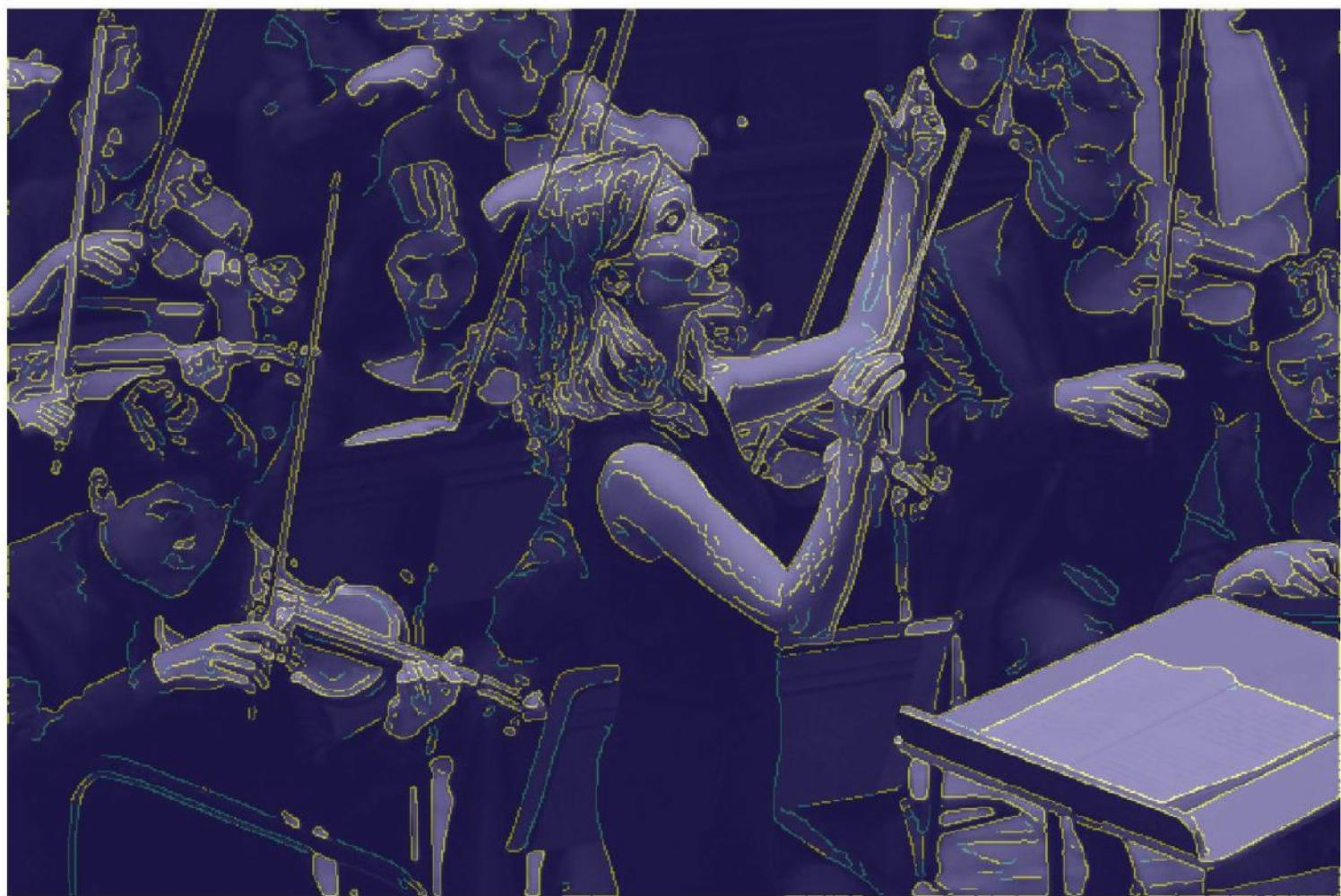




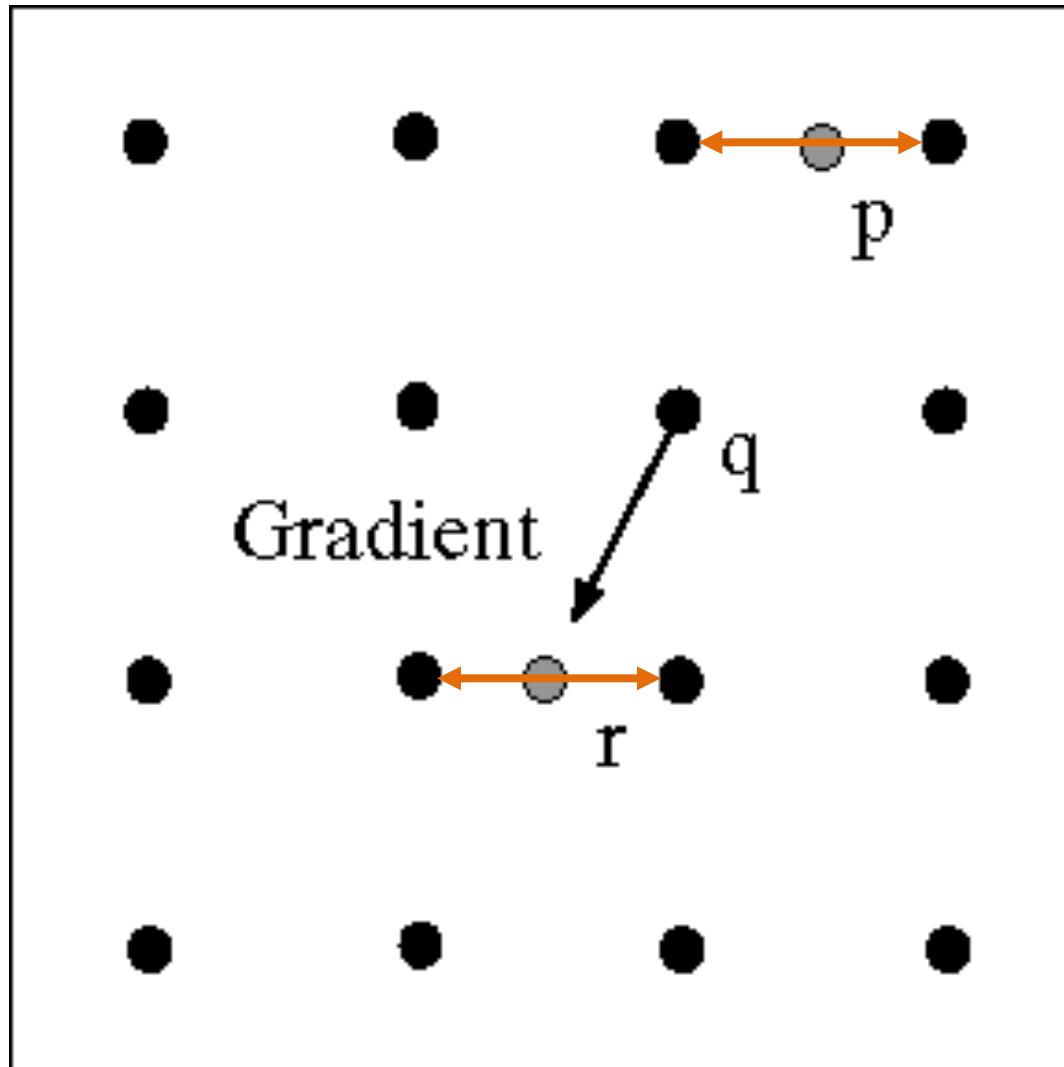
Video 3.1

Jianbo Shi



No intensity values at r and p :

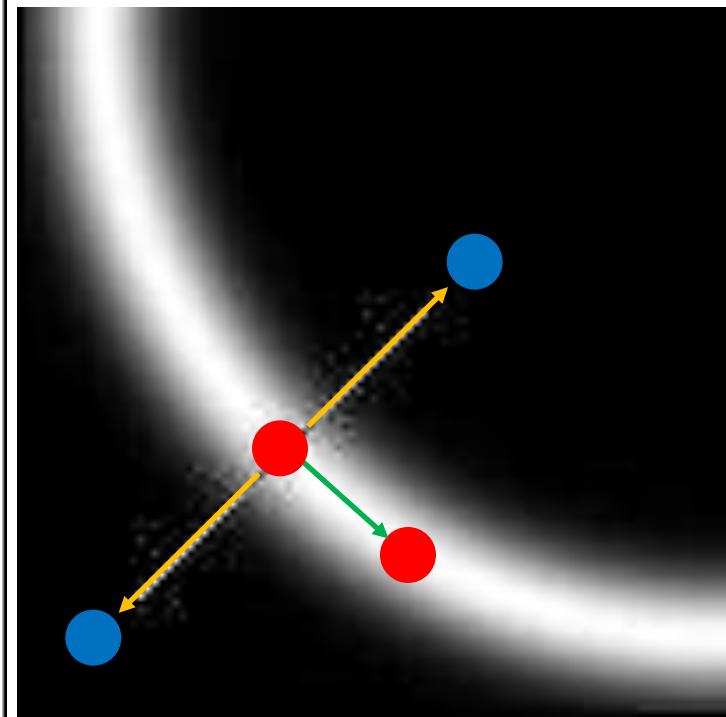
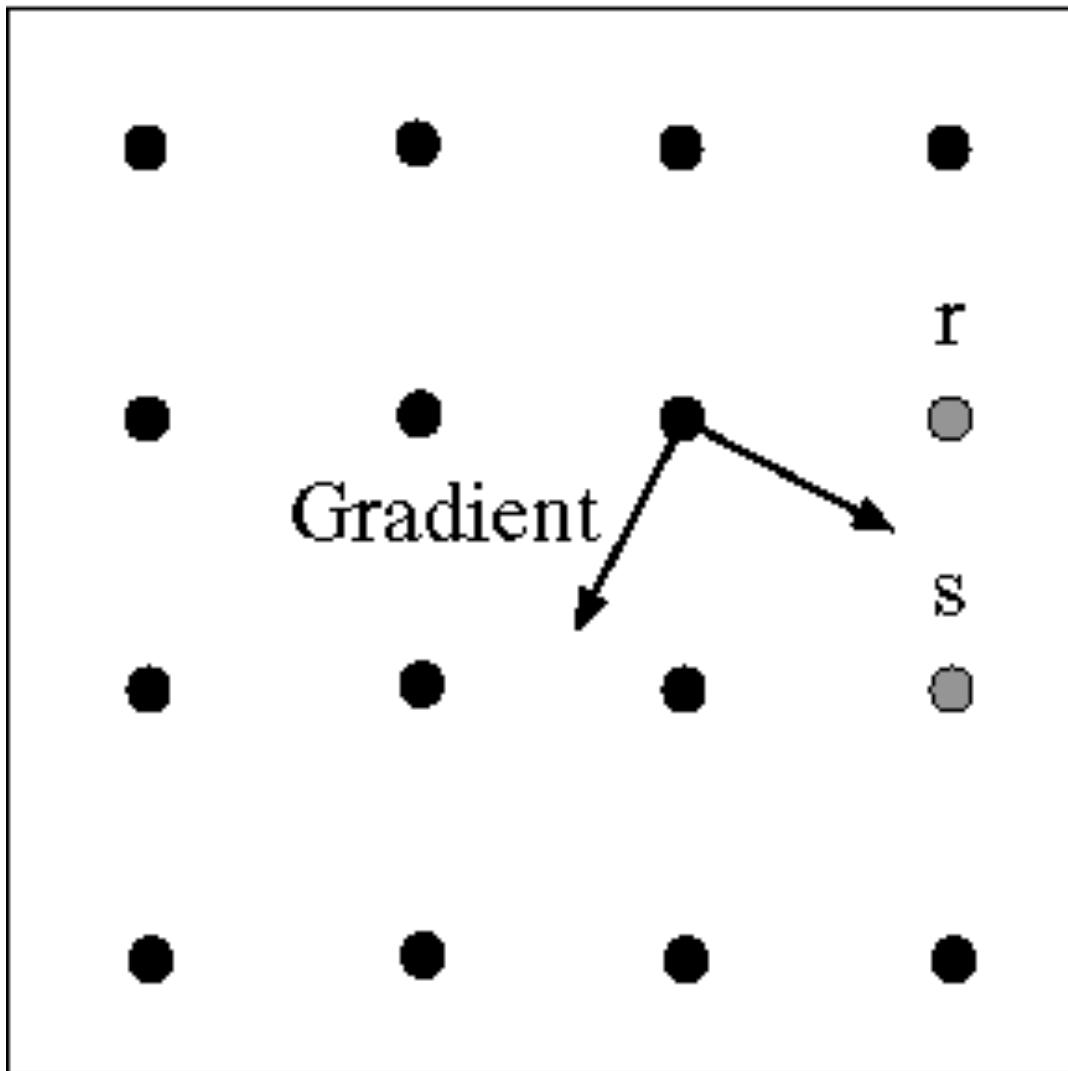
Interpolate these intensities using neighbor pixels.



Where is next edge point?

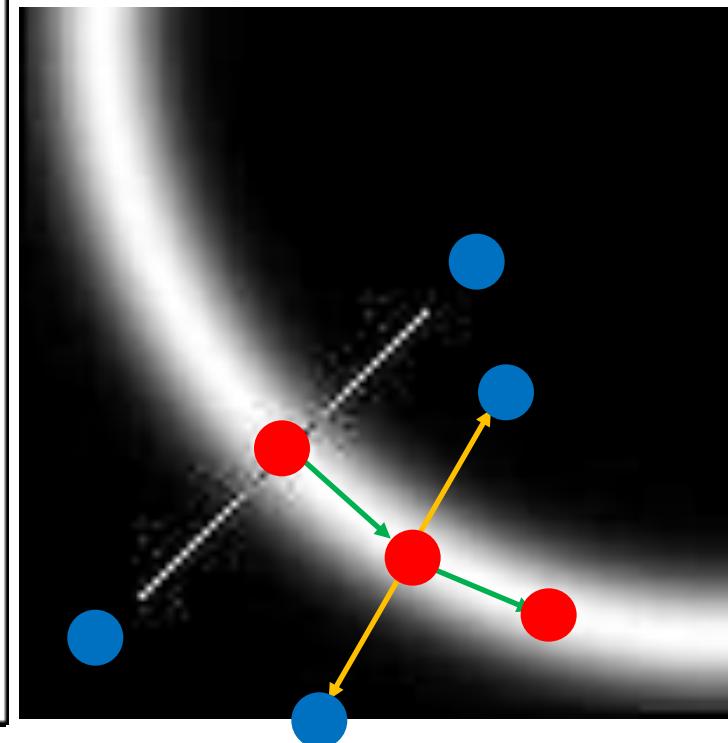
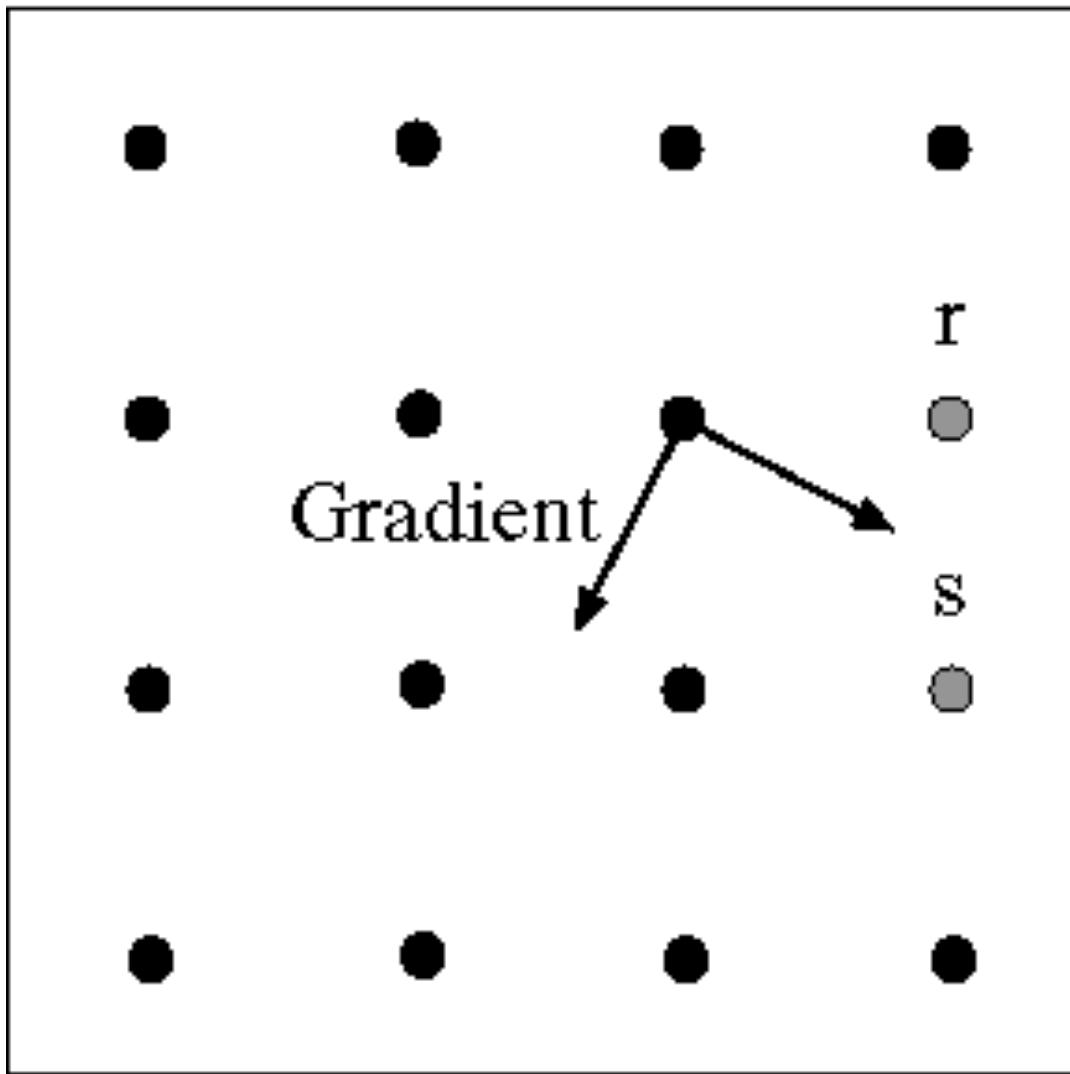
Where is next edge point?

we construct the tangent to the edge curve (which is normal to the gradient at that point) and use this to predict the next points



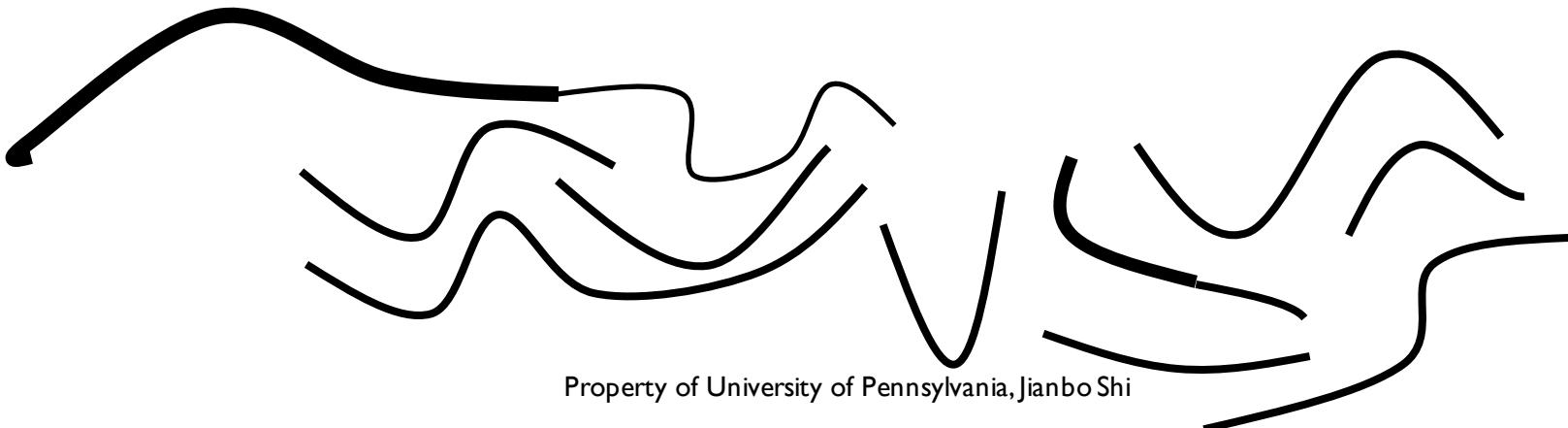
Where is next edge point?

we construct the tangent to the edge curve (which is normal to the gradient at that point) and use this to predict the next points



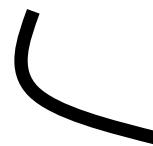
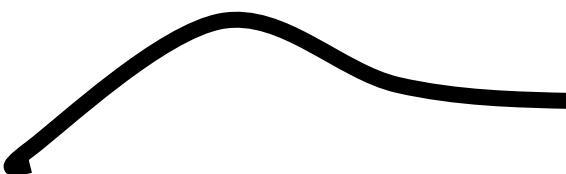
Edge Linking: Hysteresis

- Check that maximum value of gradient value is sufficiently large
 - drop-outs? use **hysteresis**
 - use a high threshold to start edge curves and a low threshold to continue them.



Edge Linking: Hysteresis

- Check that maximum value of gradient value is sufficiently large
 - drop-outs? use **hysteresis**
 - use a high threshold to start edge curves and a low threshold to continue them.

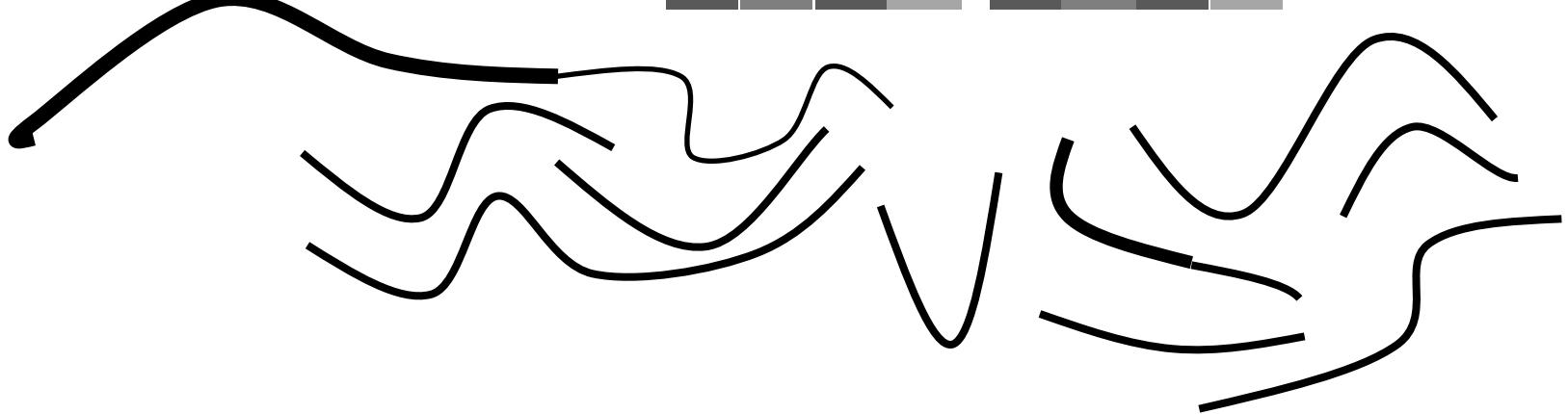


threshold_high

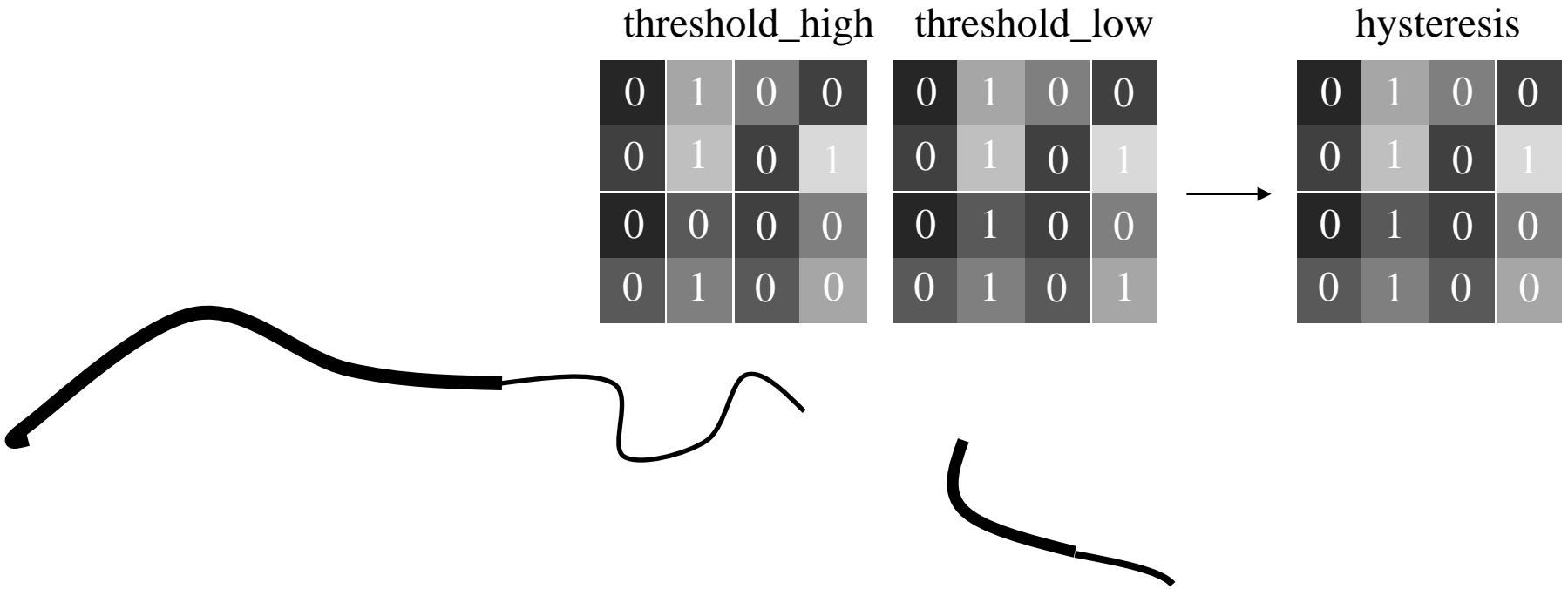
0	1	0	0
0	1	0	1
0	0	0	0
0	1	0	0

Edge Linking: Hysteresis

	threshold_high	threshold_low	
0	1	0	0
0	1	0	1
0	0	0	0
0	1	0	0



Edge Linking: Hysteresis





Canny Edge Detection

1. Filter image by derivatives of Gaussian
2. Compute magnitude of gradient
3. Compute edge orientation
4. Detect local maximum
5. Edge linking





Video 3.2

Jianbo Shi

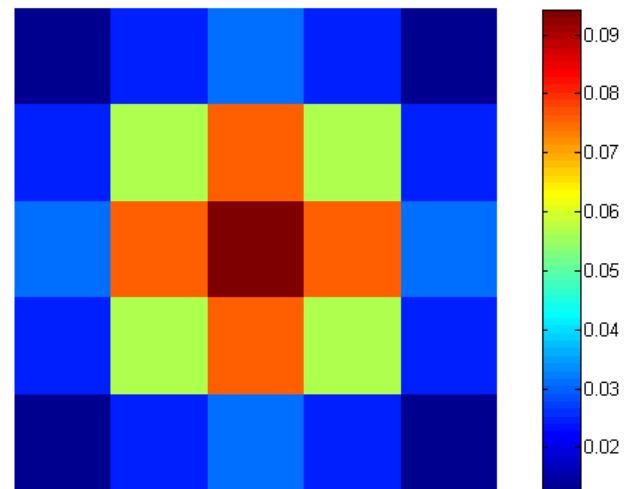
Canny Edge Implementation

```
img = imread ('image.png');  
img = rgb2gray(img);  
img = double (img);
```

```
% Value for high and low thresholding  
threshold_low = 0.035;  
threshold_high = 0.175;
```

```
%% Gaussian filter definition (https://en.wikipedia.org/wiki/Canny\_edge\_detector)  
G = [2, 4, 5, 4, 2; 4, 9, 12, 9, 4; 5, 12, 15, 12, 5; 4, 9, 12, 9, 4; 2, 4, 5, 4, 2];  
G = 1/159.* G;
```

```
%Filter for horizontal and vertical direction  
dx = [1 -1];  
dy = [1; -1];
```



Canny Edge Implementation

```
% % Convolution of image with  
Gaussian
```

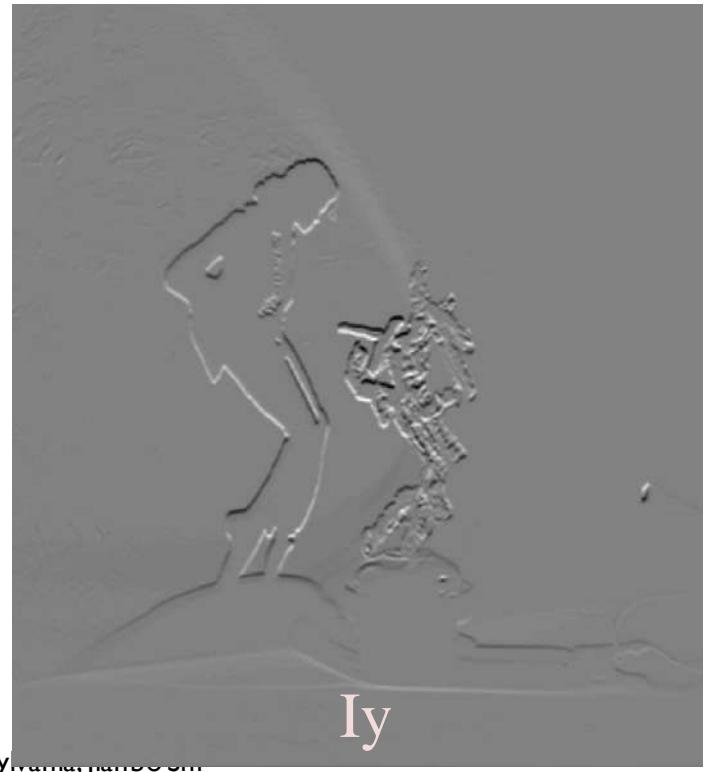
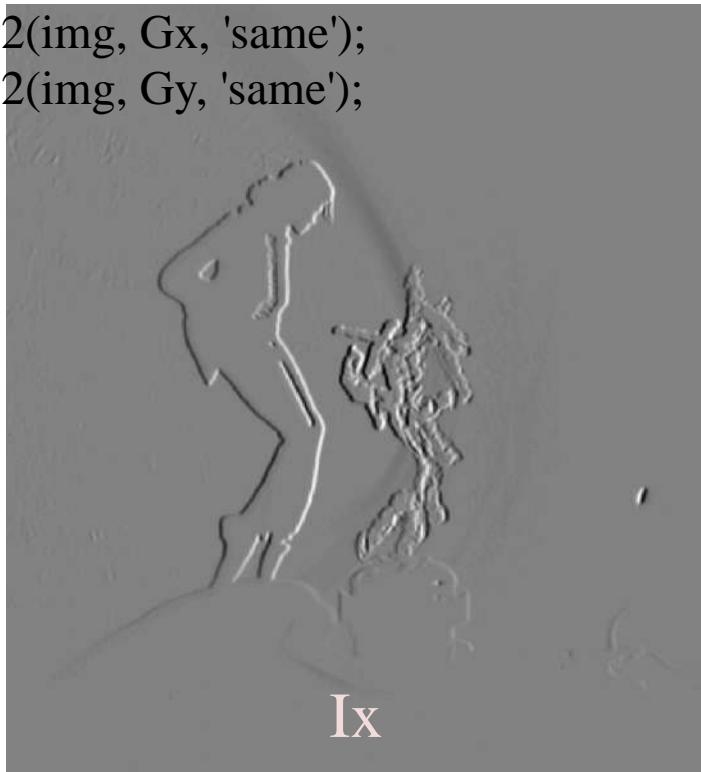
```
Gx = conv2(G, dx, 'same');
```

```
Gy = conv2(G, dy, 'same');
```

```
% Convolution of image with Gx and  
Gy
```

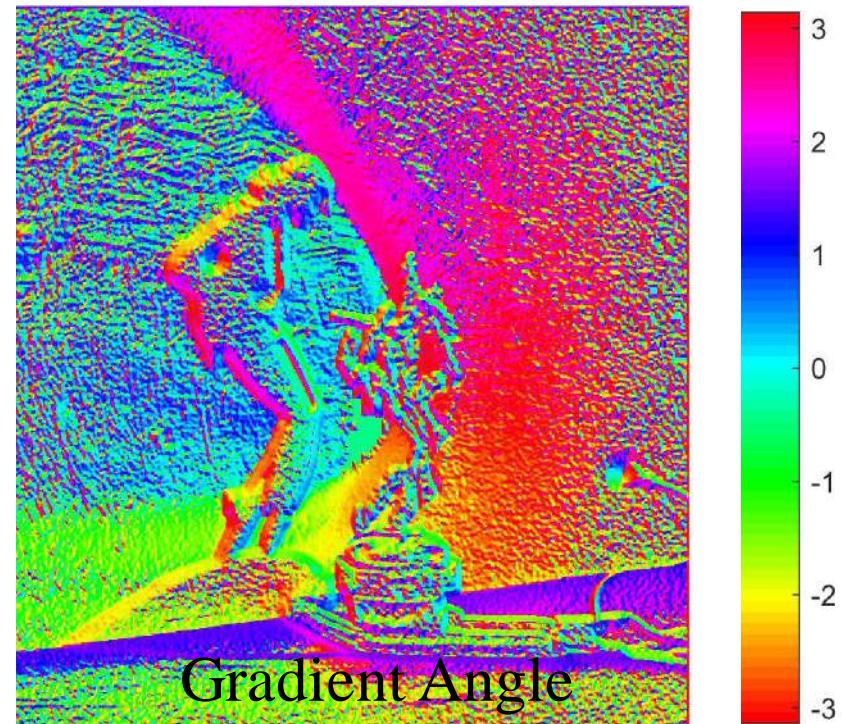
```
Ix = conv2(img, Gx, 'same');
```

```
Iy = conv2(img, Gy, 'same');
```



Canny Edge Implementation

```
angle = atan2(Iy, Ix);  
mag = sqrt(Iy.^2 + Ix.^2);
```







Canny Edge Implementation

```
%% Non-Maximum Supression
```

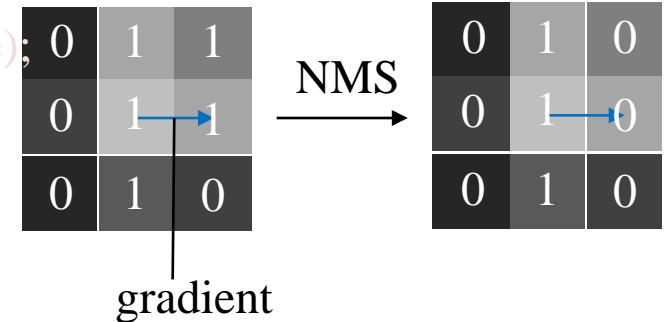
```
edge = non_maximum_suppression(magnitude, angle, edge);
```



```
low = threshold_low * max(edge(:));
```

```
high = threshold_high * max(edge(:));
```

```
linked_edge = hysteresis_thresholding(low, high);
```



threshold_high

0	1	0
0	1	0
0	0	0

threshold_low

0	1	0
0	1	0
0	1	0

hysteresis

Localized edge





Video 3.3

Jianbo Shi

```
% % Convolution of image with  
Gaussian
```

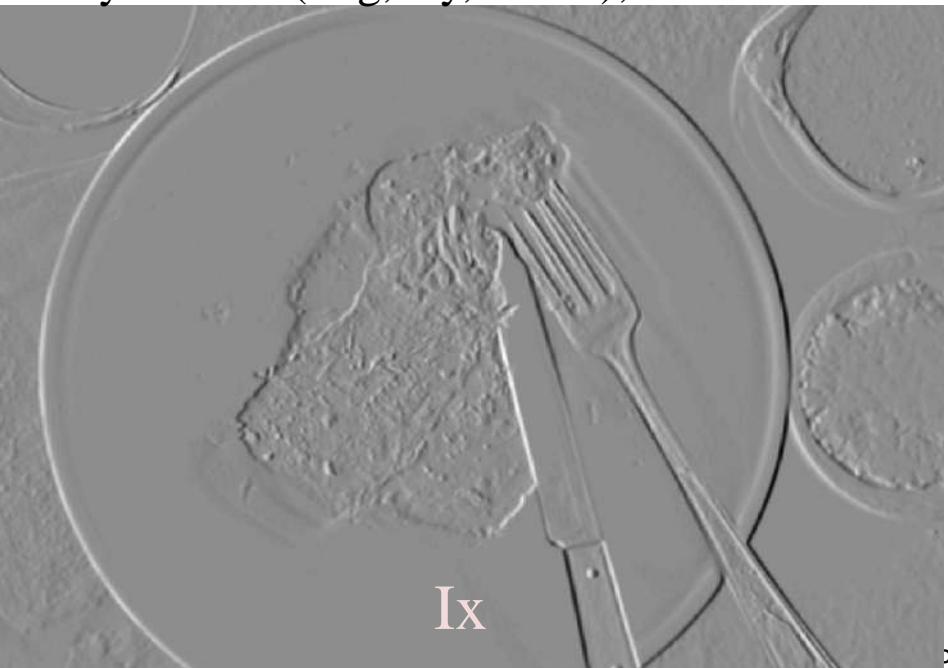
```
Gx = conv2(G, dx, 'same');
```

```
Gy = conv2(G, dy, 'same');
```

```
% Convolution of image with Gx and  
Gy
```

```
Ix = conv2(img, Gx, 'same');
```

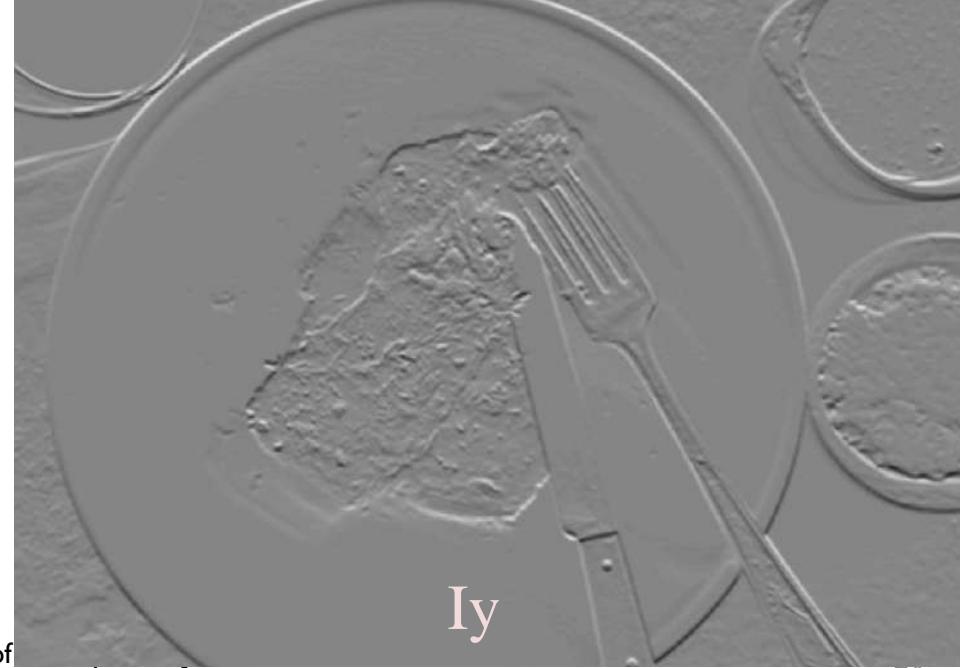
```
Iy = conv2(img, Gy, 'same');
```



I_x



I_y

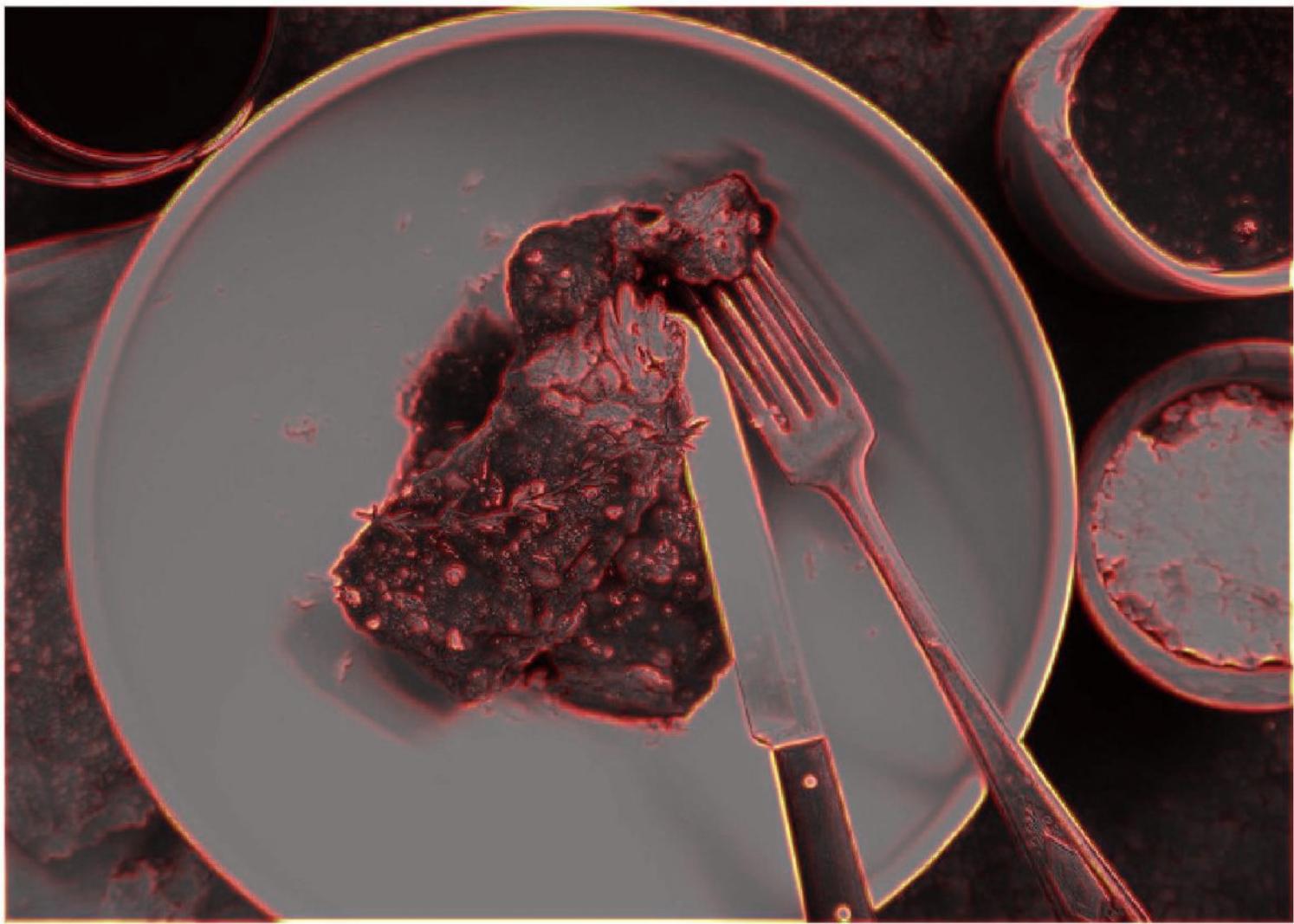


of

Canny Edge Implementation

```
angle = atan2(Iy, Ix);  
mag = sqrt(Iy.^2 + Ix.^2);
```

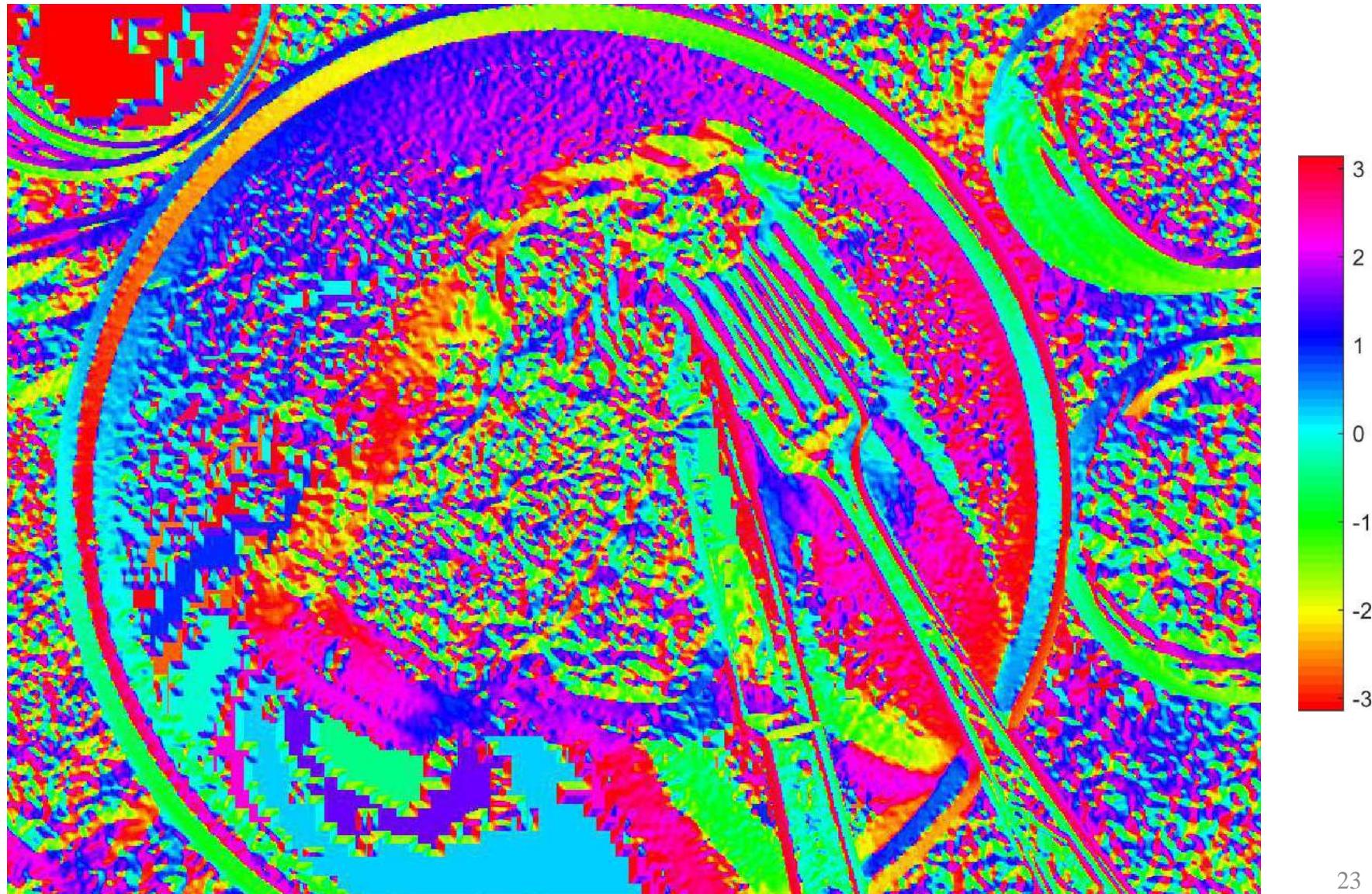
Gradient Magnitude



Canny Edge Implementation

angle = atan2(Iy, Ix);

mag = sqrt(Iy.^2 + Ix.^2);





Canny Edge Implementation

Localized edge

```
%% Non-Maximum Supression
```

```
edge = non_maximum_suppression(magnitude, angle, edge);
```

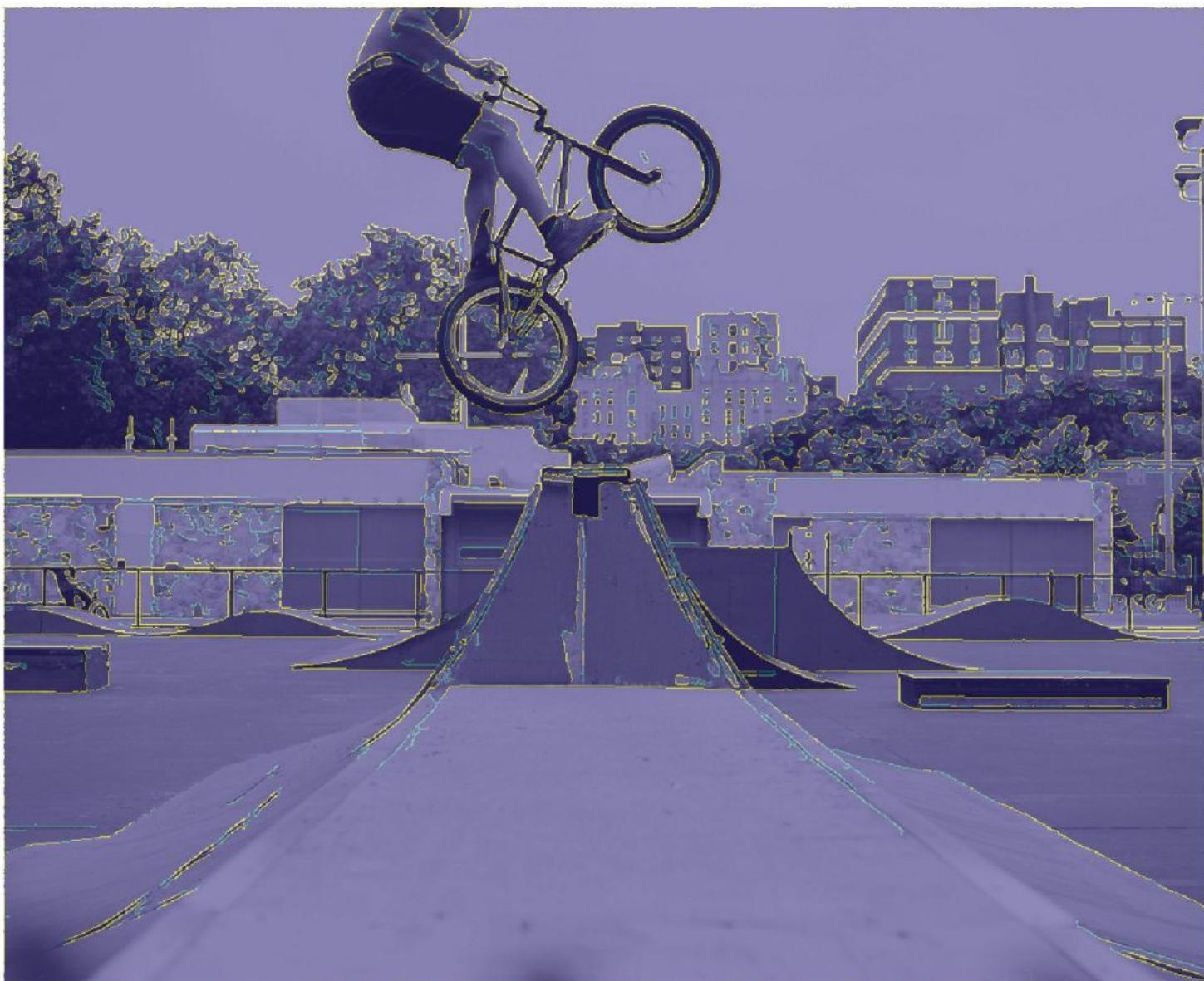
```
low = threshold_low * max(edge(:));  
high = threshold_high * max(edge(:));  
linked_edge = hysteresis_thresholding(low, high);
```





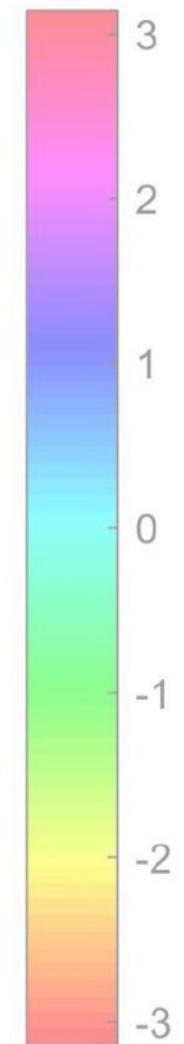


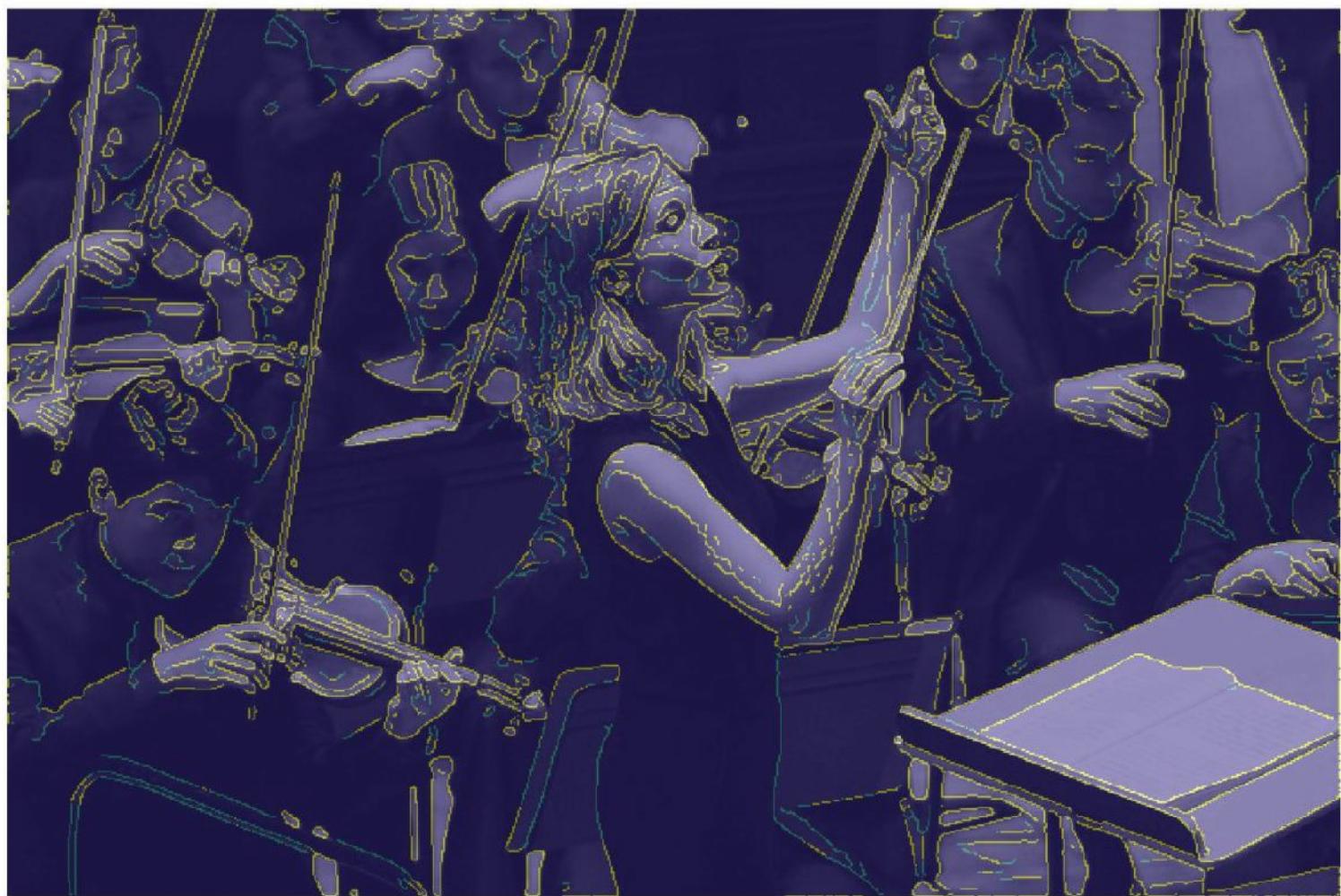






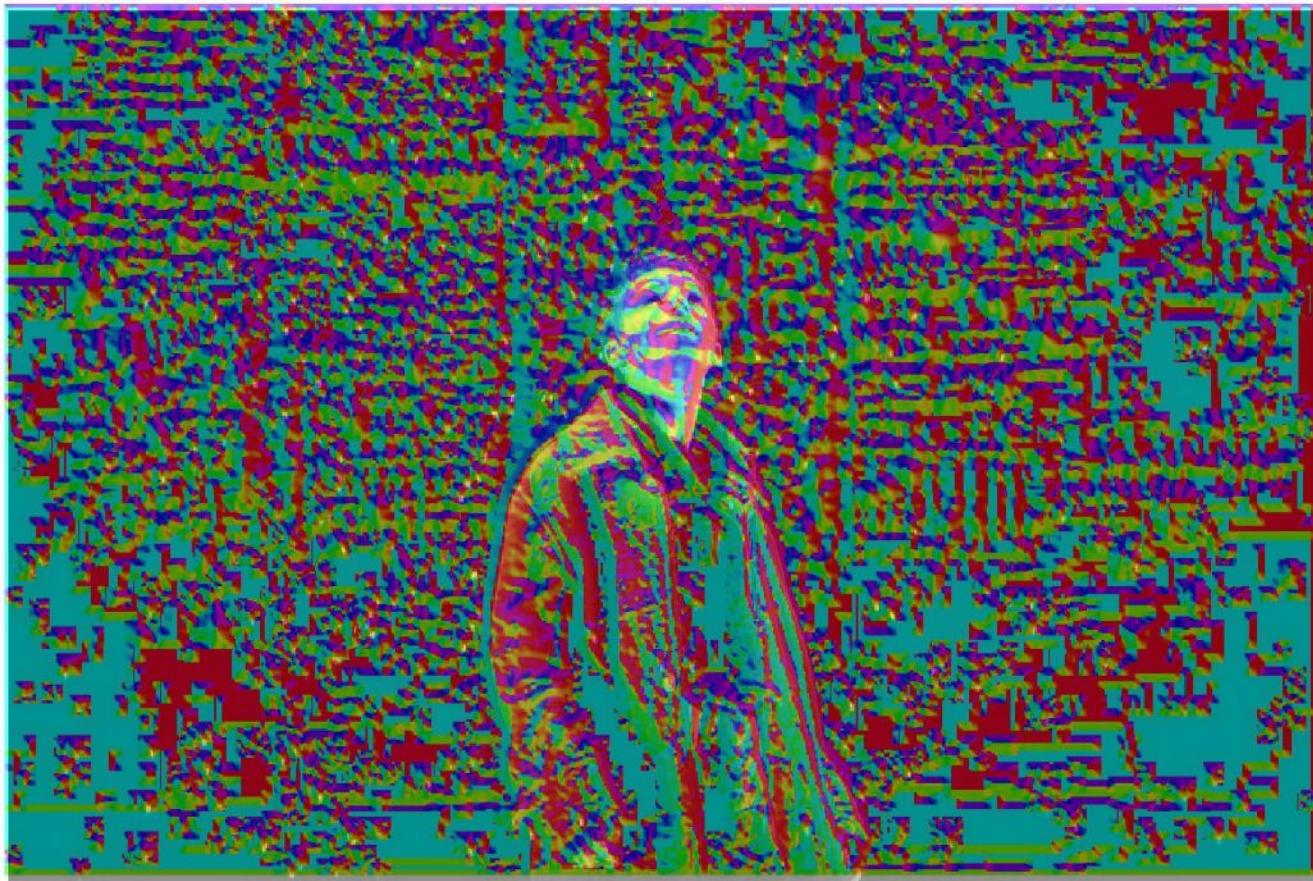


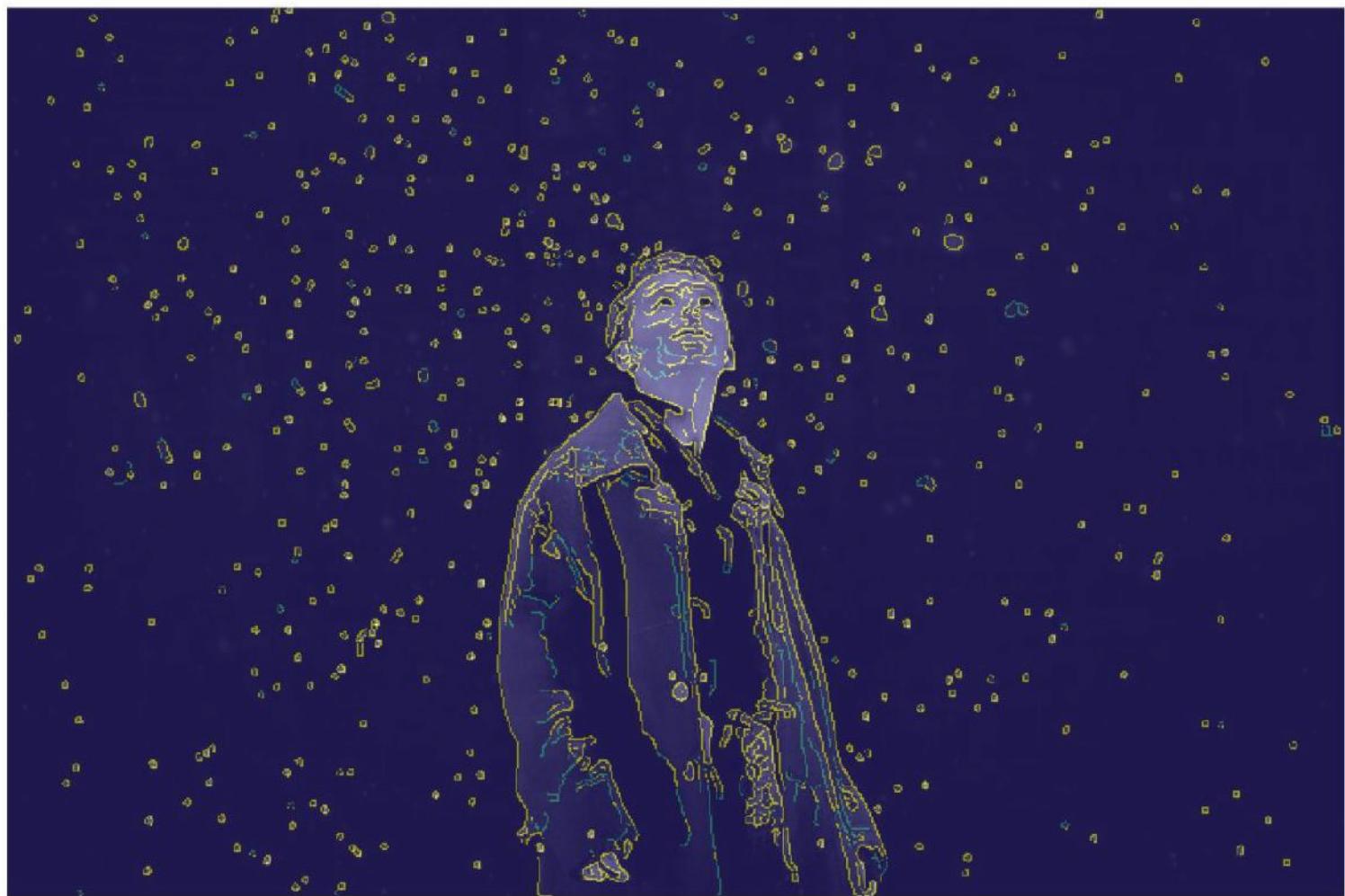












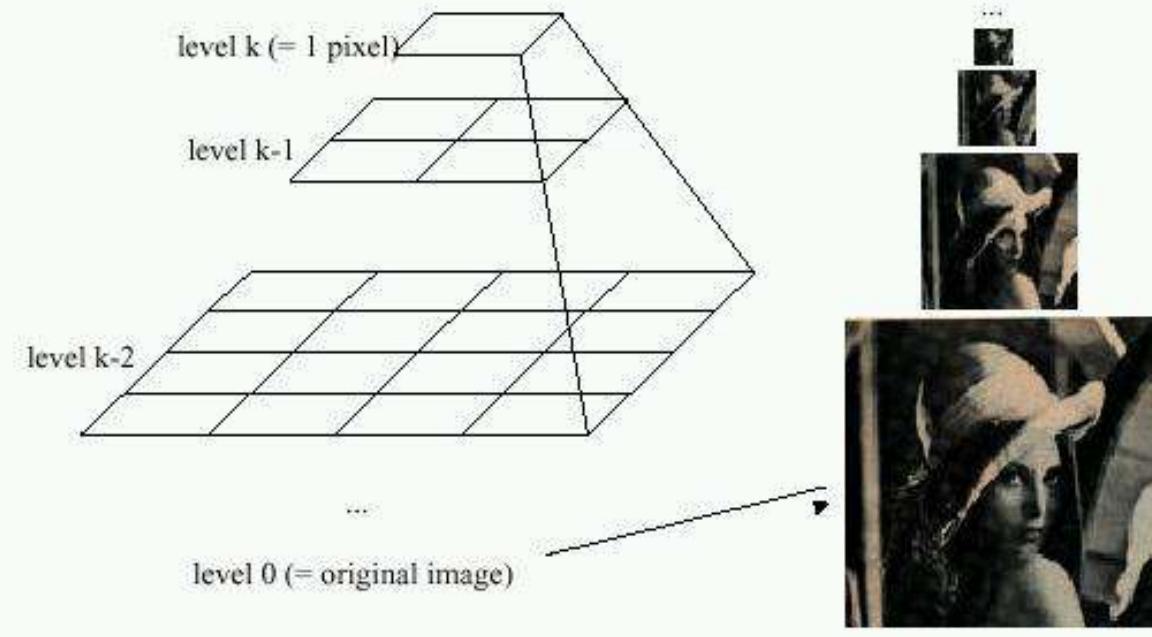


Video 3.4

Jianbo Shi

Image Pyramids

Idea: Represent $N \times N$ image as a “pyramid” of $1 \times 1, 2 \times 2, 4 \times 4, \dots, 2^k \times 2^k$ images (assuming $N=2^k$)



Known as a Gaussian Pyramid [Burt and Adelson, 1983]

- In computer graphics, a *mip map* [Williams, 1983]
- A precursor to *wavelet transform*



512

256

128

64

32

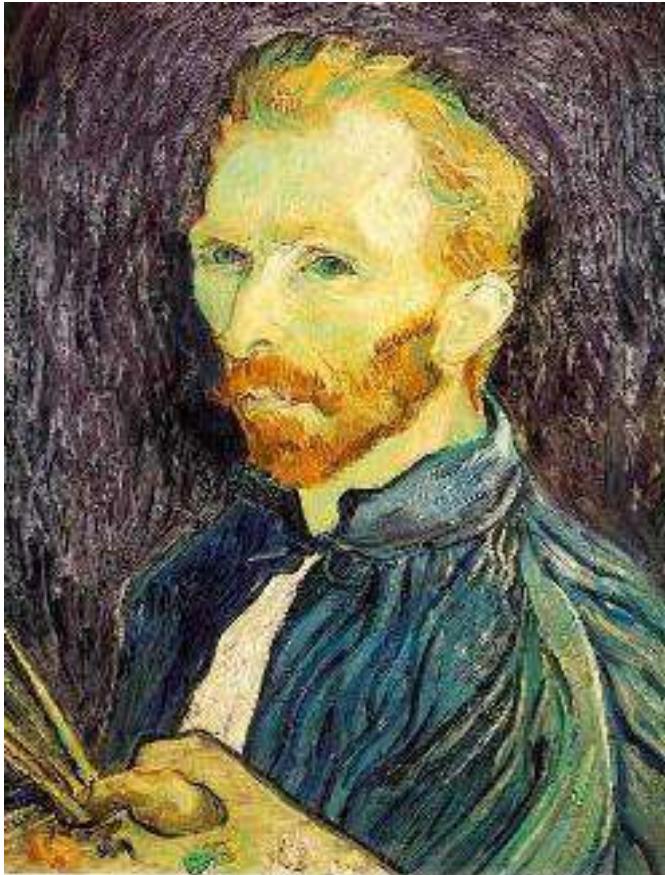
16

8



Figure from David Forsyth 11

Image sub-sampling



1/4



1/8

Throw away every other row and
column to create a $1/2$ size image
- called *image sub-sampling*

Image sub-sampling



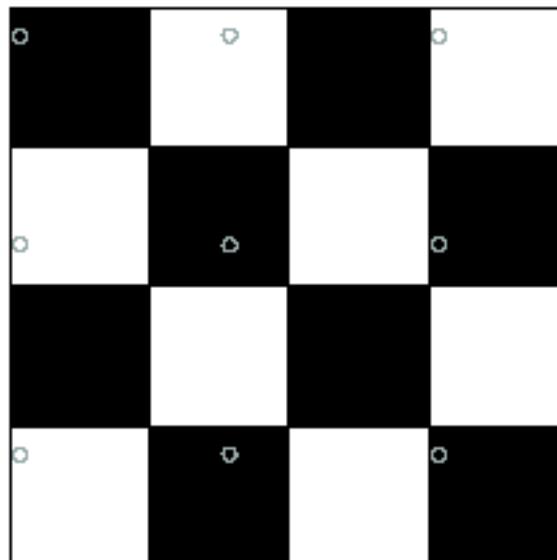
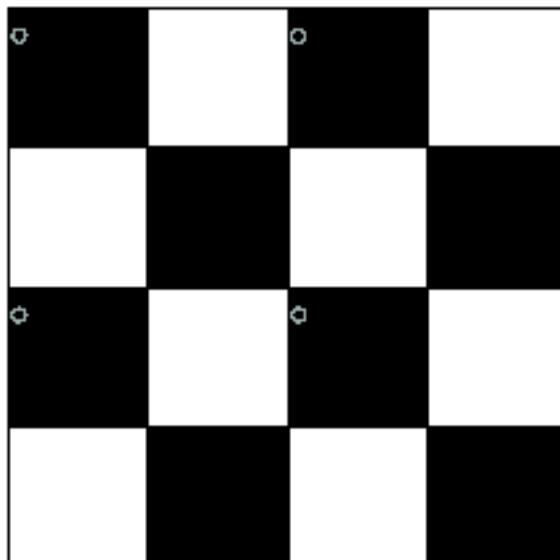
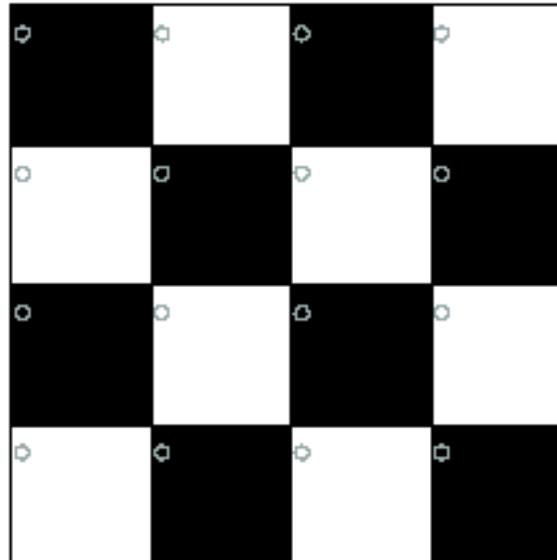
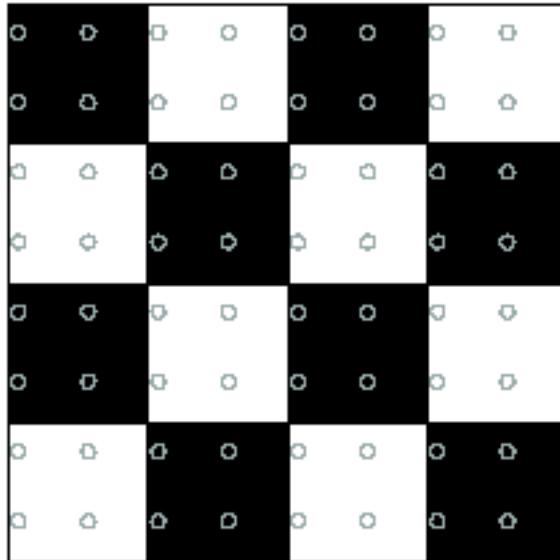
1/2

1/4 (2x zoom)

1/8 (4x zoom)

Why does this look so bad?

Sampling



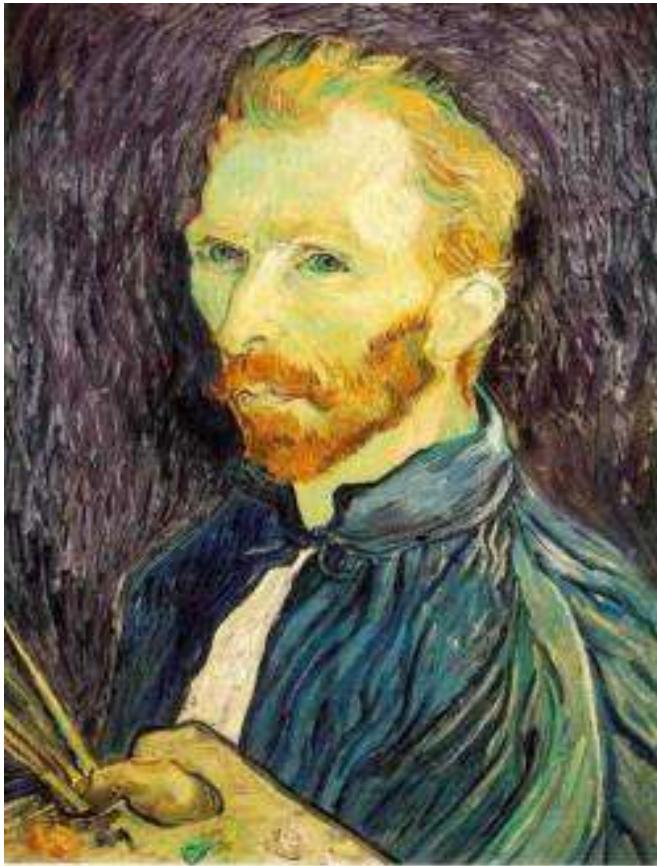
Good sampling:

- Sample often or,
- Sample wisely

Bad sampling:

- see aliasing in action!

Gaussian pre-filtering



Gaussian 1/2



G 1/4

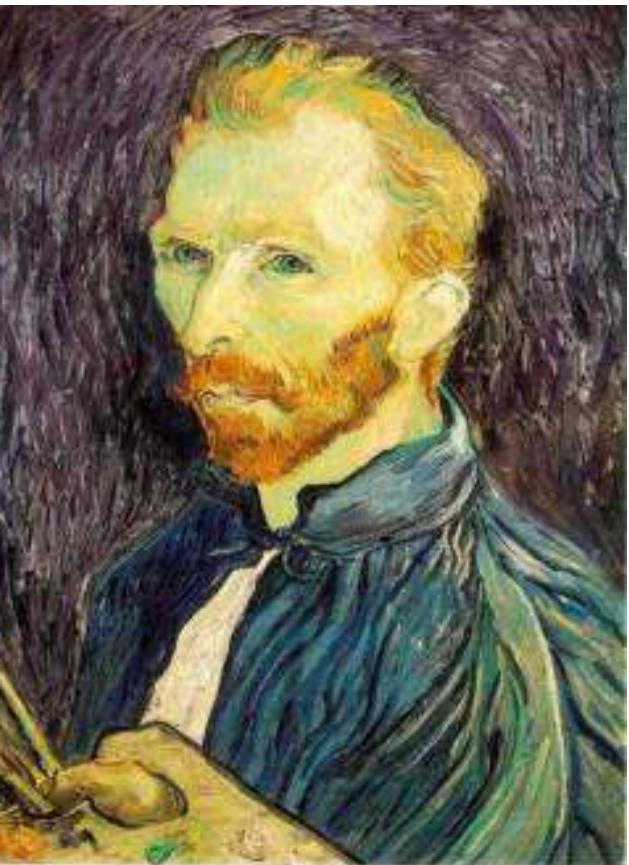


G 1/8

Solution: filter the image, *then* subsample

- Filter size should double for each $\frac{1}{2}$ size reduction. Why?

Subsampling with Gaussian pre-filtering



Gaussian 1/2



G 1/4



G 1/8

Solution: filter the image, *then* subsample

- Filter size should double for each $\frac{1}{2}$ size reduction. Why?
- How can we speed this up?



Video 3.5

Jianbo Shi

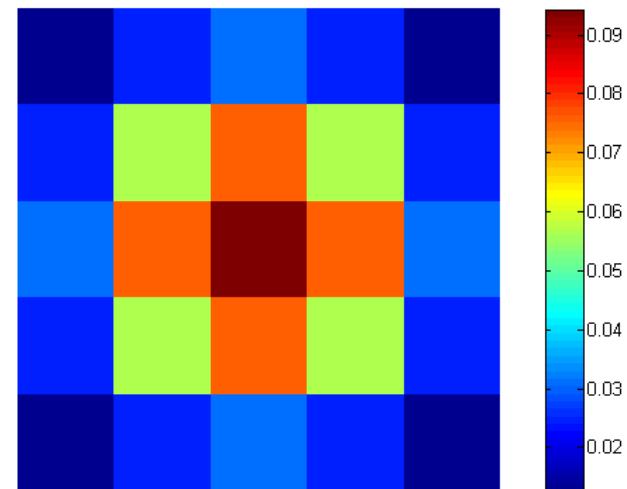
Canny Edge Implementation

```
img = imread ('image.png');  
img = rgb2gray(img);  
img = double (img);
```

```
% Value for high and low thresholding  
threshold_low = 0.035;  
threshold_high = 0.175;
```

```
%% Gaussian filter (https://en.wikipedia.org/wiki/Canny\_edge\_detector)  
G = [2, 4, 5, 4, 2; 4, 9, 12, 9, 4; 5, 12, 15, 12, 5; 4, 9, 12, 9, 4; 2, 4, 5, 4, 2];  
G = 1/159.* G;
```

```
%Filter for horizontal and vertical direction  
dx = [1 -1];  
dy = [1; -1];
```



Canny Edge Implementation

```
% % Convolution of image with Gaussian
```

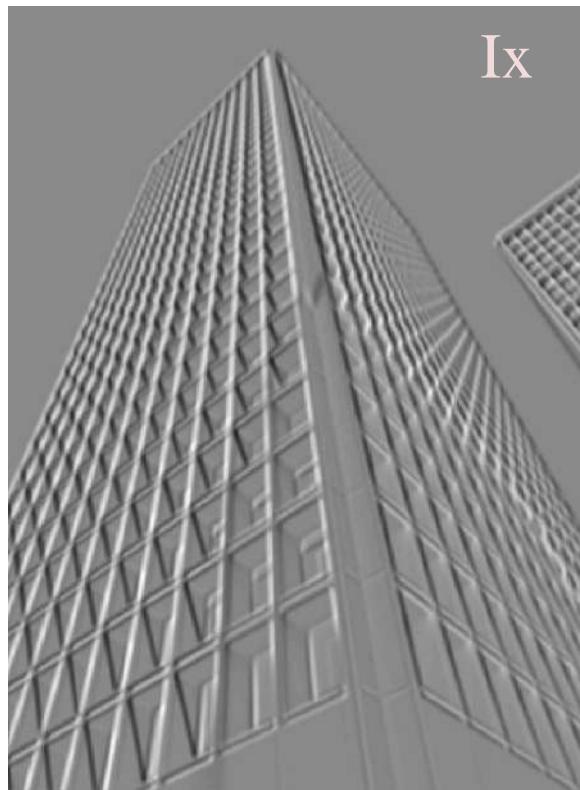
```
Gx = conv2(G, dx, 'same');
```

```
Gy = conv2(G, dy, 'same');
```

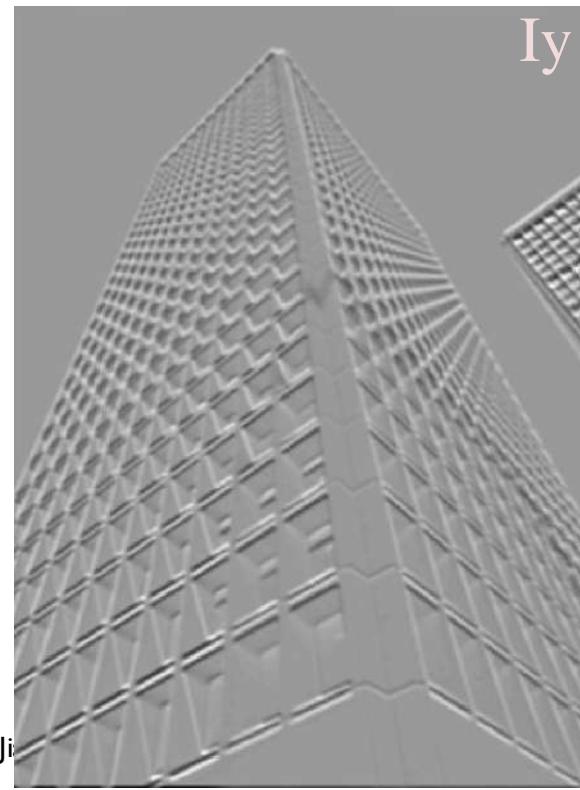
```
% Convolution of image with Gx and Gy
```

```
Ix = conv2(img, Gx, 'same');
```

```
Iy = conv2(img, Gy, 'same');
```



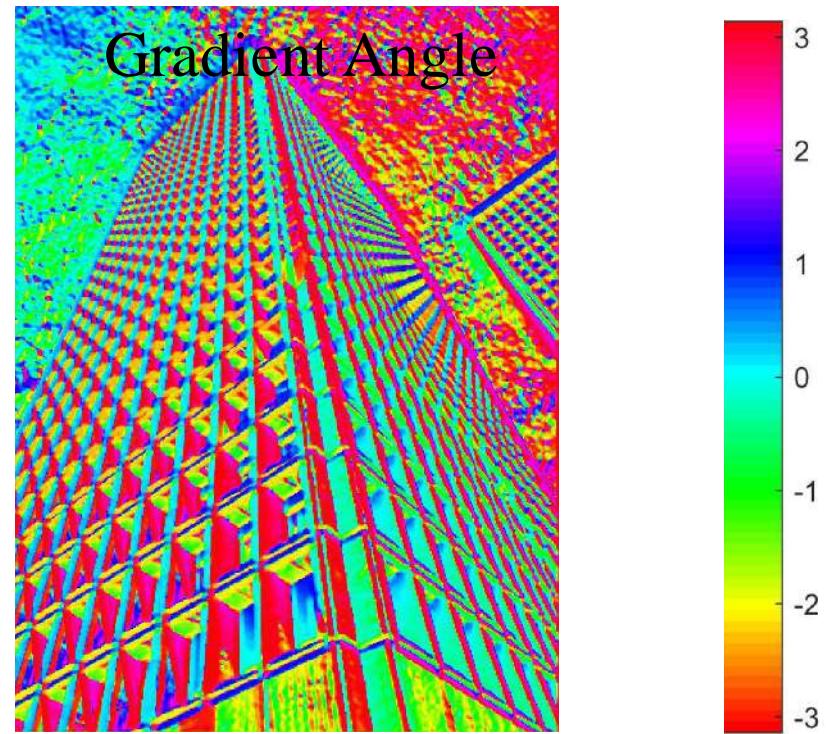
I_x



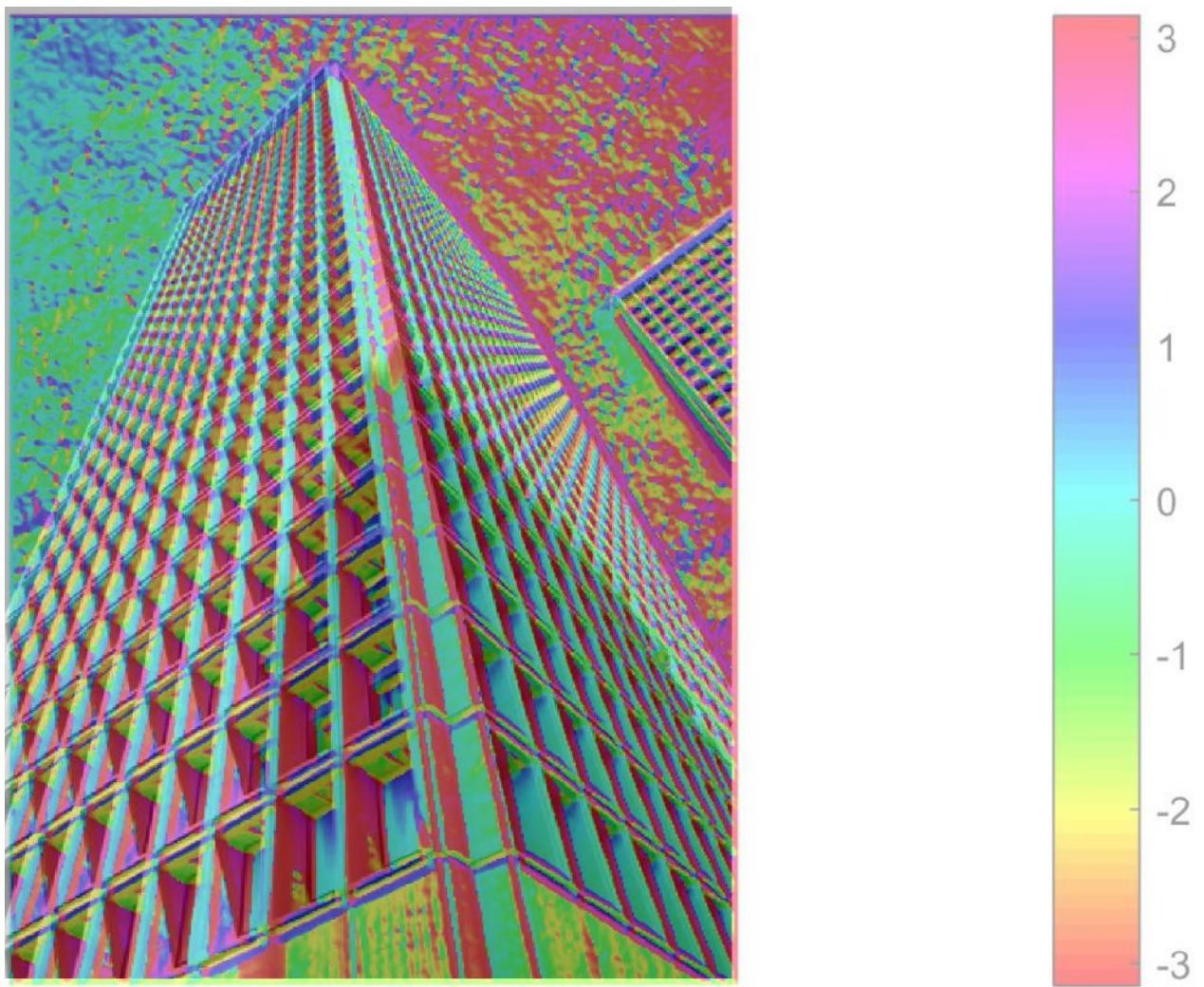
I_y

Canny Edge Implementation

```
angle = atan2(Iy, Ix);  
mag = sqrt(Iy.^2 + Ix.^2);
```



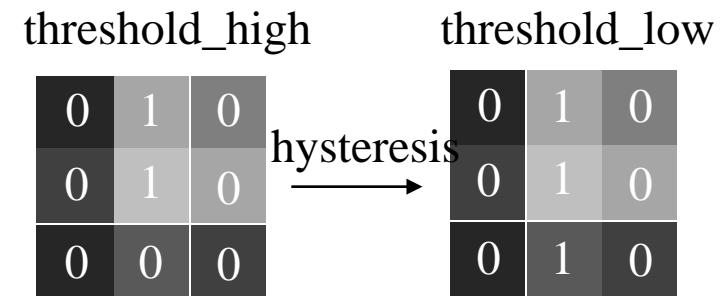
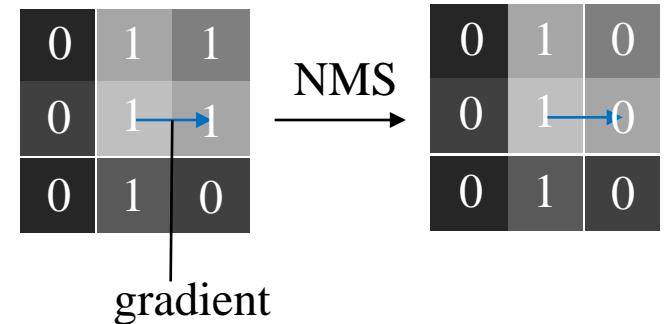
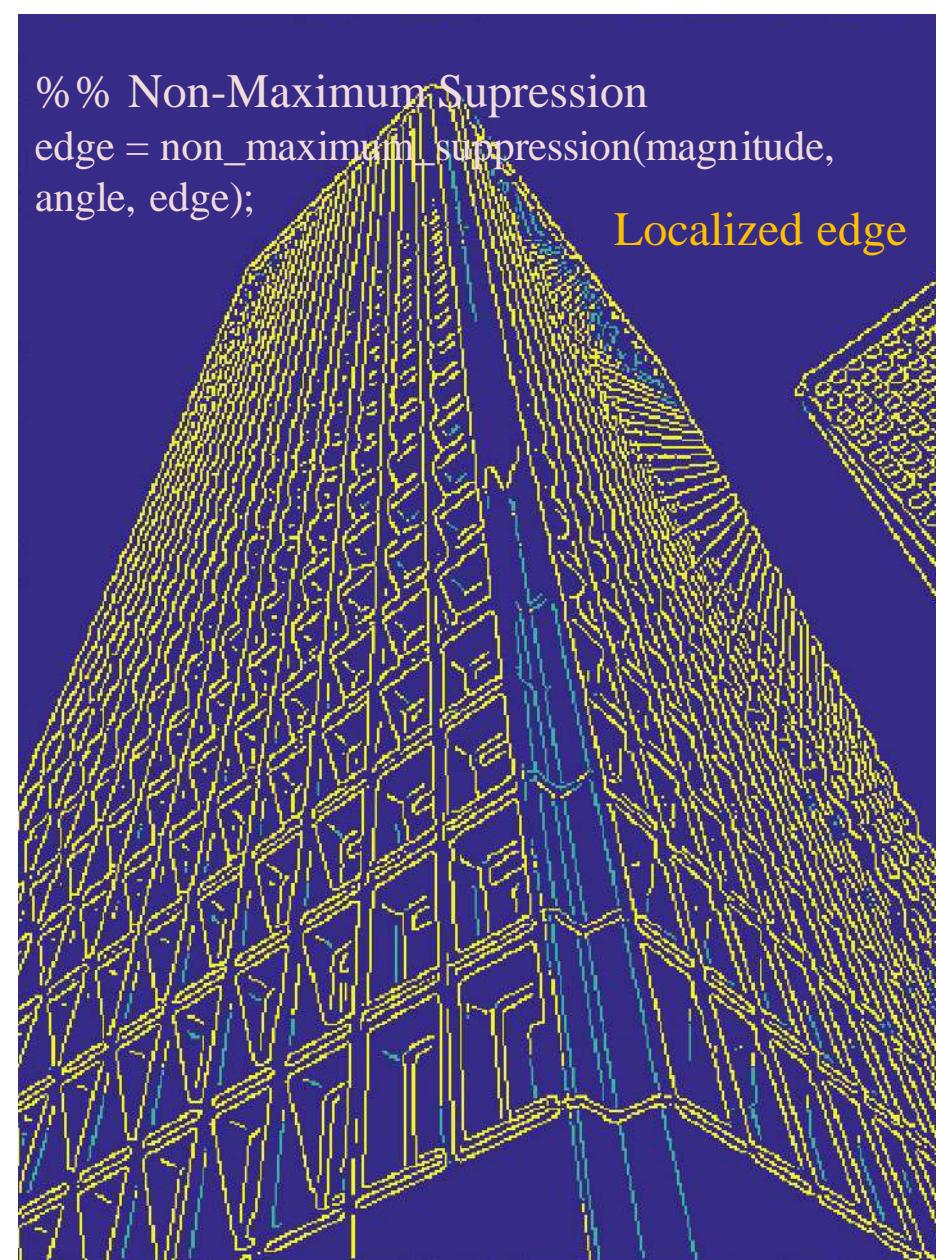




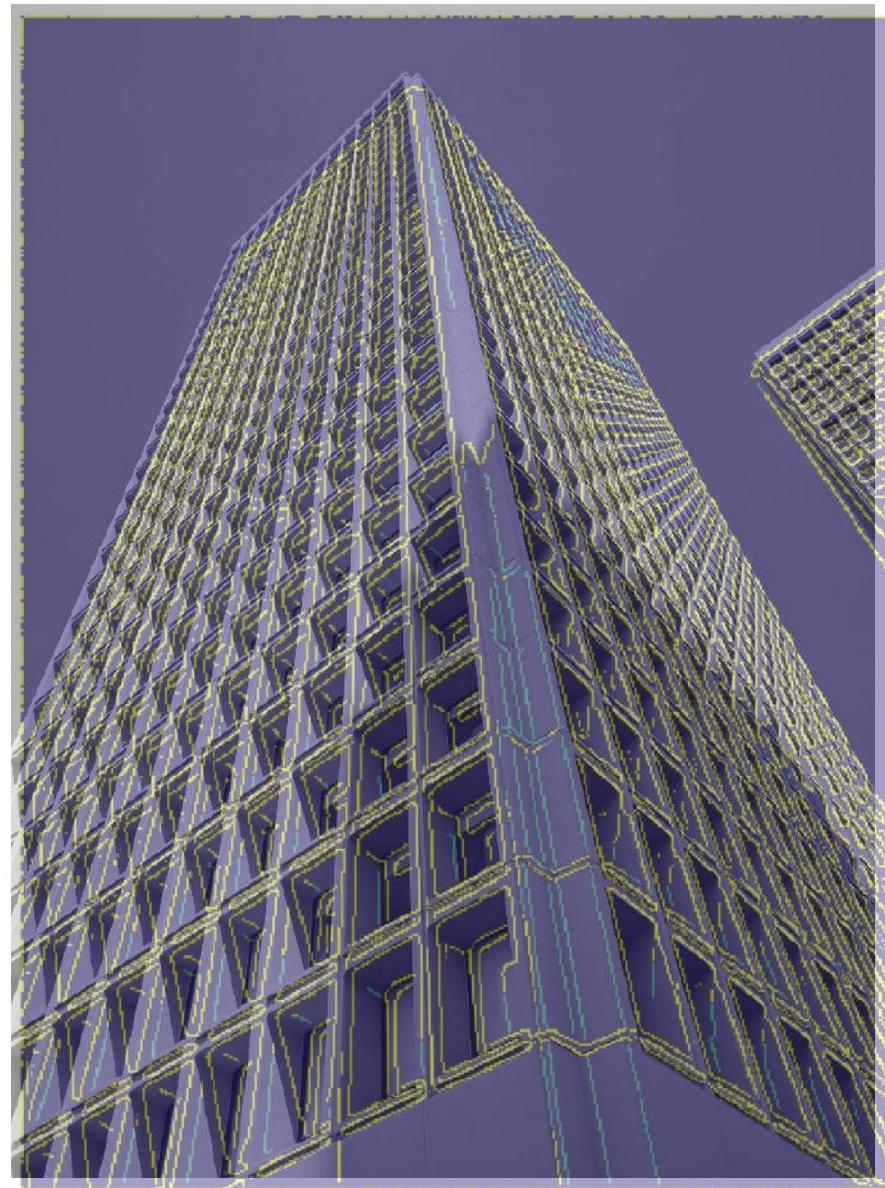
Canny Edge Implementation

```
%% Non-Maximum Suppression  
edge = non_maximum_suppression(magnitude,  
angle, edge);
```

Localized edge

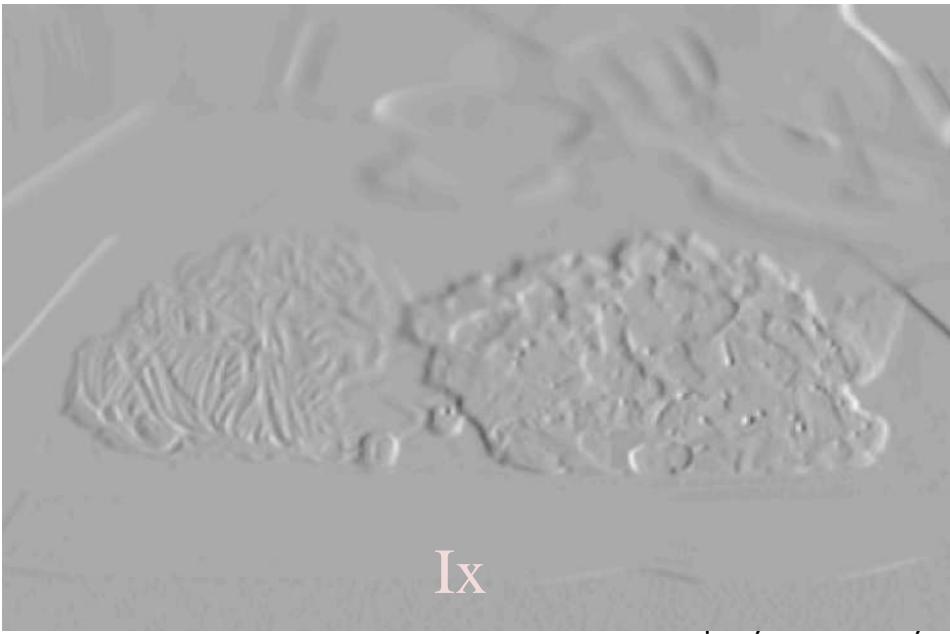


```
low = threshold_low * max(edge());  
high = threshold_high * max(edge());  
linked_edge = hysteresis_thresholding(low, high);
```

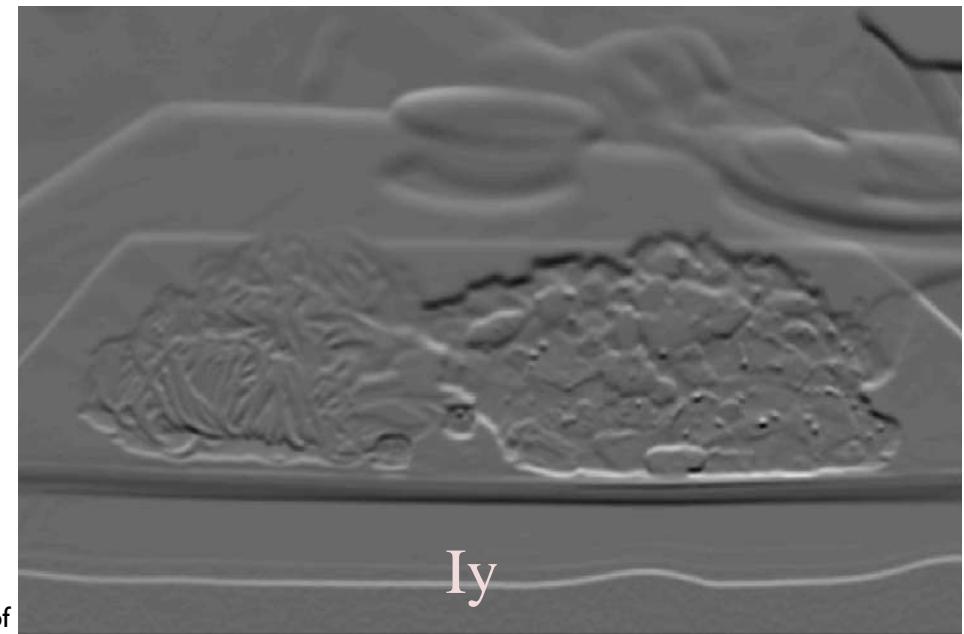


```
% % Convolution of image with Gaussian  
Gx = conv2(G, dx, 'same');  
Gy = conv2(G, dy, 'same');
```

```
% Convolution of image with Gx and Gy  
Ix = conv2(img, Gx, 'same');  
Iy = conv2(img, Gy, 'same');
```



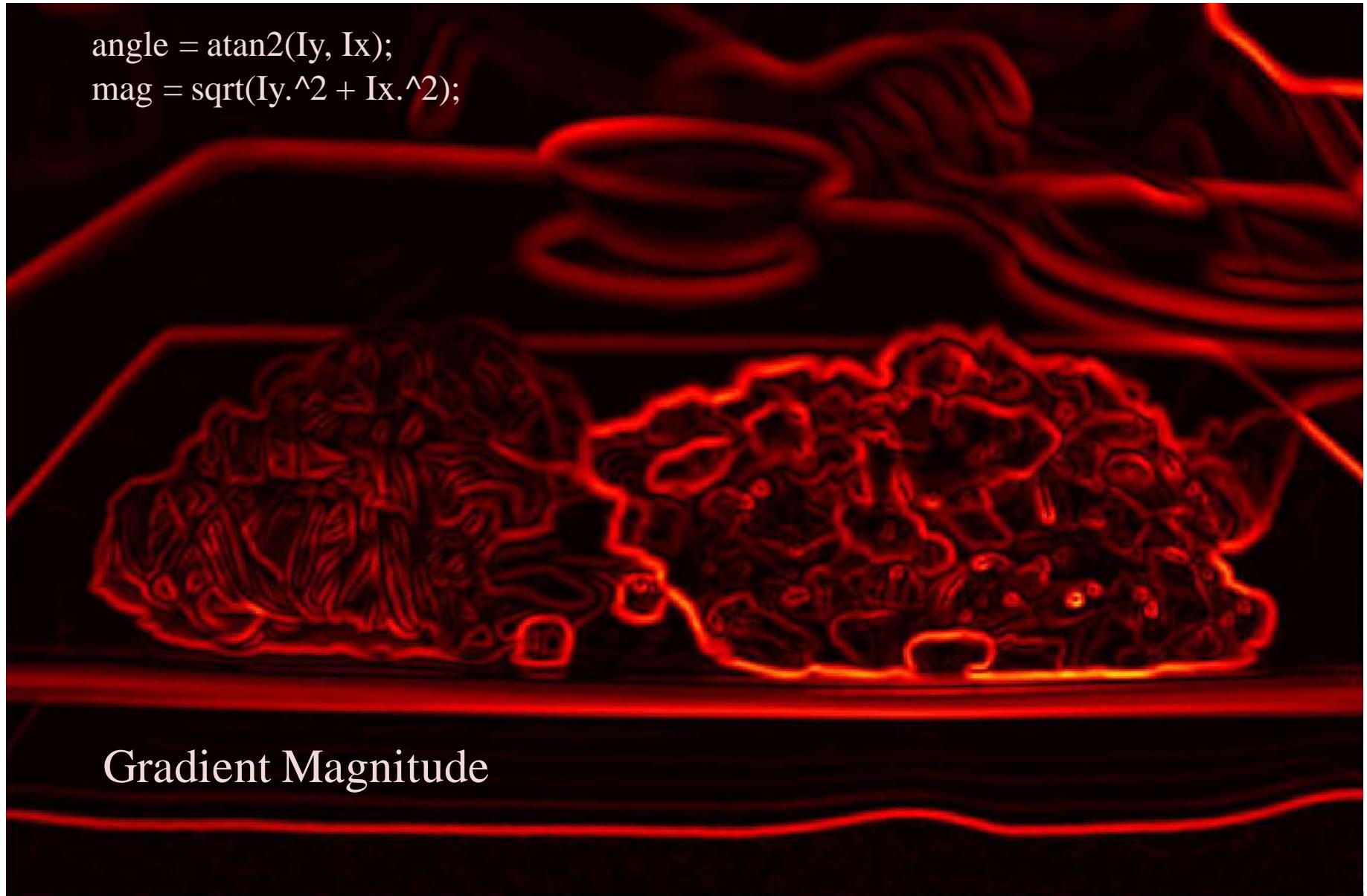
Ix



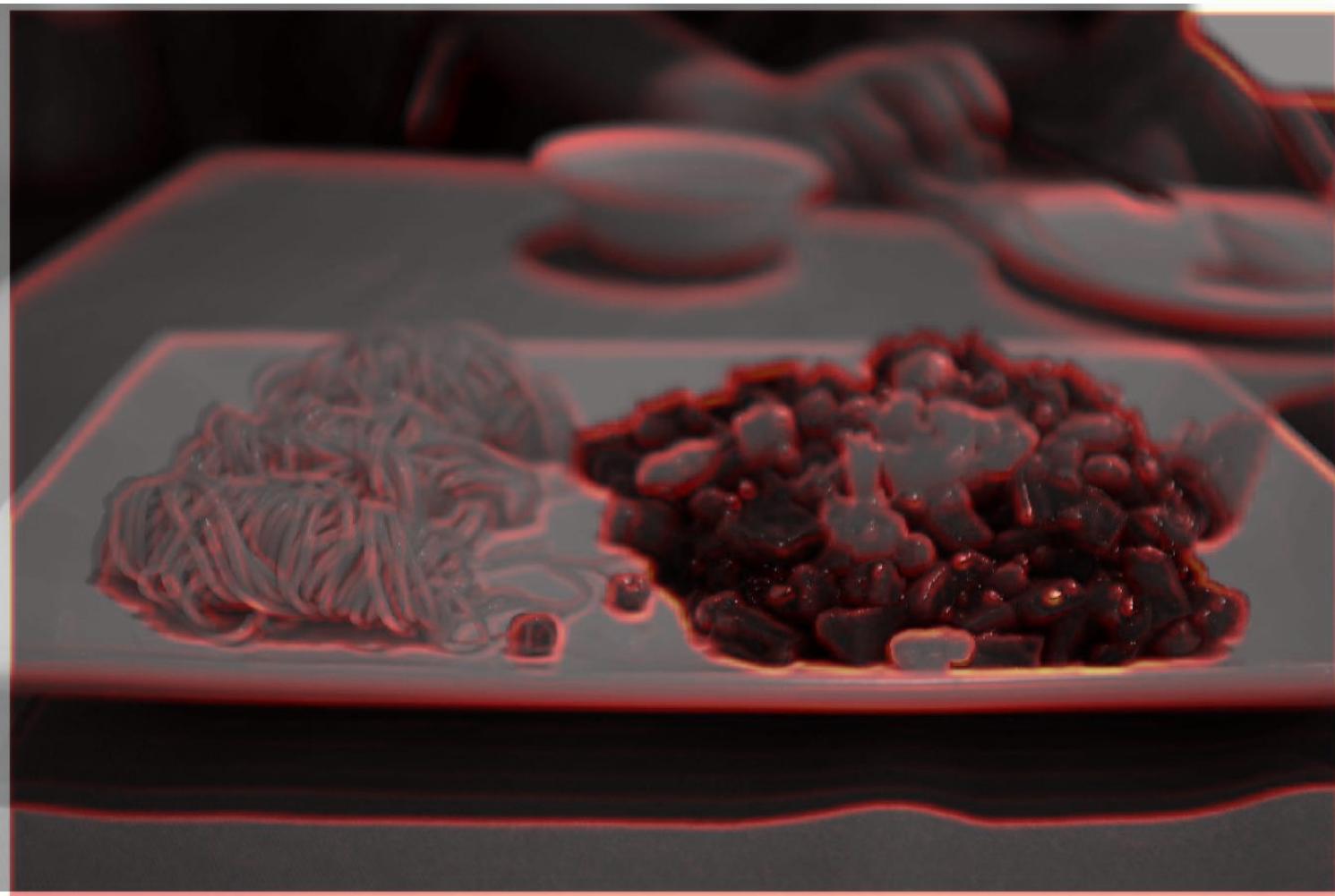
Iy

Canny Edge Implementation

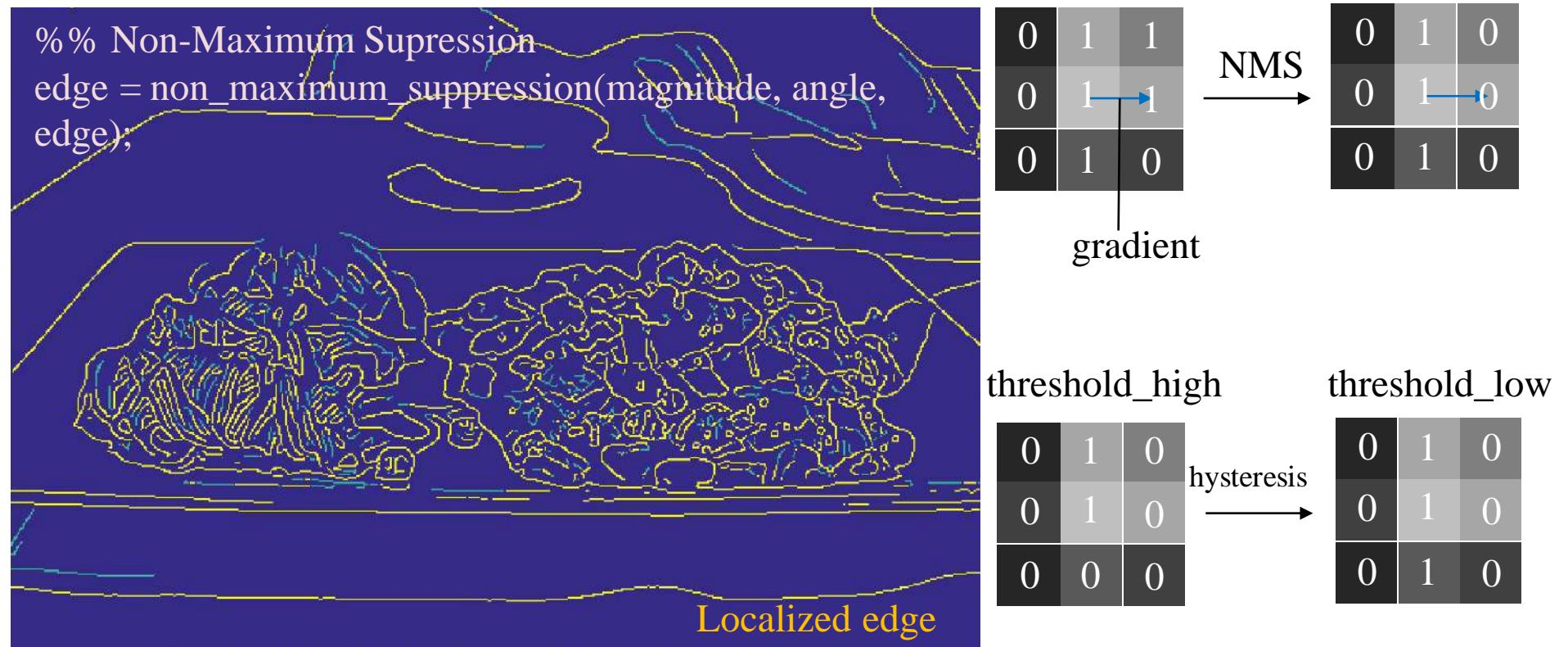
```
angle = atan2(Iy, Ix);  
mag = sqrt(Iy.^2 + Ix.^2);
```



Gradient Magnitude



Canny Edge Implementation



```
low = threshold_low * max(edge(:));  
high = threshold_high * max(edge(:));  
linked_edge = hysteresis_thresholding(low, high);
```



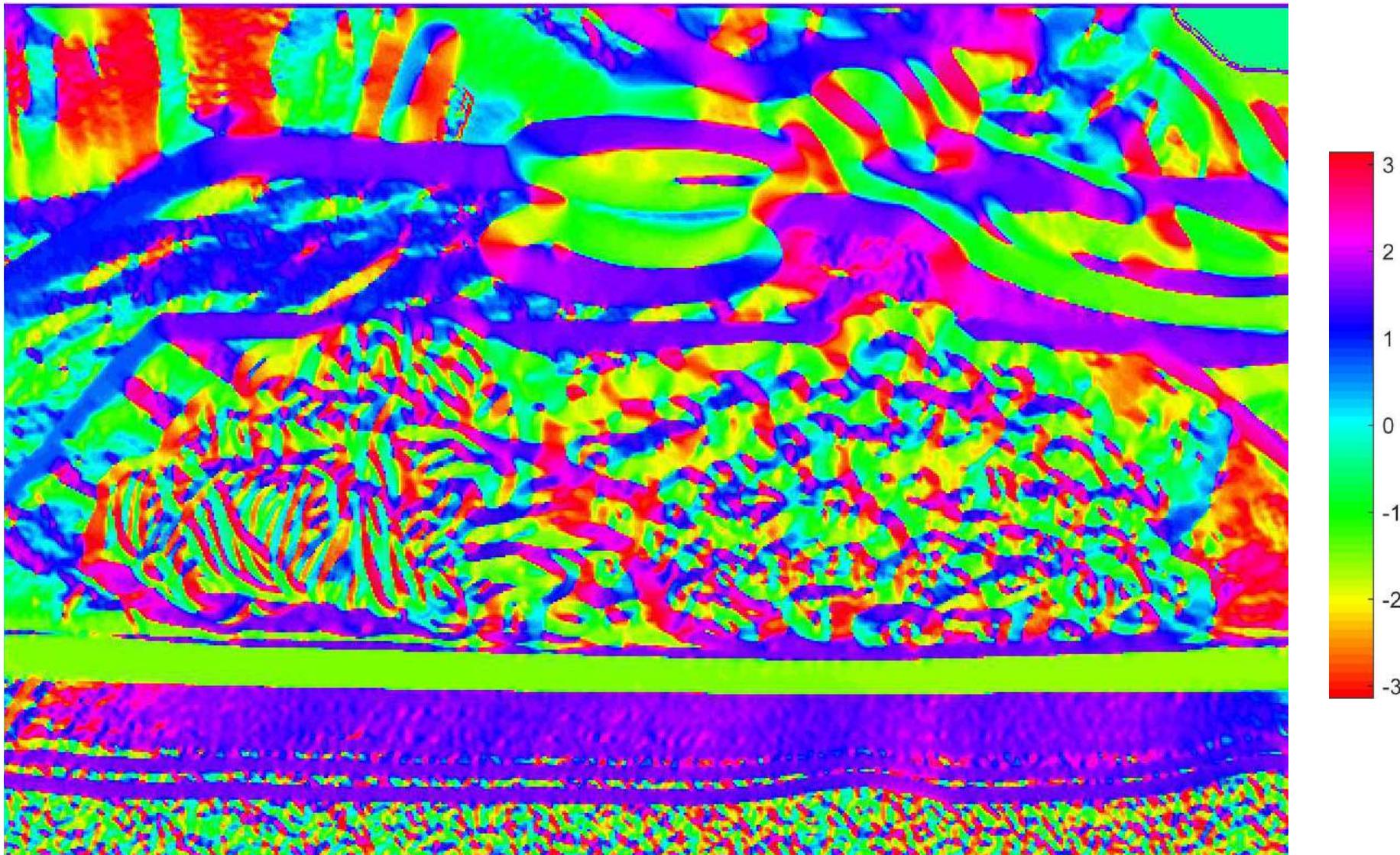
Video 3.6

Jianbo Shi

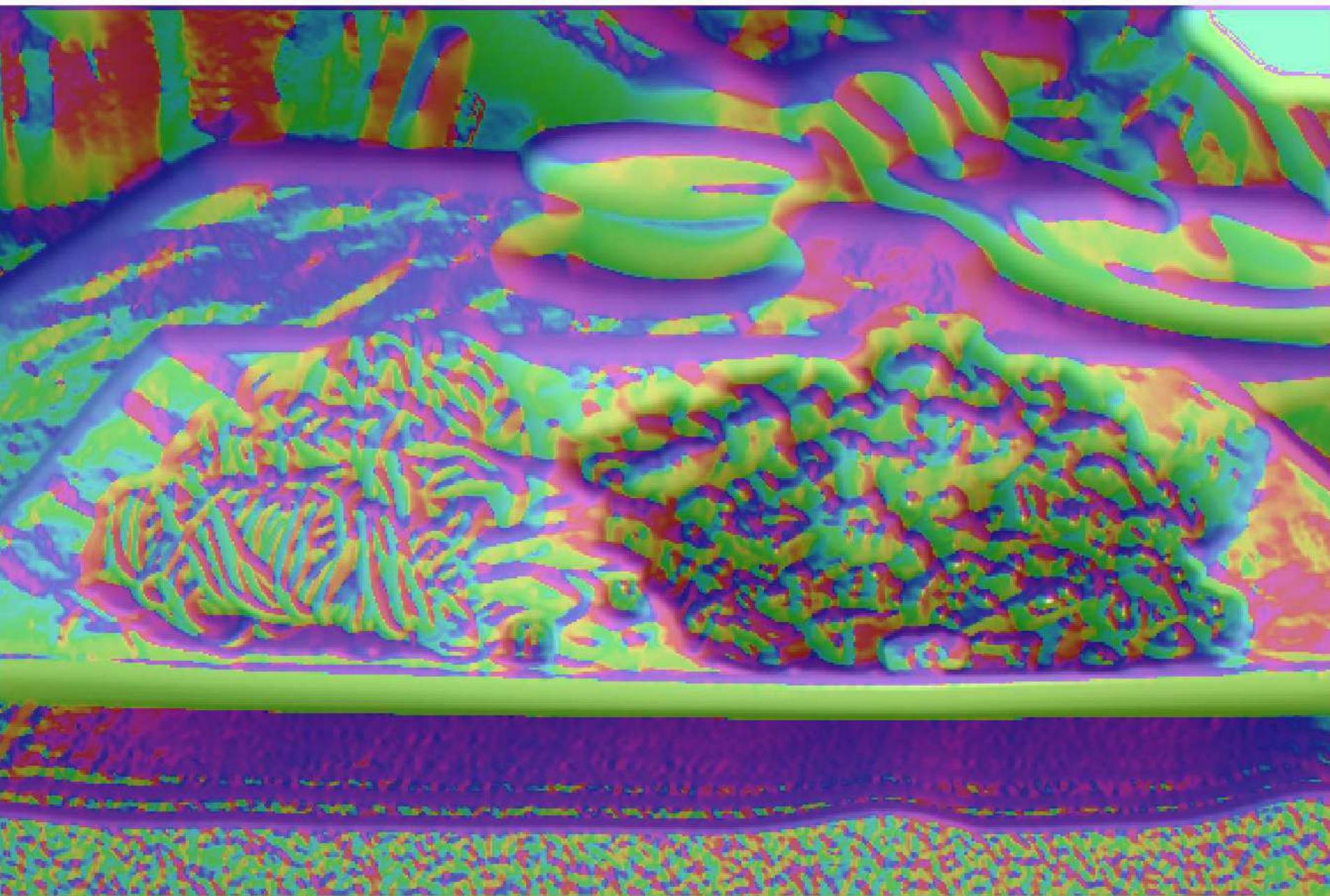
Edge Implementation

angle = atan2(Iy, Ix);
mag = sqrt(Iy.^2 + Ix.^2);

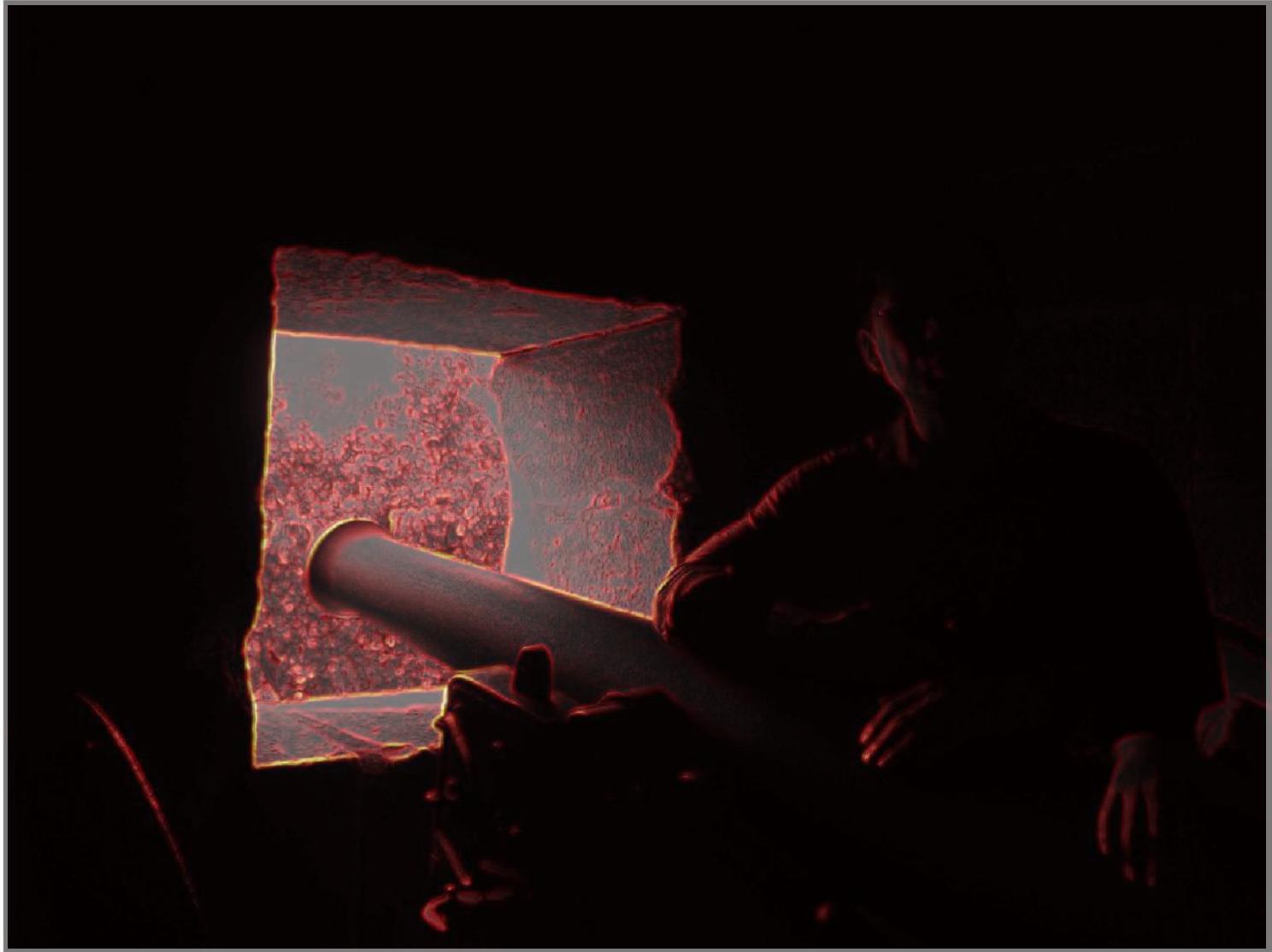
Gradient Angle

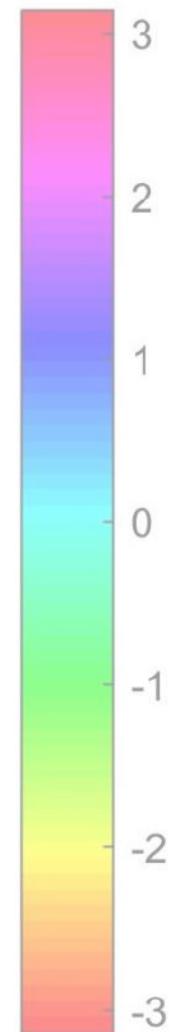
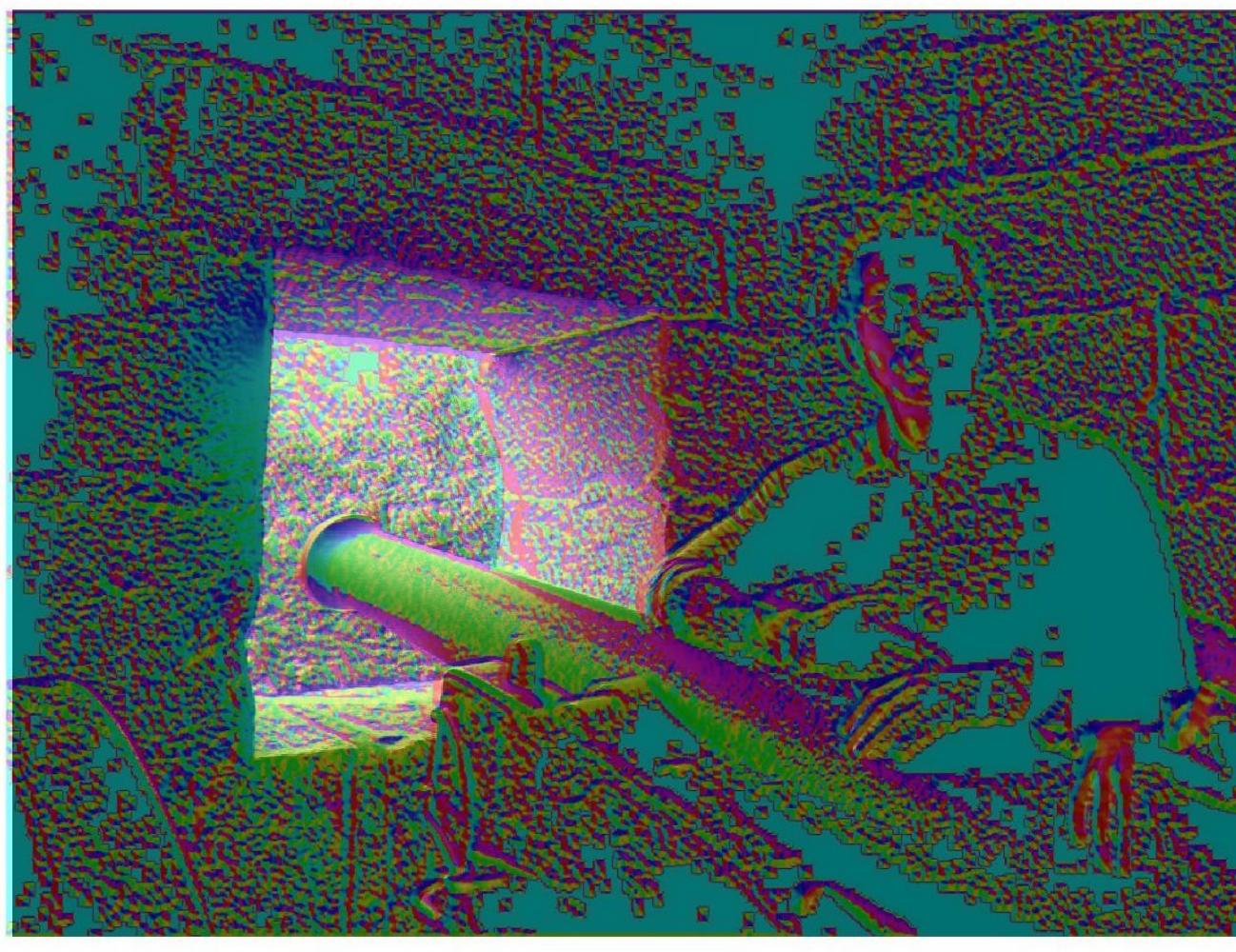


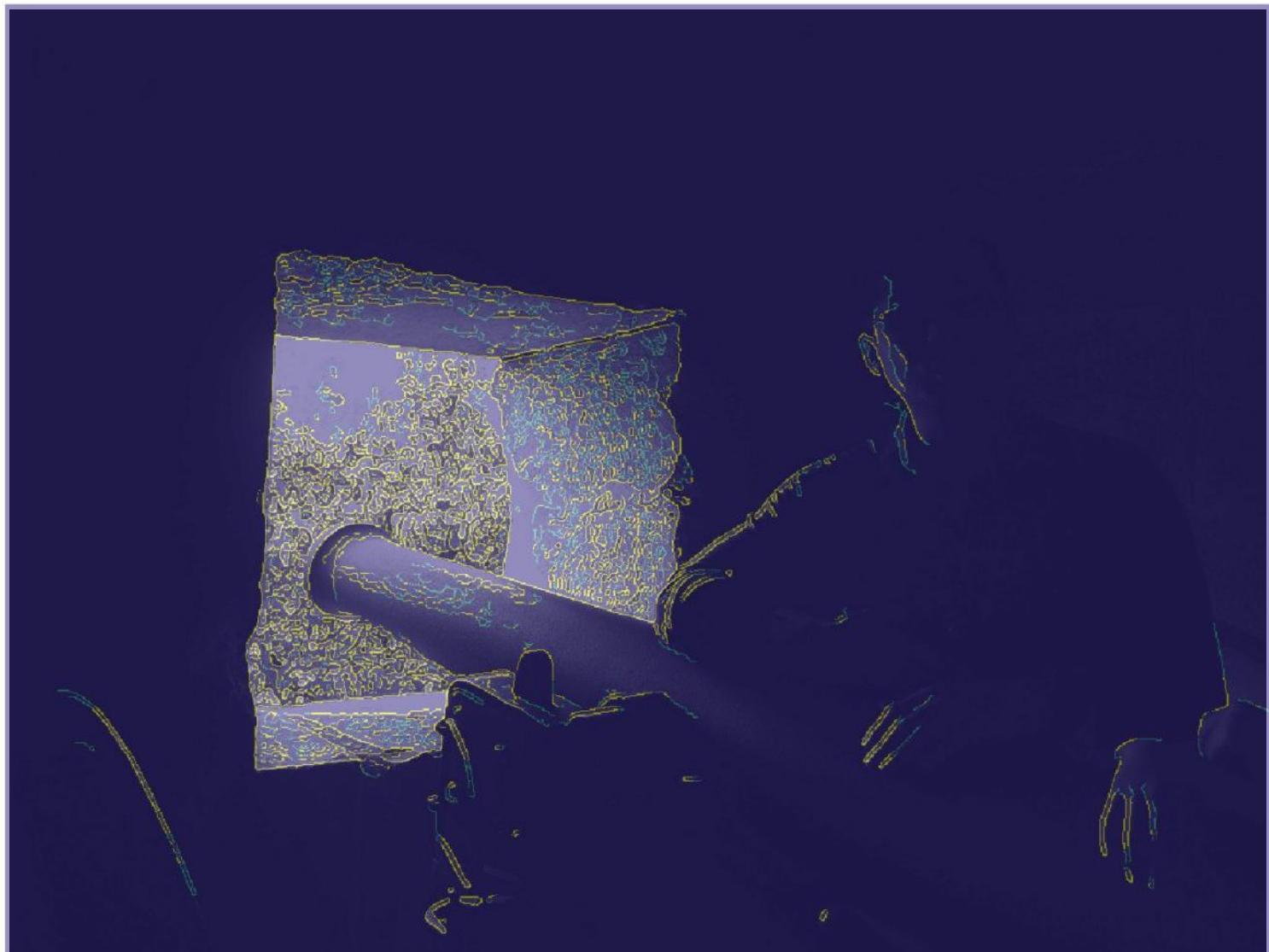






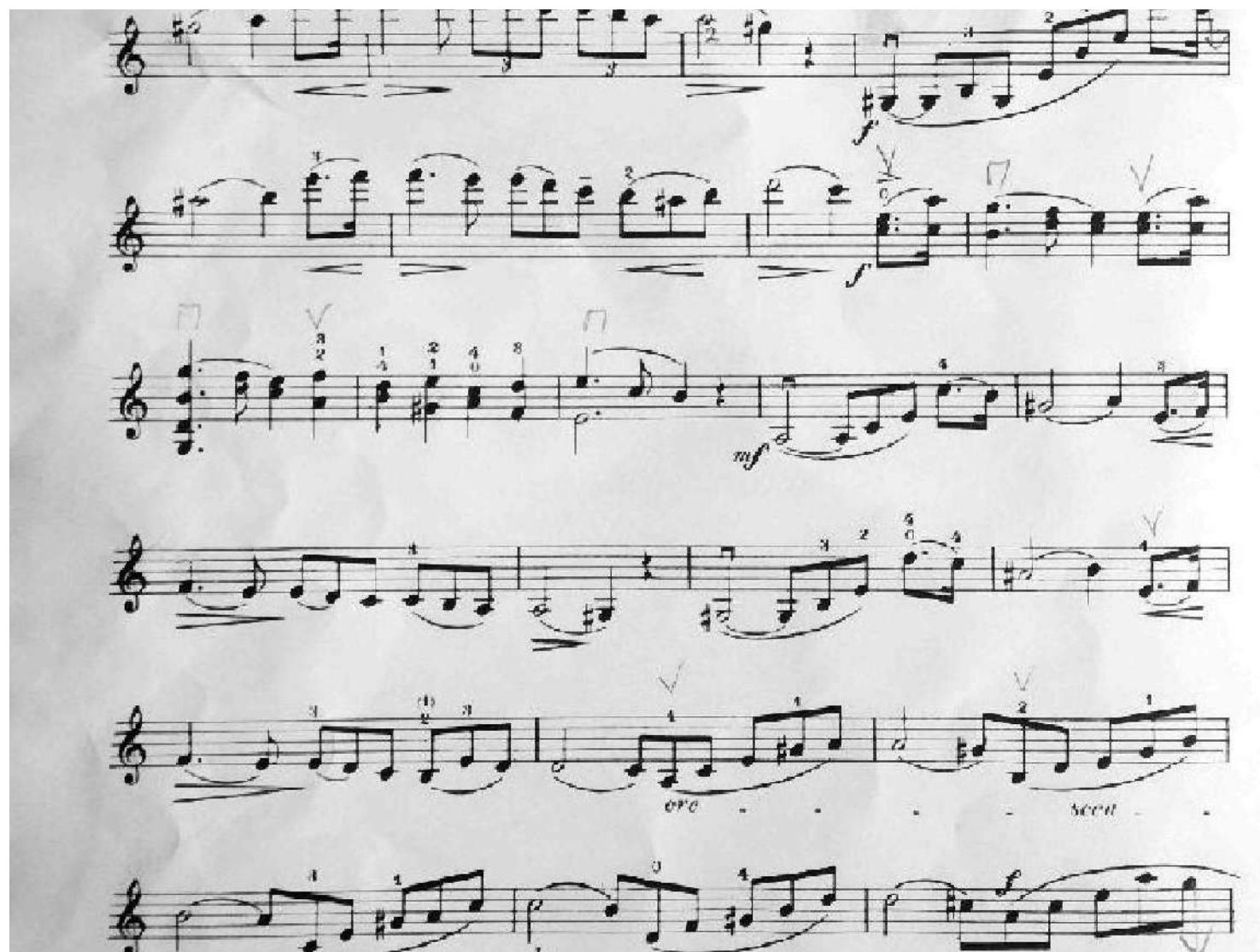






Ix

Iy



```
% % Convolution of image with Gaussian
```

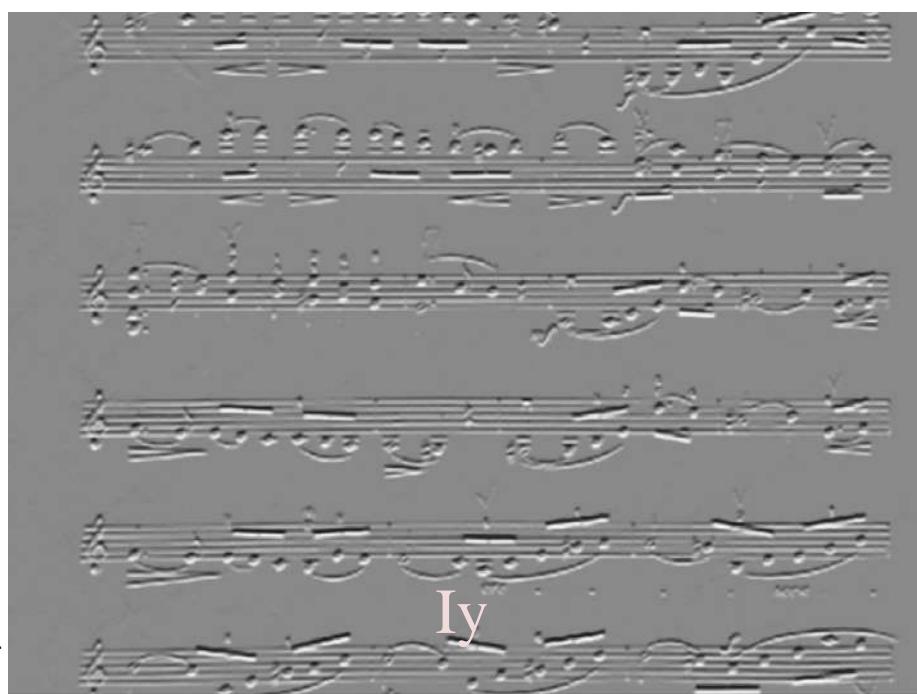
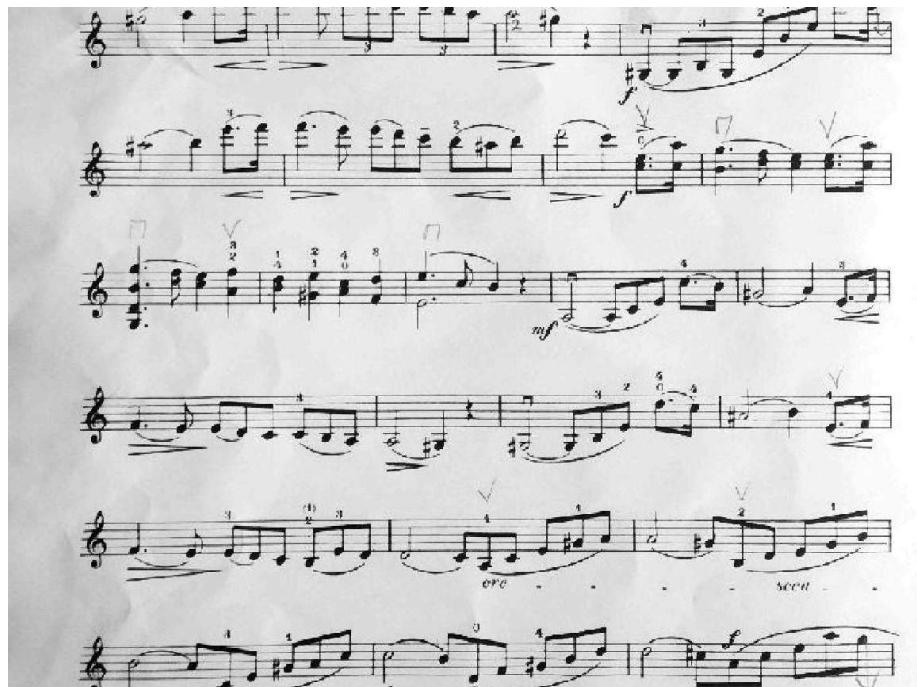
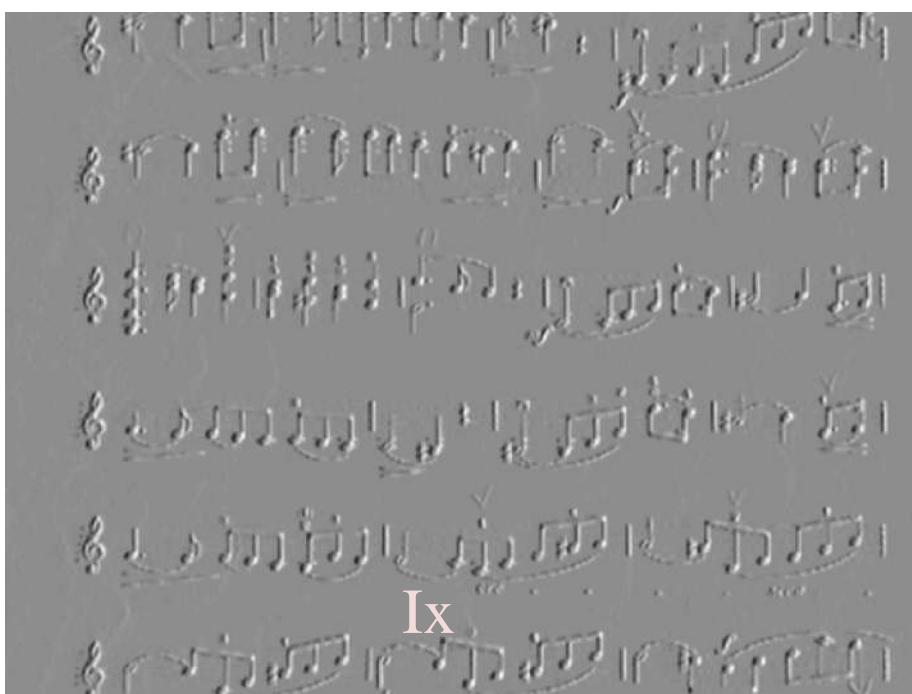
```
Gx = conv2(G, dx, 'same');
```

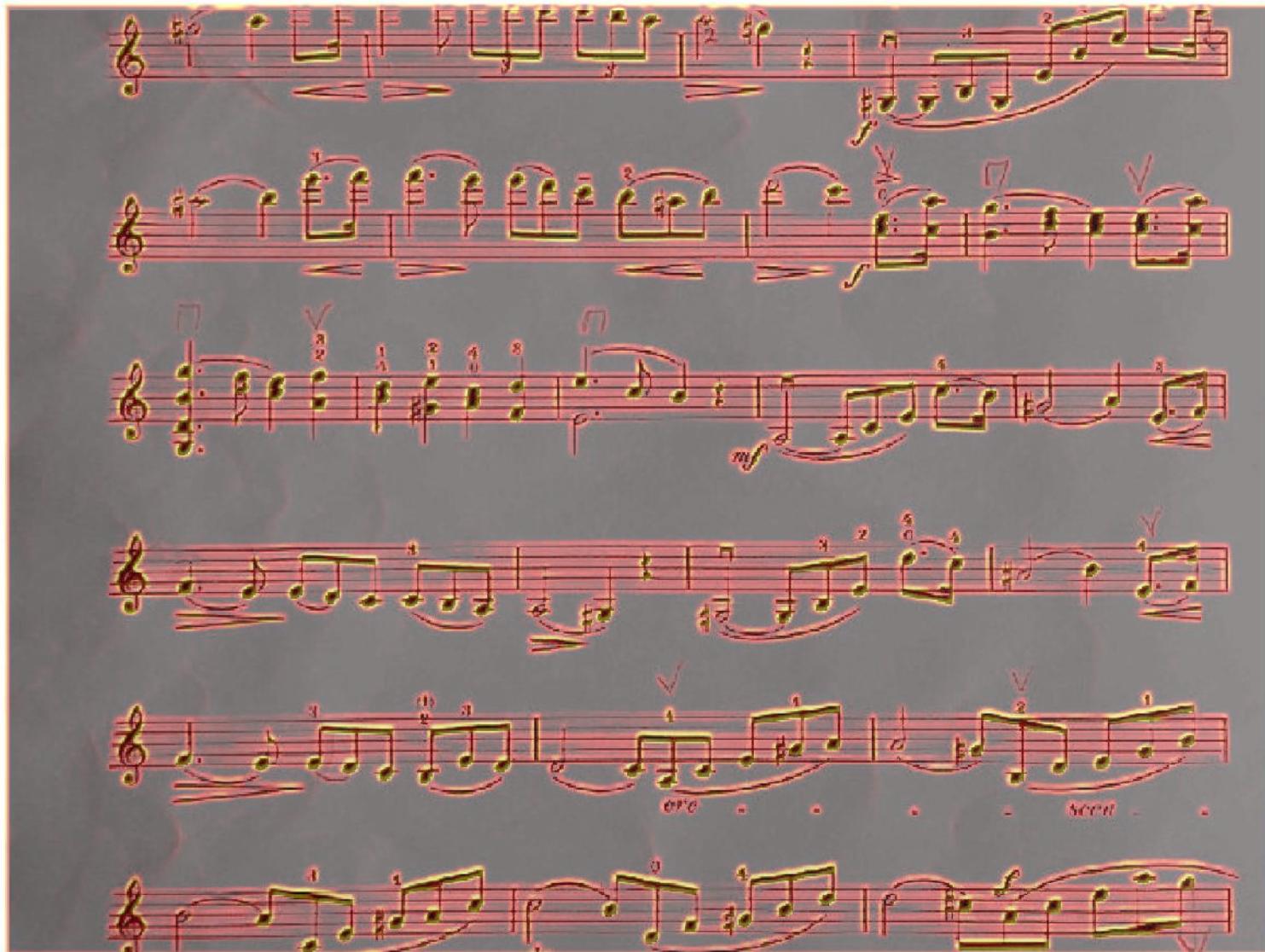
```
Gy = conv2(G, dy, 'same');
```

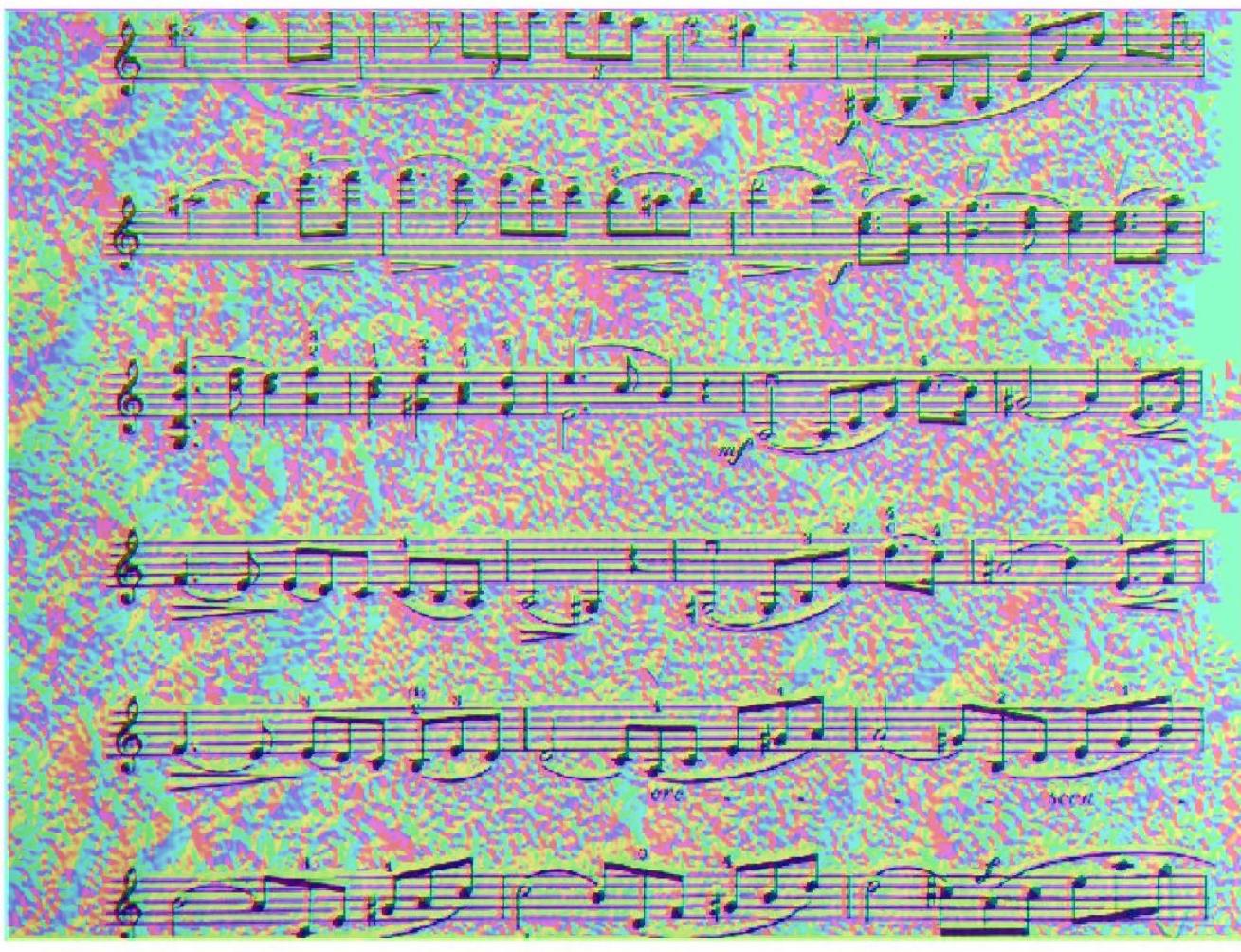
```
% Convolution of image with Gx and Gy
```

```
Ix = conv2(img, Gx, 'same');
```

```
Iy = conv2(img, Gy, 'same');
```



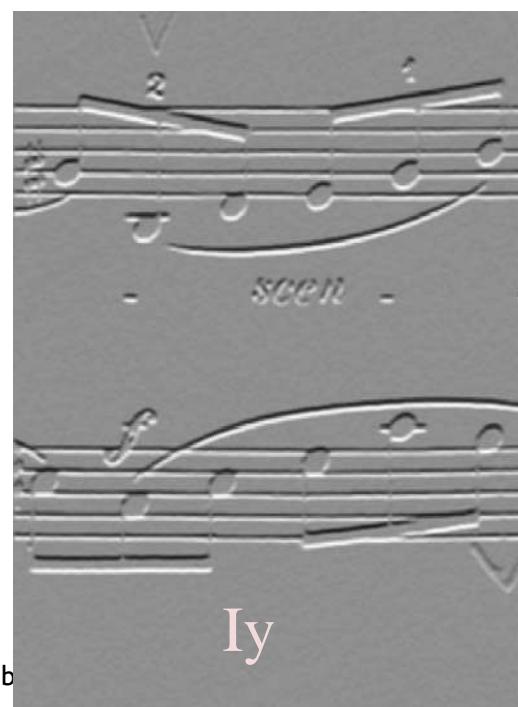


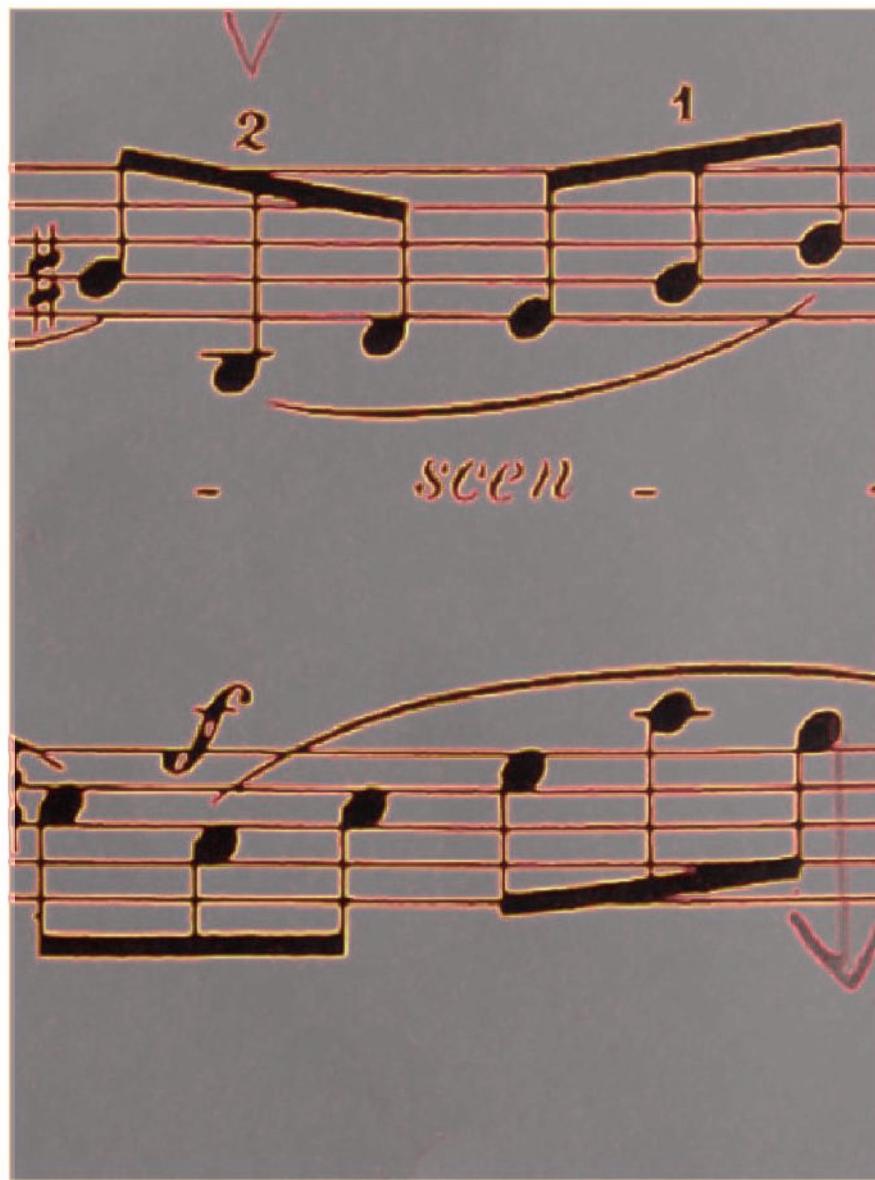




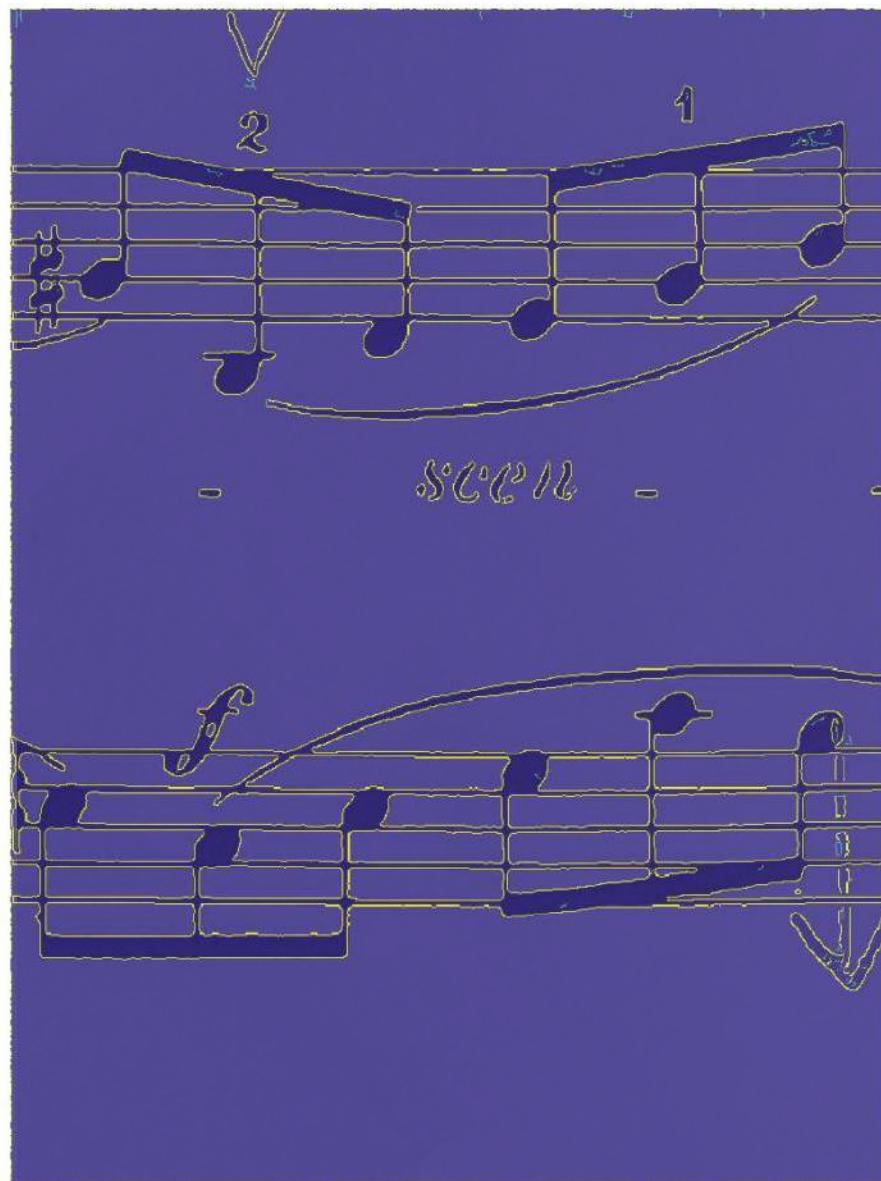
```
% % Convolution of image with Gaussian  
Gx = conv2(G, dx, 'same');  
Gy = conv2(G, dy, 'same');
```

```
% Convolution of image with Gx and Gy  
Ix = conv2(img, Gx, 'same');  
Iy = conv2(img, Gy, 'same');
```

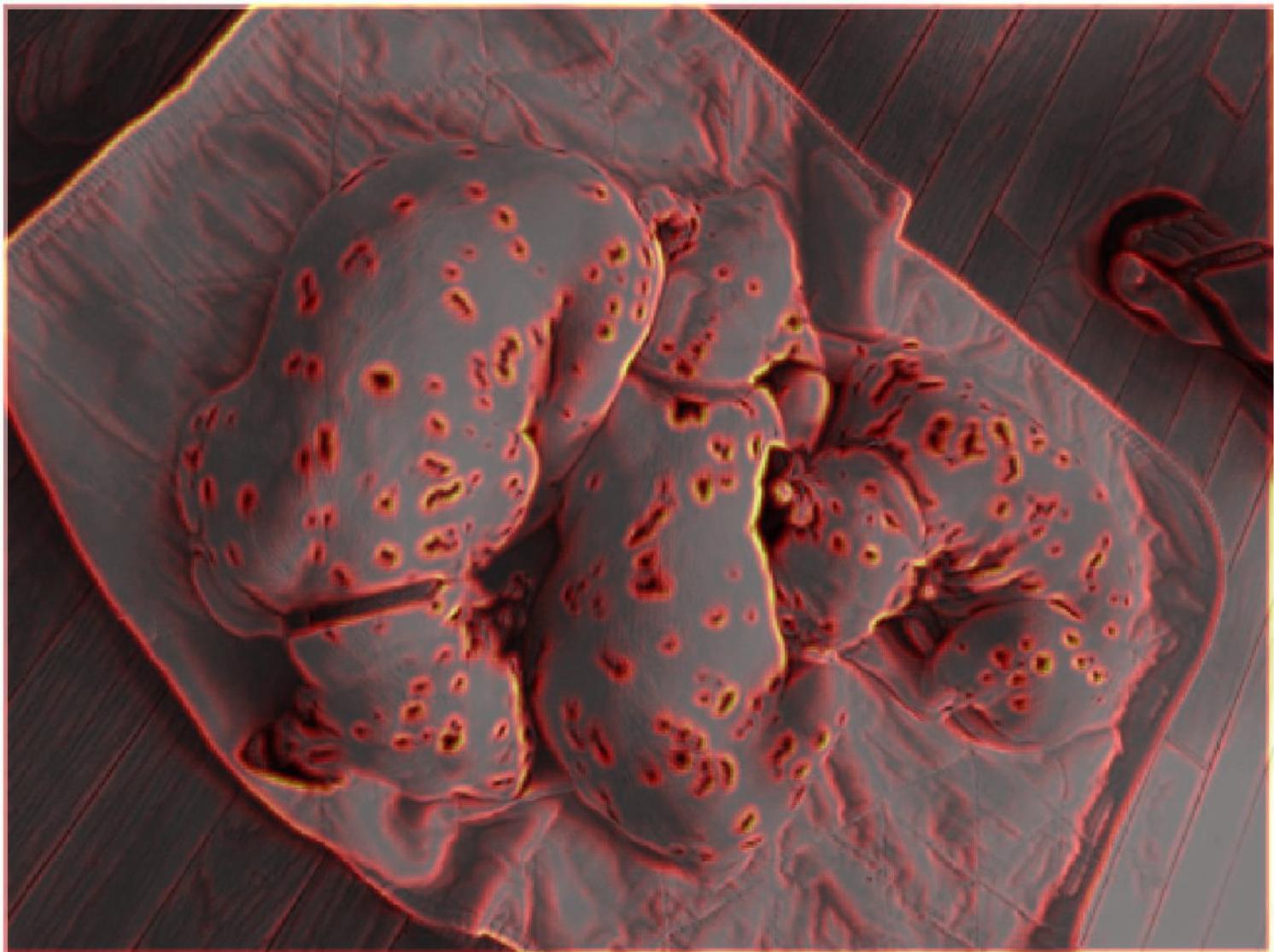


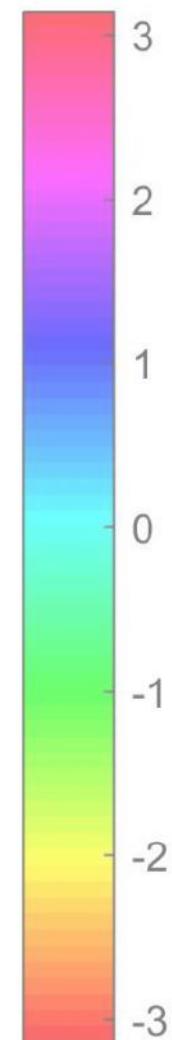
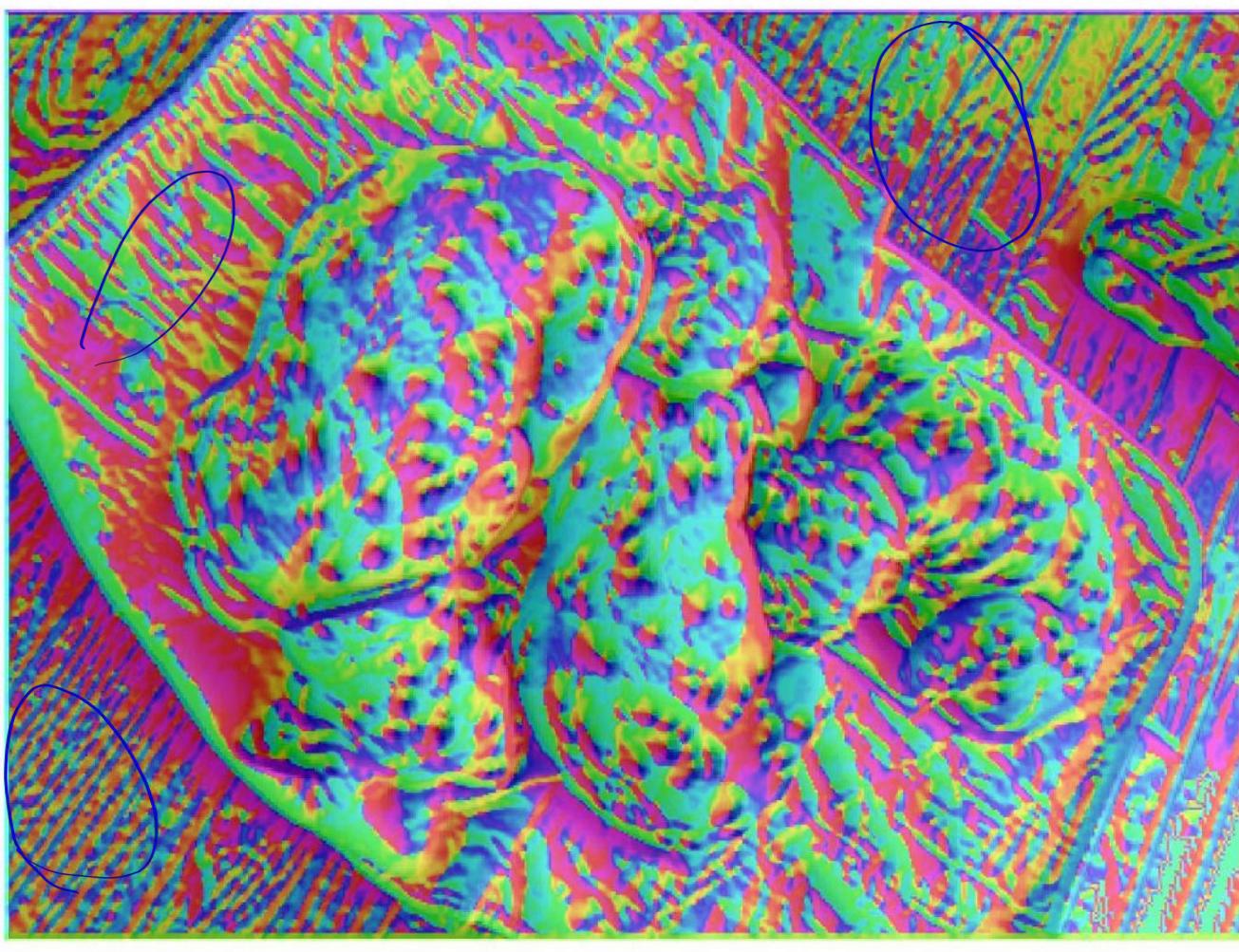


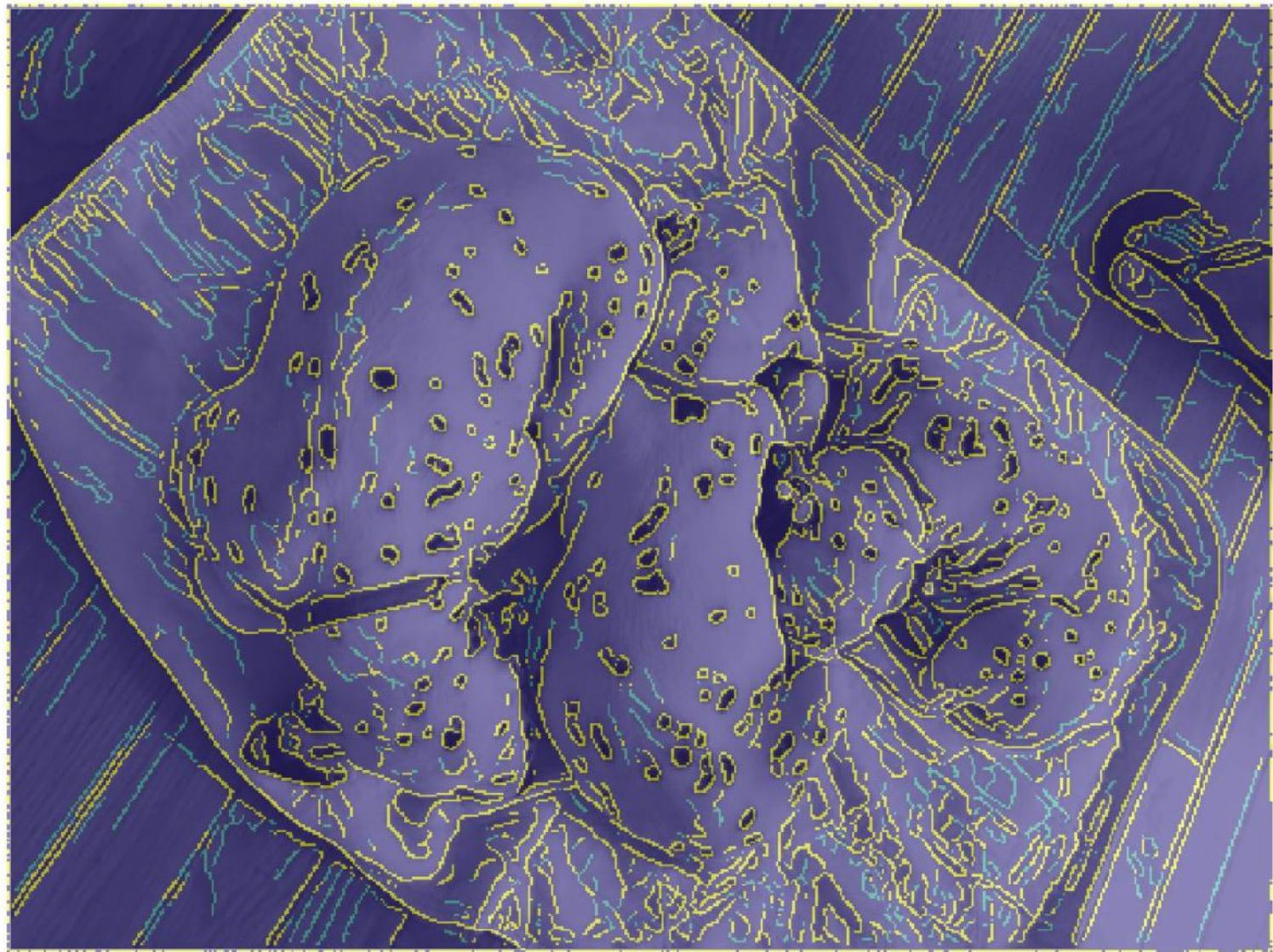










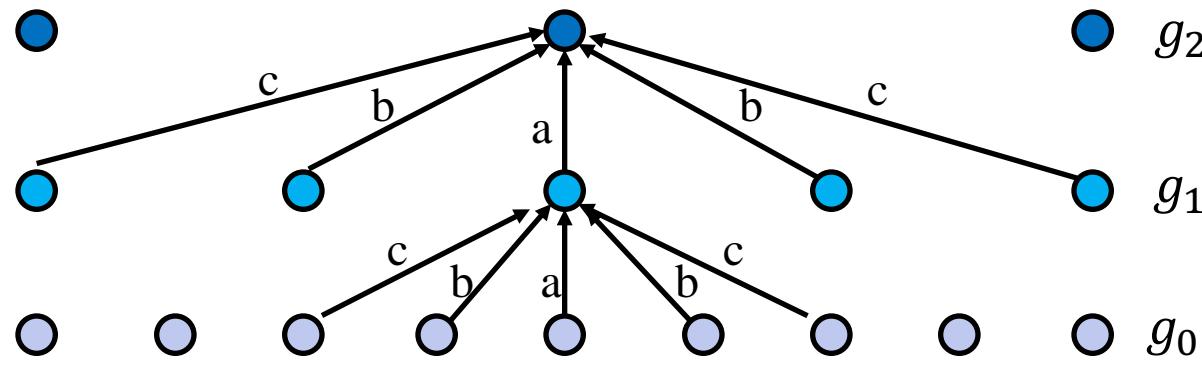




Video 3.7

Jianbo Shi

Image Reduce

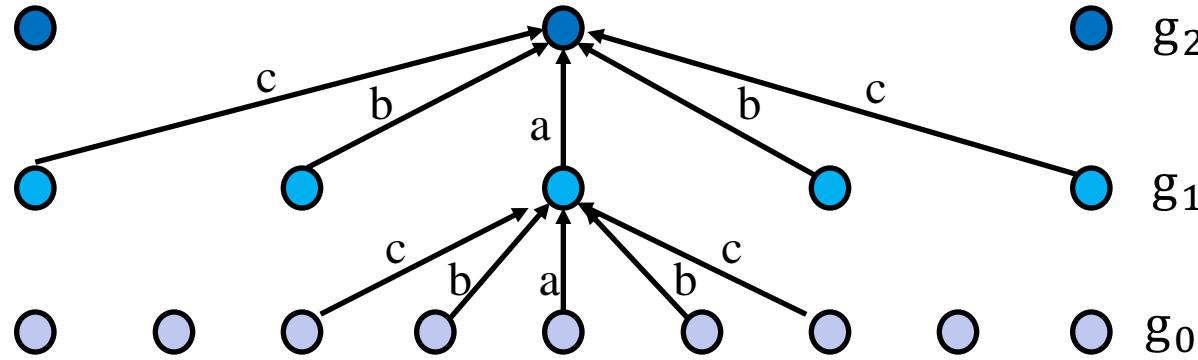


$g_0 = \text{Image}$

$g_l = \text{REDUCE}[g_{l-1}]$

[Burt & Adelson, 1983]

Image Reduce



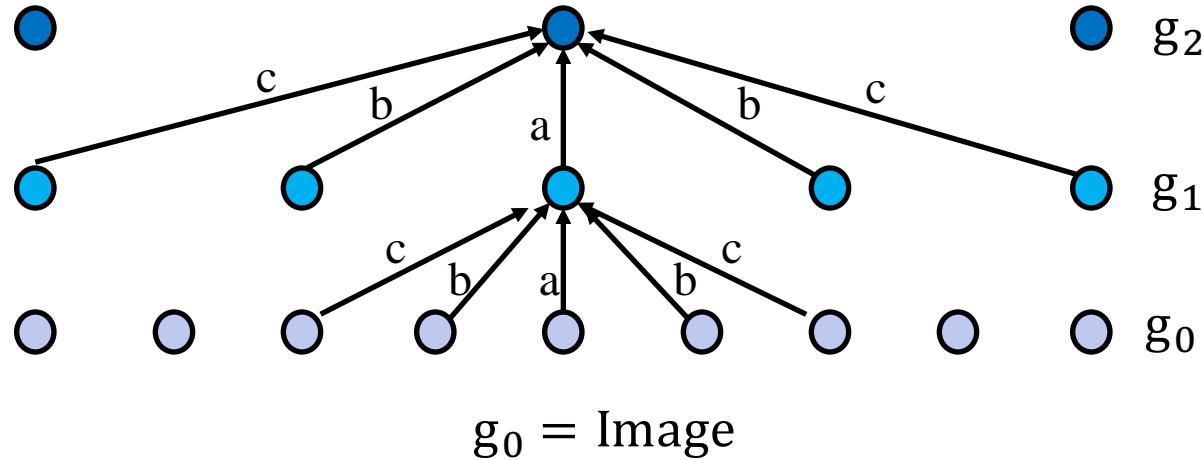
$g_0 = \text{Image}$

$g_1 = \text{REDUCE}[g_{l-1}]$

$$g_l(i,j) = \sum_{m=-2}^2 \sum_{n=-2}^2 w(m,n) g_{l-1}(2i+m, 2j+n)$$

$$w(m, n) = \widehat{w}(m)\widehat{w}(n) \quad \sum_m \widehat{w}(m) = 1 \quad \widehat{w}(m) = \widehat{w}(-m)$$

Image Reduce



$$g_l(i,j) = \sum_{m=-2}^2 \sum_{n=-2}^2 w(m,n) g_{l-1}(2i+m, 2j+n)$$

$$g_l = [g_{l-1} \otimes w] \downarrow 2$$

Choice in weighting function

$$\hat{w}(0) = a$$

$$\hat{w}(1) = \hat{w}(-1) = 1/4$$

$$\hat{w}(1) = \hat{w}(-1) = 1/4 - a/2$$

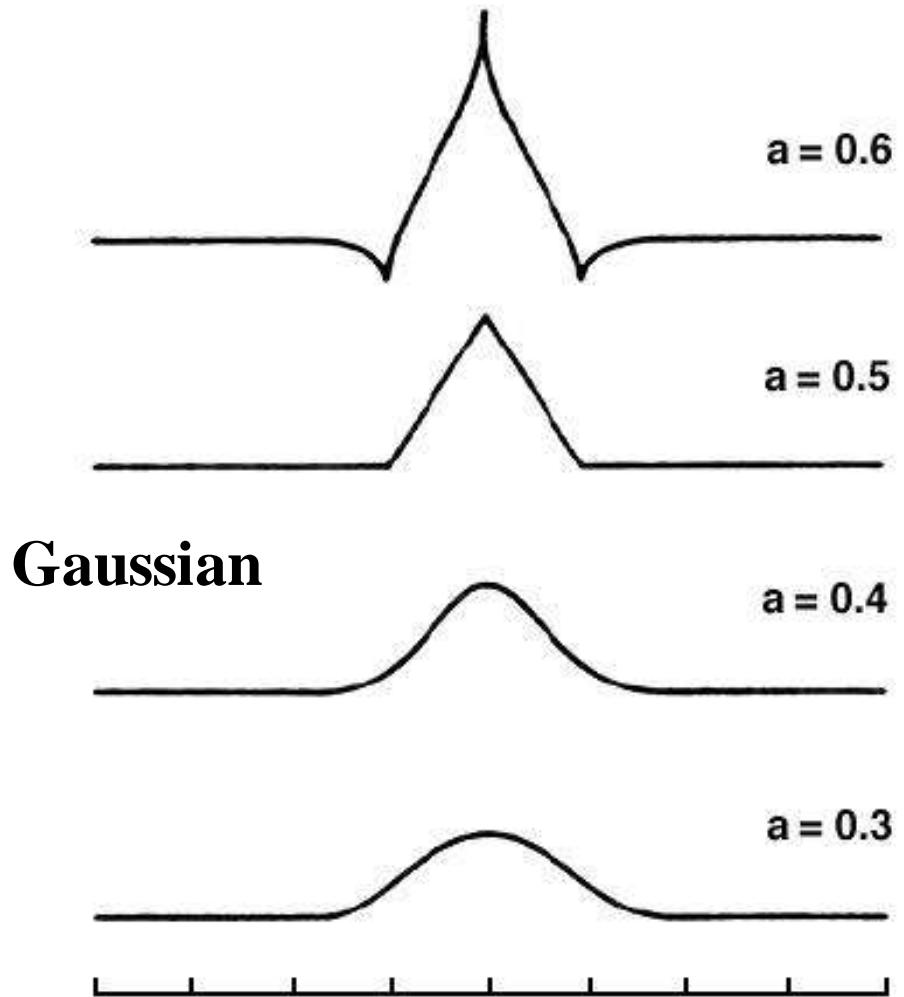


Image Expansion

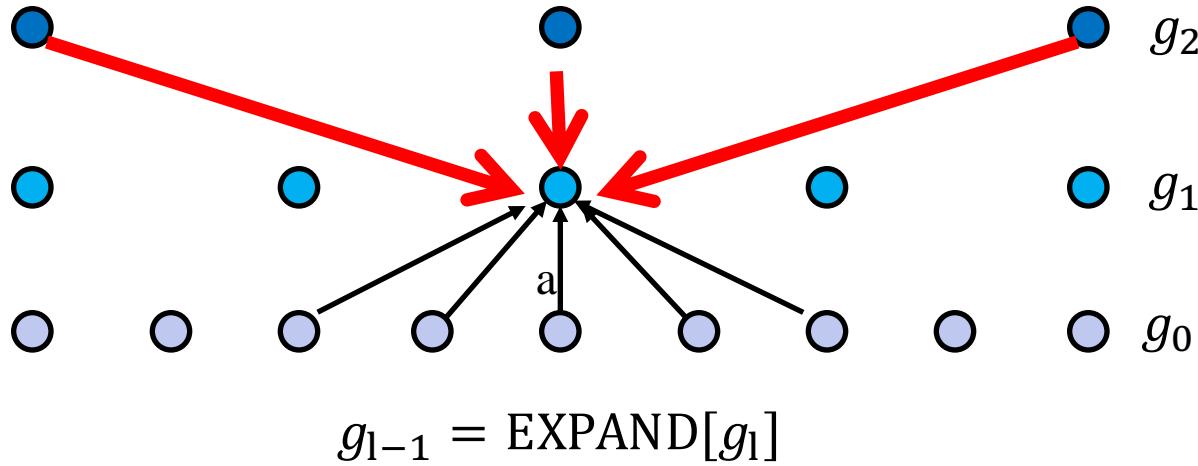
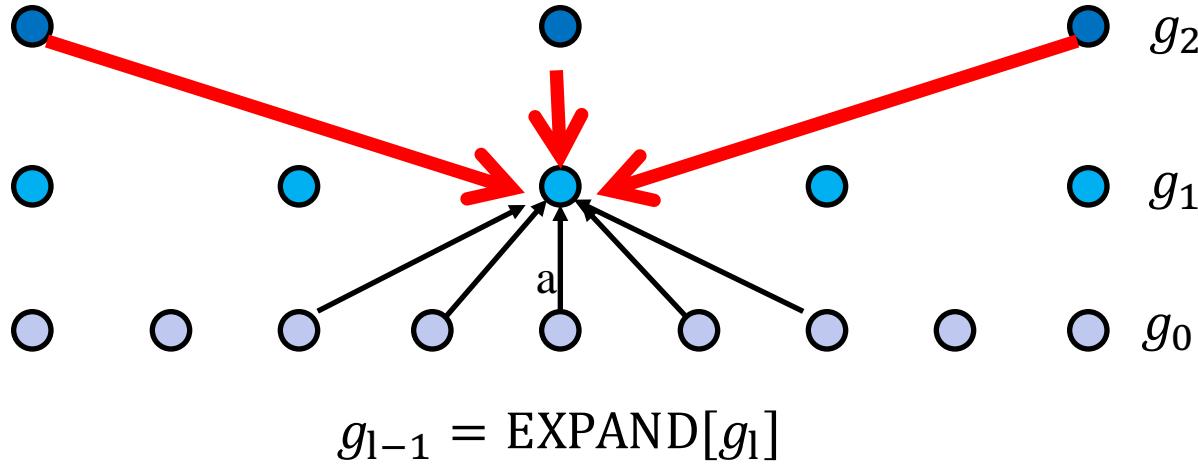


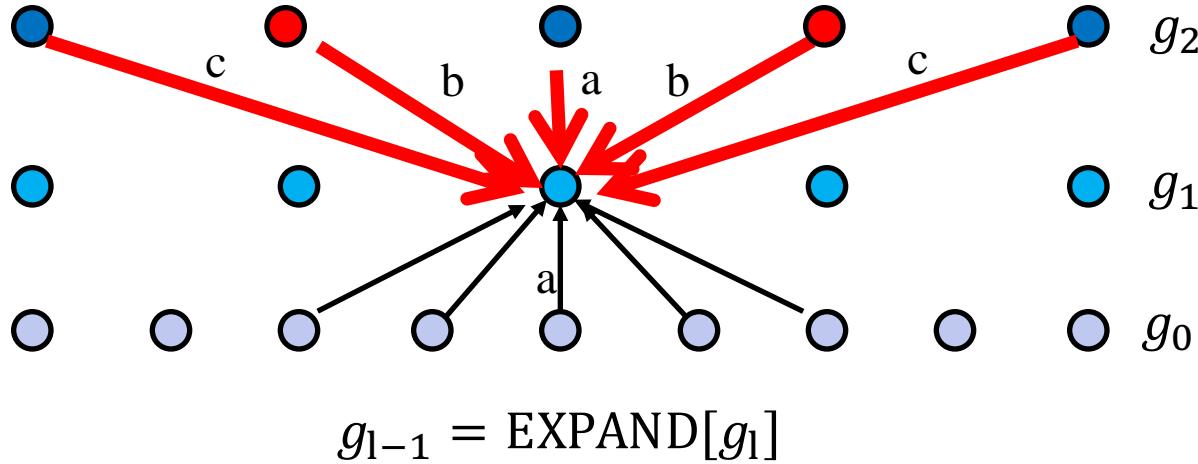
Image Expansion



$$g_l(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) \cdot g_{l+1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right)$$

$\frac{(i-m)}{2}$ and $\frac{(j-n)}{2}$ are integers

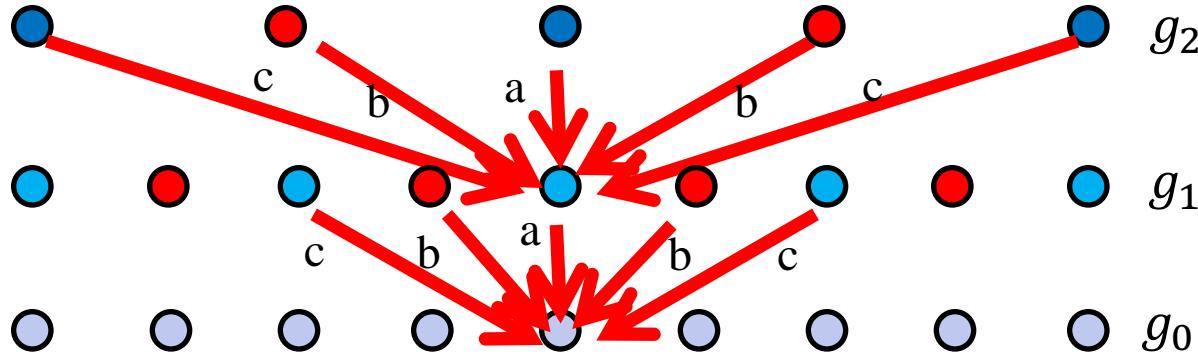
Image Expansion



$$g_l(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) \cdot g_{l+1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right)$$

$\frac{(i-m)}{2}$ and $\frac{(j-n)}{2}$ are integers

Image Expansion

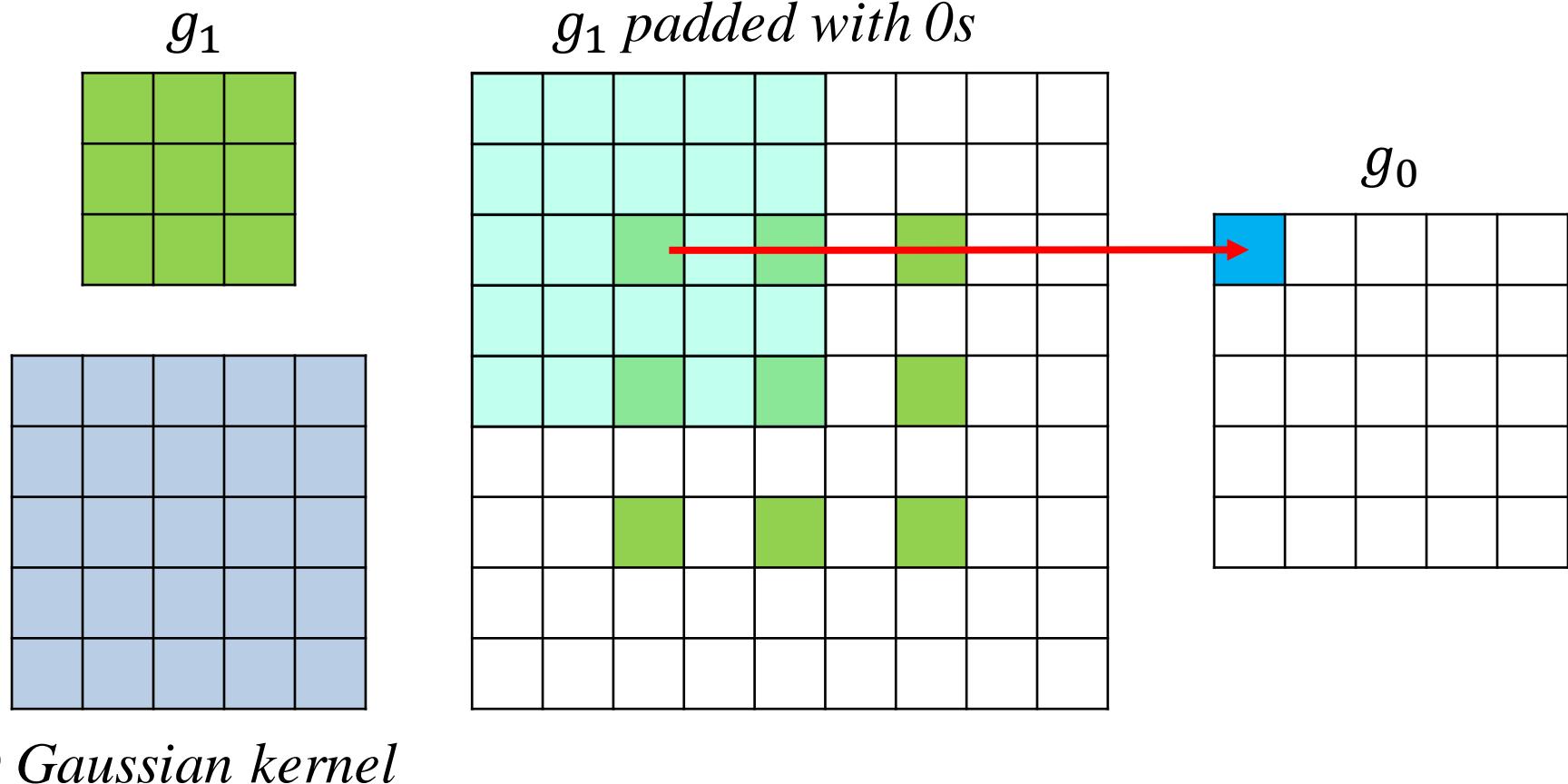


$$g_{l-1} = \text{EXPAND}[g_l]$$

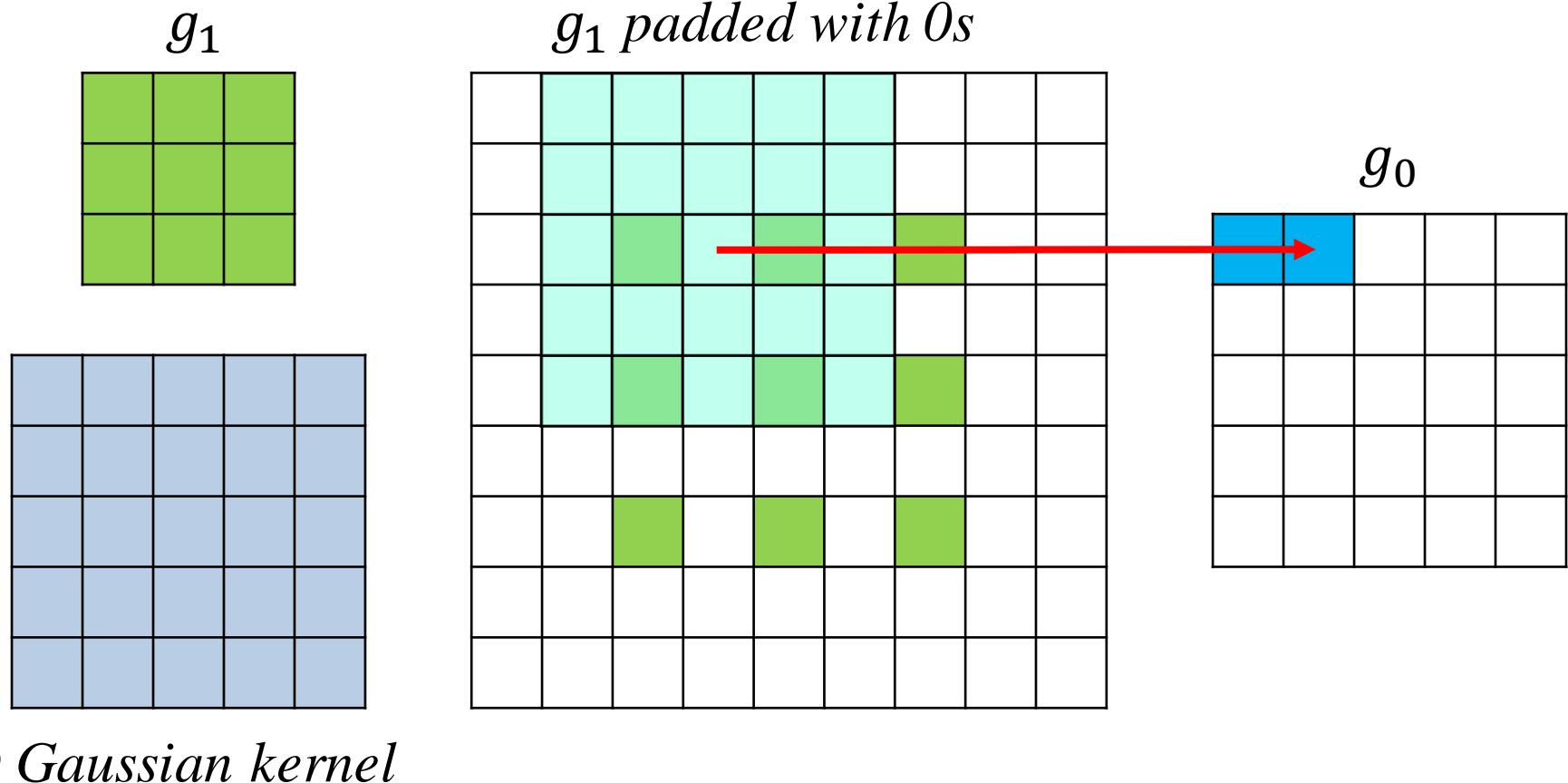
$$g_l(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) \cdot g_{l-1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right)$$

$\frac{(i-m)}{2}$ and $\frac{(j-n)}{2}$ are integers

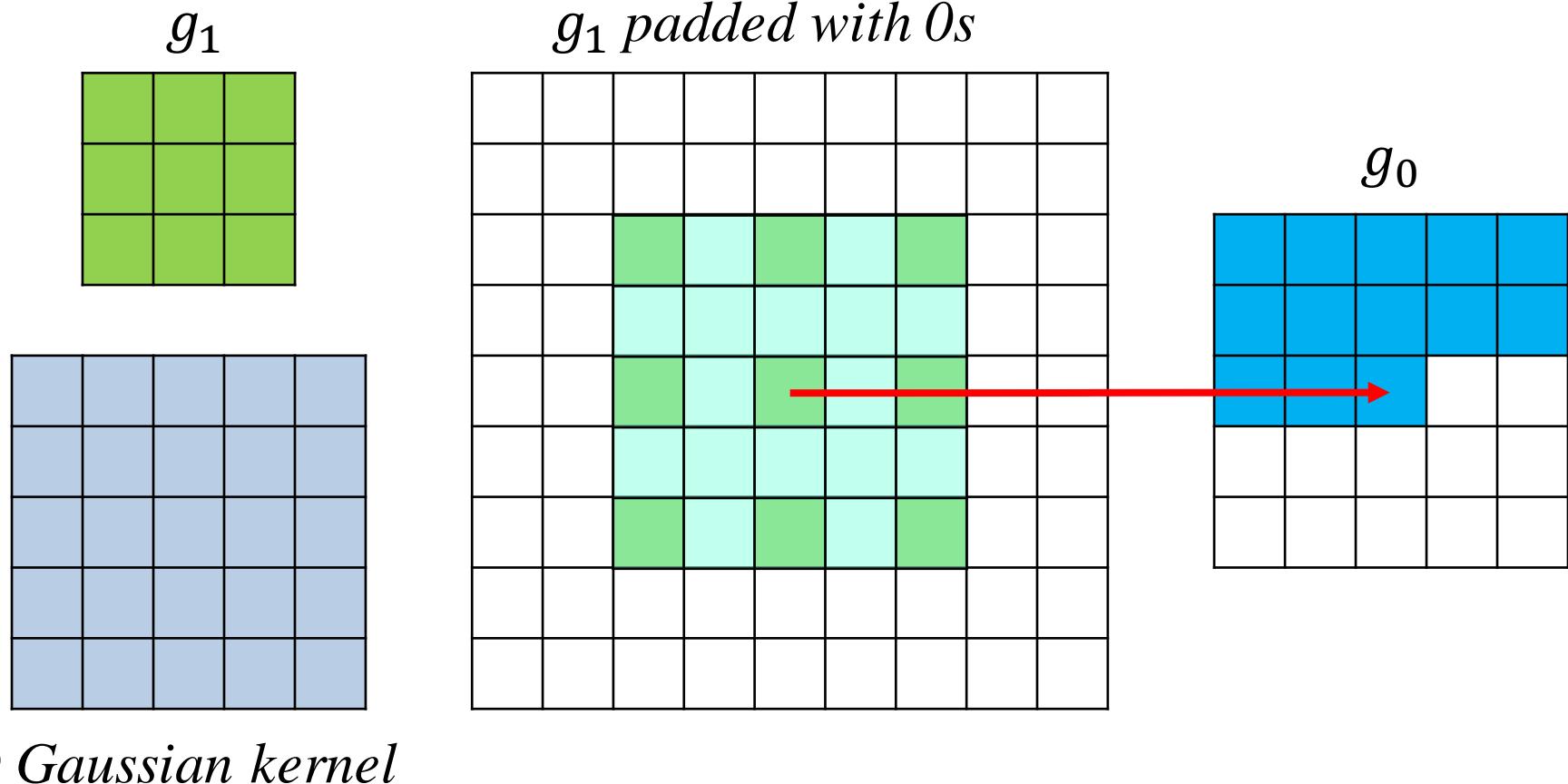
2D Image Expansion (part1)



2D Image Expansion (part2)



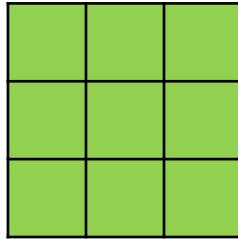
2D Image Expansion (part3)



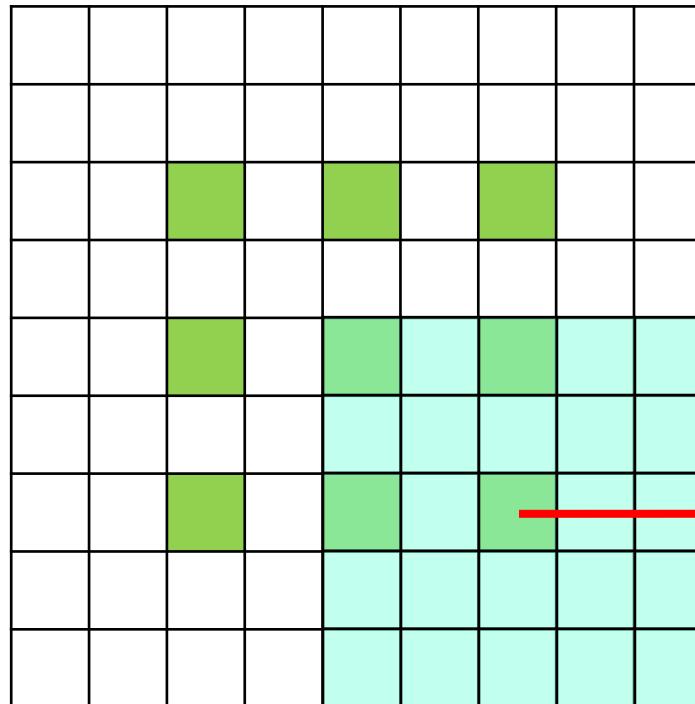


2D Image Expansion (part4)

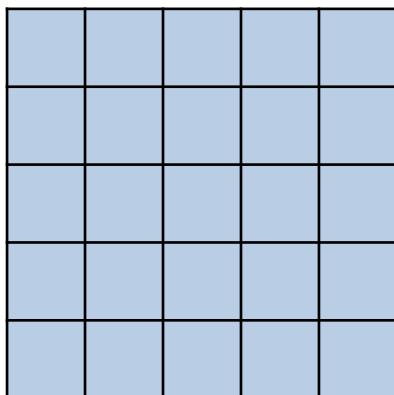
g_1



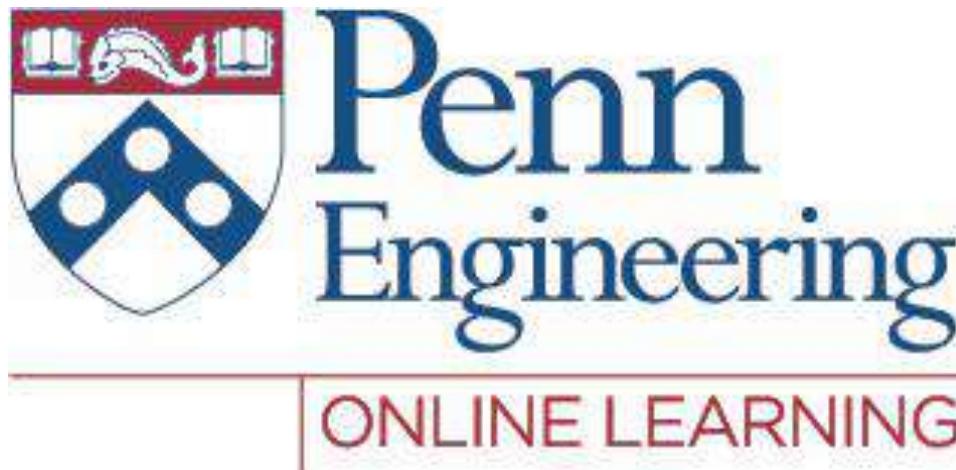
g_1 padded with 0s



g_0



2D Gaussian kernel



Video 3.8

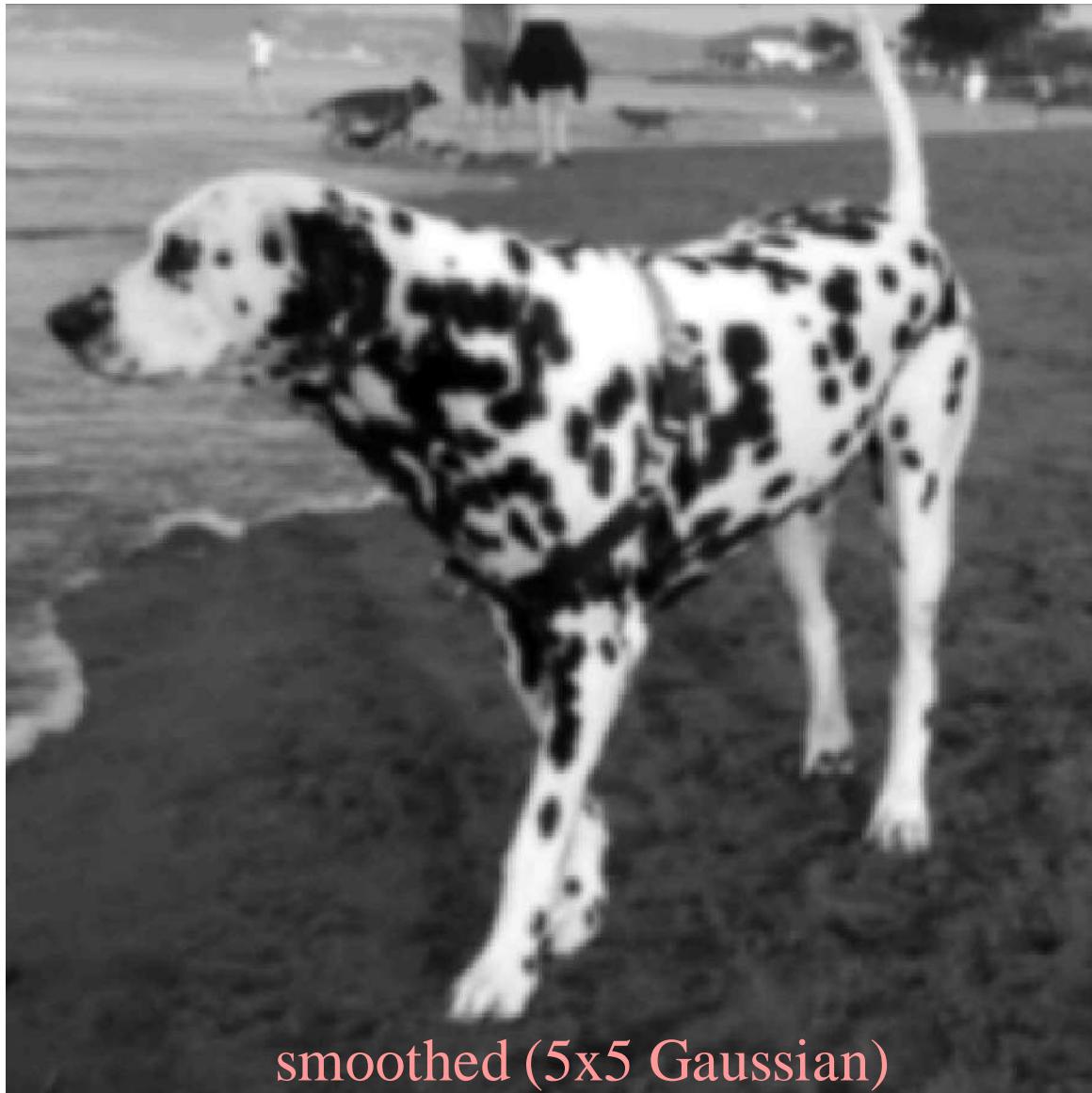
Jianbo Shi

What does blurring take away?



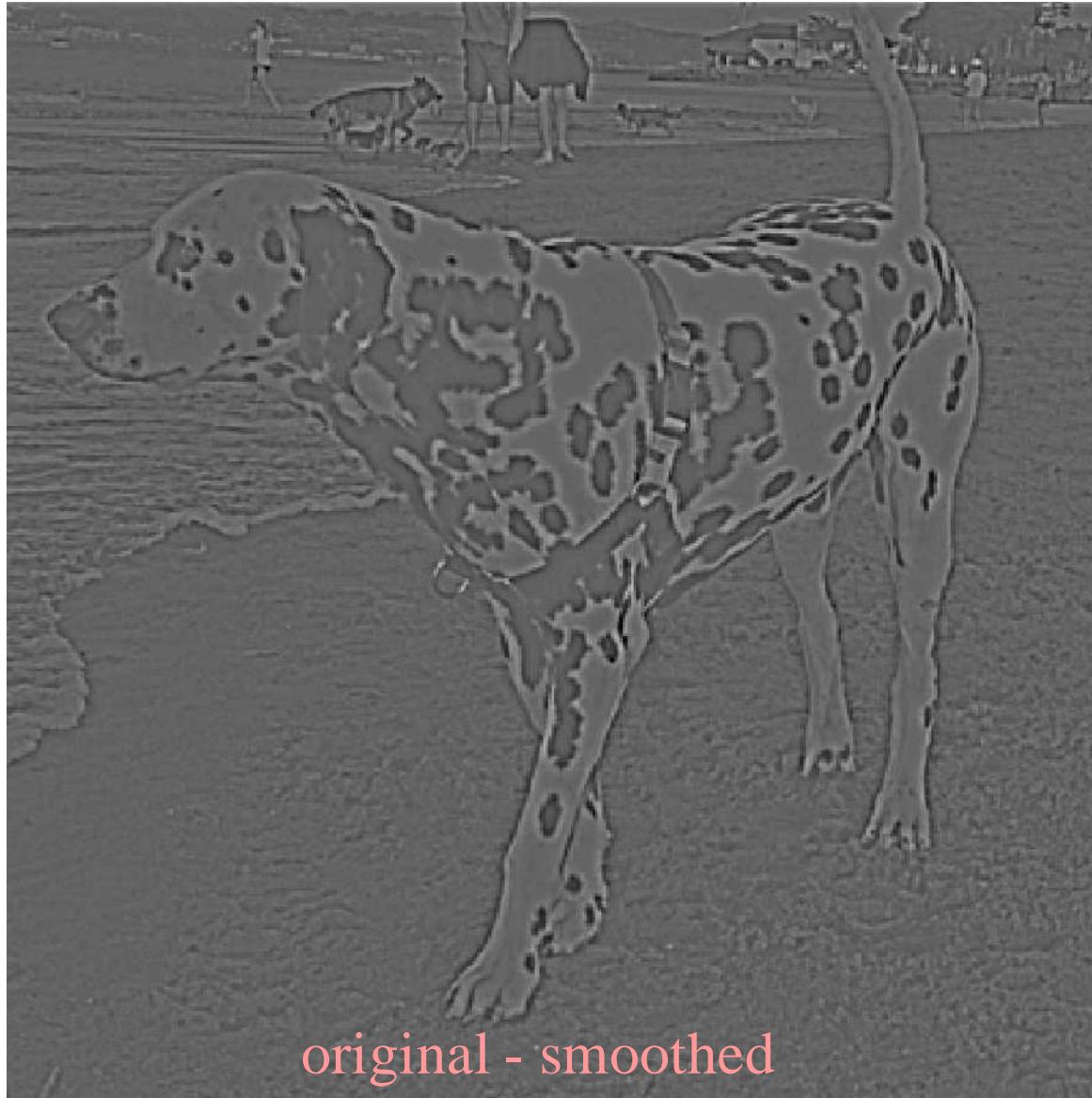
original

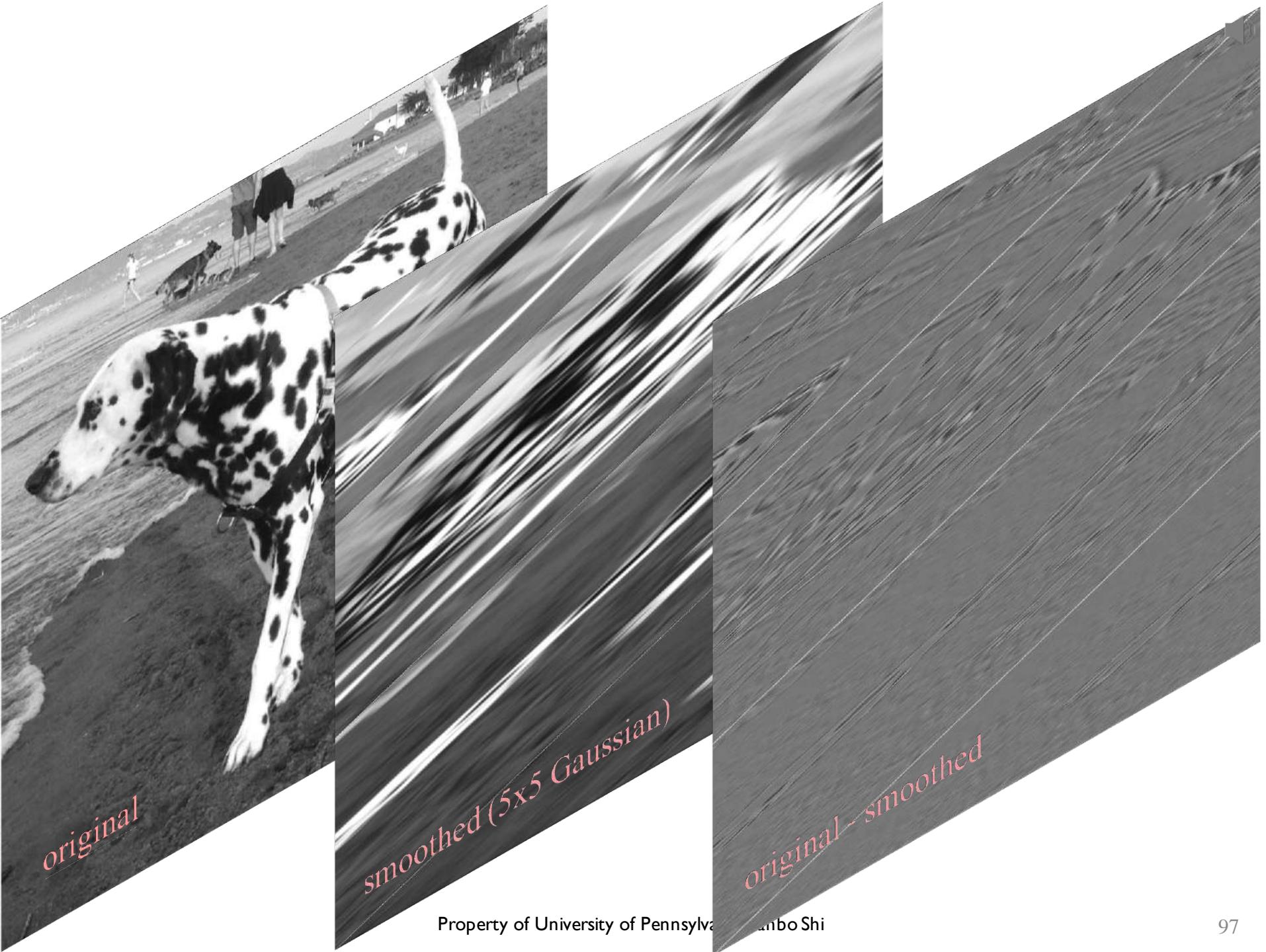
What does blurring take away?



smoothed (5x5 Gaussian)

Difference as result of smoothing





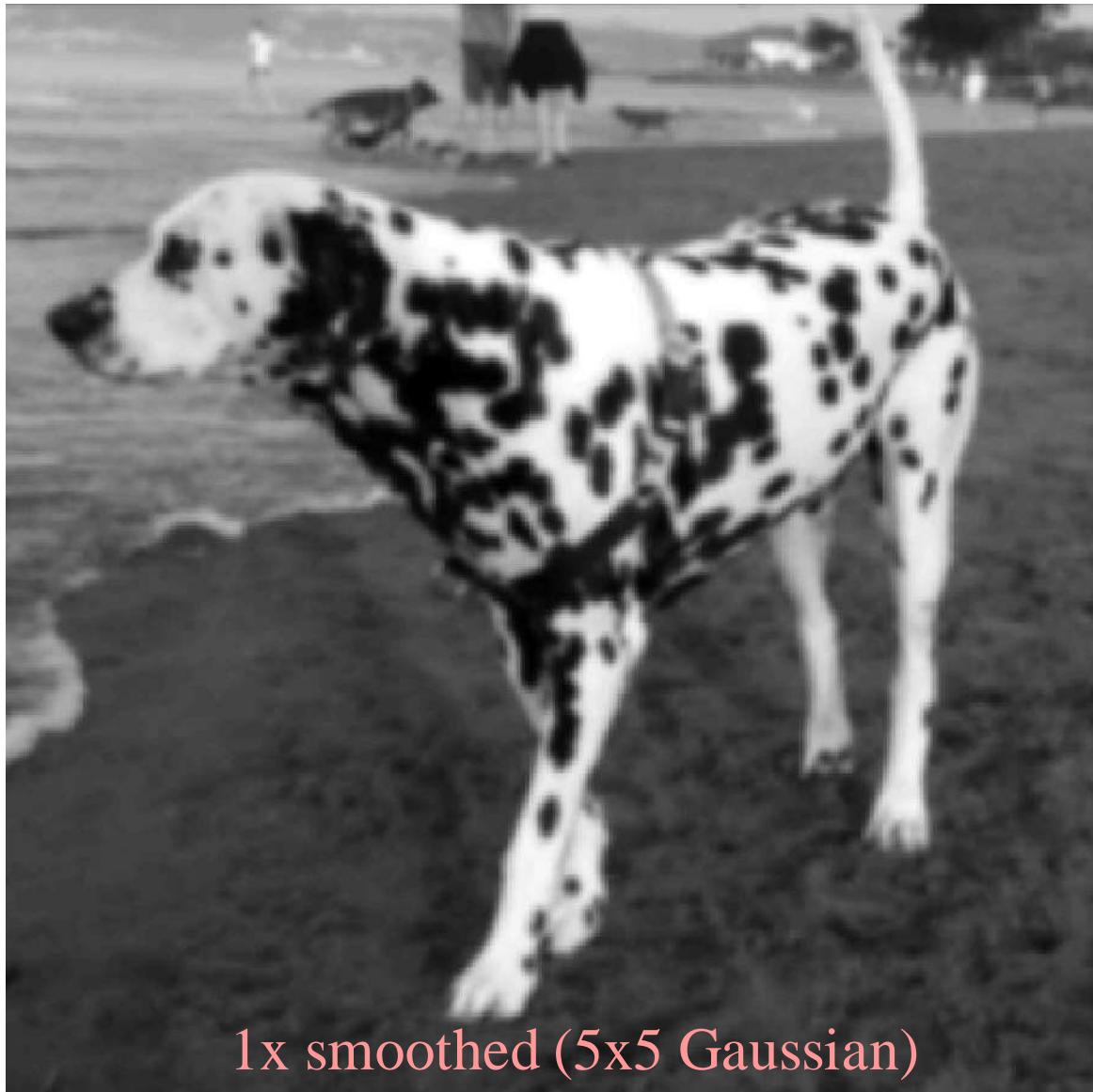


original - smoothed



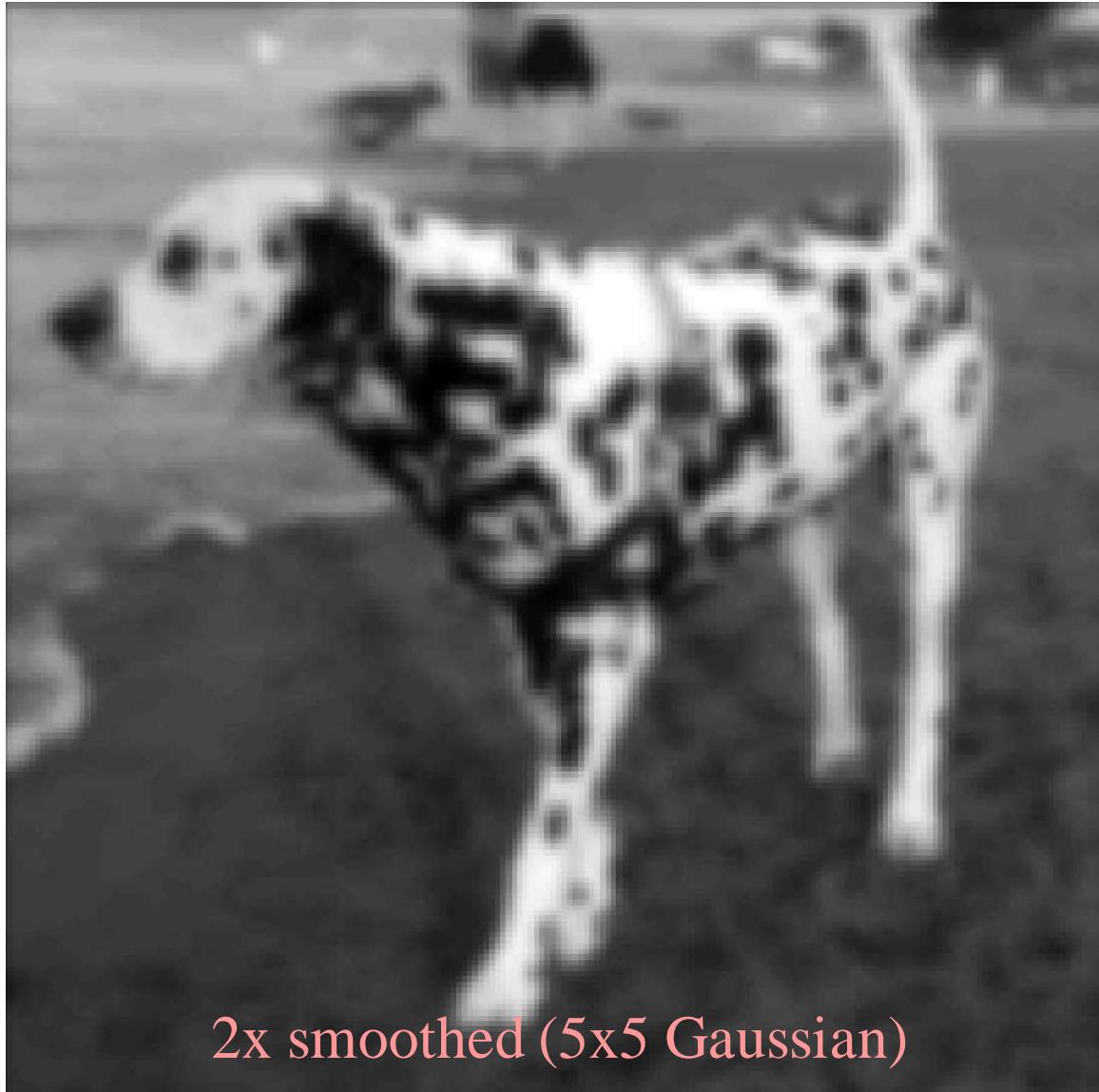
Quantize(original – smoothed)

What does blurring take away?



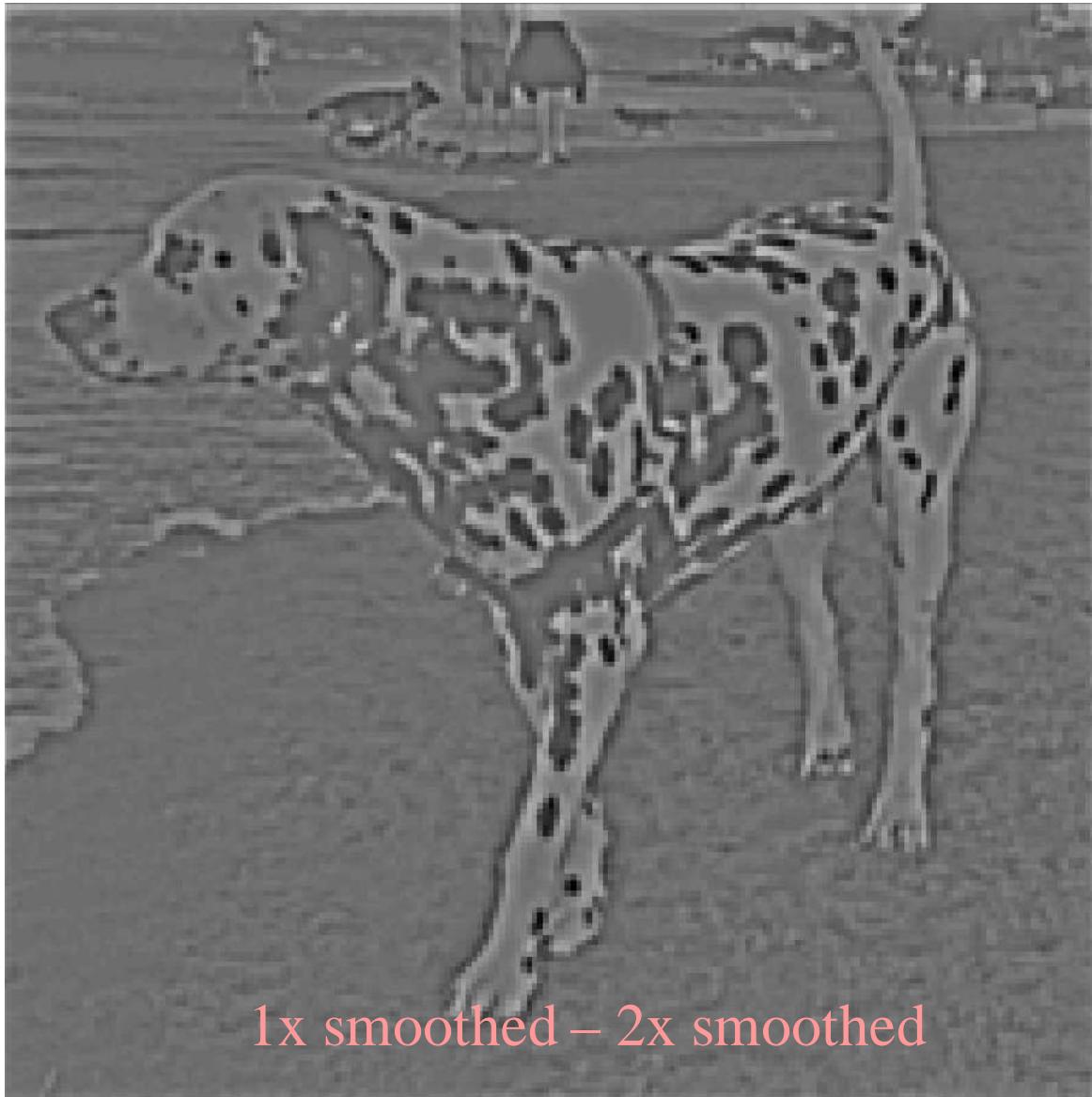
1x smoothed (5x5 Gaussian)

What does blurring take away?



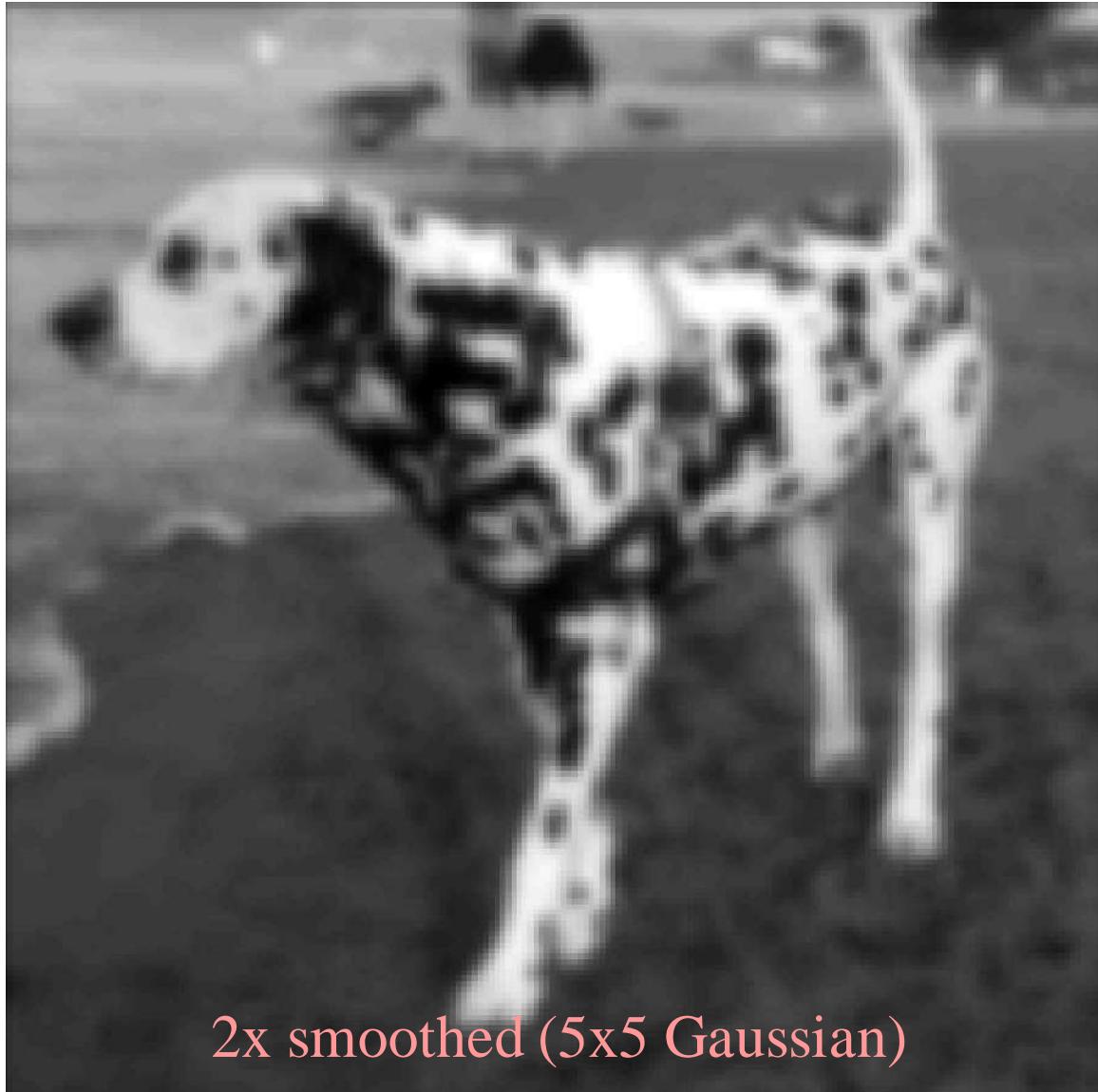
2x smoothed (5x5 Gaussian)

Difference of Gaussian



1x smoothed – 2x smoothed

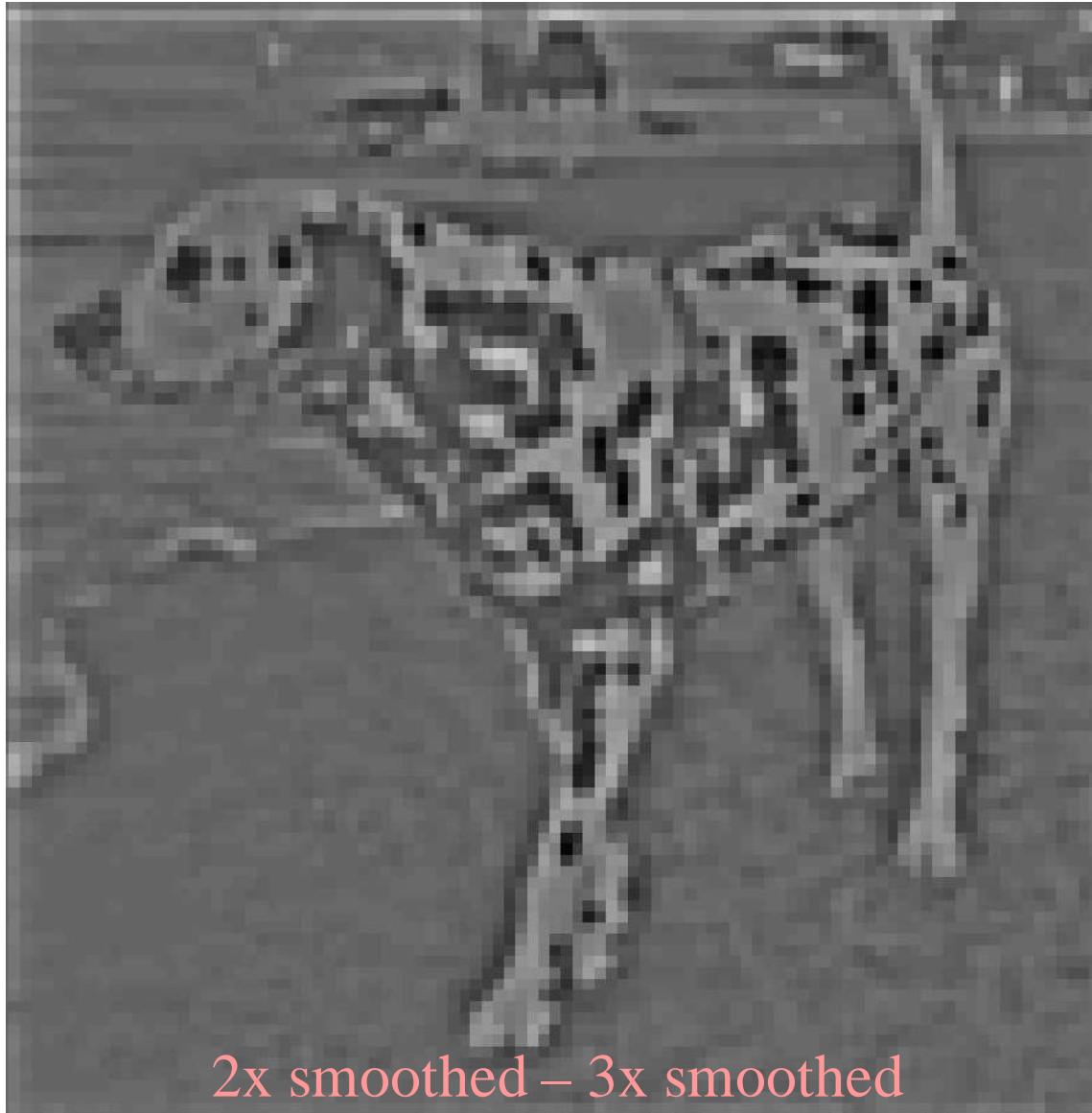
What does blurring take away?



2x smoothed (5x5 Gaussian)



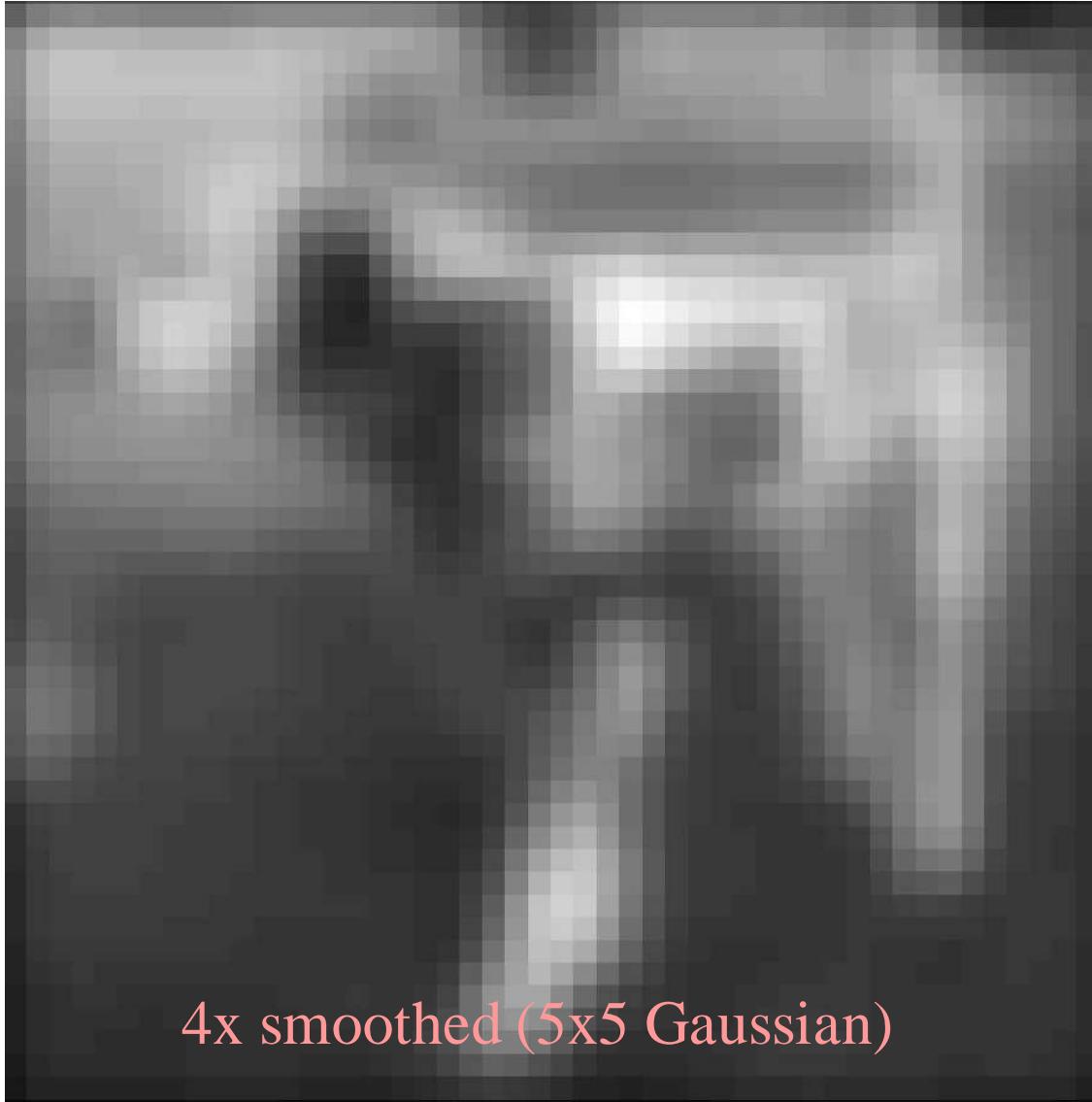
Difference of Gaussian



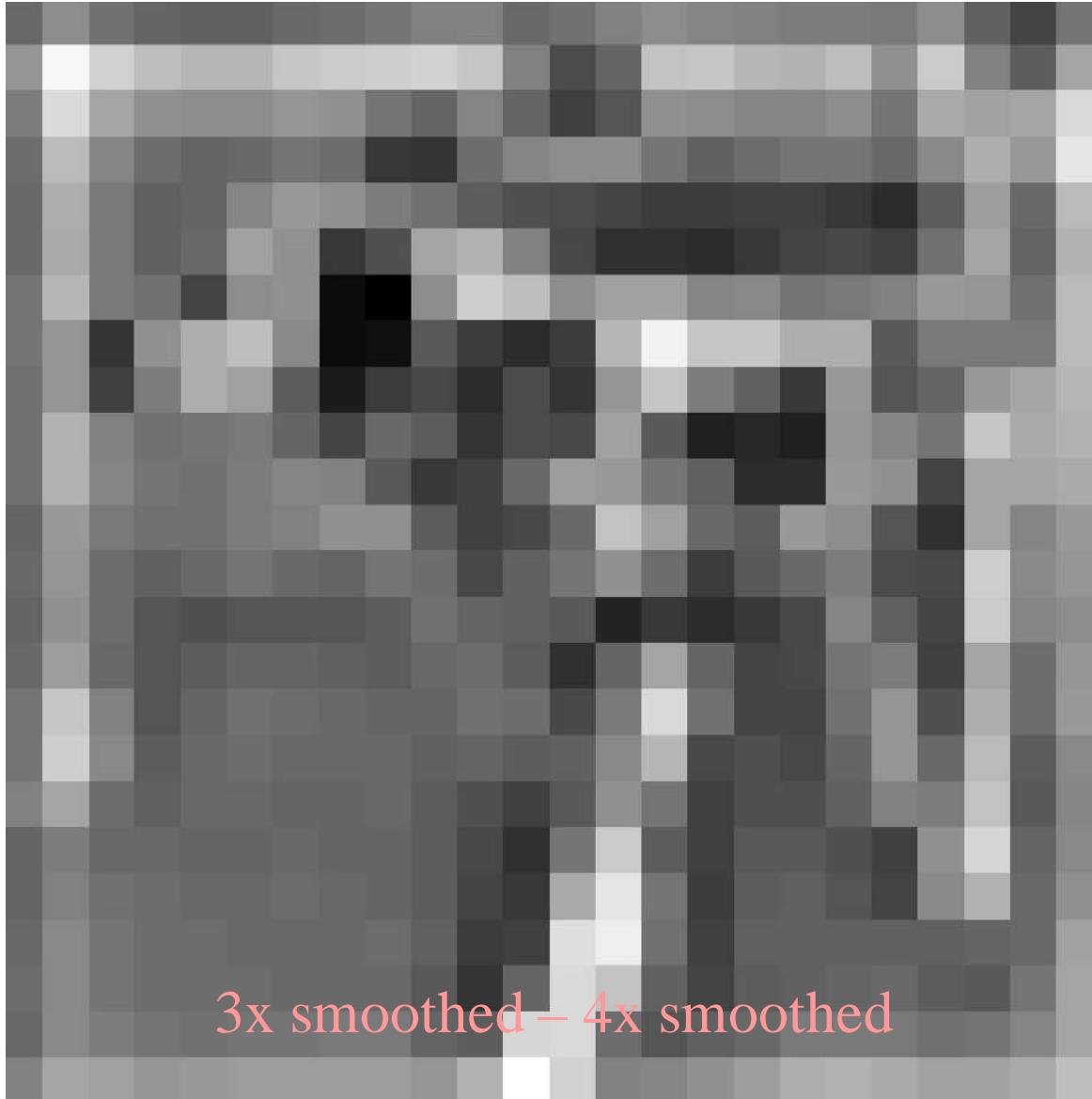
2x smoothed – 3x smoothed



3x smoothed (5x5 Gaussian)



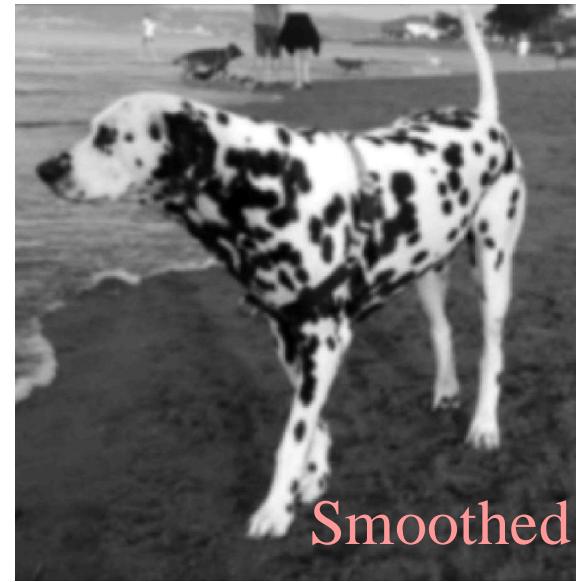
4x smoothed (5x5 Gaussian)



3x smoothed – 4x smoothed

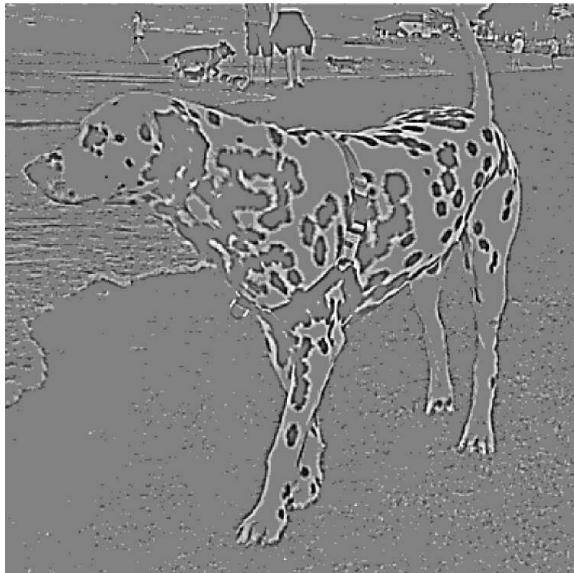


original



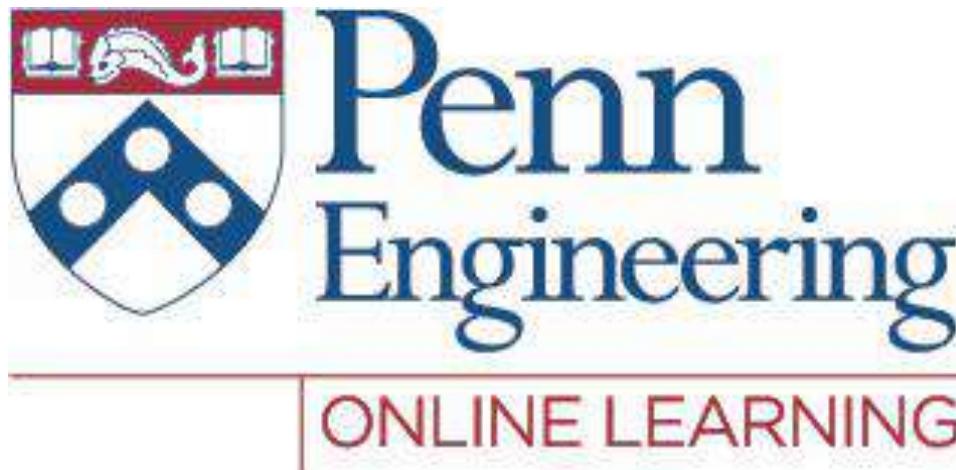
Smoothed

$$+ \downarrow - \swarrow$$



Laplacian Image

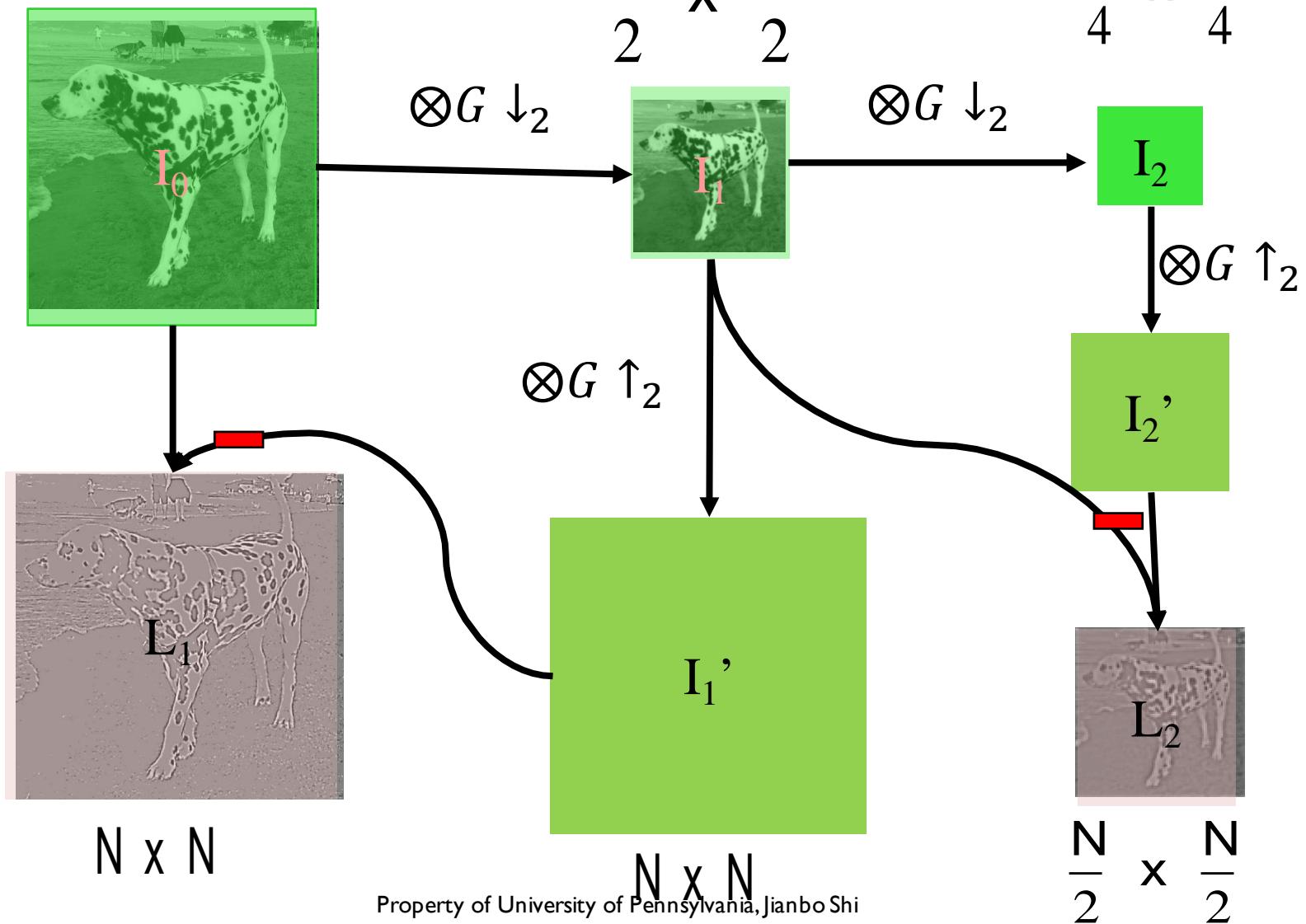
$$L_l = g_l - \text{EXPAND}[g_{l+1}]$$

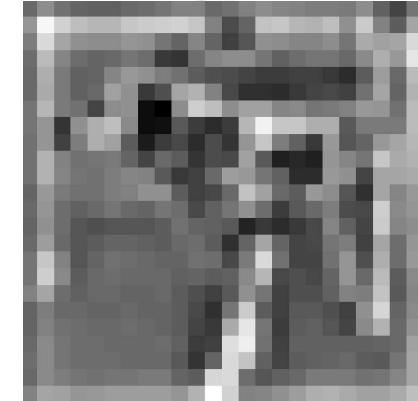
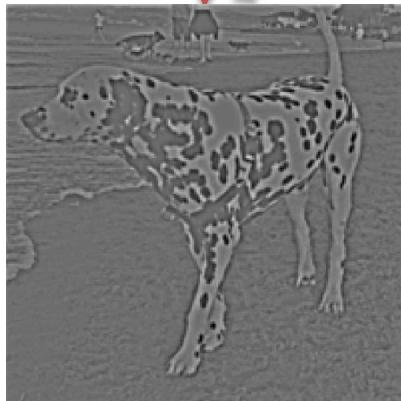
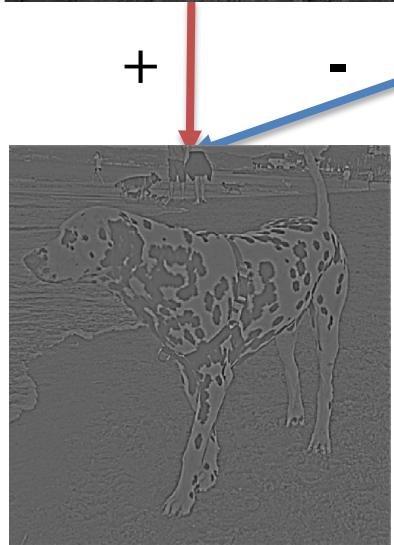
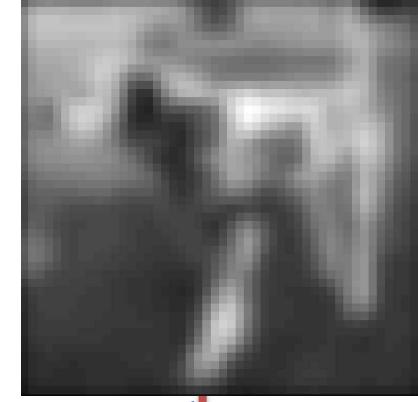
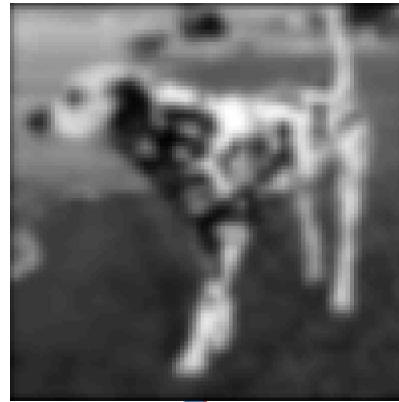
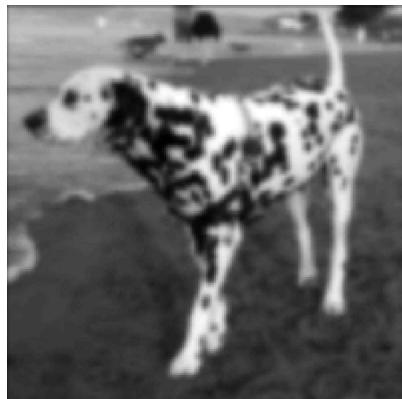
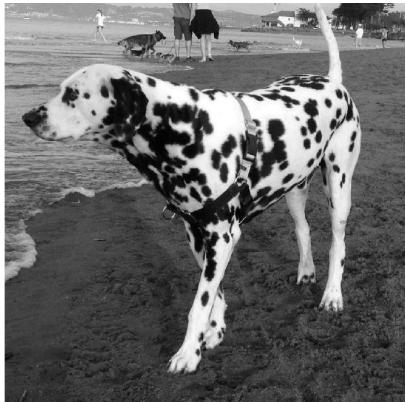


Video 3.9

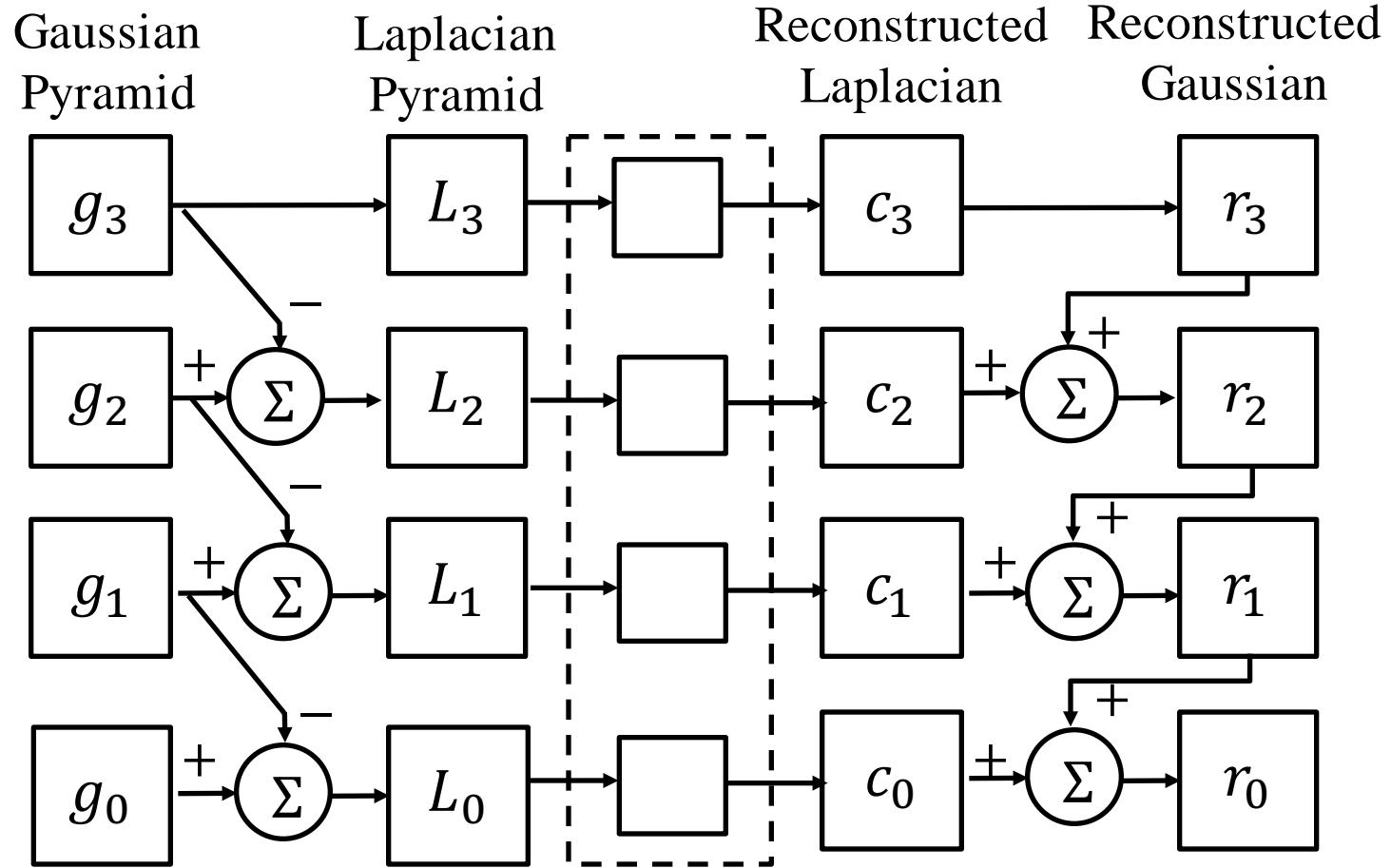
Jianbo Shi

Extraction of Laplacian





**Save only the last picture in Gaussian pyramid, and the entire Laplacian
Laplacian pyramid has narrow band of frequency=> compressed**



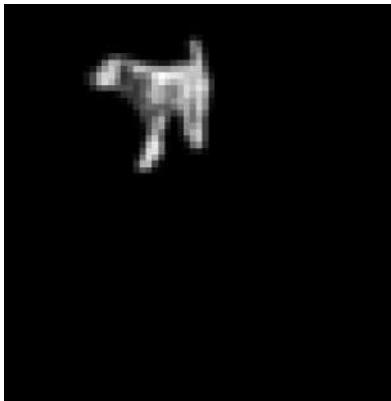
$$g_N = L_N$$

$$g_l = L_l + \text{EXPAND}[g_{l+1}]$$

Pyramid Blending



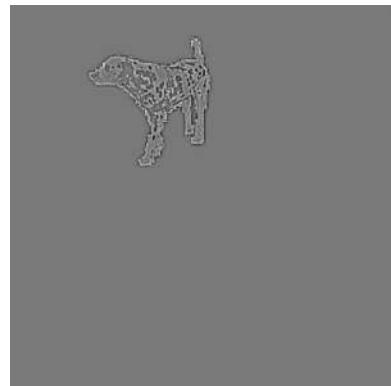
laplacian
level
4



laplacian
level
2



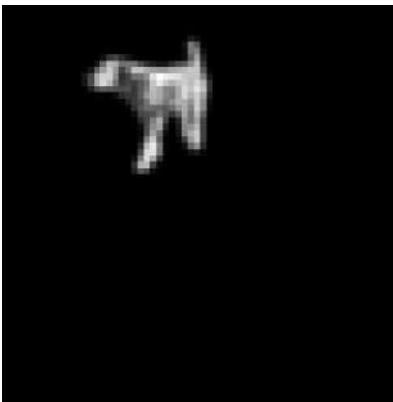
laplacian
level
0



top pyramid

bottom pyramid

laplacian
level
4



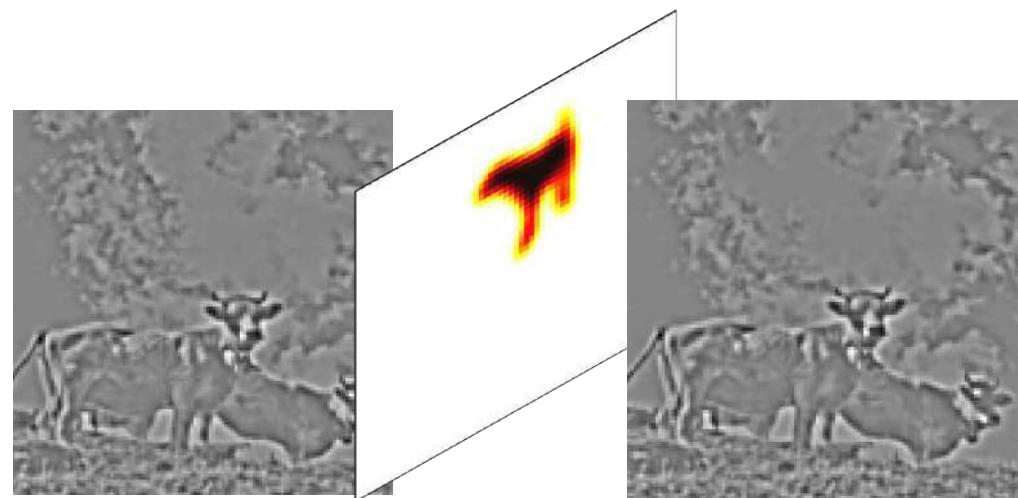
laplacian
level
2



laplacian
level
0



top pyramid



bottom pyramid

laplacian
level
4



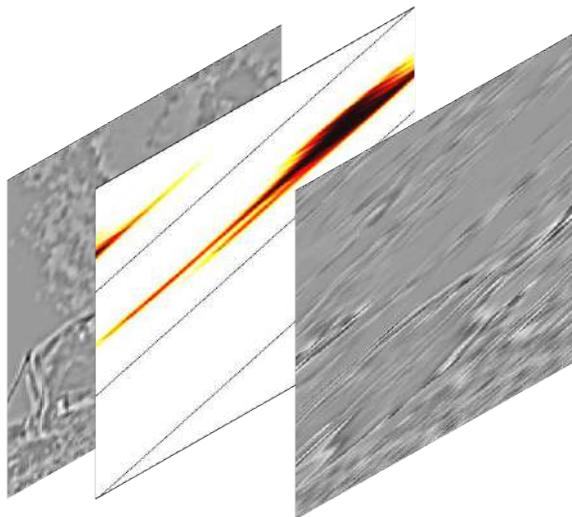
laplacian
level
2



laplacian
level
0



top pyramid



bottom pyramid

laplacian
level
4



laplacian
level
2



laplacian
level
0



top pyramid



bottom pyramid

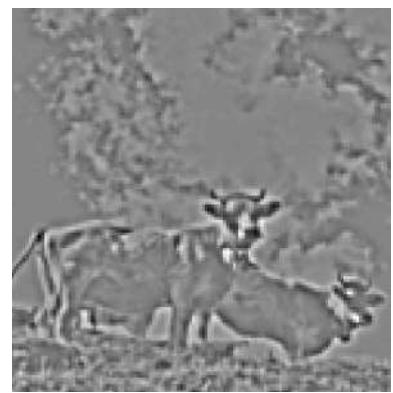


blended pyramid

laplacian
level
4



laplacian
level
2



laplacian
level
0



top pyramid

bottom pyramid

blended pyramid

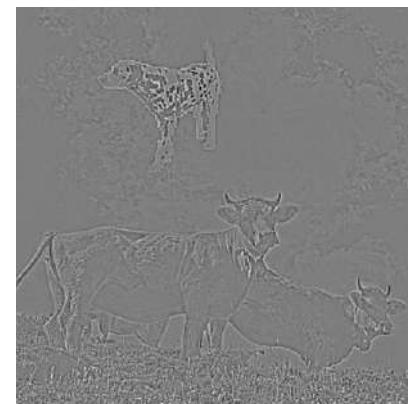
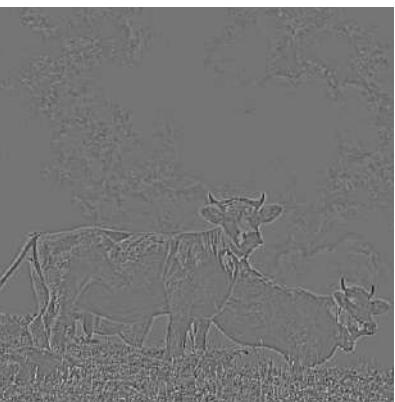
laplacian
level
4



laplacian
level
2



laplacian
level
0



top pyramid

bottom pyramid

blended pyramid

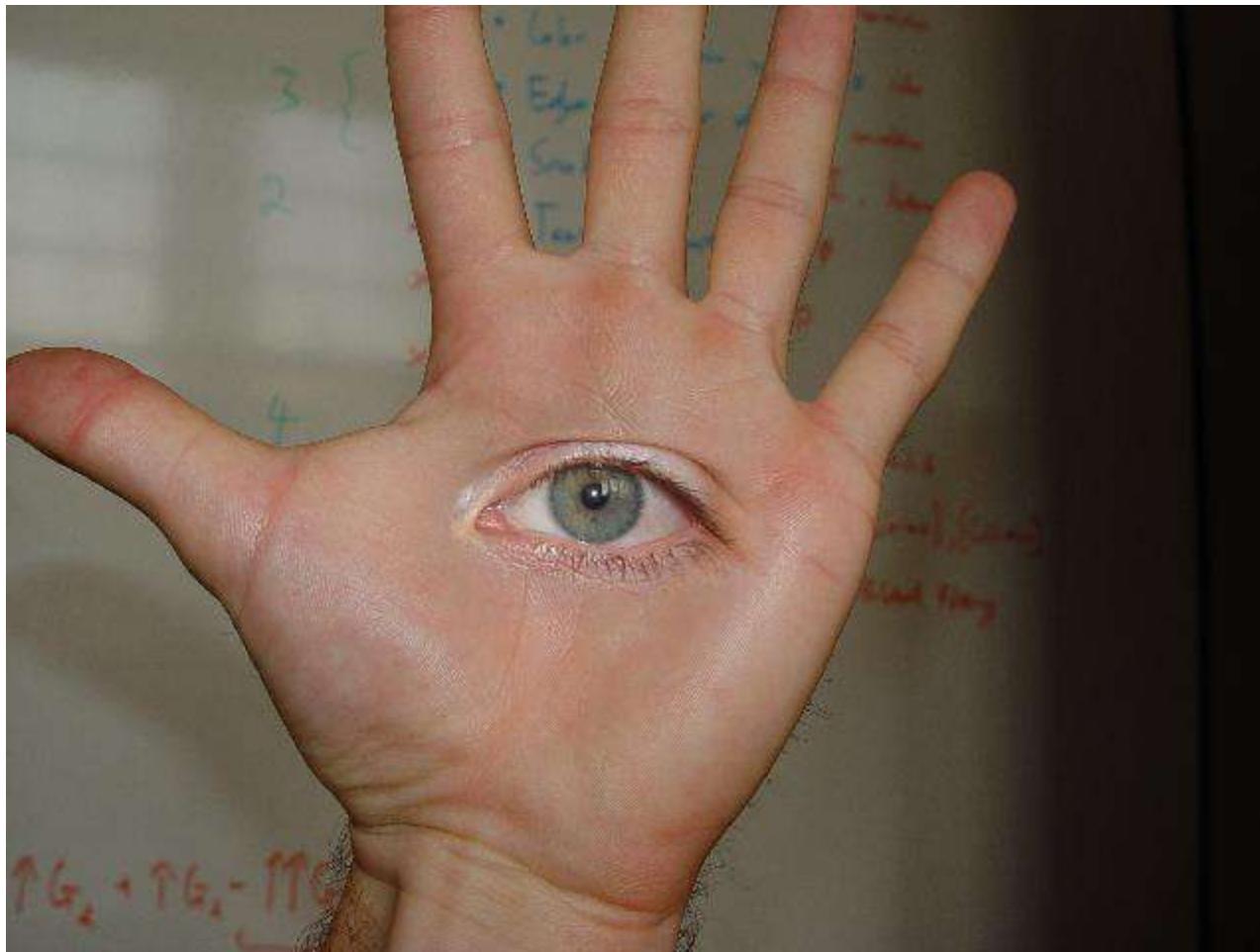
Laplacian Pyramid: Blending

General Approach:

1. Build Laplacian pyramids LA and LB from images A and B
2. Build a Gaussian pyramid $MASK$ from selected region R
3. Form a combined pyramid LS from LA and LB using nodes of GR as weights:
$$LS(i,j) = MASK(i,j) * LA(i,j) + (1 - MASK(i,j)) * LB(i,j)$$
4. Collapse the LS pyramid to get the final blended image



Horror Photo



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