



UNIVERSIDADE FEDERAL DO PARANÁ – UFPR

Departamento de Informática

Computer Vision and Perception

Image filtering

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Summary

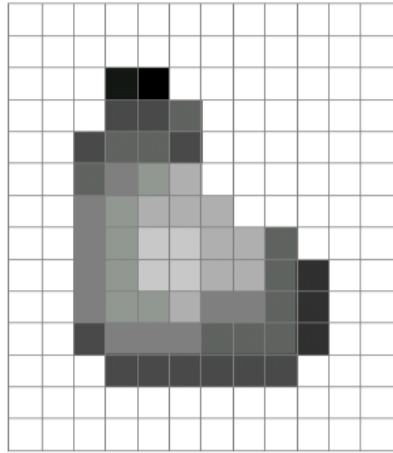
Text book

Introduction

recognition problem

image basics

Remember image structure



=

255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	20	0	255	255	255	255	255	255	255	255	255	255
255	255	255	75	75	75	255	255	255	255	255	255	255	255	255
255	255	75	95	95	75	255	255	255	255	255	255	255	255	255
255	255	96	127	145	175	255	255	255	255	255	255	255	255	255
255	255	127	145	175	175	175	255	255	255	255	255	255	255	255
255	255	127	145	200	200	175	175	95	255	255	255	255	255	255
255	255	127	145	200	200	175	175	95	47	255	255	255	255	255
255	255	127	145	145	175	127	127	95	47	255	255	255	255	255
255	255	74	127	127	127	95	95	95	47	255	255	255	255	255
255	255	255	74	74	74	74	74	74	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255	255	255	255

Filters

Filtering

Form a new image whose pixels are a combination of the original pixels

Why?

To get useful information from images

E.g., extract edges or contours (to understand shape)

To enhance the image

E.g., to remove noise

E.g., to sharpen to enhance image

Image filtering

Modify the pixels in an image based on some function of a local neighborhood of each pixel

10	5	3
4	5	1
1	1	7

Local image data

Some function



	7	

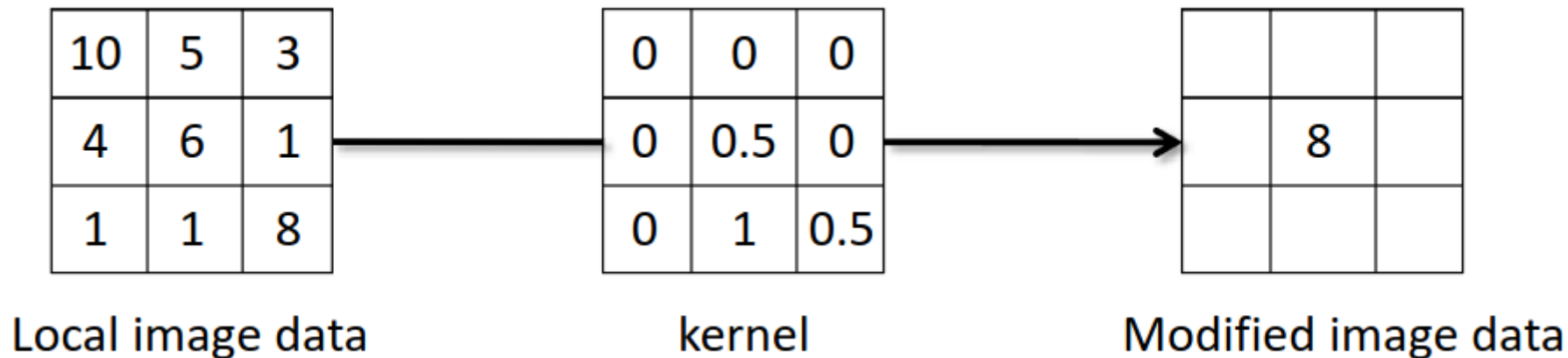
Modified image data

Linear Filtering

One simple version of filtering: linear filtering (cross-correlation, convolution)

Replace each pixel by a linear combination (a weighted sum) of its neighbors

The prescription for the linear combination is called “kernel” (or “mask”, “filter”)



Cross-correlation

Let F be the image, H be the kernel (of size $2k+1 \times 2k+1$), and let G be the output image

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

Like a “dot product”
between local neighborhood
and kernel for each pixel

Convolution

Same as cross-correlation, except that the kernel is “flipped” (horizontally and vertically)

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H * F$$

Convolution is
commutative
and
associative

Mean filtering

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

Mean filtering

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

0	10								

Mean filtering

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20						

Mean filtering

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20	30					

Mean filtering

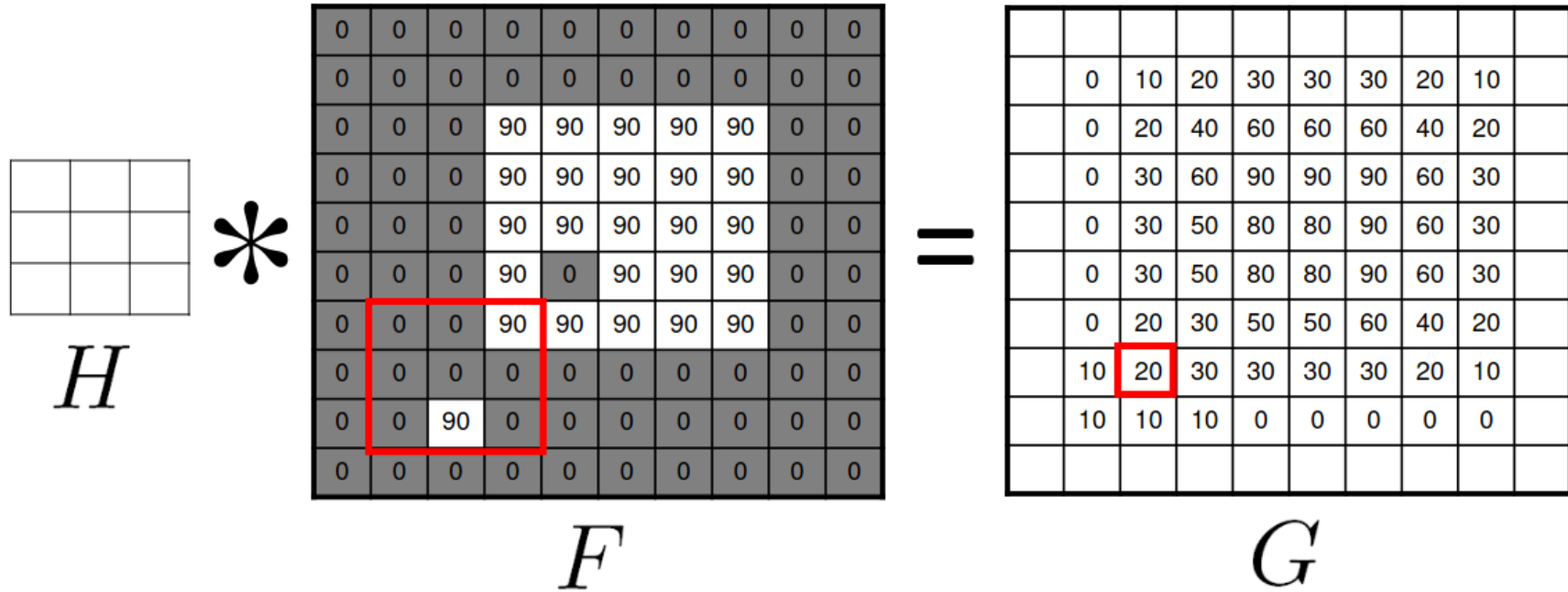
$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

Mean filtering



Linear filters



Original



0	0	0
0	1	0
0	0	0



Identical image

Linear filters

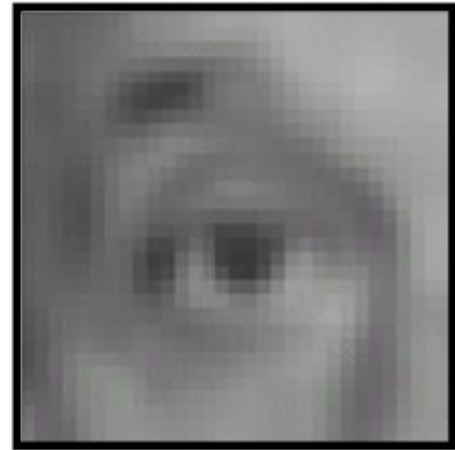


Original



$\frac{1}{9}$

1	1	1
1	1	1
1	1	1



Blur (with a mean filter)

Linear filters



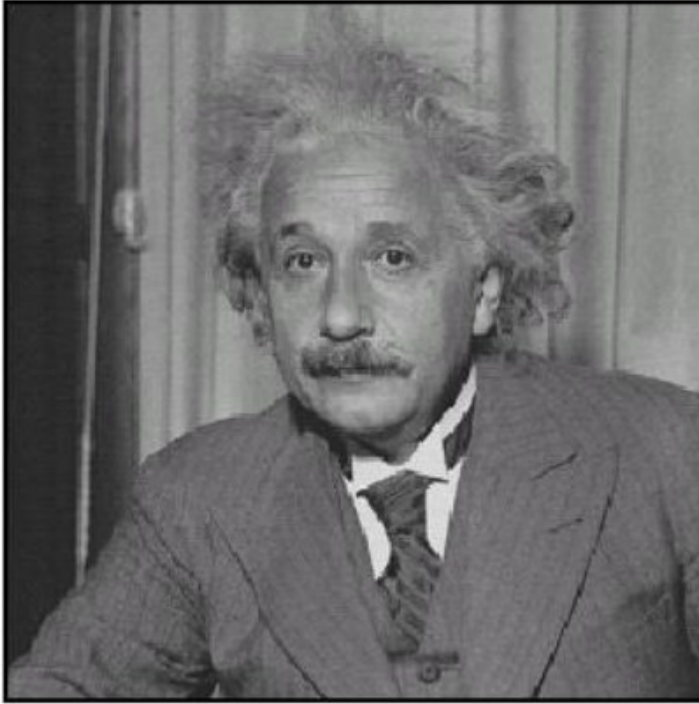
Original

$$* \left(\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \right) =$$

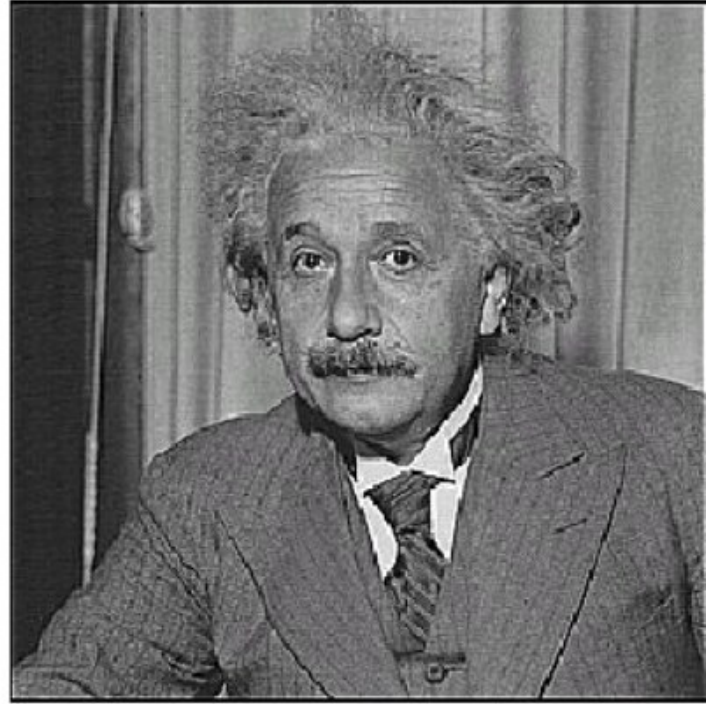


Sharpening filter
(accentuates edges)

Sharpening

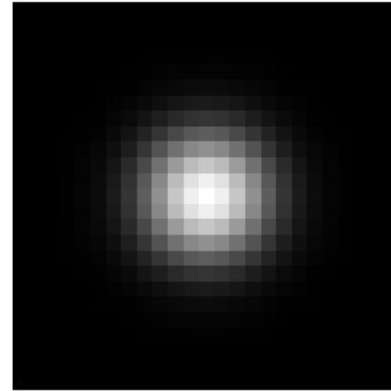
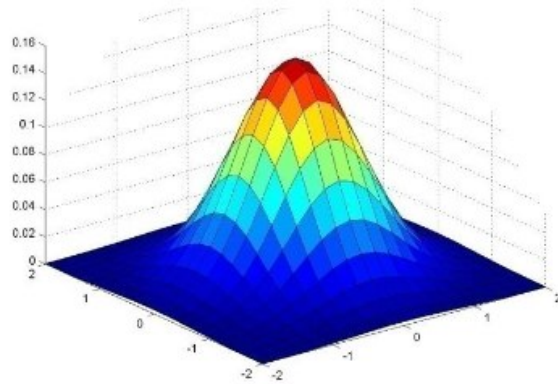


before



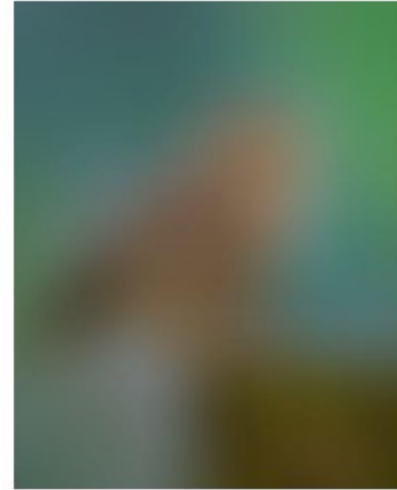
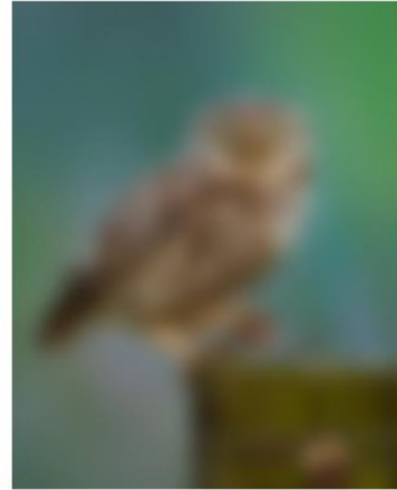
after

Gaussian Kernel

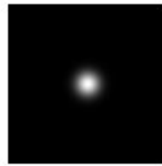


$$G_{\sigma} = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

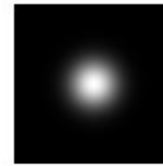
Gaussian Filters



$\sigma = 1$ pixel



$\sigma = 5$ pixels



$\sigma = 10$ pixels

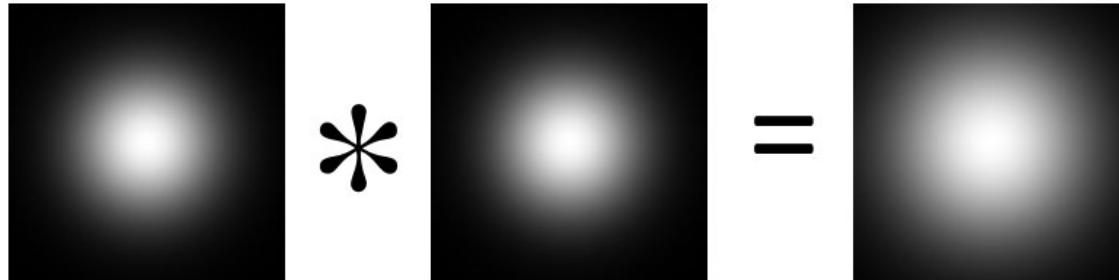


$\sigma = 30$ pixels

Gaussian Filter

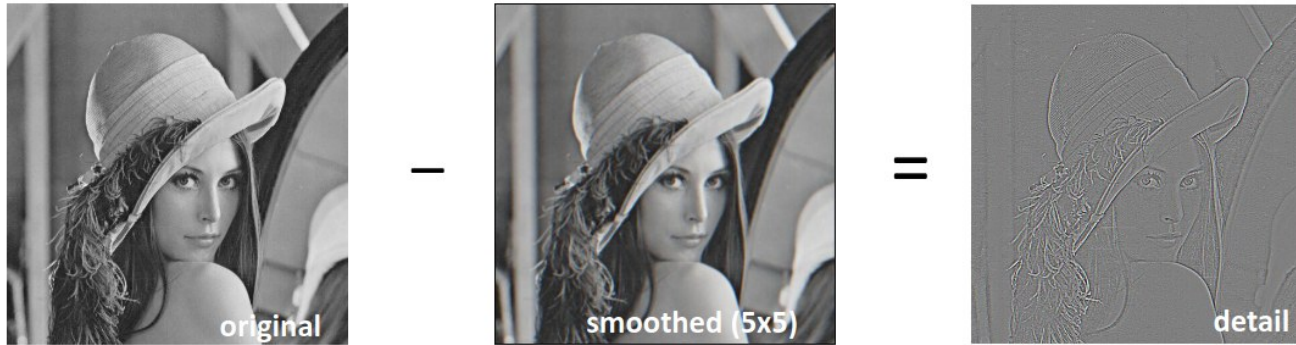
Removes “high-frequency” components from the image (low-pass filter)

Convolution with self is another Gaussian:
original width σ results width $\sigma \sqrt{2}$



Sharpening revisited

What does blurring take away?



Let's add it back:

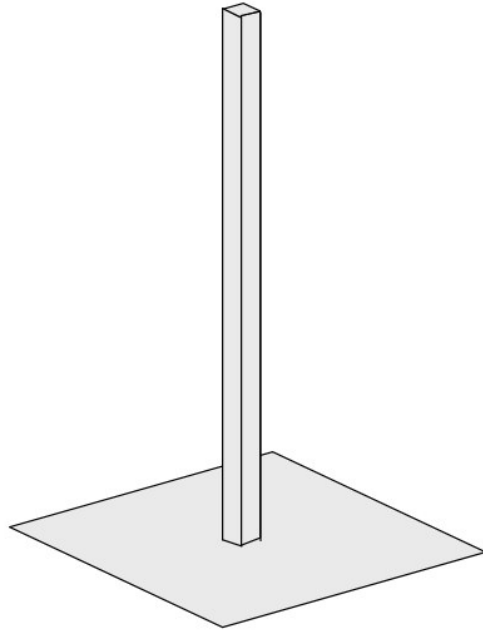


Sharpen filter

$$F + \alpha (F - \underbrace{F * H}_{\text{blurred image}})$$

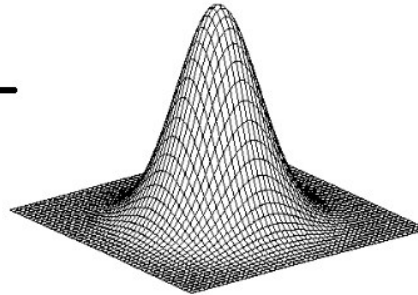
↑
image

↑
unit impulse
(identity)



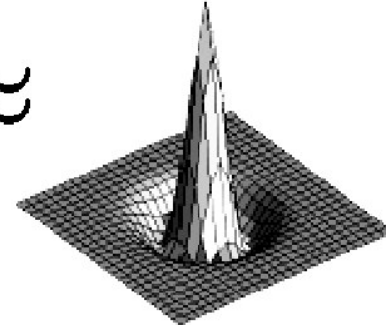
scaled impulse

—



Gaussian

≈



Laplacian of Gaussian

Sharpen filter



Optical convolution

Camera shake



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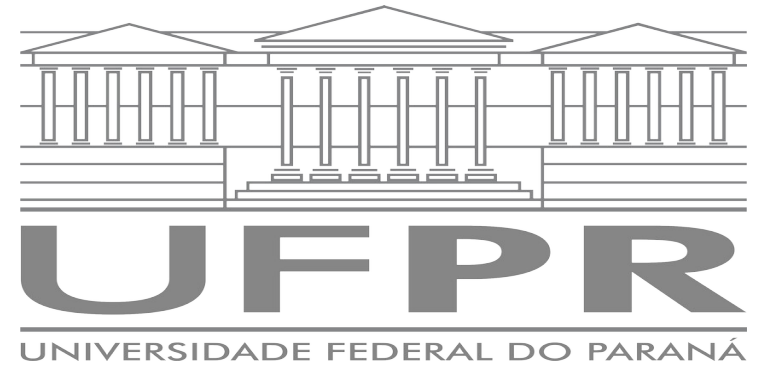


*



Source: Fergus, *et al.* "Removing Camera Shake from a Single Photograph", SIGGRAPH 2006

Gaussian Kernel



Computational Vision and Perception

