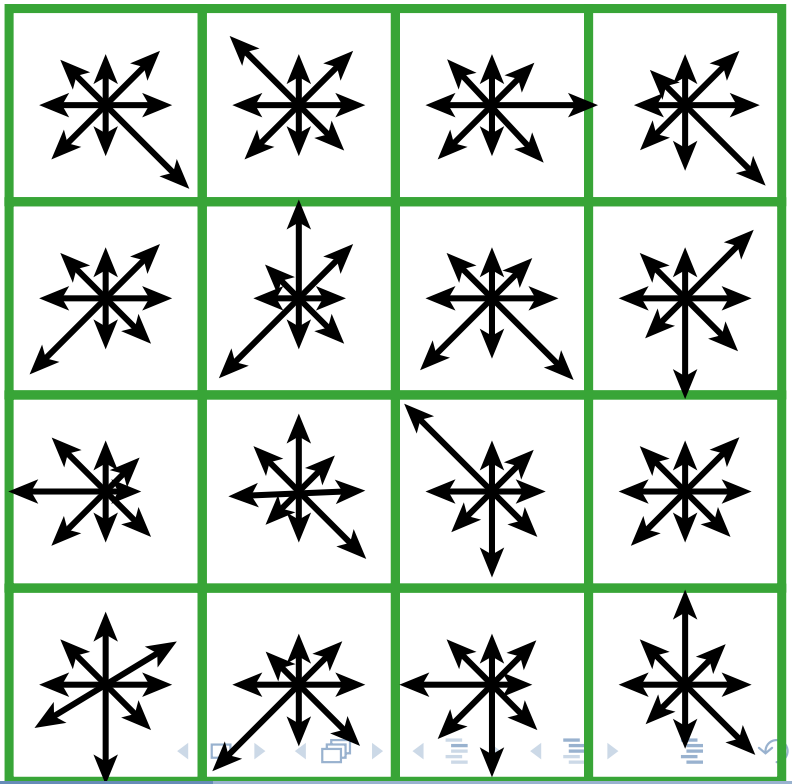
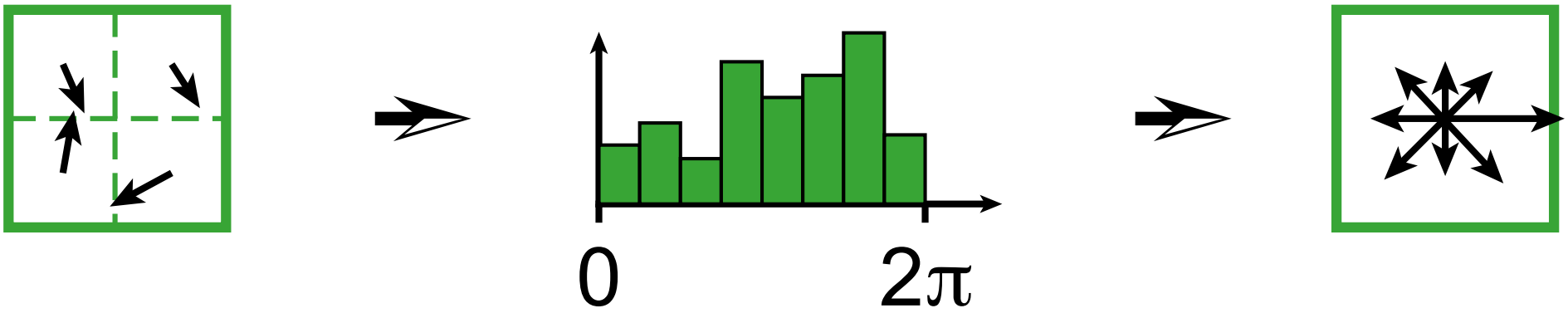
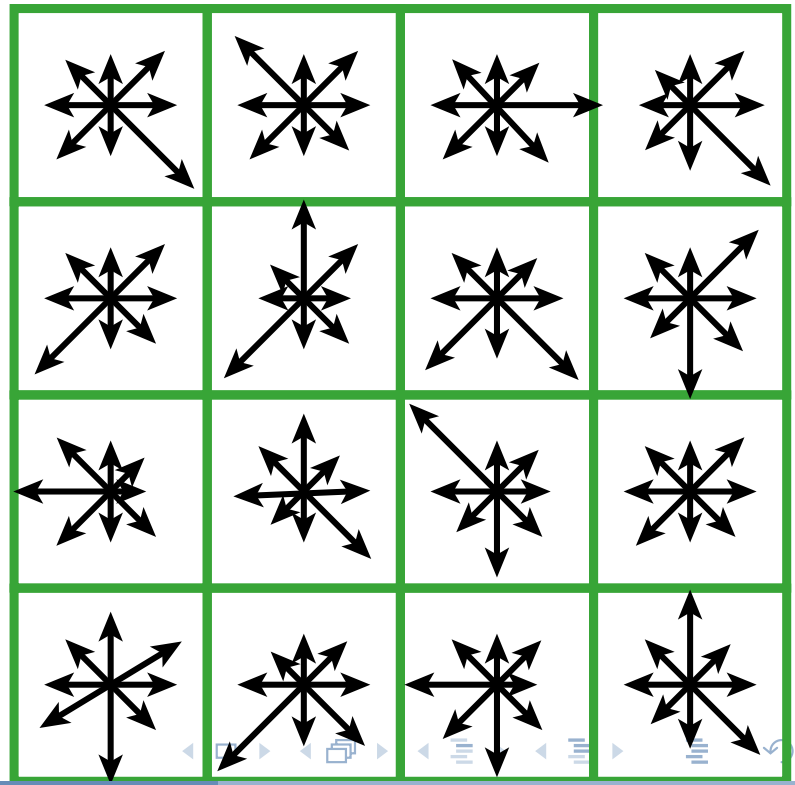


HOG Histogram of Oriented Gradients



SIFT case

- 16×16 pixels
- 4×4 descriptors of 8 bins
- Descriptor of 128 values



SIFT

Combination of

- DoG
- HOG

Additional operations

- Discard low-contrast keypoints
- Eliminate edge keypoints

Properties of invariance

- scale
- rotation (descriptor is oriented by gradient)
- translation

SIFT

Combination of

- DoG
- HOG

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SIFT

Combination of

- DoG
- HOG

Additional operations

- Discard low-contrast keypoints
- Eliminate edge keypoints

Properties of invariance

- scale
- rotation (descriptor is oriented by gradient)
- translation

SURF: feature detector

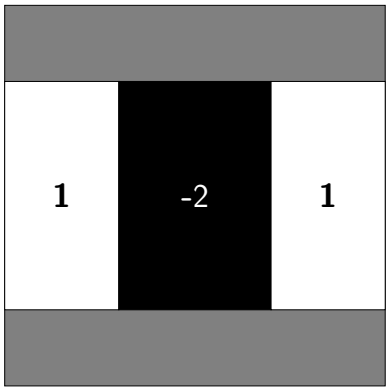
Key idea

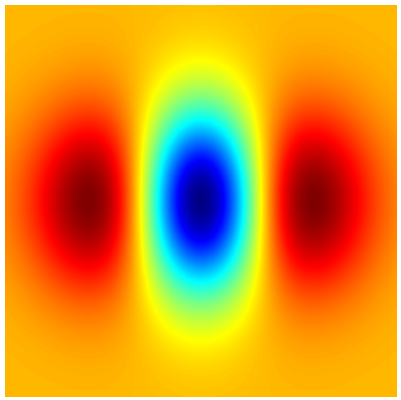
Approximation of Gaussian derivatives by using integral image, denoted by D_{xx}, D_{yy} and D_{xy}. Weight w.

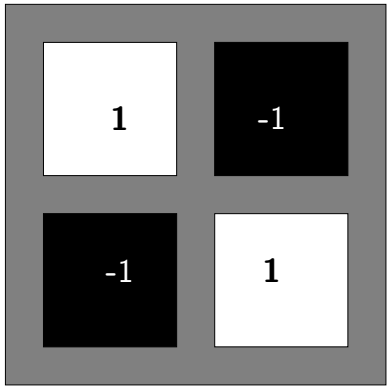
$$\det(H_{\text{approx}}) = D_{xx}D_{yy} - (wD_{xy})^2$$

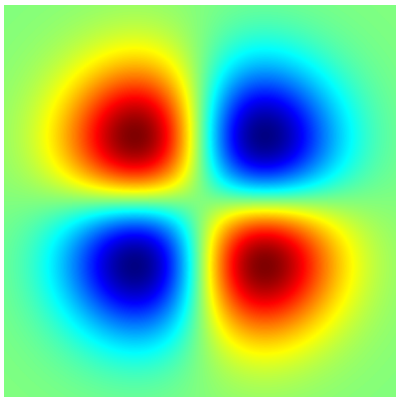
Comparison to SIFT

- much faster
- more robust
- octaves, scales per octave





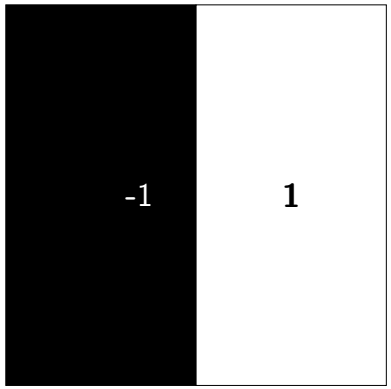


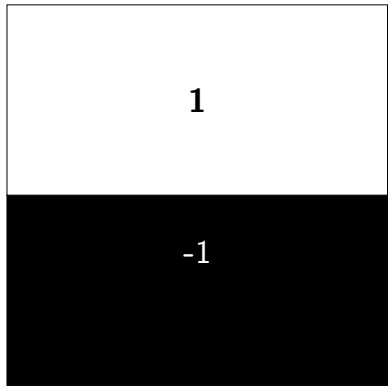


SURF: rotation invariance

Orientation estimation

- For each keypoint at scale s
- Haar response in a window of size $6s \times 6s$
- Use of integral image



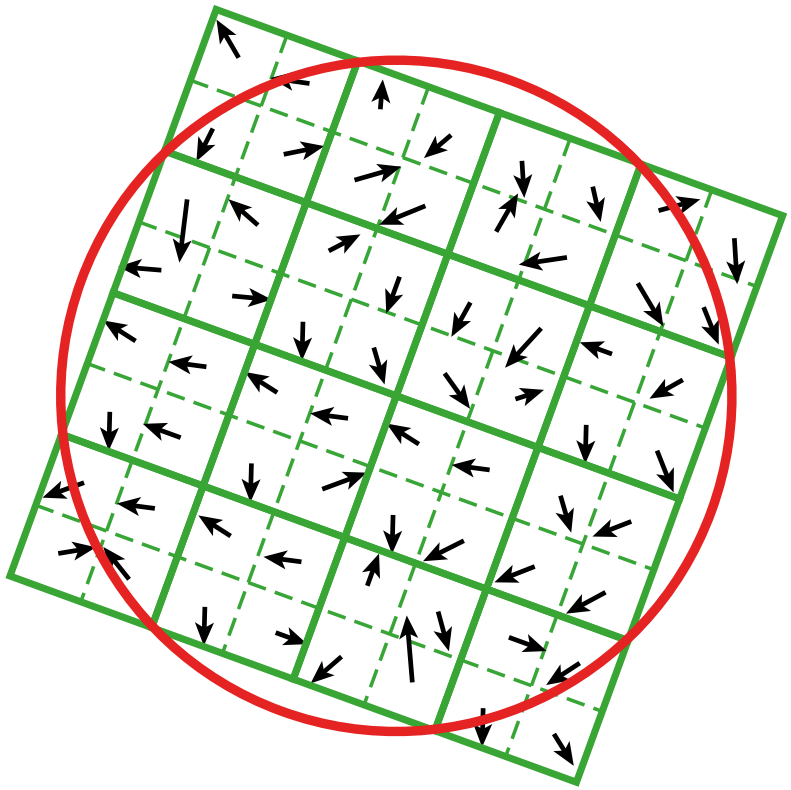


SURF: feature descriptor

Feature descriptor

- Window of size $20s \times 20s$
- Split into 4×4 areas
- Each area 5×5 squares
- Evaluate gradients in each Square
- 4 sums per area

$$\sum dx, \sum |dx|, \sum dy, \sum |dy|$$



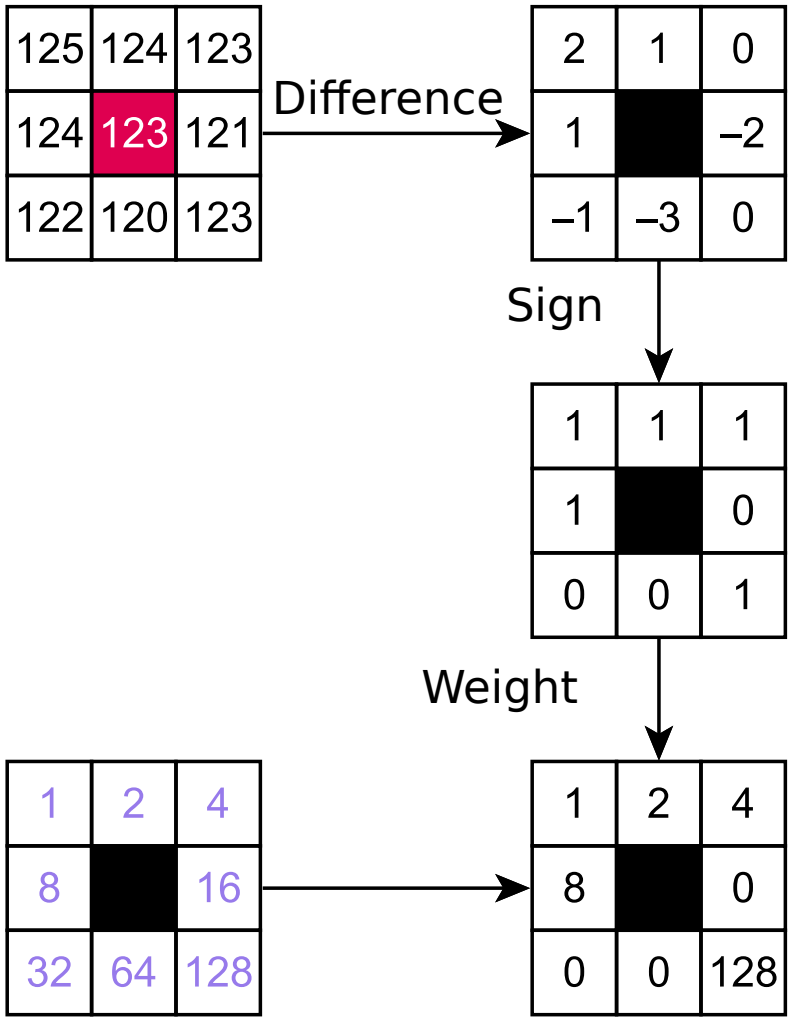
$4 \times 4 \times 4 = 64$ element descriptor

- high processing speed compared to SIFT
- Advantage to SIFT for translation, rotation, scaling, illumination changes

LBP: Local Binary Patterns

Construction

- Choose a window size

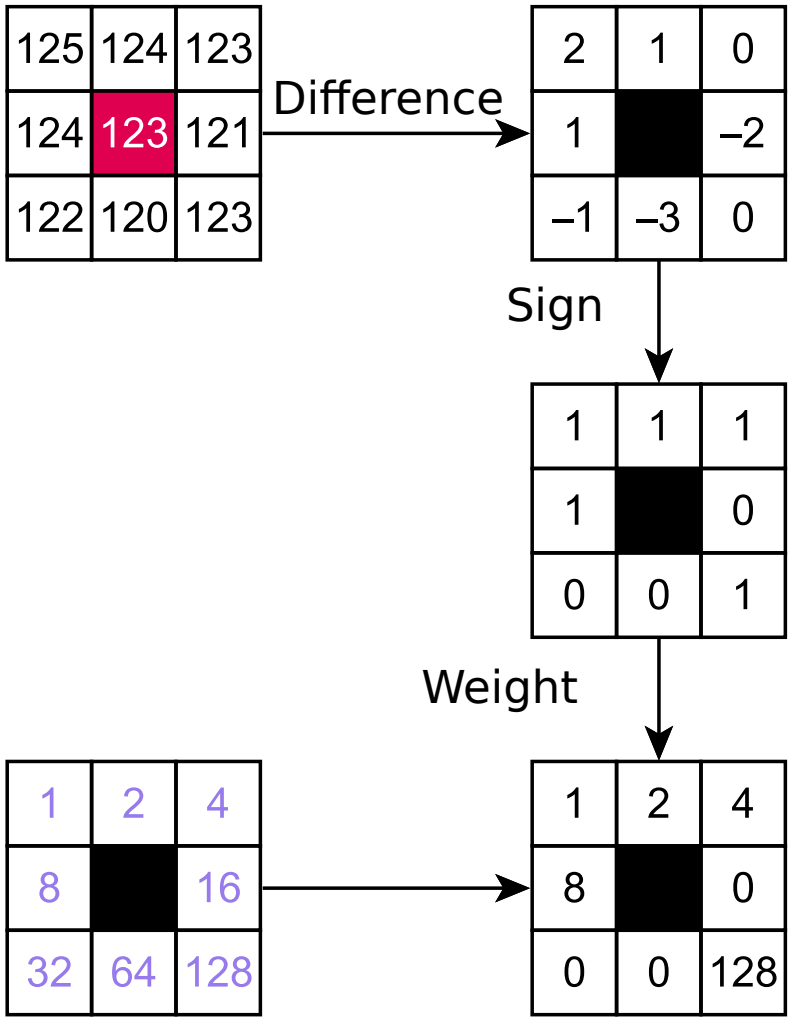


LBP = 1 + 2 + 4 + 8 + 128 = 143

LBP: Local Binary Patterns

Construction

- Choose a window size
- Each pixel in the neighborhood

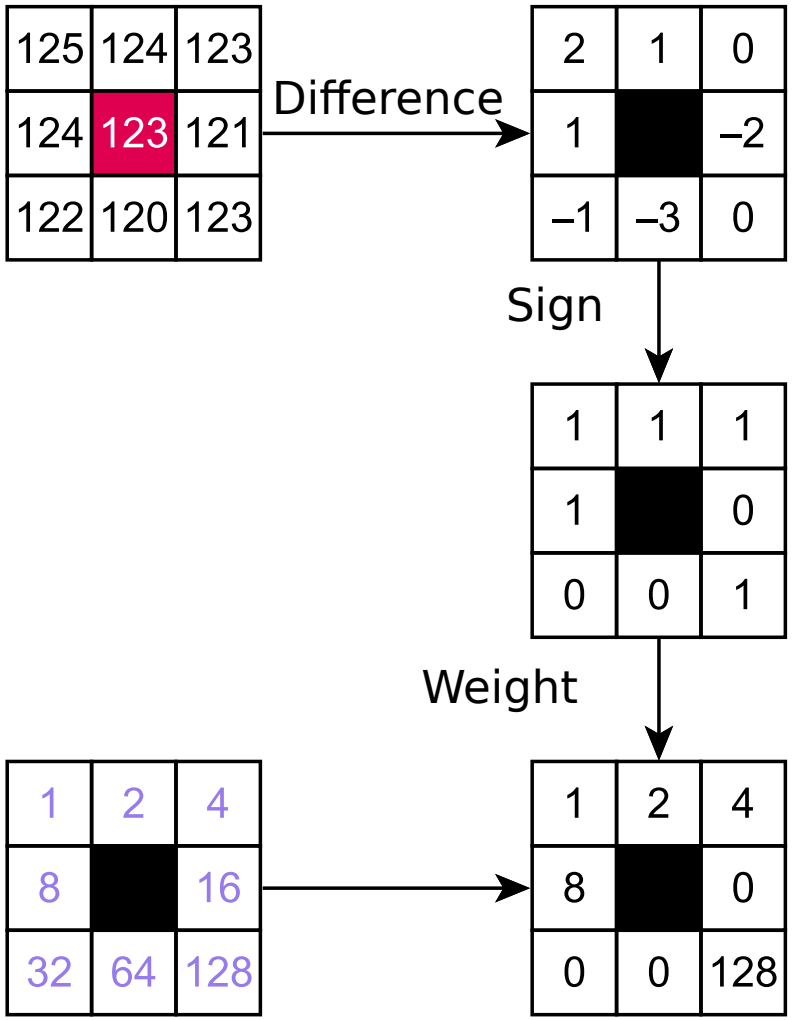


LBP = 1 + 2 + 4 + 8 + 128 = 143

LBP: Local Binary Patterns

Construction

- Choose a window size
- Each pixel in the neighborhood
- Compare to its neighbors

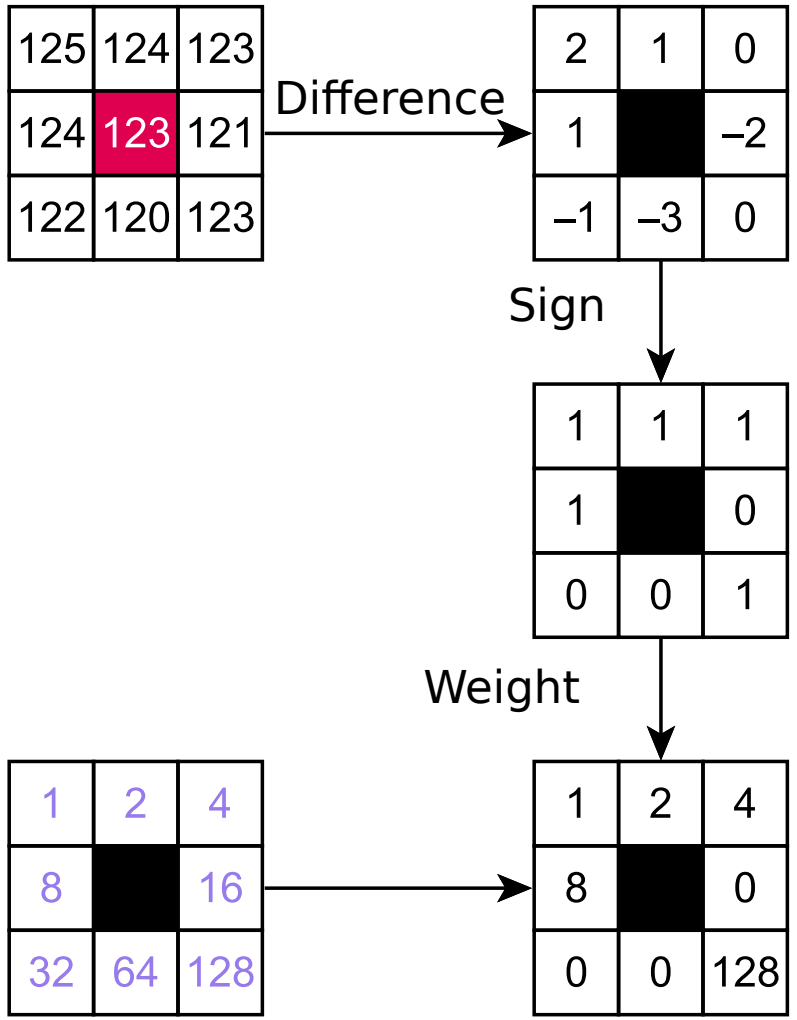


LBP = 1 + 2 + 4 + 8 + 128 = 143

LBP: Local Binary Patterns

Construction

- Choose a window size
- Each pixel in the neighborhood
- Compare to its neighbors
- Create a binary number (converted to decimal)

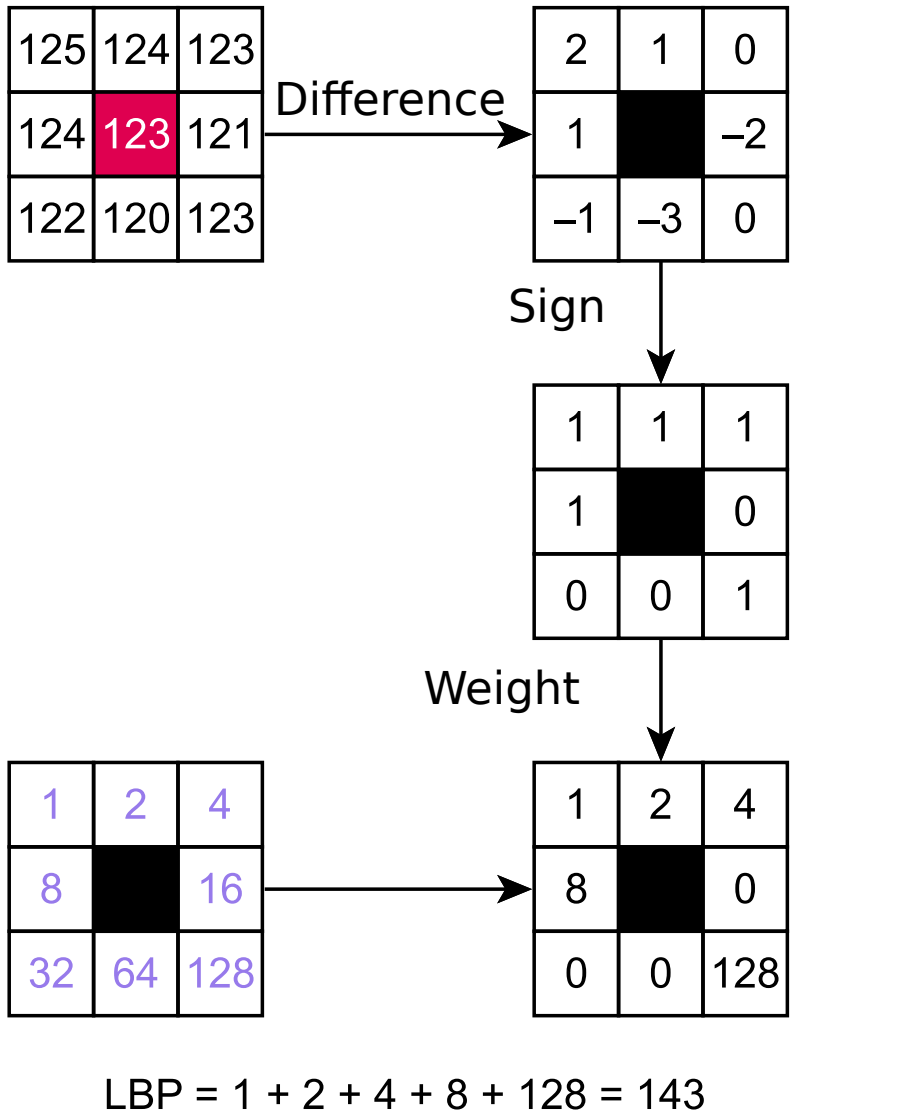


LBP = 1 + 2 + 4 + 8 + 128 = 143

LBP: Local Binary Patterns

Construction

- Choose a window size
- Each pixel in the neighborhood
- Compare to its neighbors
- Create a binary number (converted to decimal)
- Compute the histogram of all numbers in window



LBP: Local Binary Patterns

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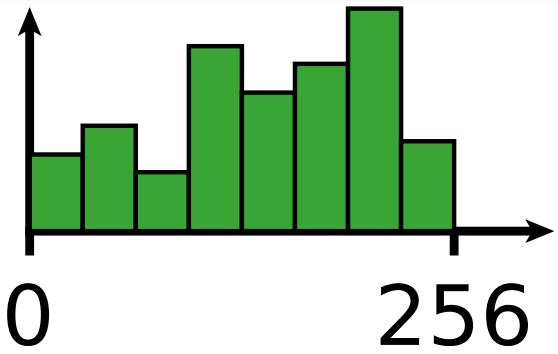
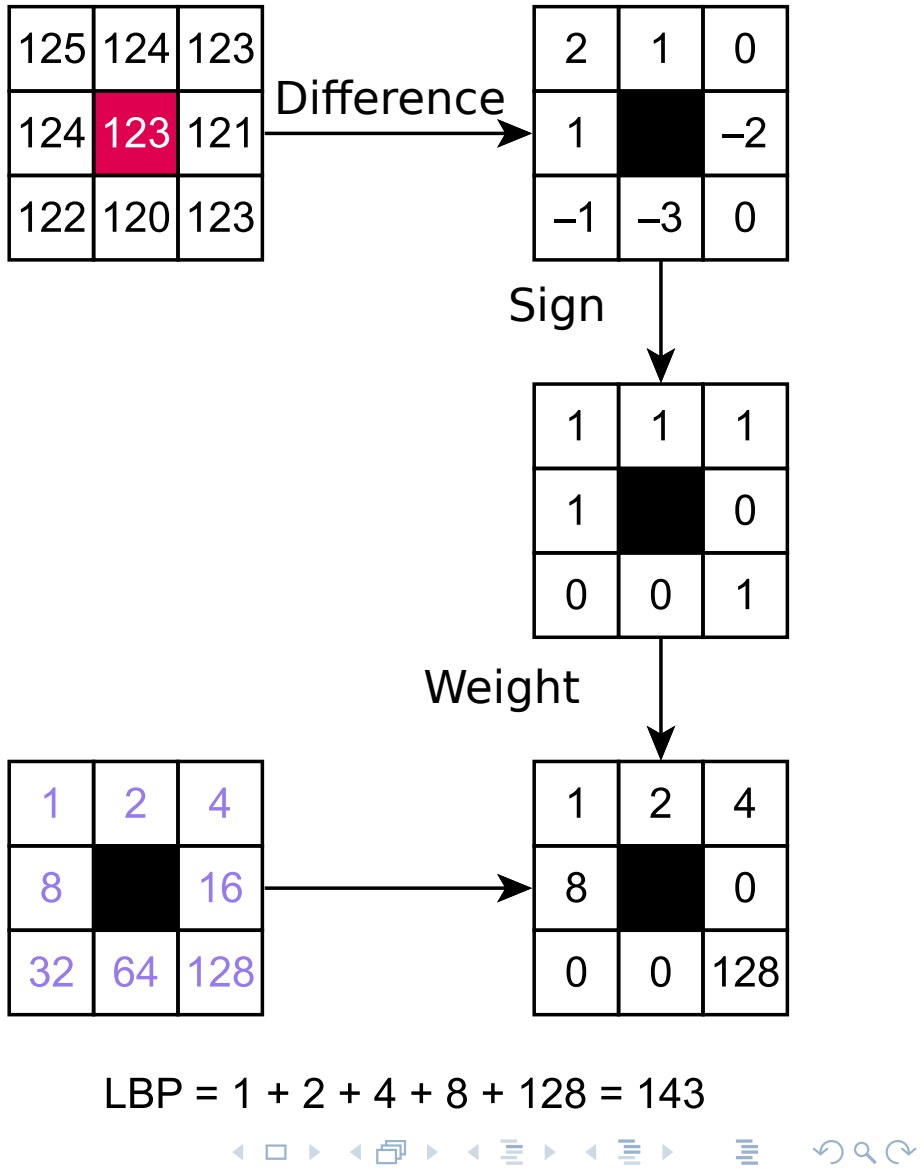


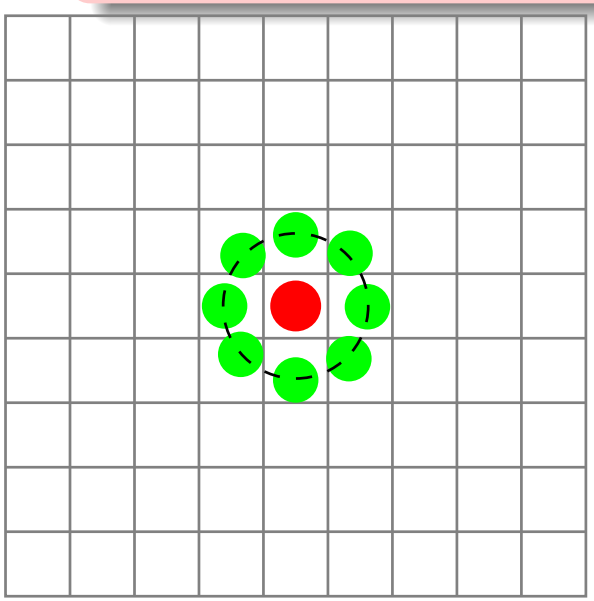


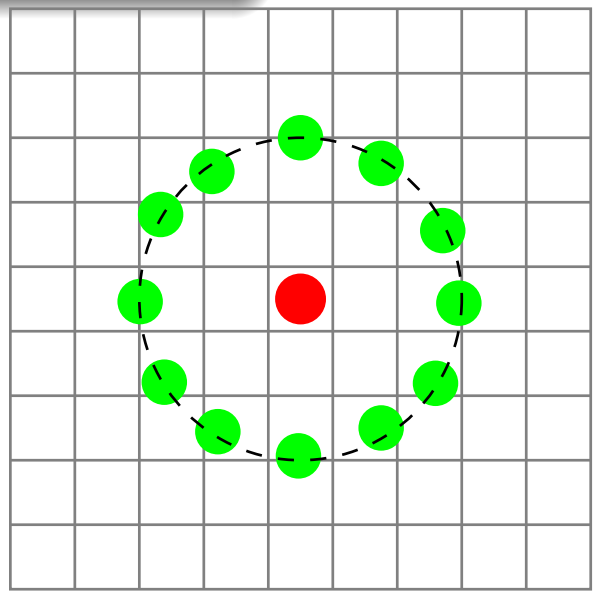
LBP

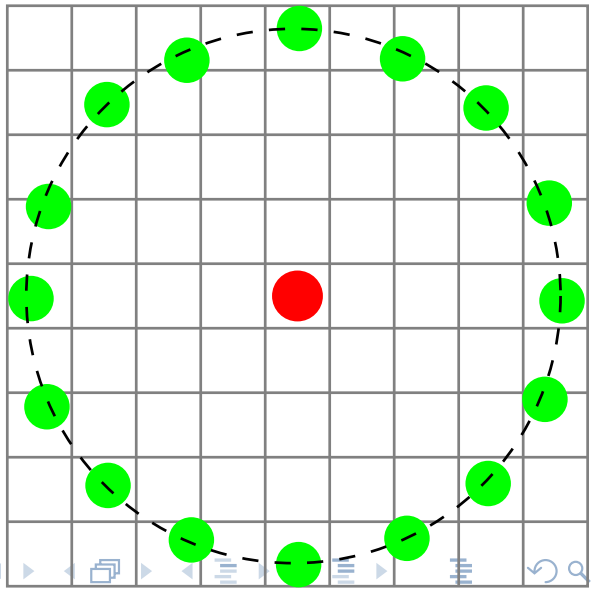
- Tolerance to illumination changes
- Computational simplicity
- Sensitive to noise
- Sensitive to scale
- Tolerant to orientation

Neighborhood

- Not classical neighborhoods
- Bilinear interpolation
- Simplicity: nearest pixel







Other binary descriptors

- BRIEF: Binary Robust Independant Elementary Features
- BRISK: Binary Robust Invariant Scalable Keypoints
- ...

Section 4

Feature matching

Feature matching

- 2 or more sets P, Q...of keypoints $p_i \in P, q_j \in Q$...
- associated descriptors: $\phi(p_i), \phi(q_j)$

Distance between features

$$d(p_i, q_j) = \|\phi(p_i) - \phi(q_j)\|$$

Nearest neighbor

of point p_0 in set Q

$$q_0 = \underset{q_j \in Q}{\operatorname{argmin}} d(p_0, q_j)$$

Solutions

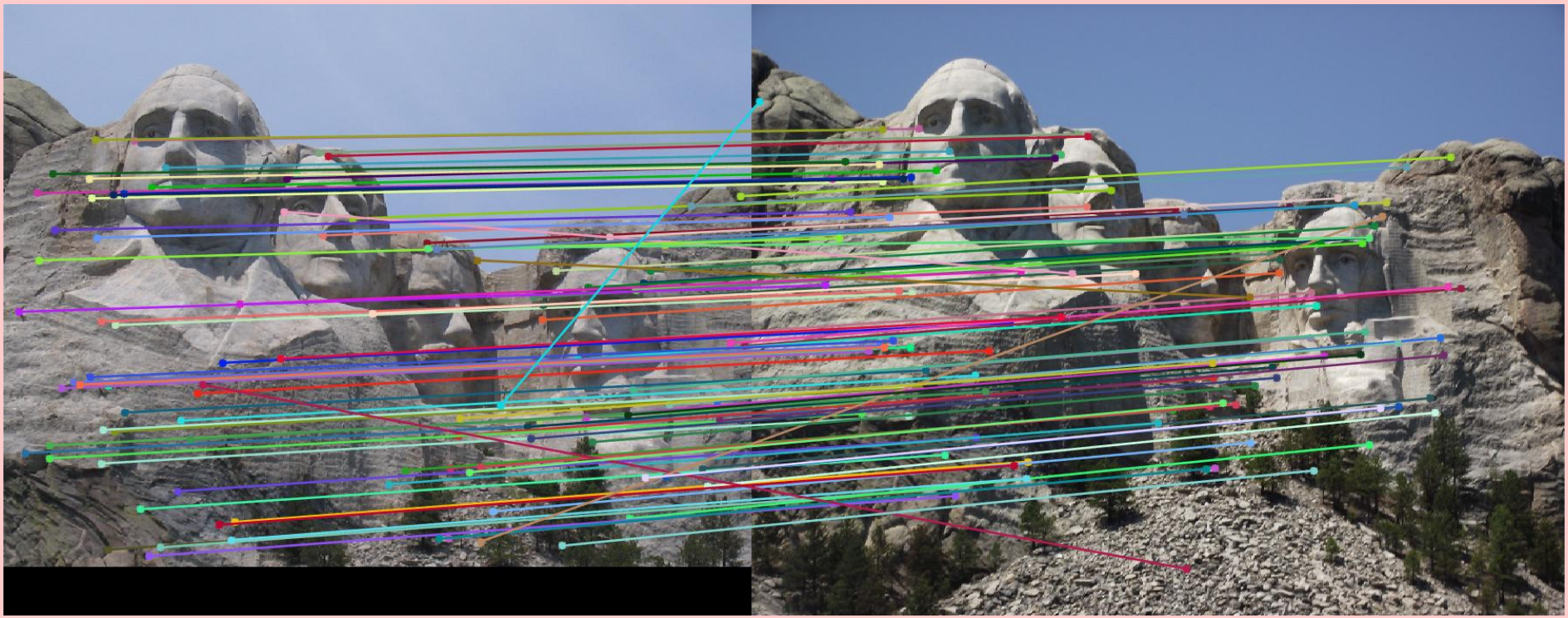
- Kd forests / Kd trees
- Nearest Neighbors, Approximate NN

Binary features

- not appropriate
- Hamming distance XOR

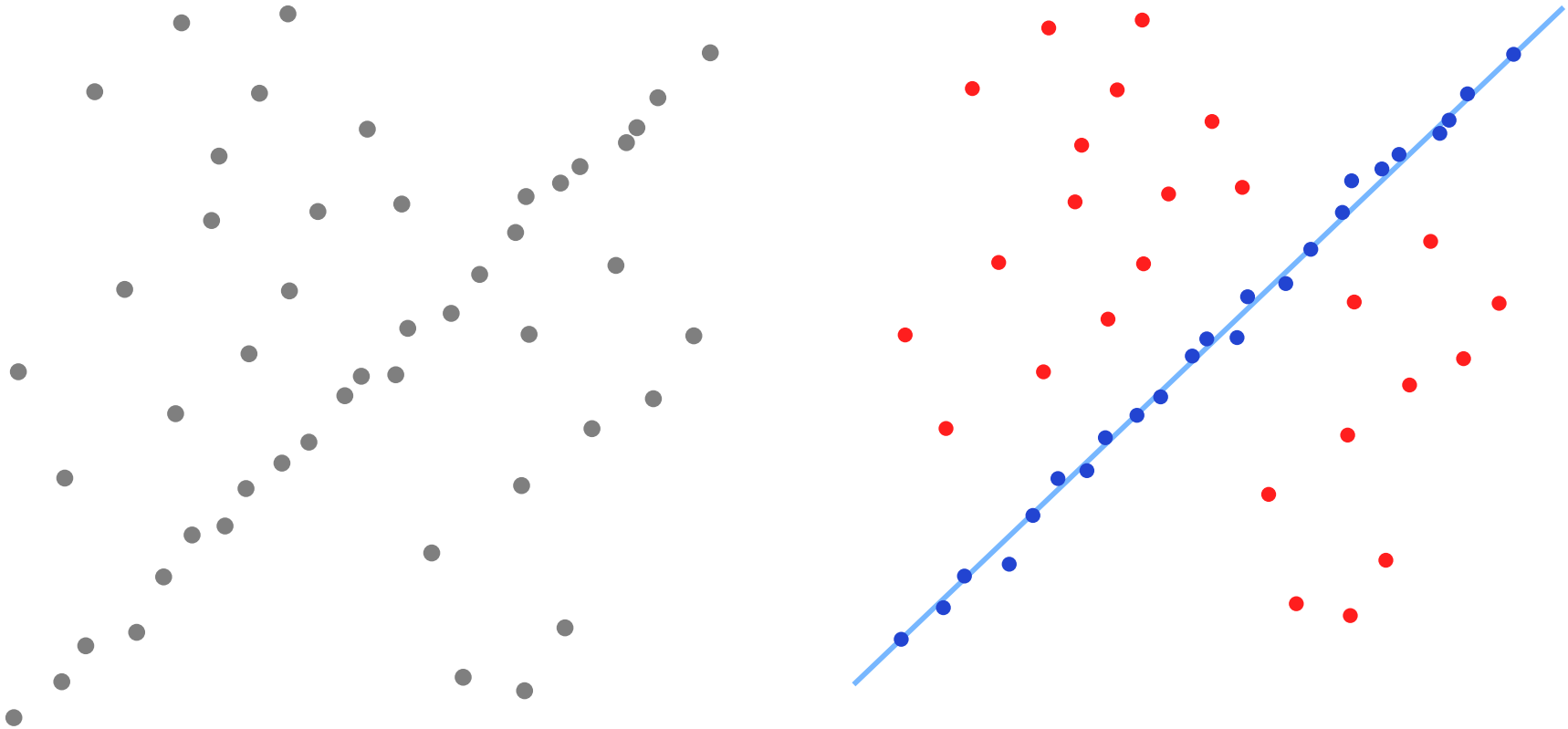
Feature matching

Problem: coherence between matchs?



Remove outliers: RANSAC

RANdom SAmple Consensus



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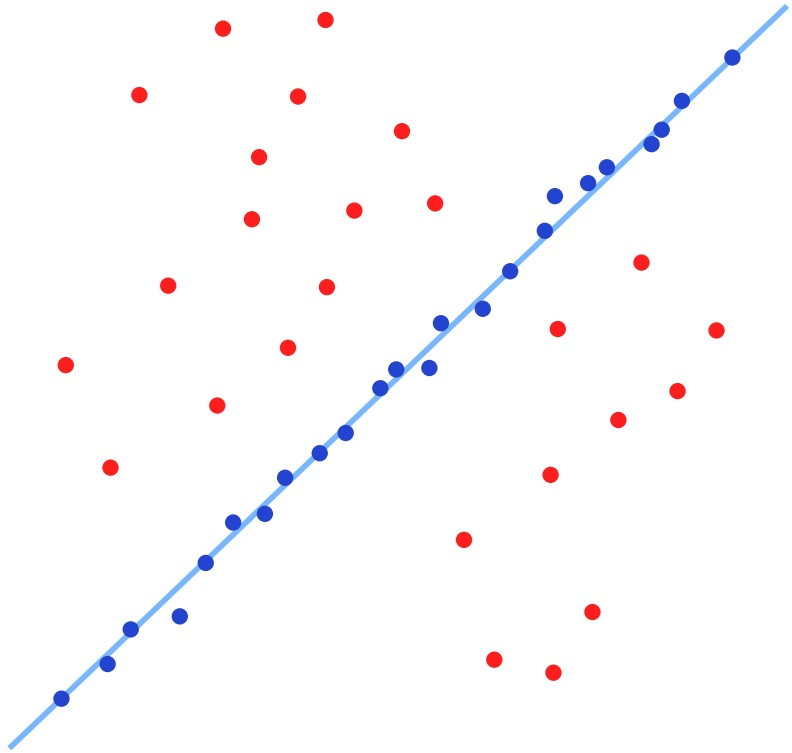
RANdom SAmple Consensus

- Least Squares method would be inefficient
- RANSAC intends to remove outliers

Principle

- random selection of subset of data
- fit hypothesis
- verify vs all data
- iterate until enough inliers



RANSAC: application to image registration

- Transform estimation via RANSAC

Image registration

1. Features detection (keypoints, Harris, FAST...)

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Elements of choice

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- Tolerance to variations (deformations, scales...)

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Elements of choice

- Tolerance to variations (deformations, scales...)
- Computation speed / real-time applications

Augmented reality


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Scale selection properties of generalized scale-space interest point detectors.
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