Python 图像处理基础

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内容

- 安装CV软件包
- Python的图像格式与存储方案
- 简单特征统计与直方图变换
- 卷积、角点
- 图像特征提取

```
import cv2 # yes, we are using opencv version 3
```

```
# code to find version of opencv
cv2.__version__
```

Conda install opencv

```
'3.4.2'
```

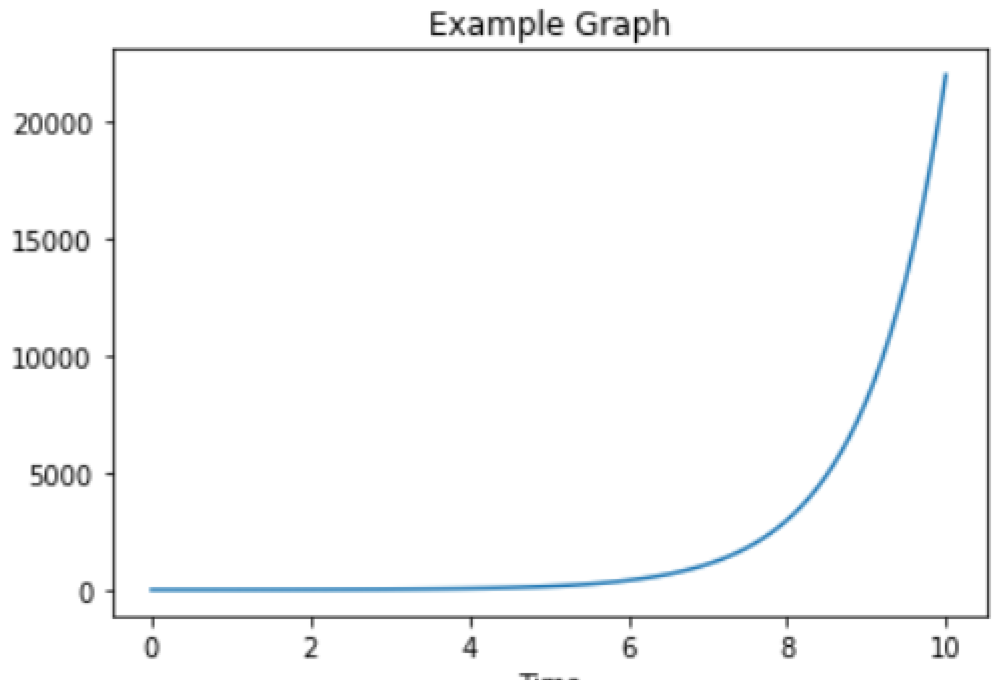
```
img_dir = 'common/'
messi_gray = cv2.imread(img_dir+'data/messi.jpg', 0)  # 第二个参数 0 grey
my_gshow(plt.gca(), messi_gray) # 图片-线... 都是 axes 的子对象
messi_gray
```

```
array([[ 43,  46,  48, ...,  55,  53,  50],
       [ 41,  46,  50, ...,  60,  58,  55],
       [ 46,  51,  56, ...,  64,  63,  60],
       ...,
       [120, 110, 107, ..., 113, 114, 124],
       [116, 119, 108, ..., 111, 122, 117],
       [107, 118, 129, ..., 104, 105, 104]], dtype=uint8)
```

Matplob get current axis

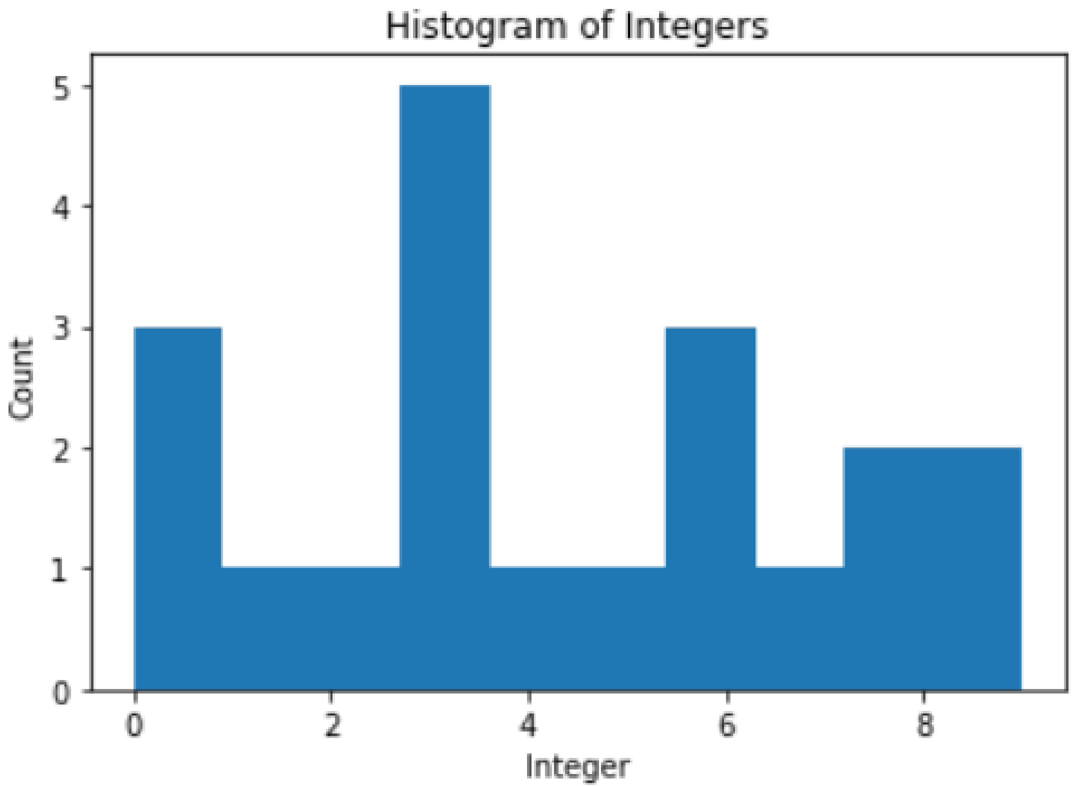
```
xs = np.linspace(0,10, 100) # 100 evenly spaced points from 0 to 10 inclusive
ys = np.exp(xs)  # y = e^x

# fig = plt.gcf() # explicitly get the default (current) figure (holder for "full" graphic) (rarely needed)
ax = plt.gca()     # explicitly get the default (current) drawing axis

ax.plot(xs, ys) # basic graph from two sequences:  x-points and y-points
ax.set_title("Example Graph")
ax.set_xlabel("Time")
# ax.axis('off');  # uncomment me to see the difference with/without spines and labels
```

```
Text(0.5,0,'Time')
```



```python
ax = plt.gca()
arr = npr.randint(0,10,20)
ax.hist(arr, bins=10)

ax.set_xlabel("Integer")
ax.set_ylabel("Count")
ax.set_title("Histogram of Integers")

import collections as co
print(co.Counter(arr)) # pure python counts of occurances
```

```
Counter({3: 5, 0: 3, 6: 3, 8: 2, 9: 2, 1: 1, 2: 1, 4: 1, 5: 1, 7: 1})
```



```
# note:  by default the range [0,1] is expanded to fill the [0,255] intensity scale
#        so:  0--->0 (black) and 1--->255 (white)

# also:  remove the x/y grid points (matplotlib calls these "spines") and the frame
ax = plt.gca()
ax.imshow(arr, cmap='gray')
ax.axis('off');
```

定义两个显示用函数

```
1  # line 5:  def my_show(**kwargs) --> takes any "extra" keyword arguments and
2  #                                     puts them in a dictionary named kwargs
3  # line 7:  ax.imshow(**kwargs)   --> takes kwargs (a dictionary) and
4  #                                     "expands" them into keyword arguments to imshow
5  def my_show(ax, img, title=None, interpolation='bicubic', **kwargs):
6      ' helper to display an image on an axes without grid/spine '
7      ax.imshow(img, interpolation = interpolation, **kwargs)
8      ax.axis('on')
9      if title:
10         ax.set_title(title)
11
12 def my_gshow(ax, img, title=None, cmap='gray', interpolation='bicubic', **kwargs):
13     ' helper to display an image, in grayscale, on an axes without grid/spine '
14     my_show(ax, img, title=title, cmap='gray', interpolation=interpolation, **kwargs)
```

采用二次插值填充

```python
fig, axes = plt.subplots(1,3,figsize=(9,3))  # 1 row, 3 columns of figures
print(fig,axes)
# axes is a numpy array with nrows, ncols ... unless one of the values is 1 ... then it is a
# 1-D thing (but see squeeze=True squeeze=False argument to subplots to keep dimensions)
arr = np.array([[0,1],
                [1,0]], dtype=np.float64)
my_show(axes[0], arr)
my_gshow(axes[1], arr)
my_gshow(axes[2], arr, interpolation=None)
```

一组axis

```
Figure(648x216) [<matplotlib.axes._subplots.AxesSubplot object at 0x000001E74CE145F8>
 <matplotlib.axes._subplots.AxesSubplot object at 0x000001E74CE522B0>
 <matplotlib.axes._subplots.AxesSubplot object at 0x000001E74CE79940>]
```

- 加载显示图像

```
img_dir = 'common/'
messi_gray = cv2.imread(img_dir+'data/messi.jpg', 0)  # 第二个参数 0 grey
my_gshow(plt.gca(), messi_gray) # 参数1:  axis 参数2: array
messi_gray
```

```
ray([[ 43,  46,  48, ...,  55,  53,  50],
     [ 41,  46,  50, ...,  60,  58,  55],
     [ 46,  51,  56, ...,  64,  63,  60],
     ...,
     [120, 110, 107, ..., 113, 114, 124],
     [116, 119, 108, ..., 111, 122, 117],
     [107, 118, 129, ..., 104, 105, 104]], dtype=uint8)
```

```
messi_color = cv2.imread(img_dir+'data/messi.jpg') # default flag is 1 "color"
print(type(messi_color), messi_color.shape, messi_color.dtype)
my_show(plt.gca(), messi_color)
# 实际编码 GBR - 习惯 RGB
```

messi_rgb = cv2.cvtColor(messi_color, cv2.COLOR_BGR2RGB)

```
<class 'numpy.ndarray'> (342, 548, 3) uint8
```

```
# opencv is GBR; matplotlib is RGB.
my_show(plt.gca(), messi_color[:,:,::-1]) # walk last axis in opposite order (we'll never do this again!)
```

```python
# we can also use scipy to read in images:
from scipy import ndimage
img = ndimage.imread(img_dir+'data/messi.jpg') # default is 1 RGB
#img1 = plt.imread(img_dir+'data/messi.jpg')
my_show(plt.gca(), img1)
img1.shape
```

```
C:\Users\hjf_p\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: DeprecationWarning: `imread` is deprecated!
`imread` is deprecated in SciPy 1.0.0.
Use ``matplotlib.pyplot.imread`` instead.
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
(342, 548, 3)
```

```
# these come up frequently.  we'll always want rgb (instead of bgr)
# and we often need both rgb and grayscale (grayscale starts many processing steps)
def my_read(filename):
    ' read from an image file to an rgb '
    img = cv2.imread(filename)
    return cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

def my_read_cg(filename):
    ' read from an image file to an rgb and a grayscale image array '
    rgb = my_read(filename)
    gray = cv2.cvtColor(rgb, cv2.COLOR_RGB2GRAY)
    return rgb, gray

# now we can do this:
messi_rgb = my_read(img_dir+'data/messi.jpg')

# or if we need both
messi_rgb, messi_gray = my_read_cg(img_dir+'data/messi.jpg')
```

返回一个tuple

```
messi_rgb = my_read(img_dir+'data/messi.jpg') # 读入时直接转换RGB
```

Since messi_rgb is "just" a NumPy array, we can do NumPy array things:

```
print(messi_rgb[100,100],       # access a pixel
      messi_rgb[300,:,:].shape) # sub-select a row; it's an array also.   tak
```

```
[200 166 156] (548, 3)
```

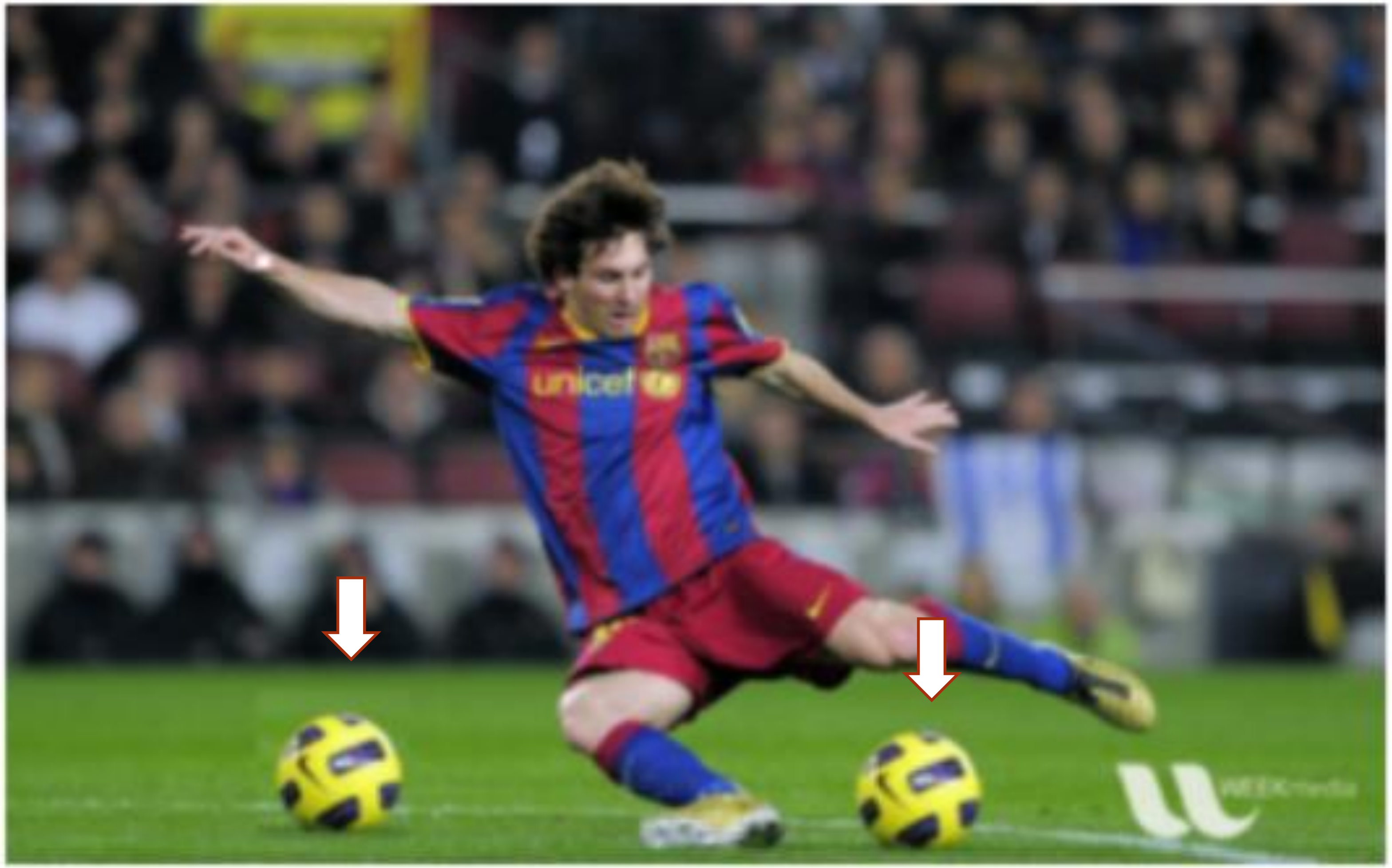
一个三通道像素，每行的数据为548*3的矩阵

```
# pixels are people ... err ... arrays too
pixel = messi_rgb[100,100]
print(type(pixel),
      pixel.shape,   # 1-D, scalar, array
      pixel)
```

```
<class 'numpy.ndarray'> (3,) [200 166 156]
```

```python
# massi's right wrist has a white spot!
messi_rgb[100:105,100:105]=[255,255,255] # white (note, our target pixel also had 3 spots
my_show(plt.gca(), messi_rgb)
```

```python
ball_soi = messi_rgb[280:340, 330:390] # "soi" = square of interest :)
messi_rgb[273:333, 100:160] = ball_soi  # copy to new area
my_show(plt.gca(), messi_rgb)
```

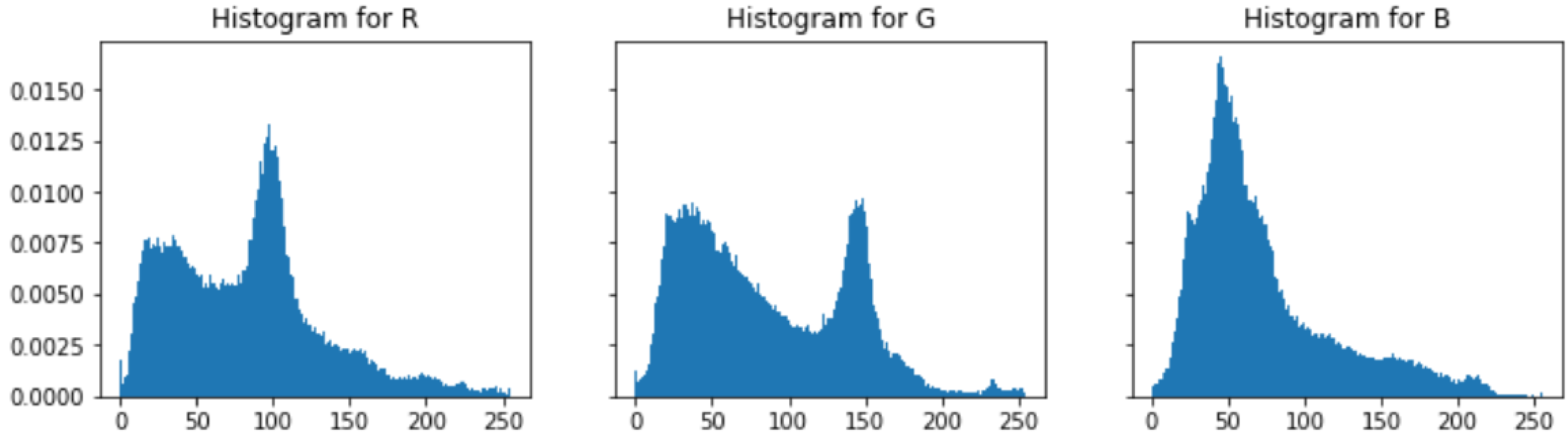


```python
# often we want to access color channels separately
# split to separate arrays per color (costly, prefer to access by indexing)
chans = r,g,b = cv2.split(messi_rgb)
restored = cv2.merge((r,g,b))
```

```python
fig, axes = plt.subplots(1,4,figsize=(12,3))
axes = axes.flat #  a numpy array of axes

# handle first as special case
first_axis = next(axes)
my_show(first_axis, messi_rgb)
first_axis.set_title("original")

# display per channel images
for ax, ch, name in zip(axes, chans, ["R", "G", "B"]):
    my_gshow(ax, g)
    ax.set_title("{} channel".format(name))
```

```python
ml   = my_read(img_dir+'/data/ml.png')
frog = my_read(img_dir+'/data/frog.jpg')
my_show(plt.gca(), ml)
min_r, min_c = (min(ml.shape[0], frog.shape[0]),
                min(ml.shape[1], frog.shape[1])) # 取得可叠加区域

# blending of two images:
# by:  img1 * wgt1 + img2 * wgt2 + wgt3
#      addWeights(img1, wgt1, img2, wgt2, wgt3)
dst = cv2.addWeighted(  ml[:min_r, :min_c], 0.7,
                      frog[:min_r, :min_c], 0.3, 0) #加权混合
my_show(plt.gca(), dst)
```

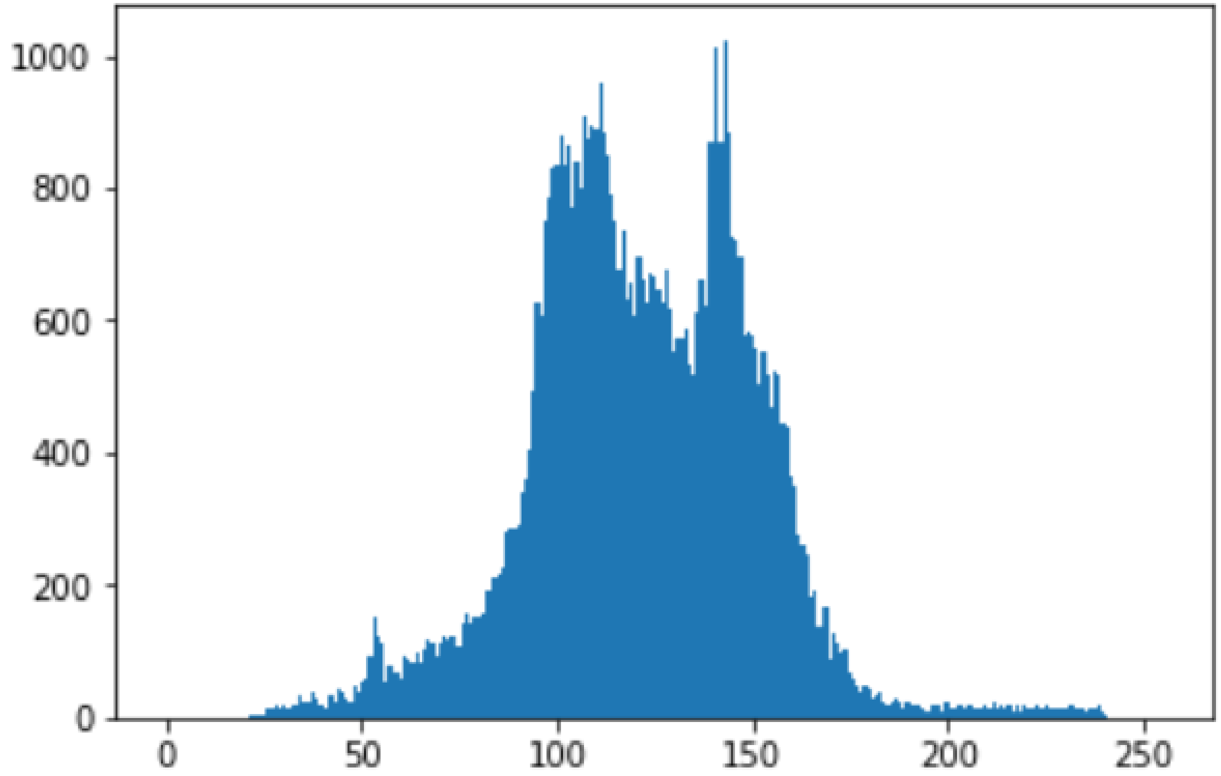
```python
1  # we can often just use indexing directly (see line 9)
2  # also show off matplotlib histograms
3
4  color_to_index = {"R":0, "G":1, "B":2}  # map strings to appropriate index in
5
6  fig, axes = plt.subplots(1,3,figsize=(12,3), sharey=True)
7  for ax, color in zip(axes, color_to_index):
8      c = color_to_index[color]
9      this_channel = messi_rgb[:,:,c].ravel() # 1D flat array view without copying
10
11     ax.hist(this_channel, 256, normed=True)
12     ax.set_title("Histogram for {}".format(color))
```



Histograms

```
apple = my_read_g(img_dir+'data/apple.png')
hist = cv2.calcHist([apple], [0], None, [256], [0,256]) # src imgs, color channels, mask
                                                        # num bins, range
plt.hist(range(256), weights=hist, bins=256)
print(hist.shape)
```

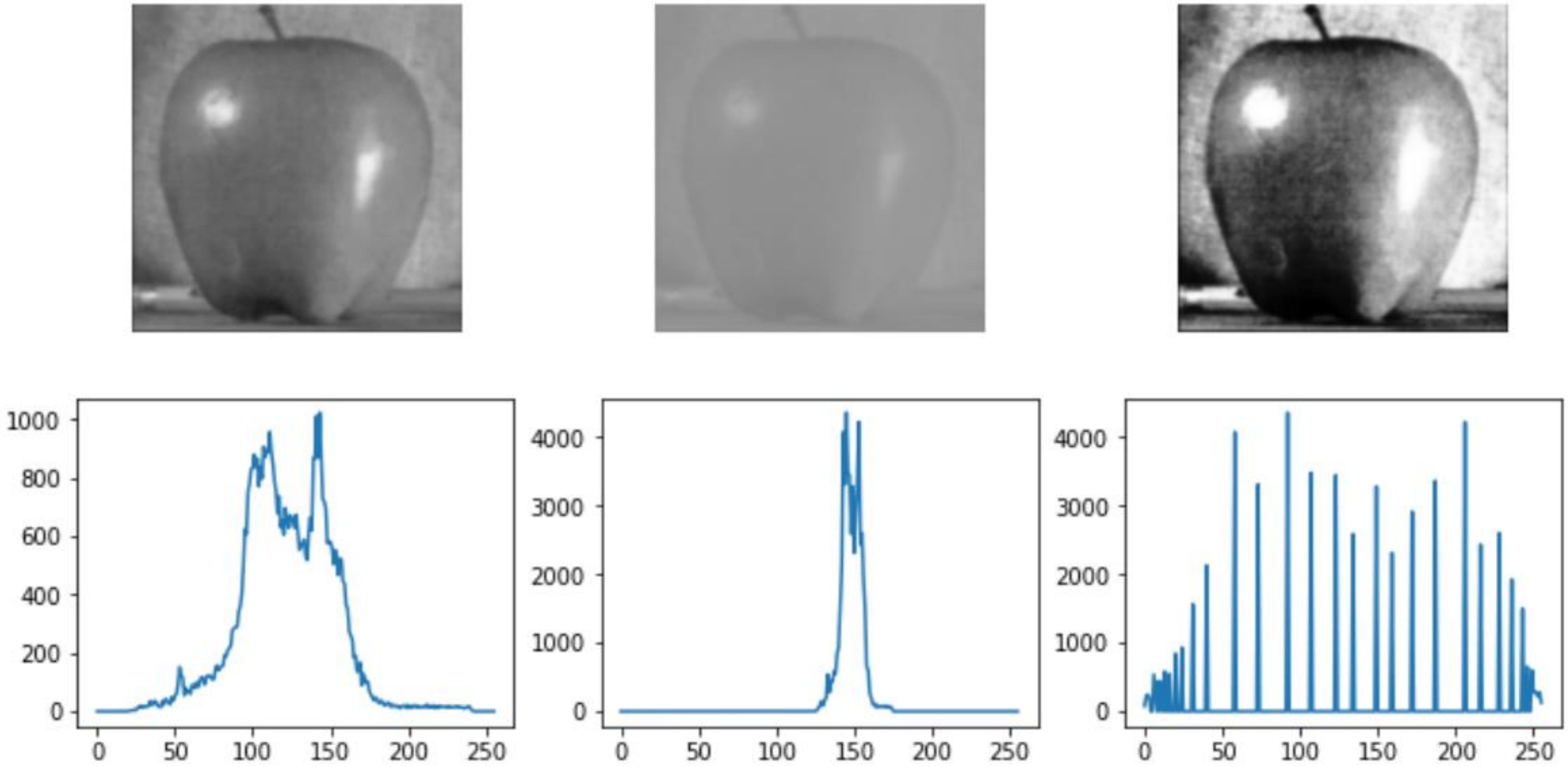
```
(256, 1)
```



Histogram Equalization

```
apple = my_read_g(img_dir+'data/apple.png')
# reduce contrast (squash intensities)
# new min:  100, new max: 175
new = np.interp(apple, [apple.min(), apple.max()], [125, 175]).astype(np.uint8)
# equalize using CDF technique
equalized = cv2.equalizeHist(new)
fig, axes = plt.subplots(2,3,figsize=(12,6))
for idx, an_apple in enumerate([apple, new, equalized]):
    # vmin/vmax set enforced min/max gray scale values ... without them
    # 125 -> 0 ... 175 --> 255 and linearly interpolated
    print("min: {} max: {}".format(an_apple.min(), an_apple.max()))
    my_gshow(axes[0, idx], an_apple, vmin=0, vmax=255)
    hist = cv2.calcHist([an_apple], [0], None, [256], [0,256])
    axes[1,idx].plot(hist)
```

```
min: 16 max: 241
min: 125 max: 175
min: 0 max: 255
```



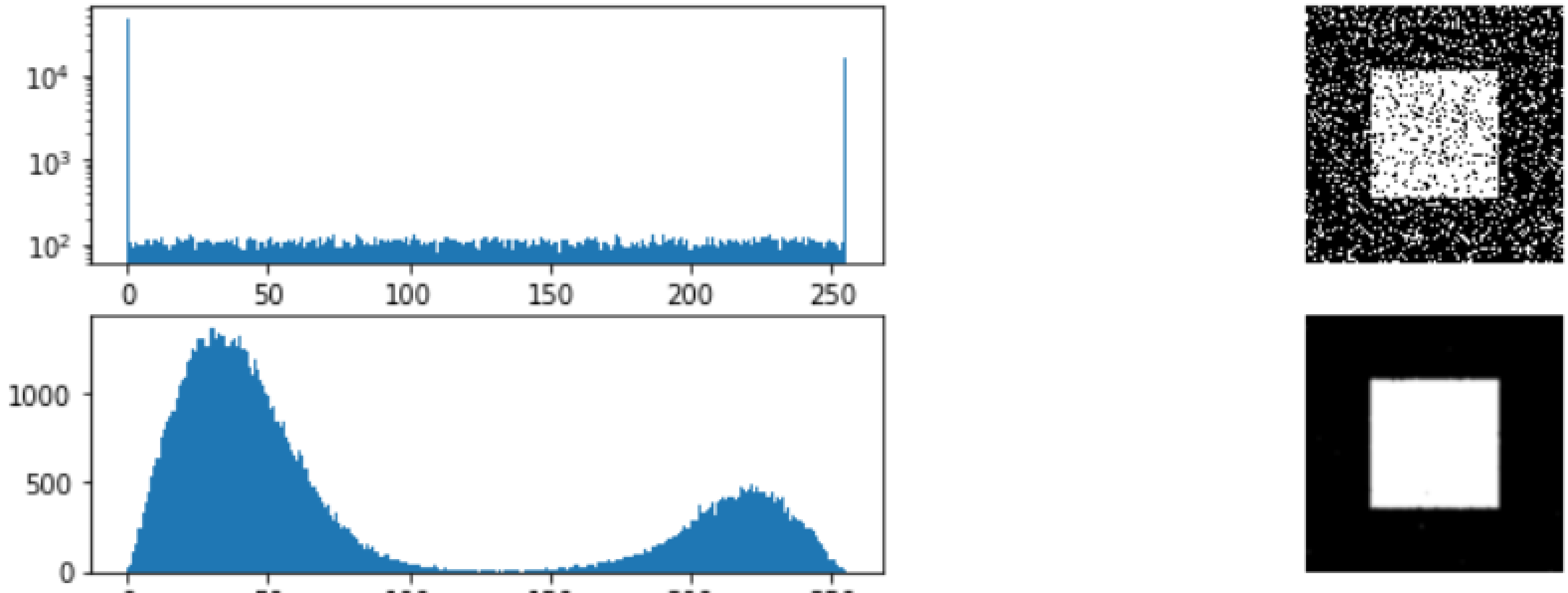
1000
800
600
400
200
0
0 50 100 150 200 250
4000
3000
2000
1000
0
0 50 100 150 200 250
4000
3000
2000
1000
0
0 50 100 150 200 250

OTSU降噪

[46]:

```python
fig,axes = plt.subplots(2,2,figsize=(12,4))
axes = axes.flat

# Otsu's thresholding
next(axes).hist(blurred.flatten(), 256, log=True)
# this seems weird:  shouldn't it be black and white?!?
thresh, th_otsu = cv2.threshold(blurred, 0, 255, cv2.THRESH_BINARY+cv2.THRESH_OTSU)
print("Optimal Thresh is", thresh)
my_show(next(axes), th_otsu, cmap='gray', interpolation=None) # force us to see what's there!

reblurred = cv2.GaussianBlur(blurred, (5,5), 0) # neighborhood, variance?
next(axes).hist(reblurred.flatten(), 256);
thresh, th_otsu = cv2.threshold(reblurred, 0, 255, cv2.THRESH_BINARY+cv2.THRESH_OTSU)
print("Optimal Thresh is", thresh)
my_show(next(axes), th_otsu, cmap='gray')# also: interpolation=None)
```

```
Optimal Thresh is 117.0
Optimal Thresh is 126.0
```



Filters and Convolutions

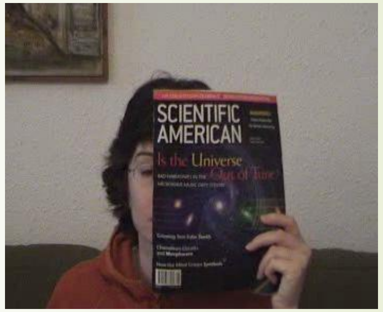
```
# simple averaging filter without scaling parameter
mean_filter = np.ones((3,3))

# creating a guassian filter
gk = cv2.getGaussianKernel(5,10)
gaussian = gk*gk.T

# different edge detecting filters
# laplacian
laplacian=np.array([[0, 1, 0],
                    [1,-4, 1],
                    [0, 1, 0]])

filters = [mean_filter, gaussian, laplacian, sobel_x, sobel_y, scharr]
filter_names = ['mean filter', 'gaussian', 'laplacian',
                'sobel x', 'sobel y', 'scharr x']

fig, axes = plt.subplots(2,3,figsize=(8,5))
for name, filt, ax in zip(filter_names, filters, axes.flat):
    # interesting variations:
    # cmap='gray', 'jet', default; interpolation = None
    my_show(ax, mag_fft(filt), cmap='jet')
    ax.set_title(name)
```

Local Invariant Features: Detection & Description

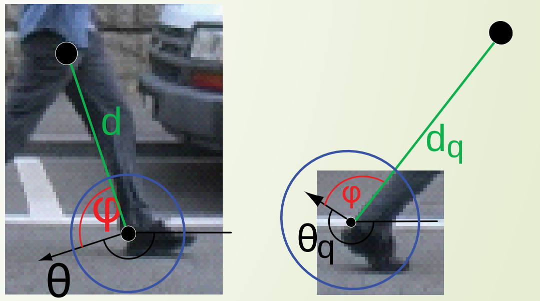
Slides credit: K. Grauman, B. Leibe

Motivation

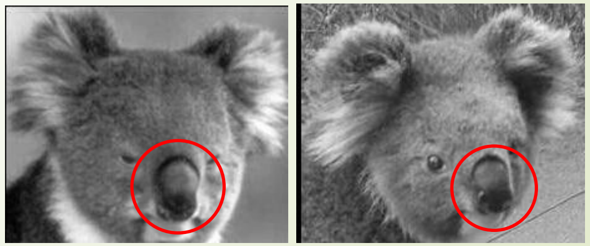
- Global representations have major limitations
- Instead, describe and match only local regions
- Increased robustness to
  - Occlusions



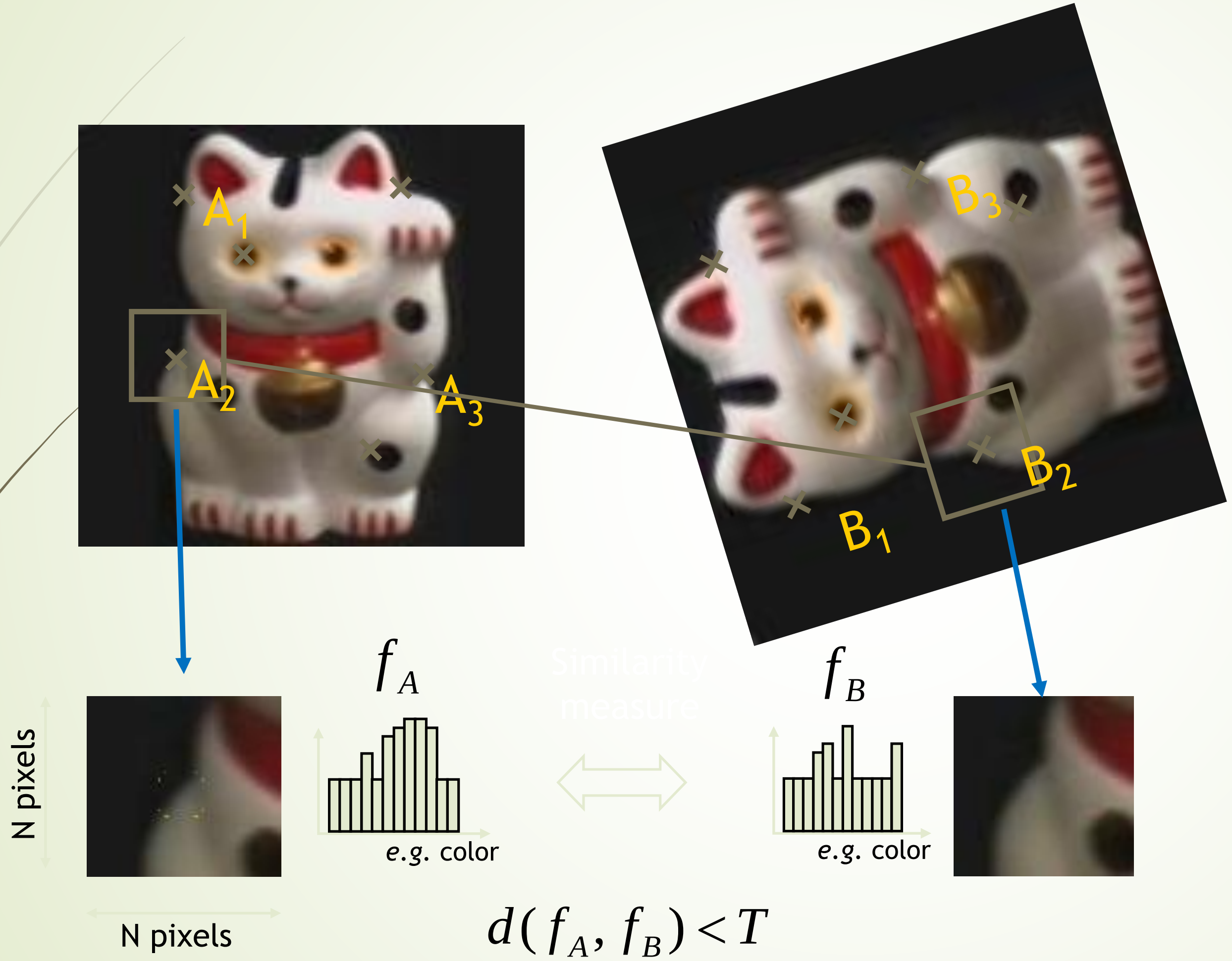
  - Articulation



  - Intra-category variations



Approach



1. Find a set of distinctive key-points
2. Define a region around each keypoint
3. Extract and normalize the region content
4. Compute a local descriptor from the normalized region
5. Match local descriptors

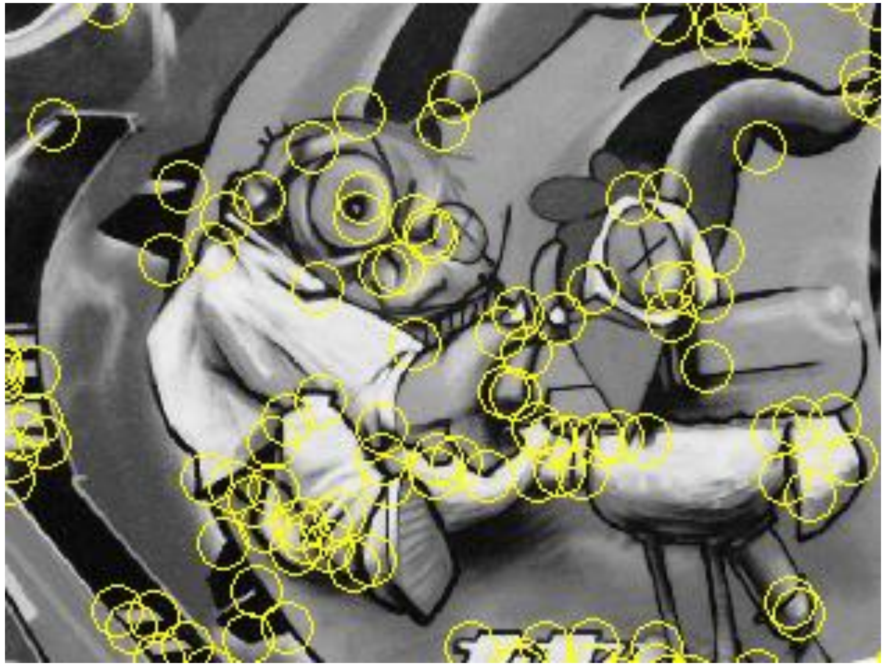
Requirements

- Region extraction needs to be repeatable and precise
  - Translation, rotation, scale changes
  - (Limited out-of-plane (≈affine) transformations)
  - Lighting variations
- We need a sufficient number of regions to cover the object
- The regions should contain “interesting” structure

Many Existing Detectors Available

- Hessian & Harris [Beaudet '78], [Harris '88]
- Laplacian, DoG [Lindeberg '98], [Lowe 1999]
- Harris-/Hessian-Laplace [Mikolajczyk & Schmid '01]
- Harris-/Hessian-Affine [Mikolajczyk & Schmid '04]
- EBR and IBR [Tuytelaars & Van Gool '04]
- MSER [Matas '02]
- Salient Regions [Kadir & Brady '01]
- Others…

Keypoint Localization



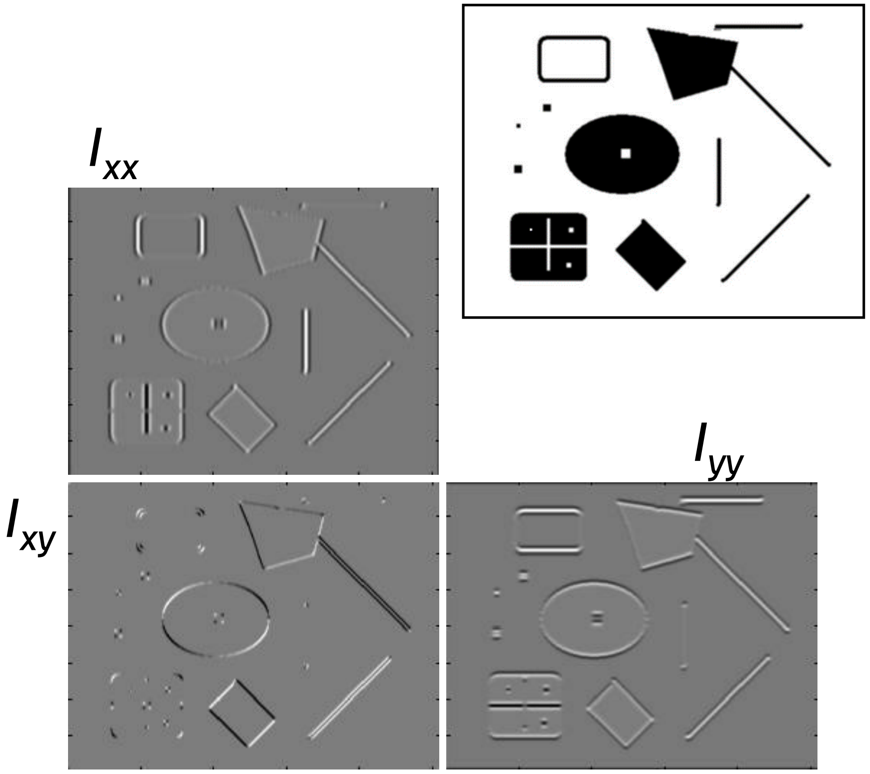
- **Goals:**
  - **Repeatable detection**
  - **Precise localization**
  - **Interesting content**

$\Rightarrow$ ***Look for two-dimensional signal changes***

Hessian Detector [Beaudet78]

- **Hessian determinant**

$$Hessian(I) = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix}$$



Intuition: **Search for strong derivatives in two orthogonal directions**

Hessian matrix

In mathematics, the **Hessian matrix** (or simply the **Hessian**) is the square matrix of second-order partial derivatives of a function; that is, it describes the local curvature of a function of many variables. The Hessian matrix was developed in the 19th century by the German mathematician Ludwig Otto Hesse and later named after him. Hesse himself had used the term "functional determinants".

Given the real-valued function

$$f(x_1, x_2, \dots, x_n),$$

if all second partial derivatives of f exist, then the Hessian matrix of f is the matrix

$$H(f)_{ij}(x) = D_i D_j f(x)$$

where $x = (x_1, x_2, \dots, x_n)$ and D_i is the differentiation operator with respect to the ith argument and the Hessian becomes

$$H(f) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1\,\partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1\,\partial x_n} \\ \frac{\partial^2 f}{\partial x_2\,\partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2\,\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n\,\partial x_1} & \frac{\partial^2 f}{\partial x_n\,\partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}.$$

Some mathematicians[1] define the Hessian as the determinant of the above matrix.

Hessian matrix

二元函数极值存在的充分条件

观察二元函数极值存在的充分条件.

设 z=f(x,y)在(x0,y0)的一个邻域内所有二阶偏导数连续，　且,

记 .

那么，海赛矩阵.

（1）若 A>0，detH=AC-B2>0，则 H 正定，从而(x0,y0)是 f(x,y)的极小点.

（2）若 A<0，detH=AC-B2>0，则 H 负定，从而(x0,y0)是 f(x,y)的极大点.

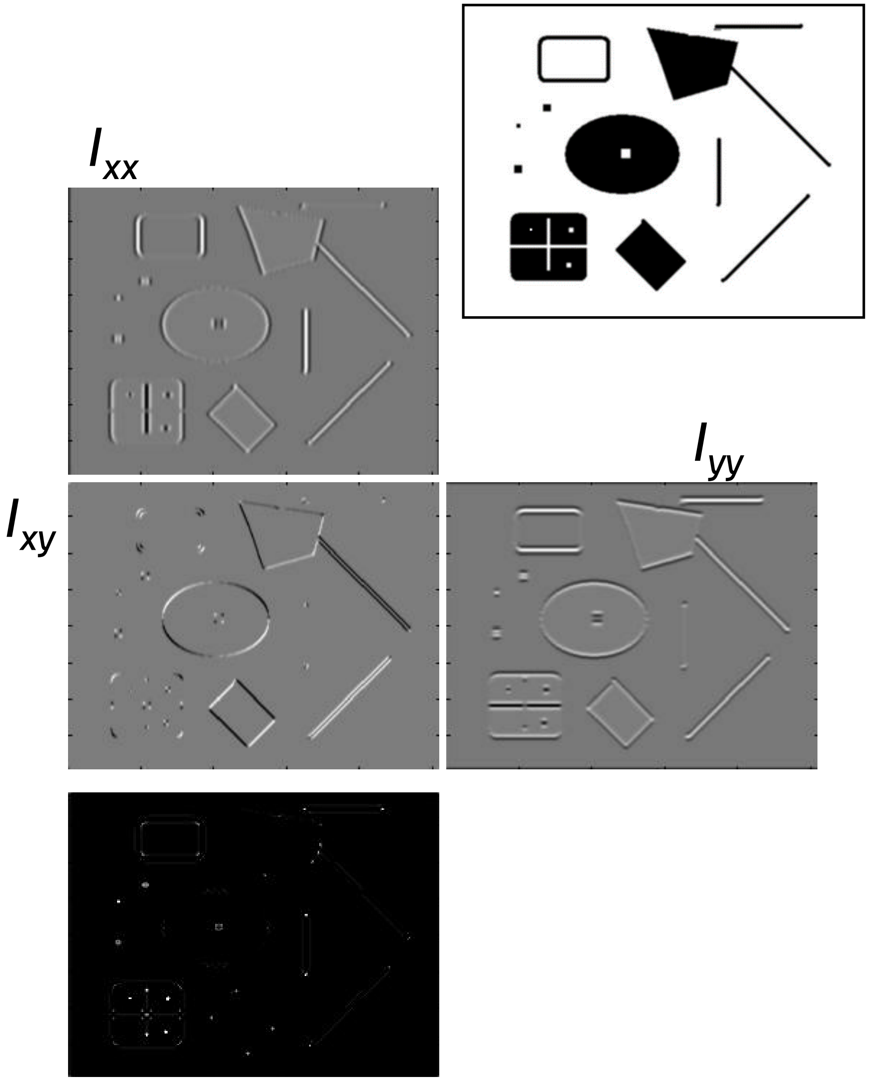
（3）若 detH=AC-B2<0，则 H 的特征根有正有负，从而(x0,y0)不是 f(x,y)的极值点.

（4）若 detH=AC-B2=0，则不能判定(x0,y0)是否为 f(x,y)的极值点.

Hessian Detector [Beaudet78]

- **Hessian determinant**

$$Hessian(I) = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix}$$

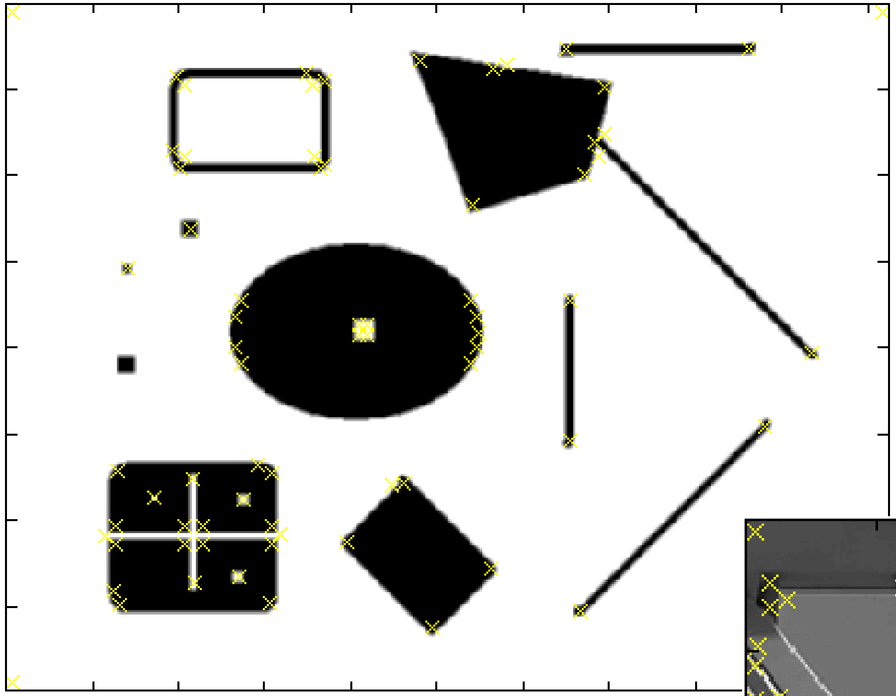


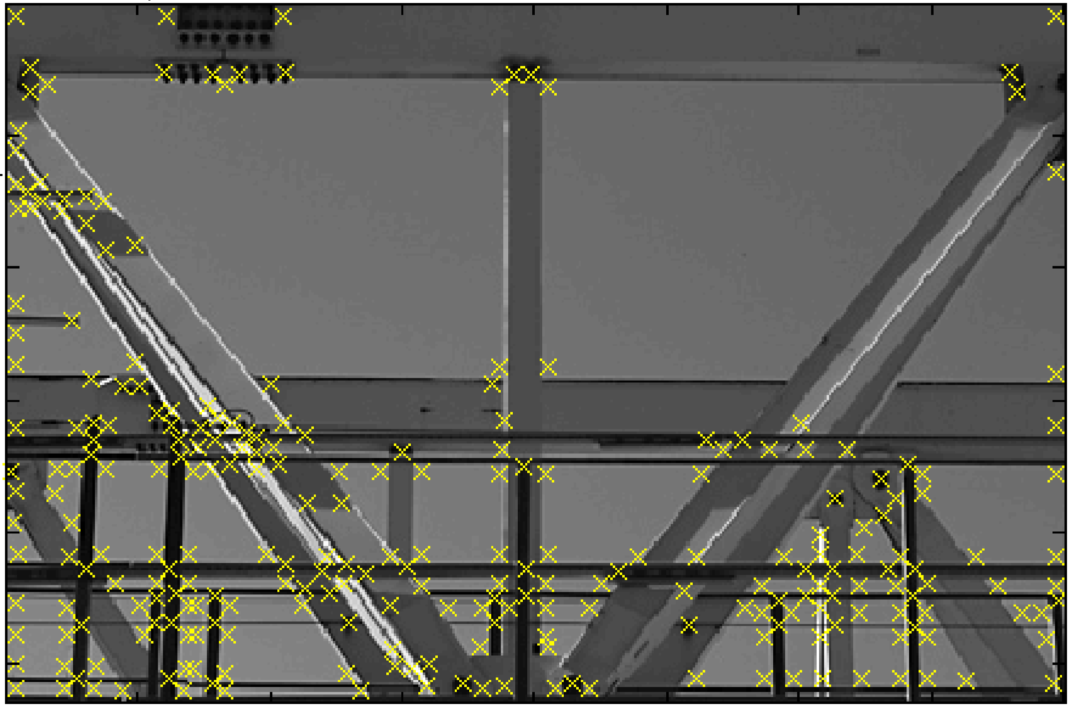
$$\det(Hessian(I)) = I_{xx} I_{yy} - I_{xy}^2$$

In Matlab:

$$I_{xx} .* I_{yy} - (I_{xy})\text{^}2$$

Hessian Detector – Responses [Beaudet78]





Effect: Responses mainly on corners and strongly textured areas.

Hessian Detector – Responses [Beaudet78]

Automatic Scale Selection

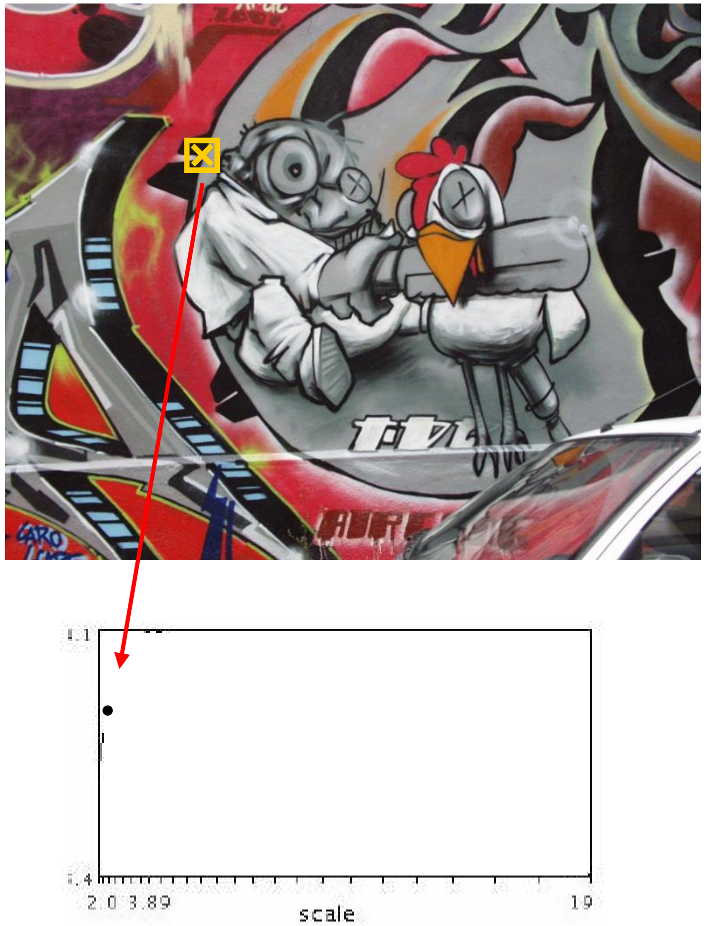
$$f(I_{i_1 \ldots i_m}(x,\sigma)) = f(I_{i_1 \ldots i_m}(x',\sigma'))$$

Same operator responses if the patch contains the same image up to scale factor

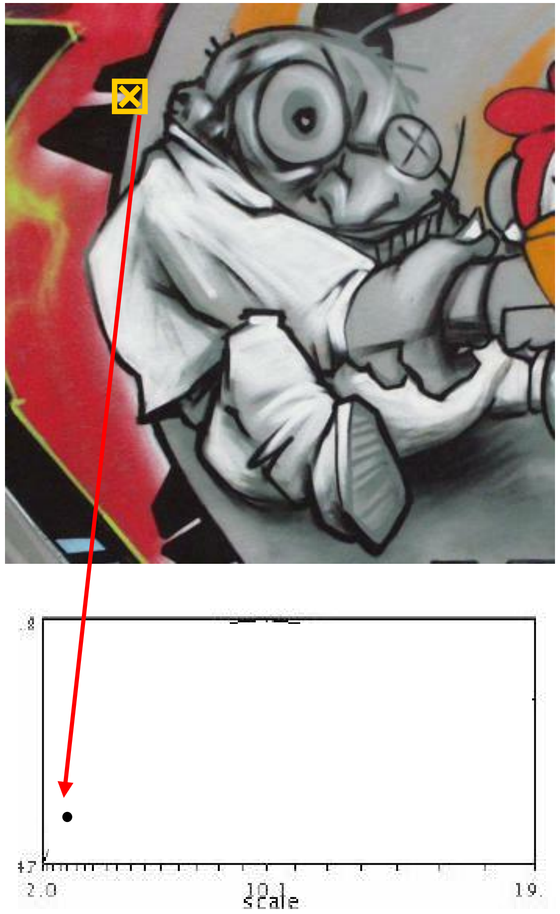
How to find corresponding patch sizes?

Automatic Scale Selection

- Function responses for increasing scale (scale signature)



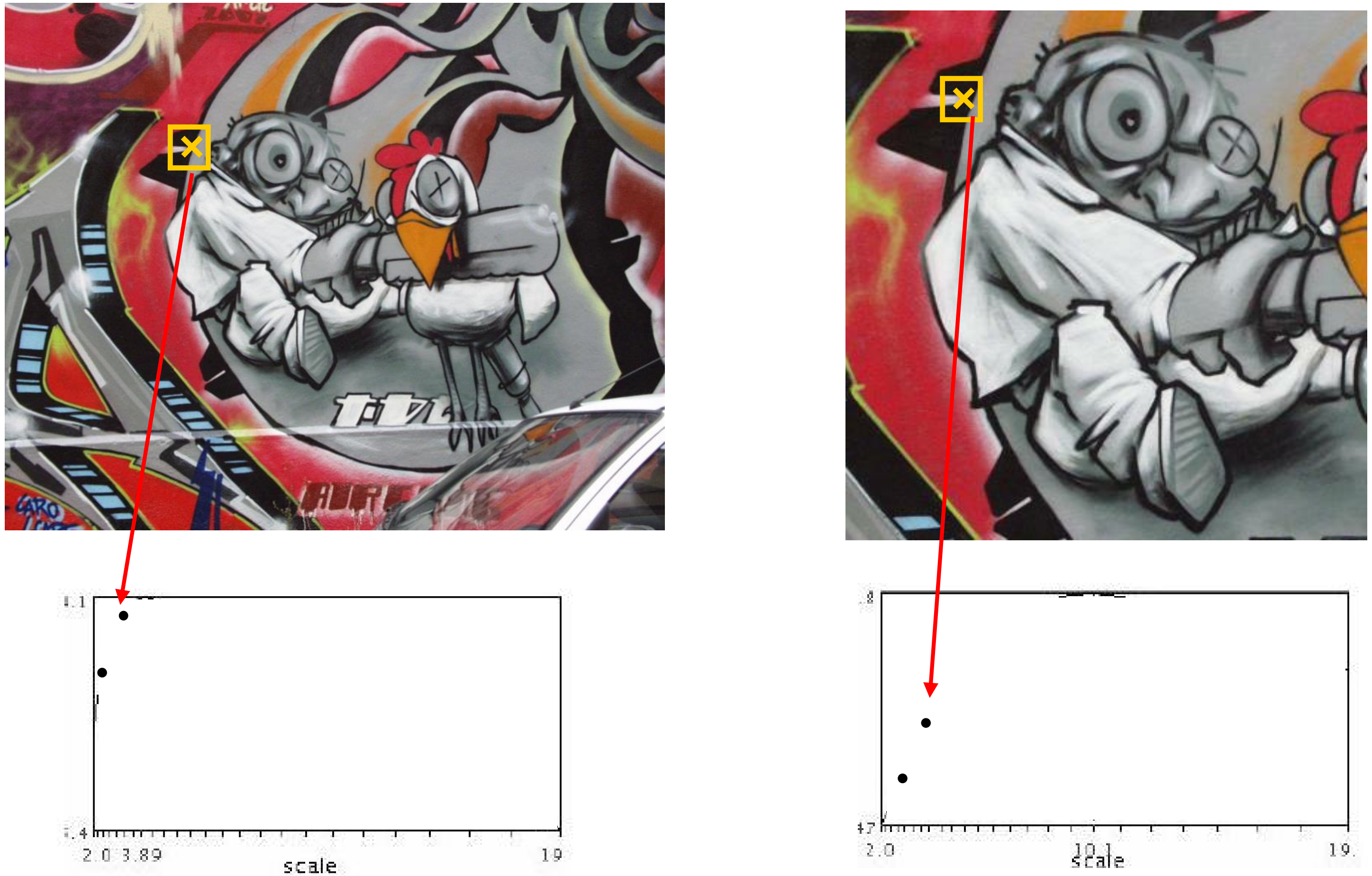
$f(I_{i_1 \ldots i_m}(x,\sigma))$



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

Automatic Scale Selection

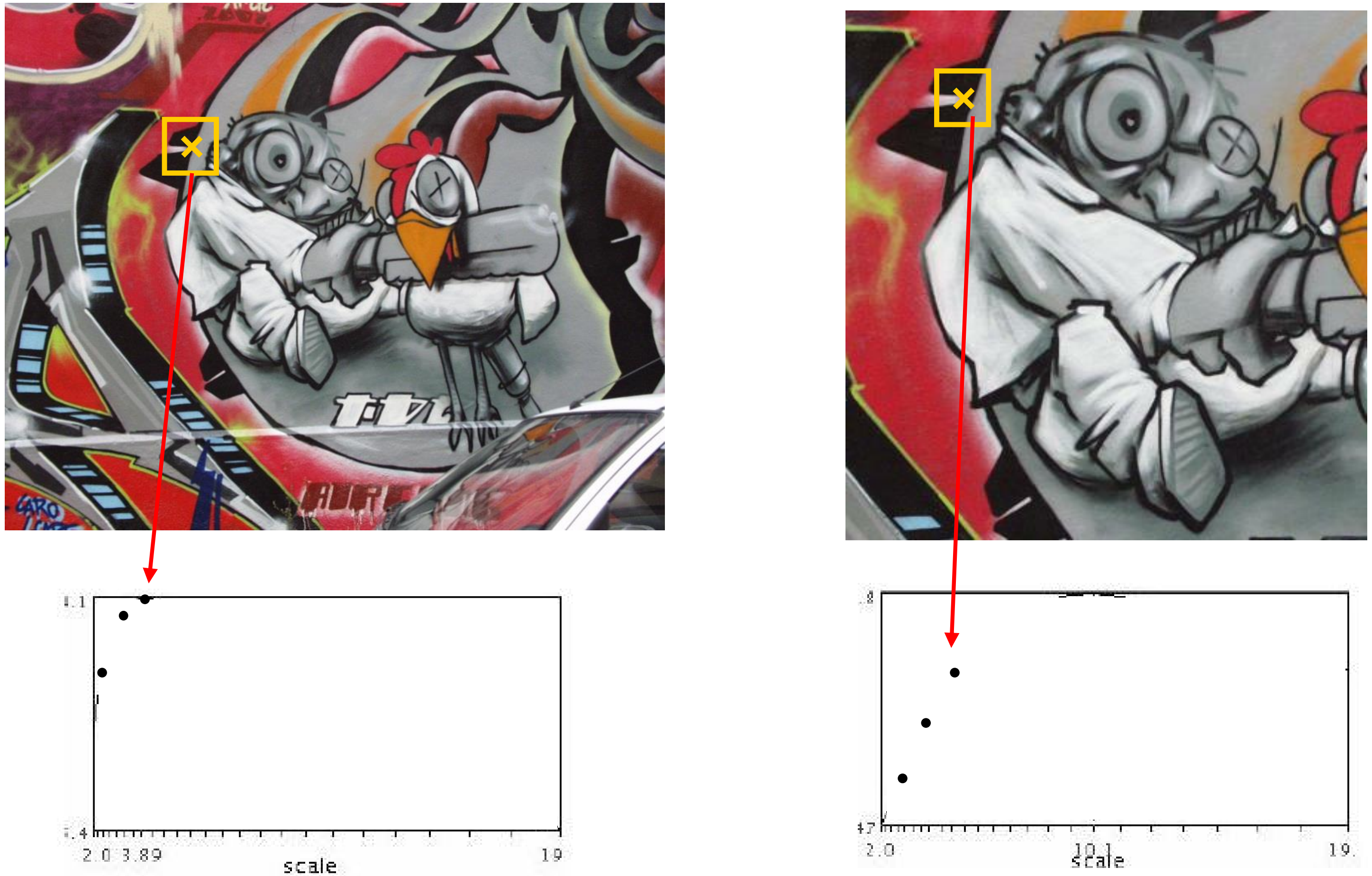
- **Function responses for increasing scale (scale signature)**



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

Automatic Scale Selection

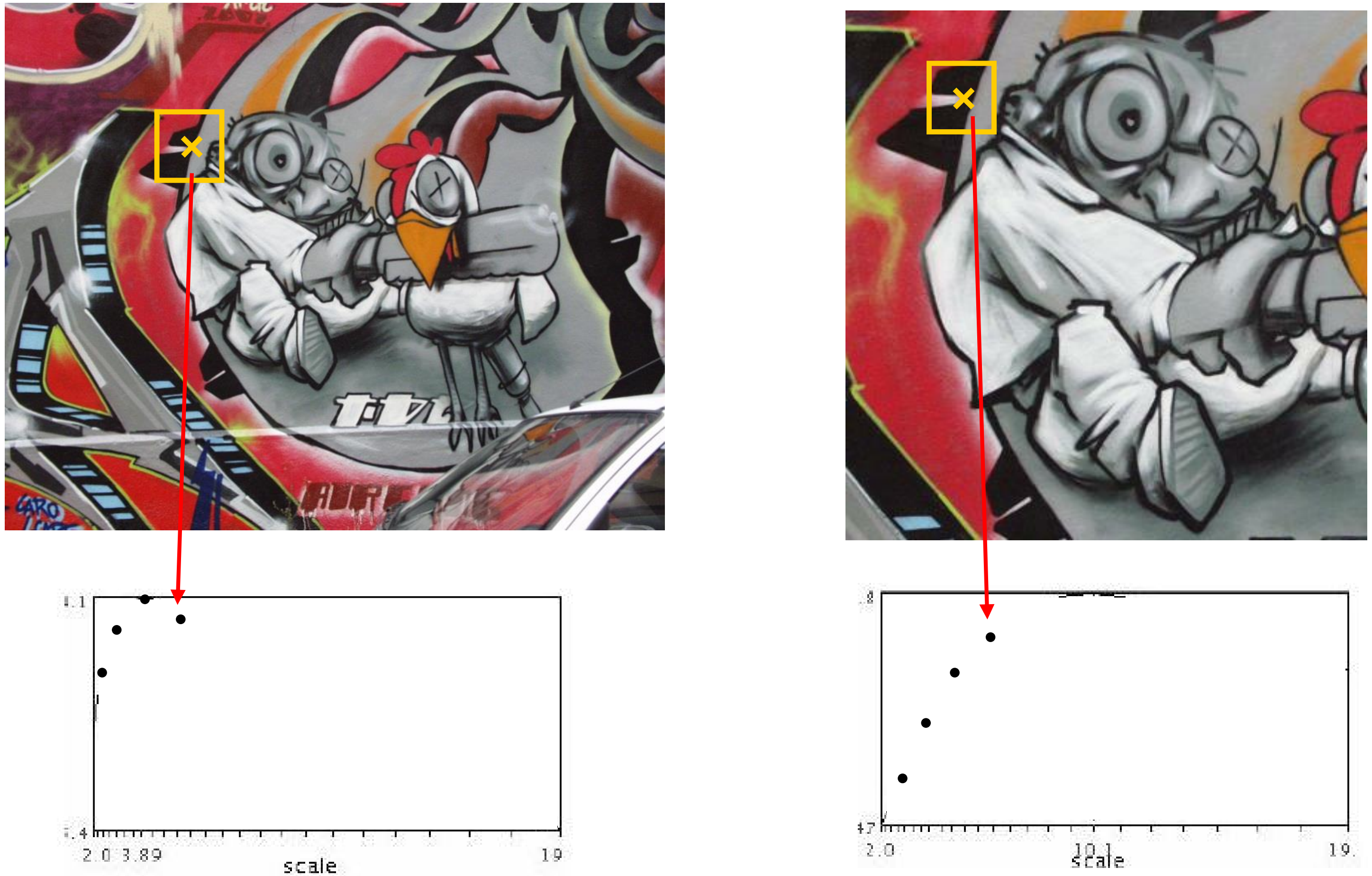
- **Function responses for increasing scale (scale signature)**



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

Automatic Scale Selection

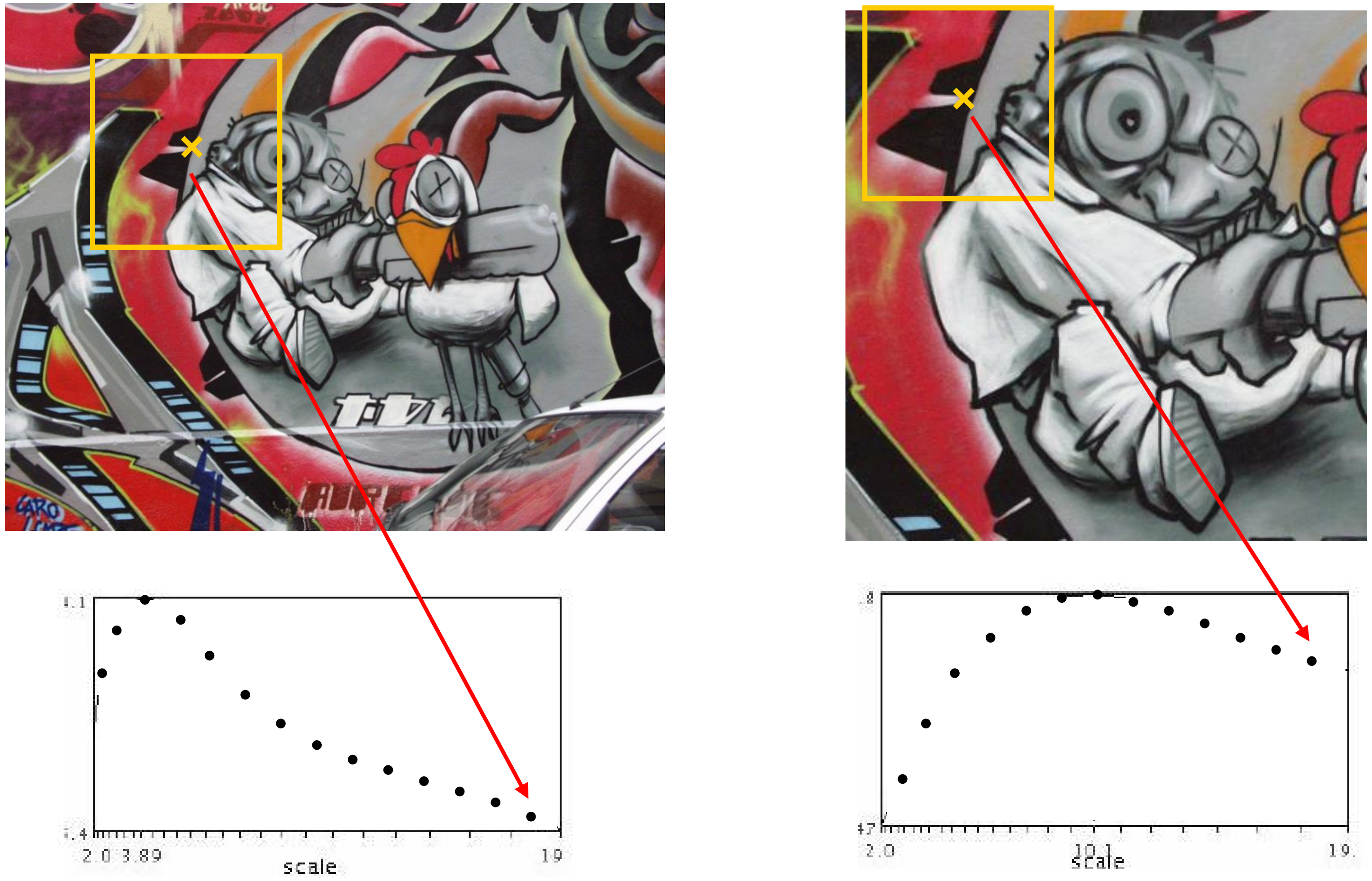
- Function responses for increasing scale (scale signature)



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

Automatic Scale Selection

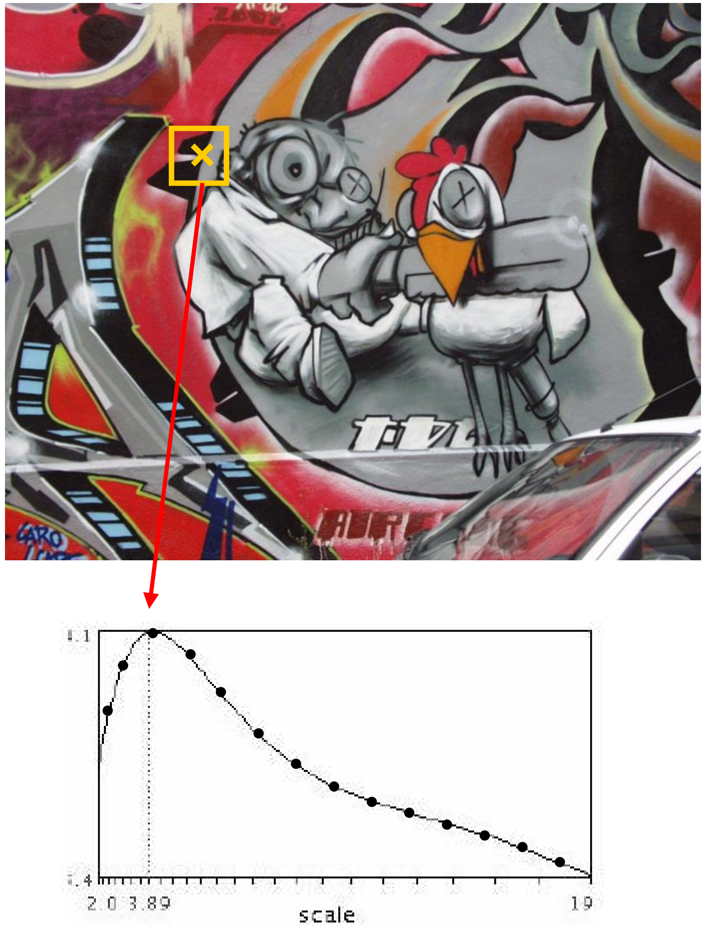
- **Function responses for increasing scale (scale signature)**



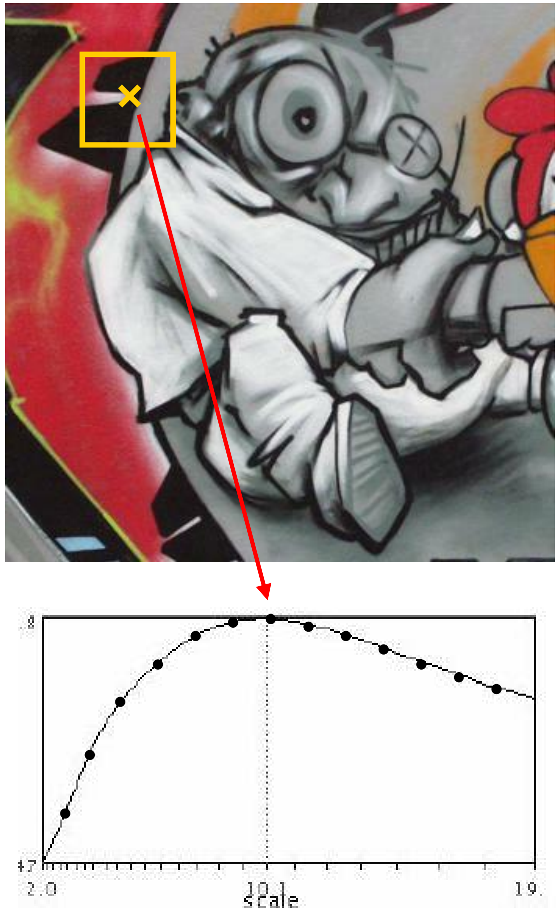
$f(I_{i_1 \ldots i_m}(x,\sigma))$ $\quad$ $f(I_{i_1 \ldots i_m}(x',\sigma))$

Automatic Scale Selection

- **Function responses for increasing scale (scale signature)**

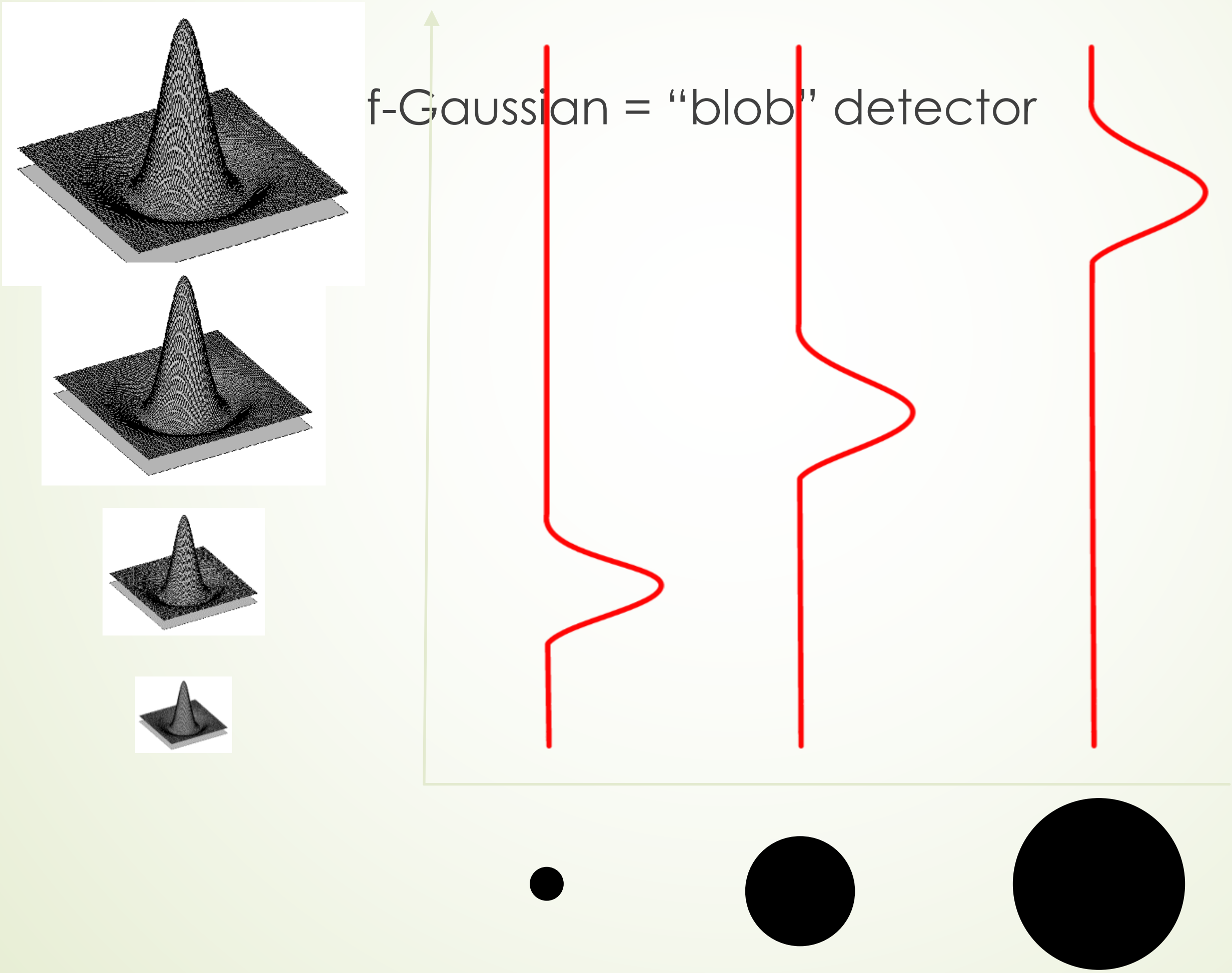


$f(I_{i_1 \ldots i_m}(x, \sigma))$



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

What Is A Useful Signature Function?



Laplacian-of-Gaussian (LoG)

- **Local maxima in scale space of Laplacian-of-Gaussian**

$$L_{xx}(\sigma) + L_{yy}(\sigma)$$

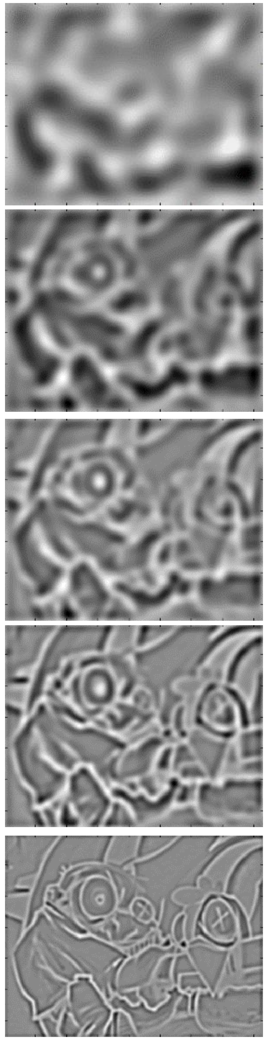
σ^5

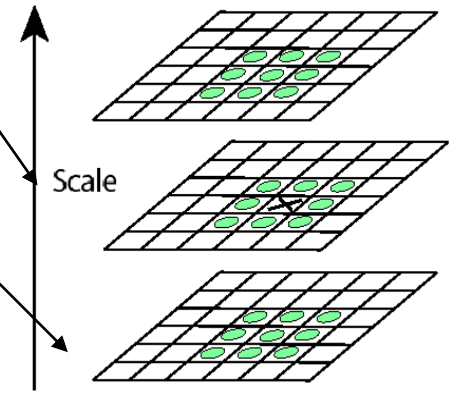
σ^4

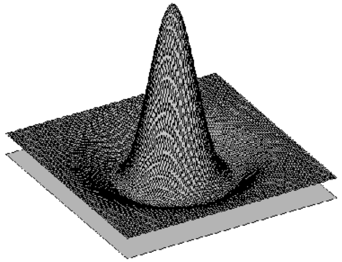
σ^3

σ^2

σ

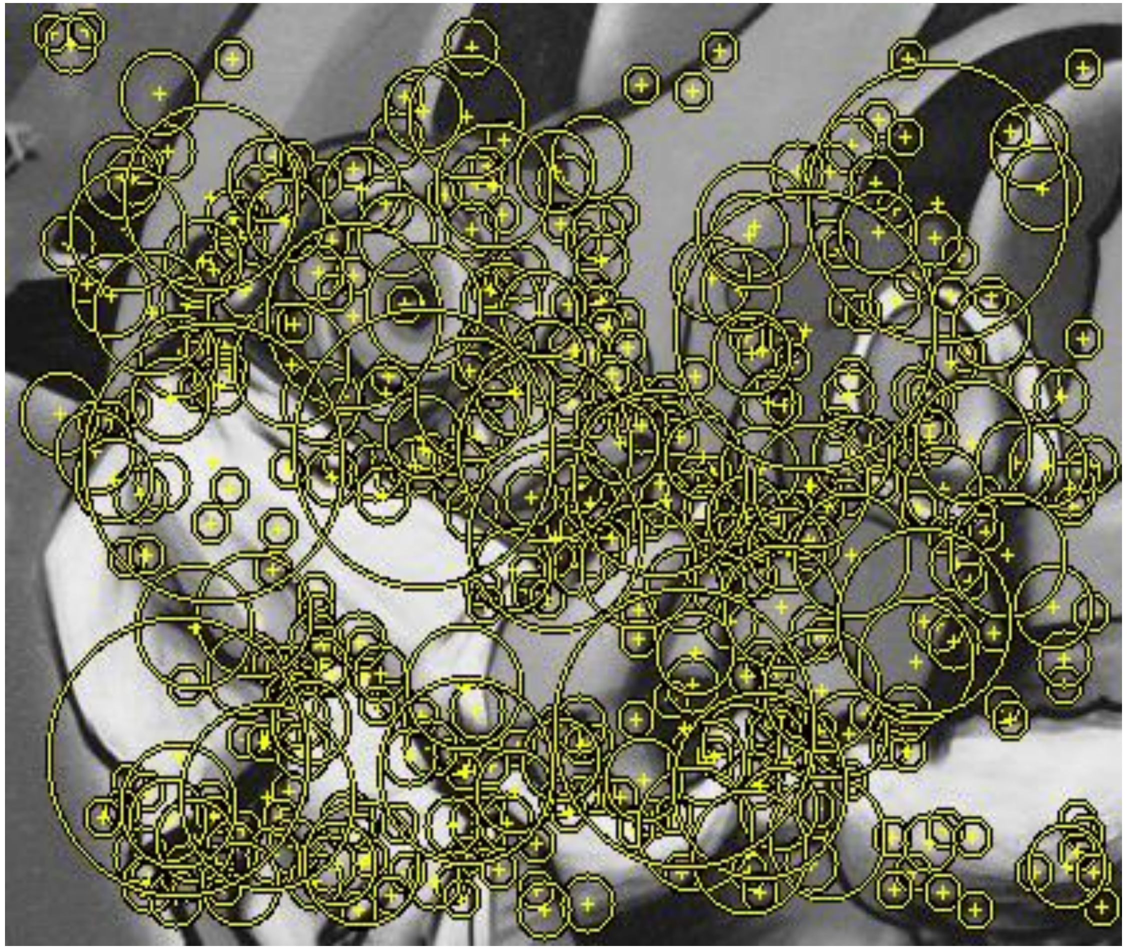






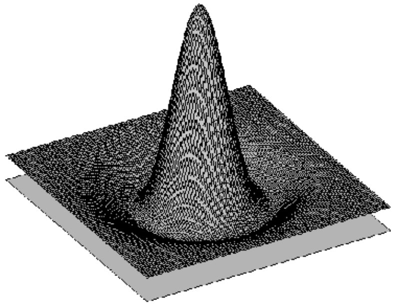
$\Rightarrow$ List of *(x, y, s)*

Results: Laplacian-of-Gaussian



Difference-of-Gaussian (DoG)

- **Difference of Gaussians as approximation of the Laplacian-of-Gaussian**



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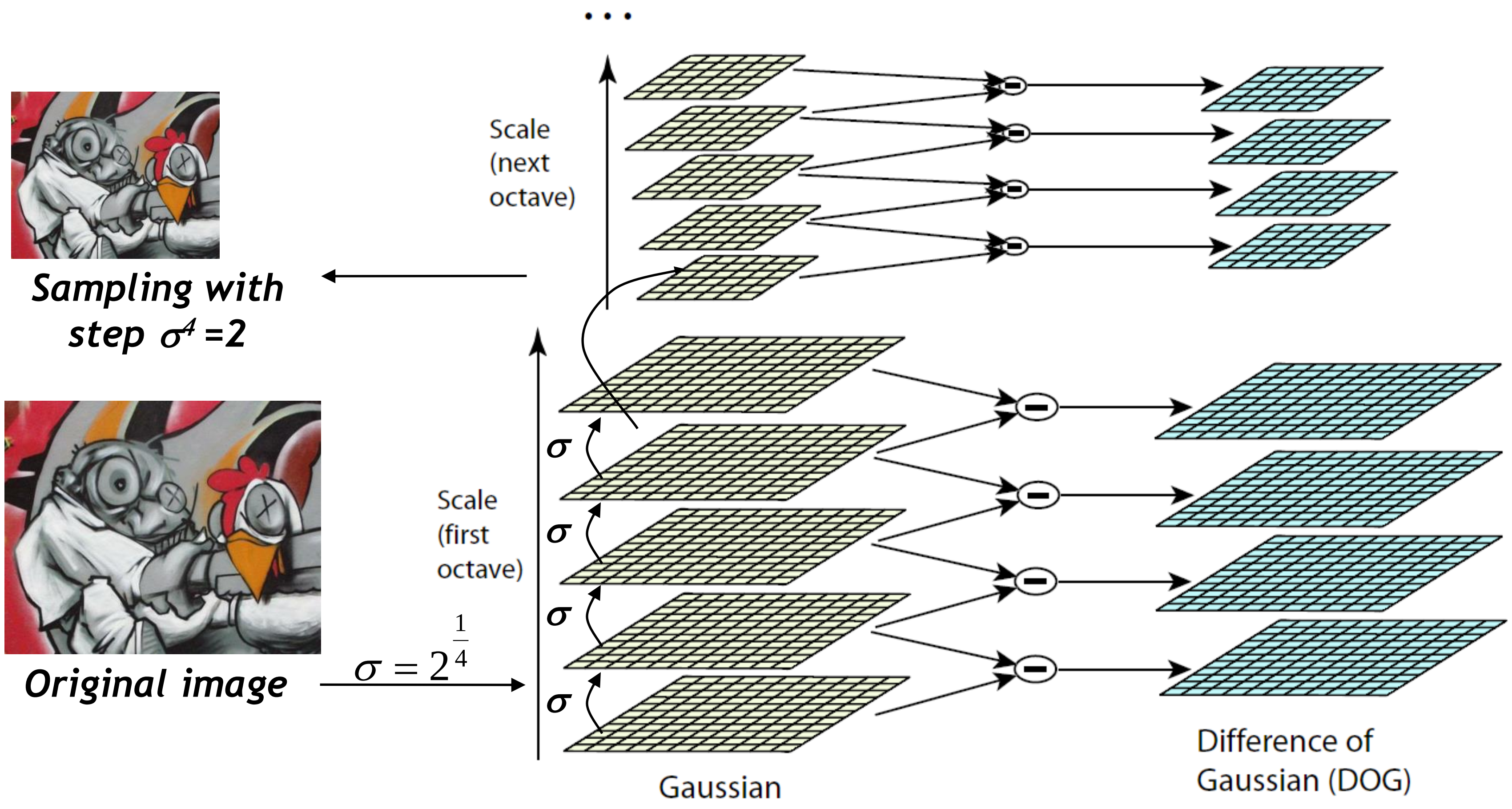
DoG - Efficient Computation

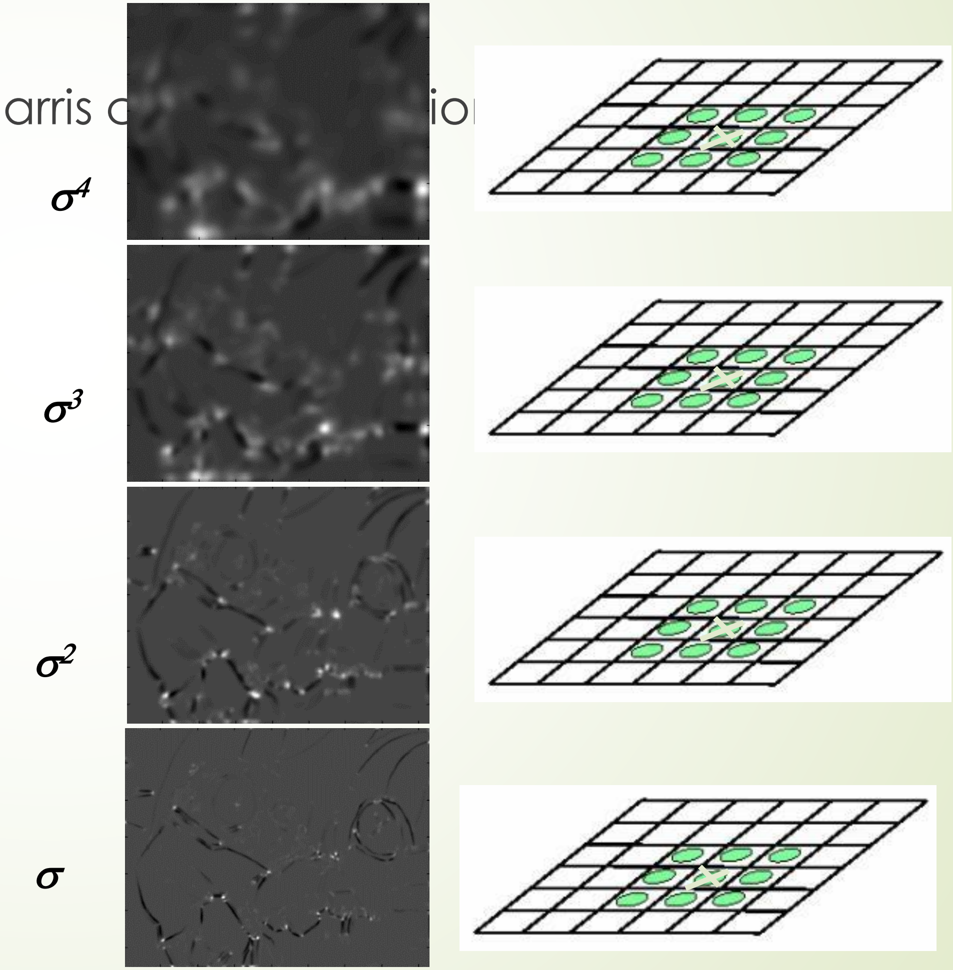
- Computation in Gaussian scale pyramid



Results: Lowe’s DoG

Harris-Laplace [Mikolajczyk ‘01]

1. Initialization: Multiscale Harris c io

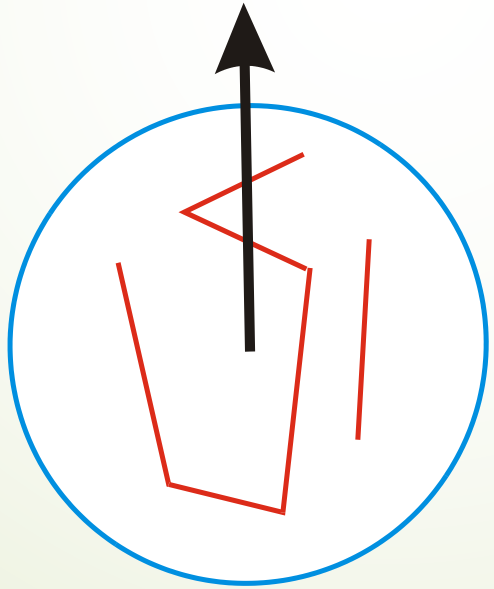


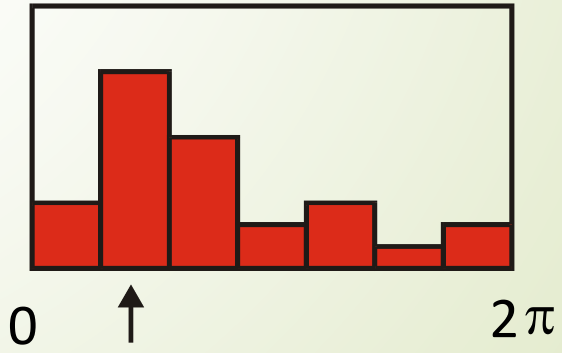
Computing Harris function **Detecting local maxima**

Orientation Normalization（方向正则化）

[Lowe, SIFT, 1999]

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

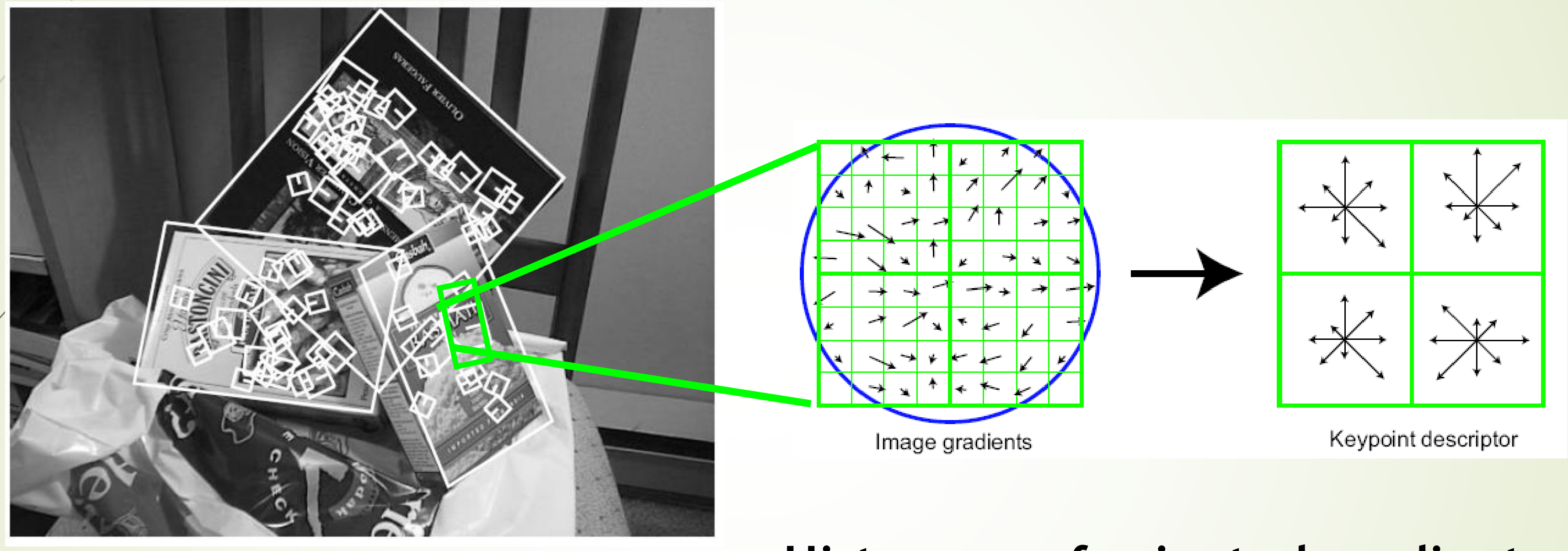




Local Descriptors（局部特征表达向量）

- The ideal descriptor should be
  - Repeatable
  - Distinctive
  - Compact
  - Efficient
- Most available descriptors focus on edge/gradient information
  - Capture texture information
  - Color still relatively seldomly used
    (more suitable for homogenous regions)

Local Descriptors: SIFT Descriptor



Histogram of oriented gradients

- **Captures important texture information**
- **Robust to small translations / affine deformations**

[Lowe, ICCV 1999]

HOG特征：

方向梯度直方图（Histogram of Oriented Gradient, HOG）通过计算和统计图像局部区域的梯度方向直方图来构成特征。具备尺度不变性的特点。但不具备旋转不变性。常用于行人、车辆这类物体的检测以及人脸识别等

提取流程：

1）灰度化（将图像看做一个x,y,z（灰度）的三通道图像）；

2）采用Gamma校正法对输入图像进行颜色空间的标准化（归一化）；（类似灰度直方图变换的一个幂函数映射）

3）计算图像每个像素的梯度（包括大小和方向）；主要是为了捕获轮廓信息，同时进一步弱化光照的干扰。

4）将图像划分成小cells（例如6*6像素/cell）；

5）统计每个cell的梯度直方图（不同梯度的个数），即可形成每个cell的descriptor；

6）将每几个cell组成一个block（例如3*3个cell/block），在block级别再做一次对比度均衡。一个block内所有cell的特征descriptor串联起来便得到该block的HOG特征

7）将图像image内的所有block的HOG特征descriptor串联起来就可以得到该image（你要检测的目标）的HOG特征descriptor及可供分类使用的特征向量

作业课后布置