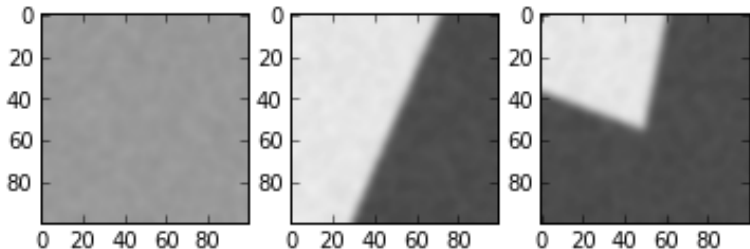




# Sample Ideal Corner Images

```
1 ys,xs = mgrid[:100,:100]
2 flat = clip(G(0.2*rand(100,100)+0.5,2),0,1)
3 edge = clip(G(0.2*rand(100,100)+0.2+0.6*(0.3*ys+0.7*xs<50),2),0,1)
4 corner = clip(G(0.2*rand(100,100)+0.2+0.6*(0.1*ys+0.5*xs<30))*(0.8*
   ys-0.3*xs<30),2),0,1)
5 subplot(131); imshow(flat,vmin=0,vmax=1)
6 subplot(132); imshow(edge,vmin=0,vmax=1)
7 subplot(133); imshow(corner,vmin=0,vmax=1)
```



# Idea behind Harris

## Corners / interest points

- ▶ corners are places where edges of different orientations meet
- ▶ interest points are places that can be detected stably

# Stability

## Stable corner locations

Let's define stability as the difference between the shifted image and the image, averaged over a window  $w$ .

$$S(x, y) = \sum_u \sum_v w(u, v) (I(u + x, v + y) - I(x, y))^2$$

$I(u + x, v + y)$  can be approximated by a Taylor series:

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

This then gives rise to:

$$S(x, y) \approx \sum_u \sum_v w(u, v) (I_x(u, v)x + I_y(u, v)y)^2$$

## Matrix expression

$$S(x, y) \approx \sum_u \sum_v w(u, v) (I_x(u, v)x + I_y(u, v)y)^2$$

This can be written in matrix form:

$$S(x, y) \approx (x \ y) A \begin{pmatrix} x \\ y \end{pmatrix}$$

$$A = \sum_u \sum_v w(u, v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

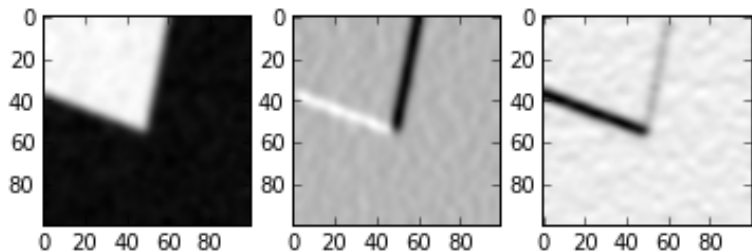


That derivation is fine, but another derivation is perhaps more straightforward.

## Diversity of Gradient Orientations

## gradient computation

```
1 dx = filters.gaussian_filter(corner,1,(0,1))  
2 dy = filters.gaussian_filter(corner,1,(1,0))  
3 subplot(131); imshow(corner)  
4 subplot(132); imshow(dx)  
5 subplot(133); imshow(dy)
```

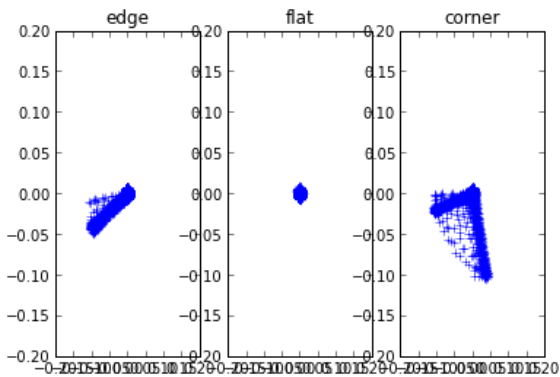


## gradient histograms

```
1 dx = filters.gaussian_filter(flat,1,(0,1))
2 dy = filters.gaussian_filter(flat,1,(1,0))
3 fgs = c_[dx.ravel(),dy.ravel()]
4 dx = filters.gaussian_filter(edge,1,(0,1))
5 dy = filters.gaussian_filter(edge,1,(1,0))
6 egs = c_[dx.ravel(),dy.ravel()]
7 dx = filters.gaussian_filter(corner,1,(0,1))
8 dy = filters.gaussian_filter(corner,1,(1,0))
9 cgs = c_[dx.ravel(),dy.ravel()]
```

## gradient histograms

```
1 subplot(131); xlim((-0.2,0.2)); ylim((-0.2,0.2)); plot(egs[:,0],egs  
  [:,1], 'b+'); title("edge")  
2 subplot(132); xlim((-0.2,0.2)); ylim((-0.2,0.2)); plot(fgs[:,0],fgs  
  [:,1], 'b+'); title("flat")  
3 subplot(133); xlim((-0.2,0.2)); ylim((-0.2,0.2)); plot(cgs[:,0],cgs  
  [:,1], 'b+'); title("corner")
```



```
1 print eig(dot(fgs.T, fgs)) [0]
2 print eig(dot(egs.T, egs)) [0]
3 print eig(dot(cgs.T, cgs)) [0]
```

```
[ 0.05539413  0.0514928 ]
[ 4.91494968  0.07114731]
[ 2.77089285  2.13992565]
```

The matrix we are computing the eigenvalues of is similar to the covariance matrix (we already know that the "mean" should be at (0,0))

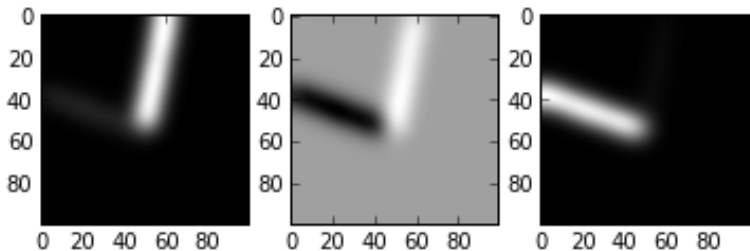
$$A = \left( \sum_i (g_i^x)^2 \sum_i g_i^x g_i^y \right)$$

$$\sum_i g_i^x g_i^y \sum_i (g_i^y)^2$$

Computing this over a patch is the same as summing  $g^x$  and  $g^y$  locally with a uniform filter. However, we can generalize this and use a Gaussian filter, giving smoother estimates.

```
1 dx = filters.gaussian_filter(corner, 1, (0, 1))
2 dy = filters.gaussian_filter(corner, 1, (1, 0))
3 sxx = filters.gaussian_filter(dx**2, 5.0)
4 sxy = filters.gaussian_filter(dx*dy, 5.0)
5 syy = filters.gaussian_filter(dy**2, 5.0)
```

```
1 subplot(131); imshow(sxx)
2 subplot(132); imshow(sxy)
3 subplot(133); imshow(syy)
```





## Eigenvalue computation

The eigenvalue computation requires solving:

$$(A - \lambda I) v = 0$$

In the  $2 \times 2$  case:

$$\det \begin{pmatrix} \lambda - a & -b \\ -c & \lambda - d \end{pmatrix} = 0$$

This gives rise to the quadratic equation:

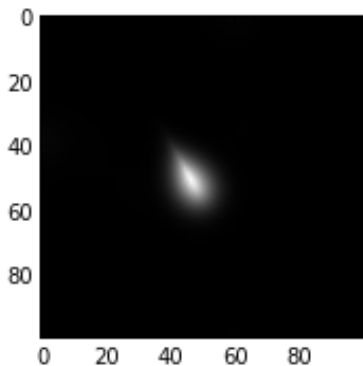
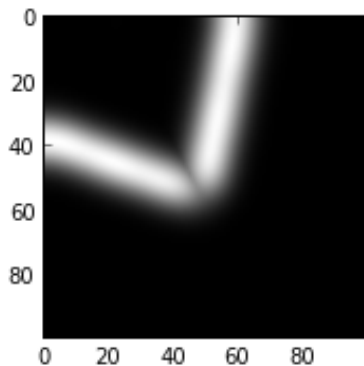
$$\lambda^2 - (a + d)\lambda + (ad - bc) = \lambda^2 - \lambda \operatorname{tr}(A) + \det(A) = 0$$

The solution is given by:

$$\lambda = \frac{\operatorname{tr}(A) \pm \sqrt{\operatorname{tr}^2(A) - 4\det(A)}}{2}$$

# Eigenvalue computation

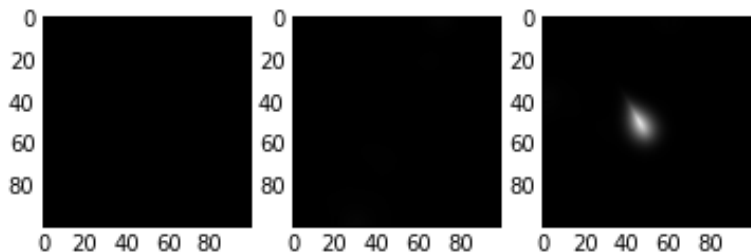
```
1 T = sxx+syy
2 D = sxx*syy-sxy**2
3 R = (T**2-4*D)**.5
4 hi = (T+R)/2
5 lo = (T-R)/2
6 subplot(121); imshow(hi)
7 subplot(122); imshow(lo)
```



```
1 def harris(image, sigma=1.0, area=5.0):
2     dx = filters.gaussian_filter(image, sigma, (0,1))
3     dy = filters.gaussian_filter(image, sigma, (1,0))
4     sxx = filters.gaussian_filter(dx**2, area)
5     sxy = filters.gaussian_filter(dx*dy, area)
6     syy = filters.gaussian_filter(dy**2, area)
7     T = sxx+syy
8     D = sxx*syy-sxy**2
9     R = (T**2-4*D)**.5
10    hi = (T+R)/2
11    lo = (T-R)/2
12    return lo
```

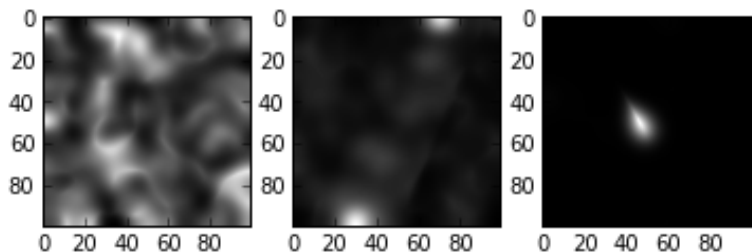
# Harris corner detector

```
1 subplot(131); imshow(harris(flat),vmax=0.002)
2 subplot(132); imshow(harris(edge),vmax=0.002)
3 subplot(133); imshow(harris(corner),vmax=0.002)
```



## Harris corner detector (relative corners)

```
1 subplot(131); imshow(harris(flat))  
2 subplot(132); imshow(harris(edge))  
3 subplot(133); imshow(harris(corner))
```



```
1 import tables
2 hdf = tables.openFile("1k.h5")
3 images = hdf.root.icons
4 image = mean(crop_black(images[77]),2)
5 imshow(image)
```



```
1 imshow(harris(image, sigma=2.0, area=7.0))
```

