

# Image processing



# References

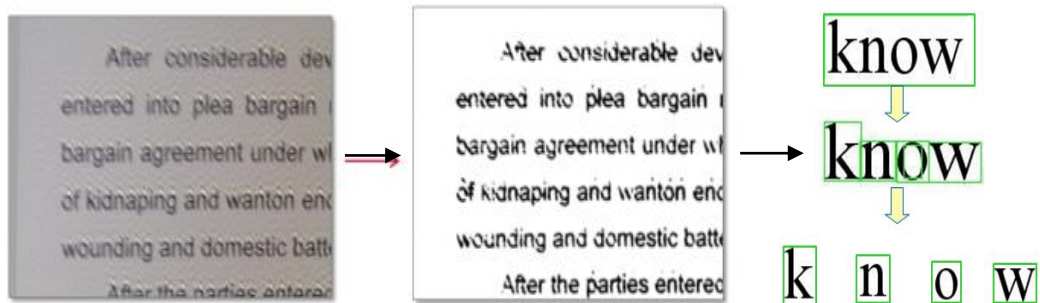
- <http://szeliski.org/Book/>
- <http://www.cs.cornell.edu/courses/cs5670/2019sp/lectures/lectures.html>
- <http://www.cs.cmu.edu/~16385/>

# Some motivation



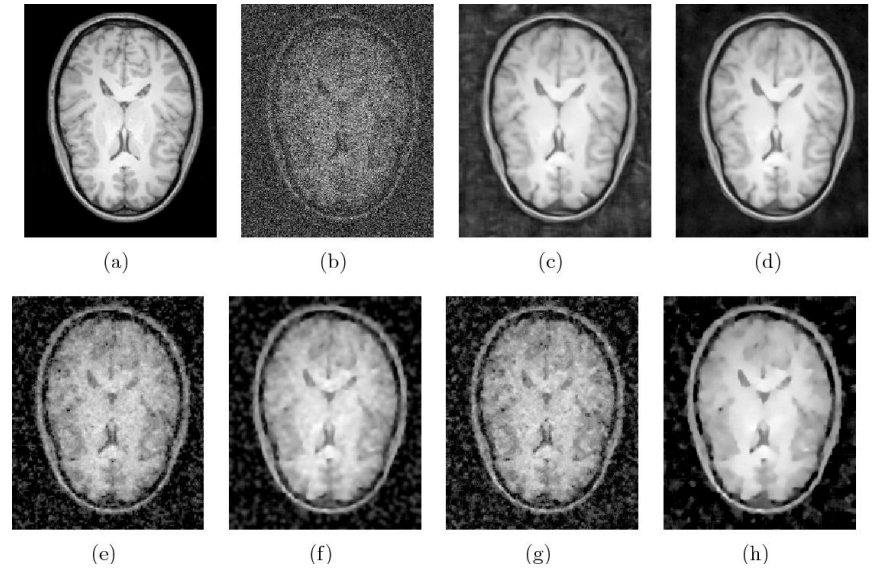
Art

(Photoshop image correction)



Robotics

(OCR – optical character recognition)



Medicine

(MRI denoising)



Agriculture

(color ripeness detection)

# contents

- **Image representation**
- Pixel-wise operations
- Noise and filtering
- Frequency representation
- Morphology operators
- Connected components



# Image representation

- We can think of image as a 3d matrix of discrete RGB values.
- The values mark the intensity of each color channel and are usually of type `uint8 = {0, ..., 255}`.



# Image representation

- We can also think of an image as a function  $f(x, y)$  .



# contents

- Image representation
- **Pixel-wise operations**
- Noise and filtering
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# Pixel-wise operators

- Pixel-wise operators, or point operators, are defined as such that each output pixel's value depends on only the corresponding input pixel value.



# Pixel-wise operators

original



$x$

darken



lower contrast



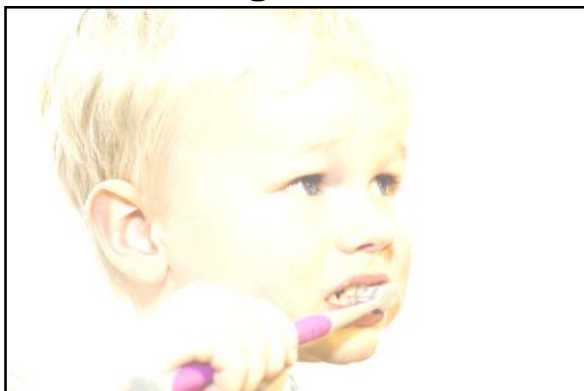
Gamma compression



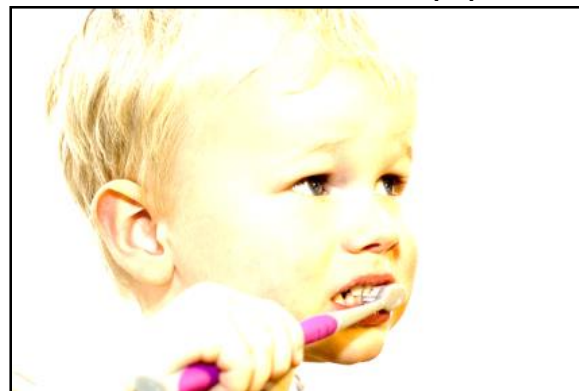
invert



lighten



raise contrast (?)



Gamma expansion



# Pixel-wise operators

original



$x$

darken



lower contrast



Gamma compression



invert



$255 - x$

lighten



raise contrast (?)



Gamma expansion



# Pixel-wise operators

original



$$x$$

darken



$$x - 128$$

lower contrast



Gamma compression

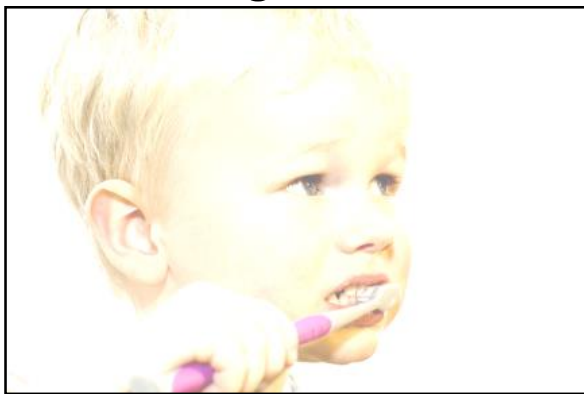


invert



$$255 - x$$

lighten



raise contrast (?)



Gamma expansion





# Pixel-wise operators

original



$$x$$

darken



$$x - 128$$

lower contrast



Gamma compression

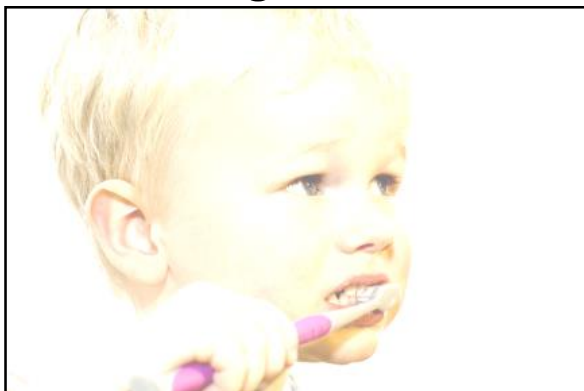


invert



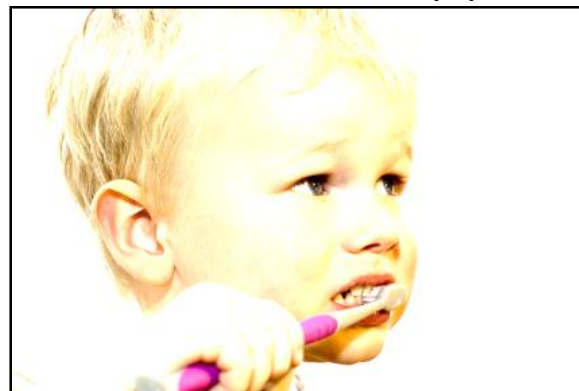
$$255 - x$$

lighten



$$x + 128$$

raise contrast (?)



Gamma expansion



# Pixel-wise operators

original



$$x$$

darken



$$x - 128$$

lower contrast



$$\frac{x}{2}$$

Gamma compression



invert



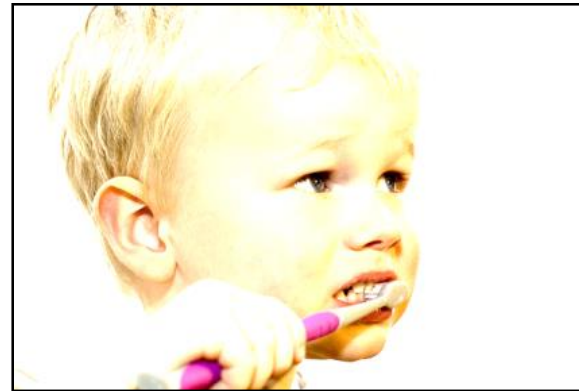
$$255 - x$$

lighten



$$x + 128$$

raise contrast (?)



Gamma expansion





# Pixel-wise operators

original



$$x$$

darken



$$x - 128$$

lower contrast



$$\frac{x}{2}$$

Gamma compression

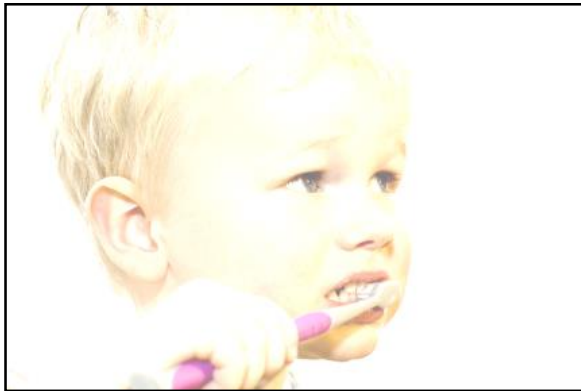


invert



$$255 - x$$

lighten



$$x + 128$$

raise contrast (?)



$$x \times 2$$

Gamma expansion



# Contrast

- **Contrast** in visual perception is the difference in appearance of two or more parts of a field seen.
- The human visual system is more sensitive to contrast than absolute luminance;
- **Contrast ratio**, or **dynamic range**, is the ratio between the largest and smallest values of the image or :

$$CR = \frac{V_{max}}{V_{min}}$$



# Pixel-wise operators

original



$$x$$

darken



$$x - 128$$

lower contrast



$$\frac{x}{2}$$

Gamma compression



$$\left(\frac{x}{255}\right)^{1/3} \times 255$$

invert



$$255 - x$$

lighten



$$x + 128$$

raise contrast (?)



$$x \times 2$$

Gamma expansion





# Pixel-wise operators

original



$$x$$

darken



$$x - 128$$

lower contrast



$$\frac{x}{2}$$

Gamma compression



$$\left(\frac{x}{255}\right)^{1/3} \times 255$$

invert



$$255 - x$$

lighten



$$x + 128$$

raise contrast (?)



$$x \times 2$$

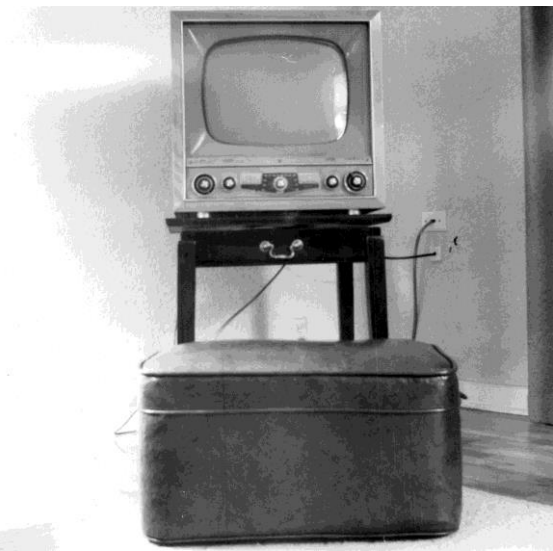
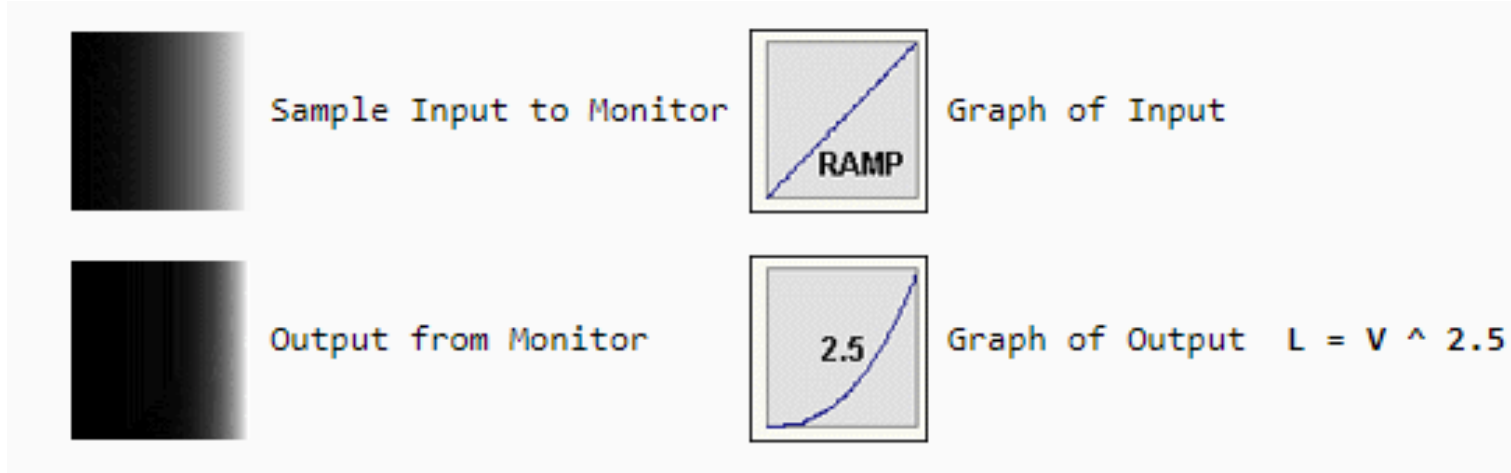
Gamma expansion



$$\left(\frac{x}{255}\right)^2 \times 255$$

# Gamma correction

- Originally, Due to non-linearities in the old CRT televisions, intensities was seen different then they are.



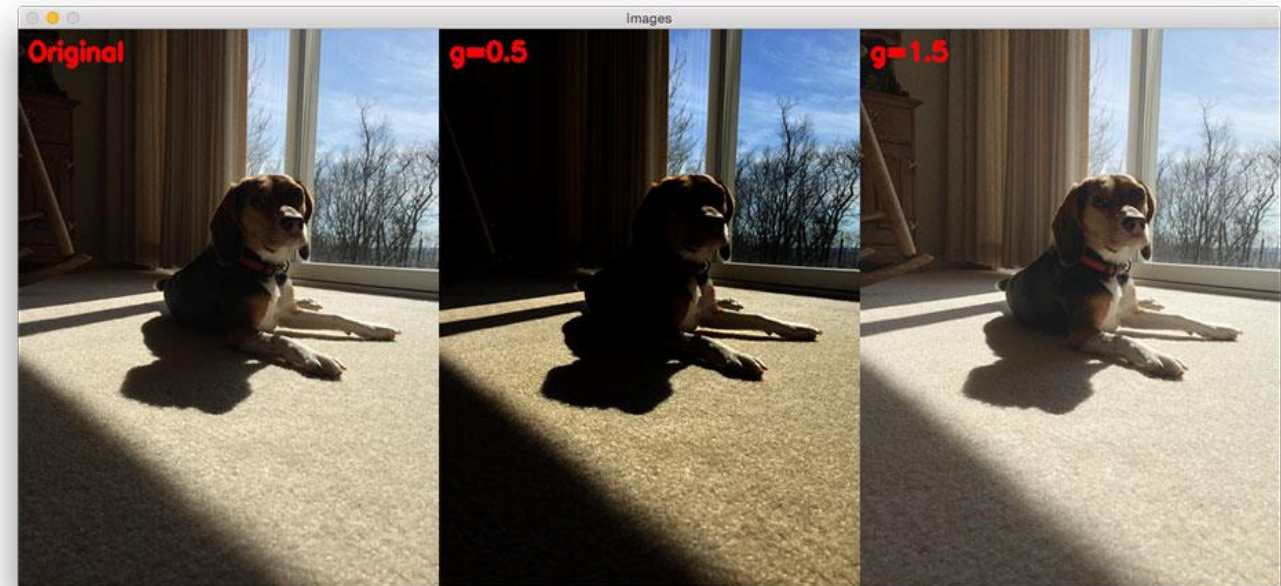
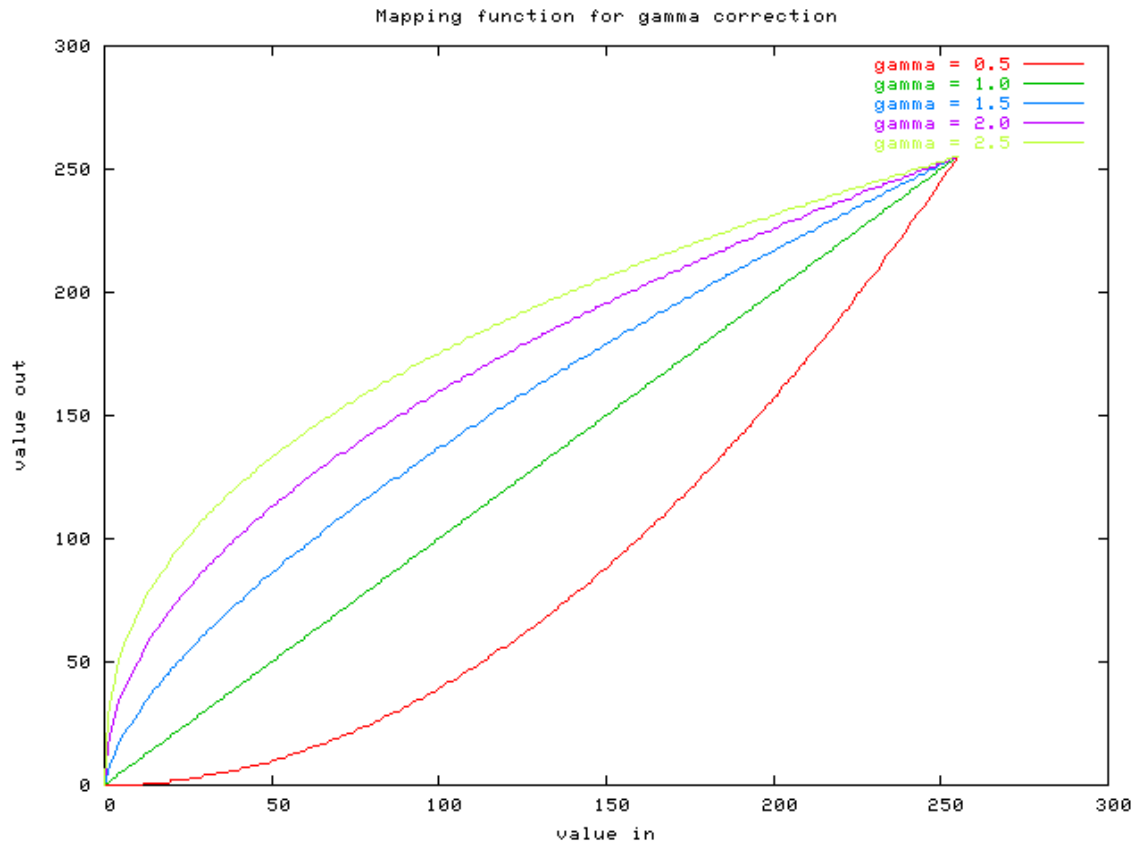


# Gamma correction

- To correct this non linear transformation, gamma correction was done:

$$V_{out} = V_{in}^{\gamma}$$

- This is, of course, also applicable for image enhancements.



# contents

- Image representation
- Pixel-wise operations
- **Noise and filtering**
- Frequency representation
- Morphology operators
- Connected components

# Gaussian Noise

- Gaussian noise is an additive noise that can appear in images due to the system electrical circuitry.
- This noise is independent of signal strength and independent at each pixel (IID).

$$p(z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

Gaussian Noise  $\sigma=0.01$



SNR=34.0206

Gaussian Noise  $\sigma=0.05$



SNR=19.1825

Gaussian Noise  $\sigma=0.1$



SNR=13.7121

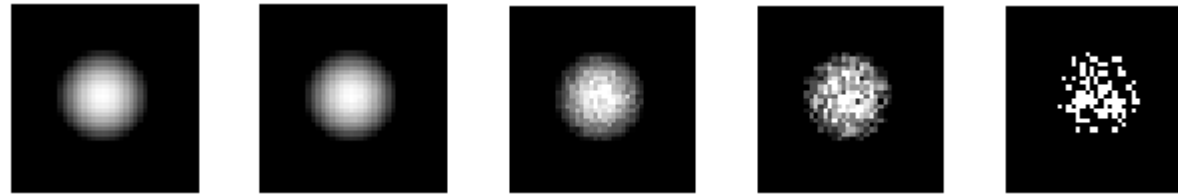
# Salt & Pepper noise

- Noise that can be caused by analog-to-digital converter errors, bit errors in transmission, etc.
- This noise is **not** additive to the signal strength (a replacement of original value with noise value).
- This noise is independent of signal strength and independent at each pixel.

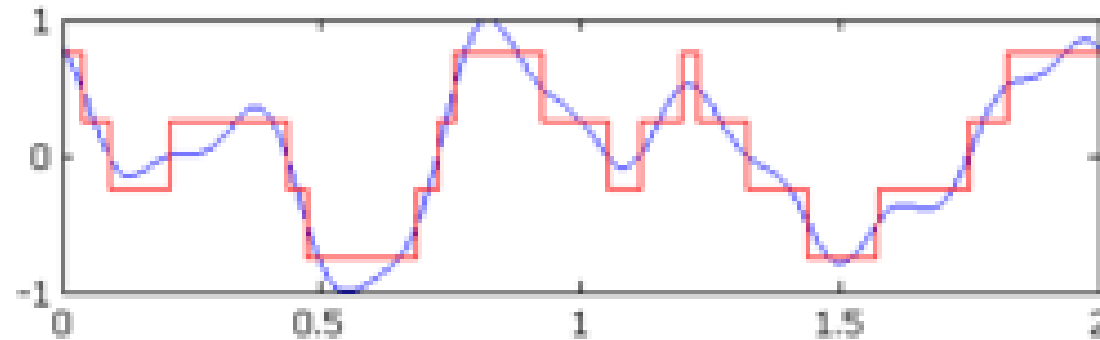


# And some more noise

- **Shot noise** - caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level in the darker parts of an image (where there are just few photons that enter each pixel “bin”). Modeled as Poisson noise.



- **Quantization noise** – caused by quantizing the pixels of a sensed image to several discrete levels (analog to digital conversion).





# Noise reduction with LTI filters

- **linear filtering operators**, which involve weighted combinations of pixels in small neighborhood.
- The combination is determined by the filter's *kernel*.
- The same kernel is *shifted* to all pixel locations so that all pixels use the same linear combination of their neighbors.
- That's why it's called **linear shift-invariance** (LTI) filter.

# Convolution

- Works on LTI filters.
- Let  $h$  be the image,  $f$  be the kernel (of size  $2k+1 \times 2k+1$ ), and  $g$  be the output image:

$$g(i, j) = \sum_{u=-k}^k \sum_{v=-k}^k h[u, v] f[i - u, j - v]$$

- **Note:** by definition, this operator flips the kernel both horizontally and vertically.
- This operation is called **convolution operator** and is more compactly noted as:

$$g = h * f$$

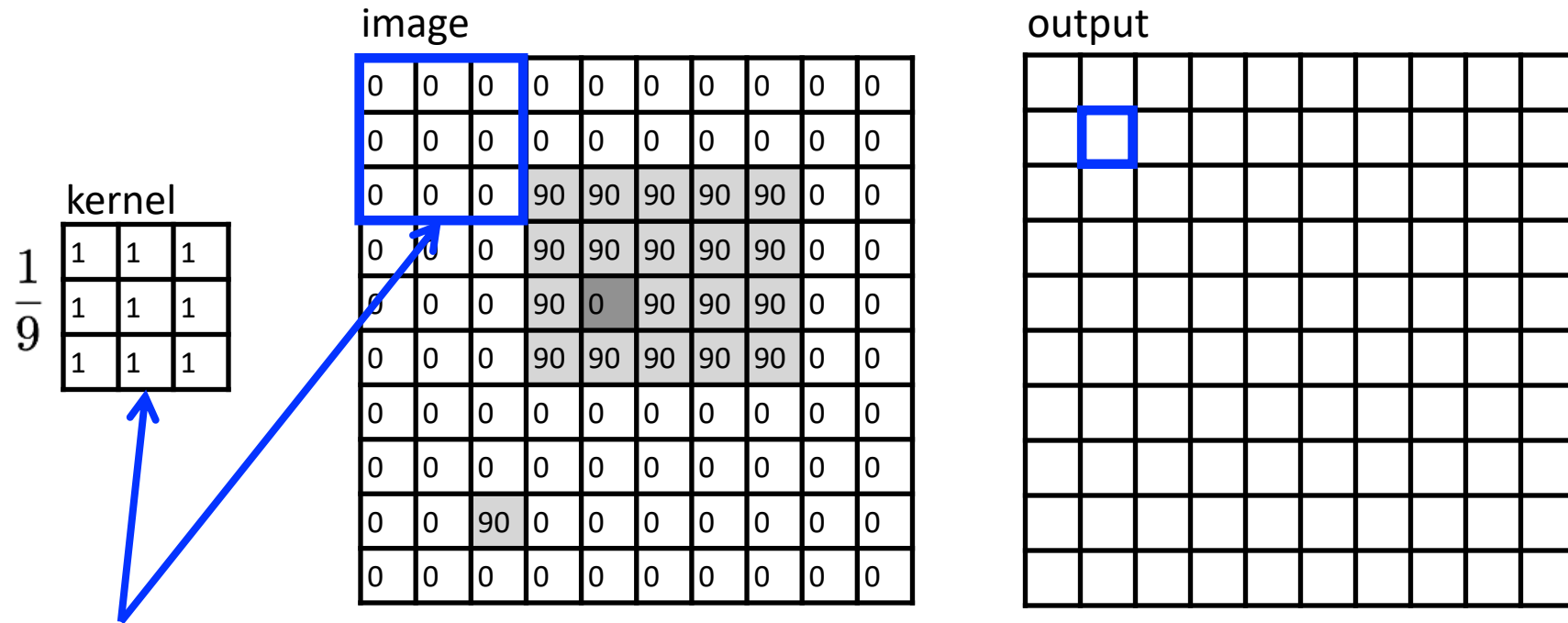
# Example: mean filter

- The kernel is:

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

- Replaces pixel with local average.
- Has smoothing (blurring) effect
- The kernel can be in any other size as well (see .ipynb).

# Run the filter



Note that we assume that the kernel coordinates are centered.

Here the kernel is symmetric horizontally and vertically, so the flipping is not noticeable.

## Run the filter

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline \text{kernel} & & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

image

[illegible]

output

A 10x10 grid where the top-left cell contains the number 0.



# Run the filter

$\frac{1}{9}$

kernel		
1	1	1
1	1	1
1	1	1

image

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	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	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

output

0									

shift-invariant:  
as the pixel  
shifts, so does  
the kernel

## Run the filter

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline \text{kernel} & & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

image

[illegible]

output

[illegible]

# Run the filter

$$\frac{1}{9} g[\cdot, \cdot]$$

1	1	1
1	1	1
1	1	1

image  $f[\cdot, \cdot]$

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	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	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

output  $h[\cdot, \cdot]$

	0	10	20						

$$h[m, n] = \sum_{k, l} g[k, l] f[m + k, n + l]$$

output
 $k, l$ 
filter
image (signal)

## Run the filter

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline \text{kernel} & & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

image

[illegible]

output

[illegible]

## Run the filter

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline \text{kernel} & & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

image

[illegible]

output

[illegible]

## Run the filter

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline \text{kernel} & & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

[illegible][illegible]

## ... and the result is

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline \text{kernel} & & \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

image

[illegible]

output

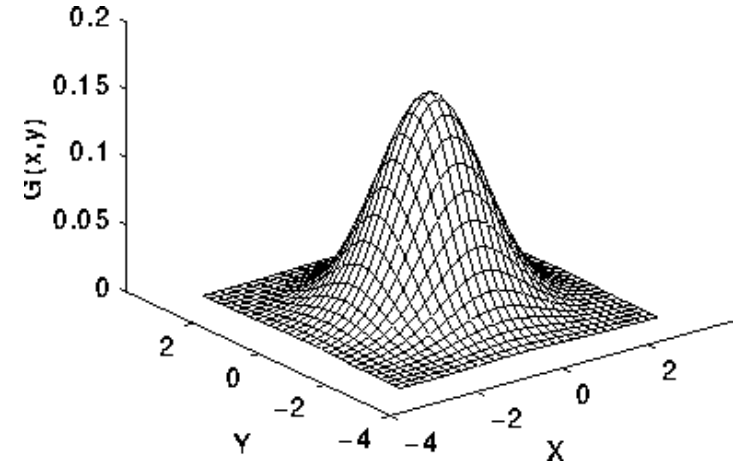
[illegible]



# Gaussian filter

- Another kind of blur filter.
- this filter can be controlled by its size and STD.

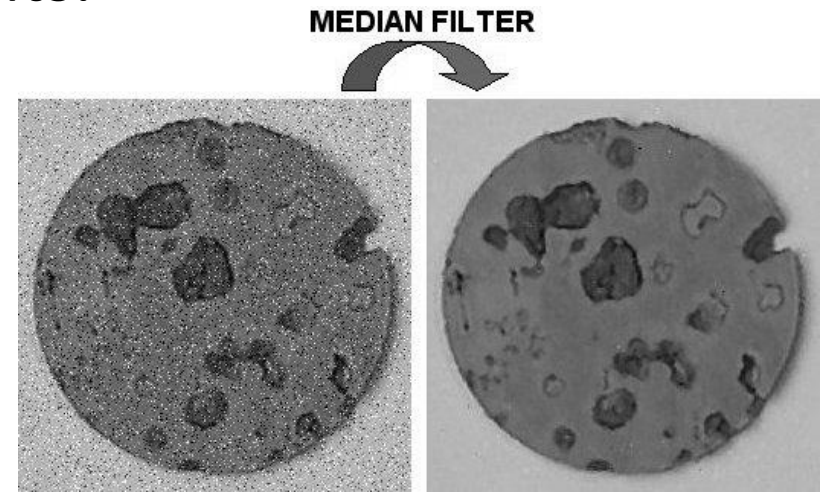
$$h(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}}$$



- The kernel is discretized to bins according to the wanted kernel size.
- Isn't Gaussian function infinite?
  - Most often, the kernel cuts out the remaining lower bins (usually at 2-3  $\sigma$ ).
- **Both Gaussian and mean filters are good against Gaussian noise, but not effective against S&P noise.**

# Median filter

- Takes the median value from the given neighbors (and hence can also be considered as a “blurring effect”).
- For example:
  - The median of  $[1, 0, 100]$  is 1.
- **Median filter is good against salt and pepper noise, and against Gaussian noise (but not as effective).**
- **Median filter is also more computationally expansive.**
- This filter is not LTI because it's not linear on its weights.



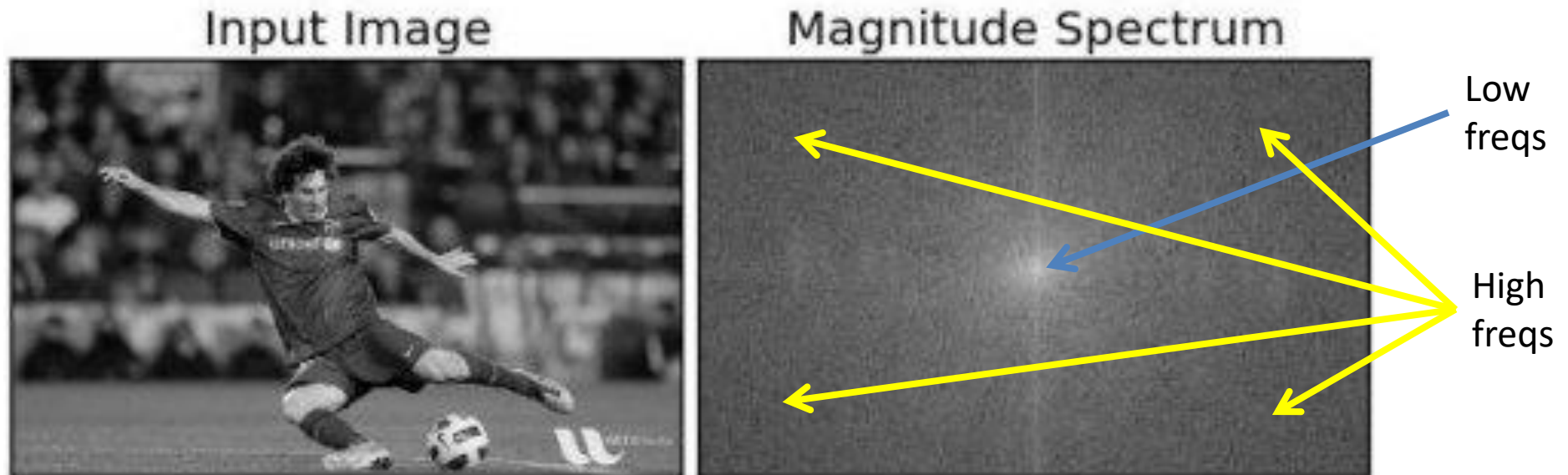
# Example in .ipynb

# contents

- Image representation
- Pixel-wise operations
- Noise and filtering
- **Frequency representation**
- Morphology operators
- Connected components

# FFT of an image

- Frequency analysis is not in the scope of the course and is not needed for the rest of the course, but here it can give some intuition.
- In audio signals (or any other 1D signals) Lower frequencies change less over time than higher frequencies.
  - In images, the change is represented in change in distance, so images that changes slowly from pixel to pixel has more lower frequencies than others.
- Natural images are mainly built from low frequencies.





# Convolution in frequency domain

- Recall: in time (space) domain:

$$g(i, j) = \sum_{u=-k}^k \sum_{v=-k}^k h[u, v] f[i - u, j - v]$$

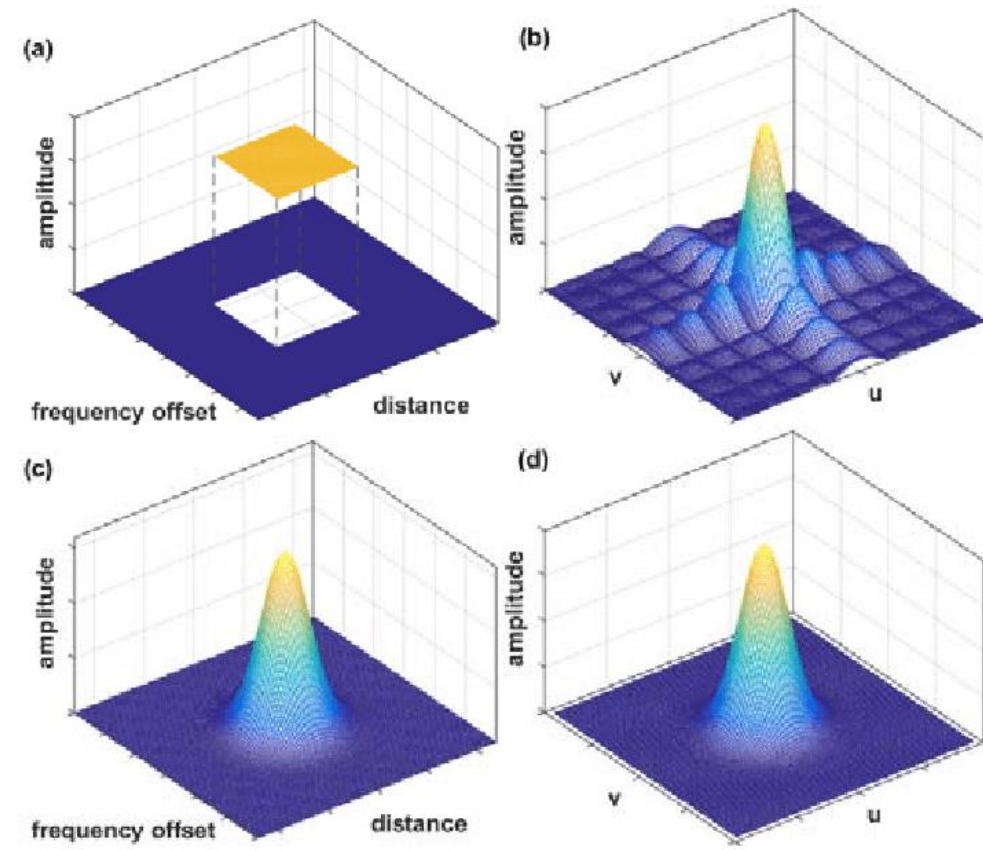
$$g = h * f$$

- In frequency domain- simple multiplication:

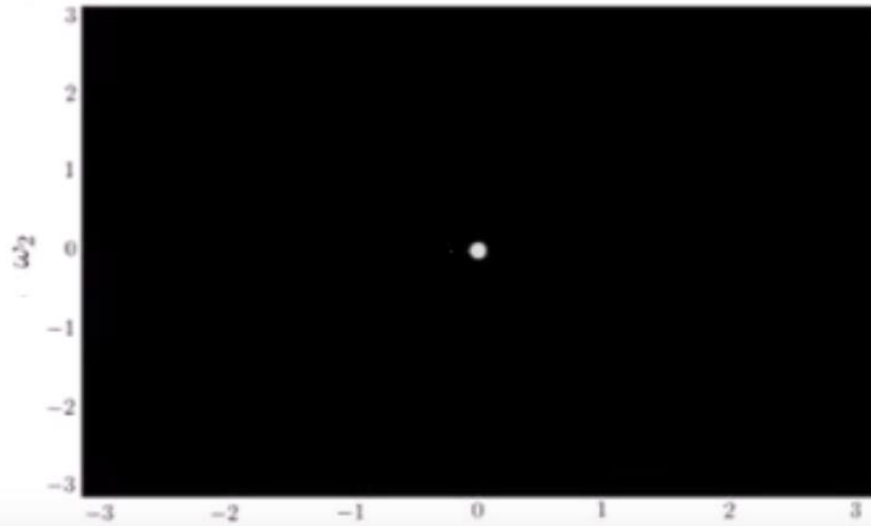
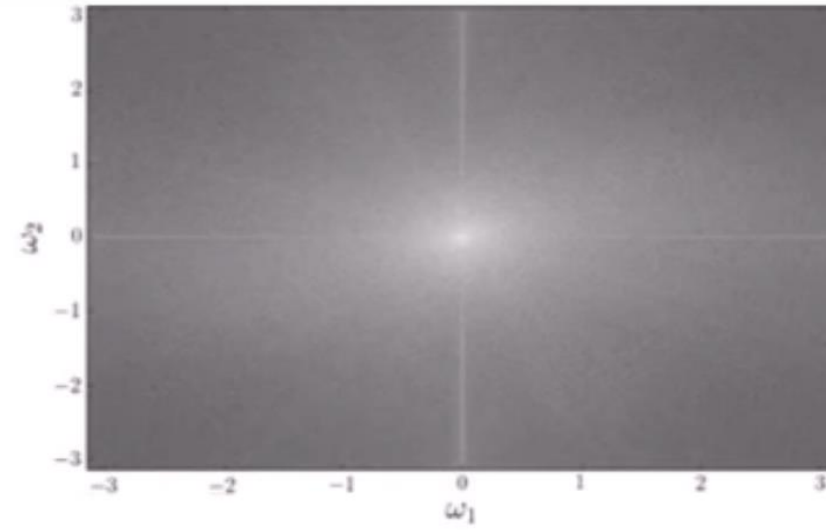
$$G = H \cdot F$$

# Low-pass filters

- Both mean and Gaussian filters are considered low-pass filters because in the frequency domain, they have higher values in the lower frequencies- and when multiplied with frequency spectrums, the high frequencies get smaller.
- When image is left only with the lower frequencies, the rapidly changes parts of the image (e.g.: edges, noise) are smoothen.

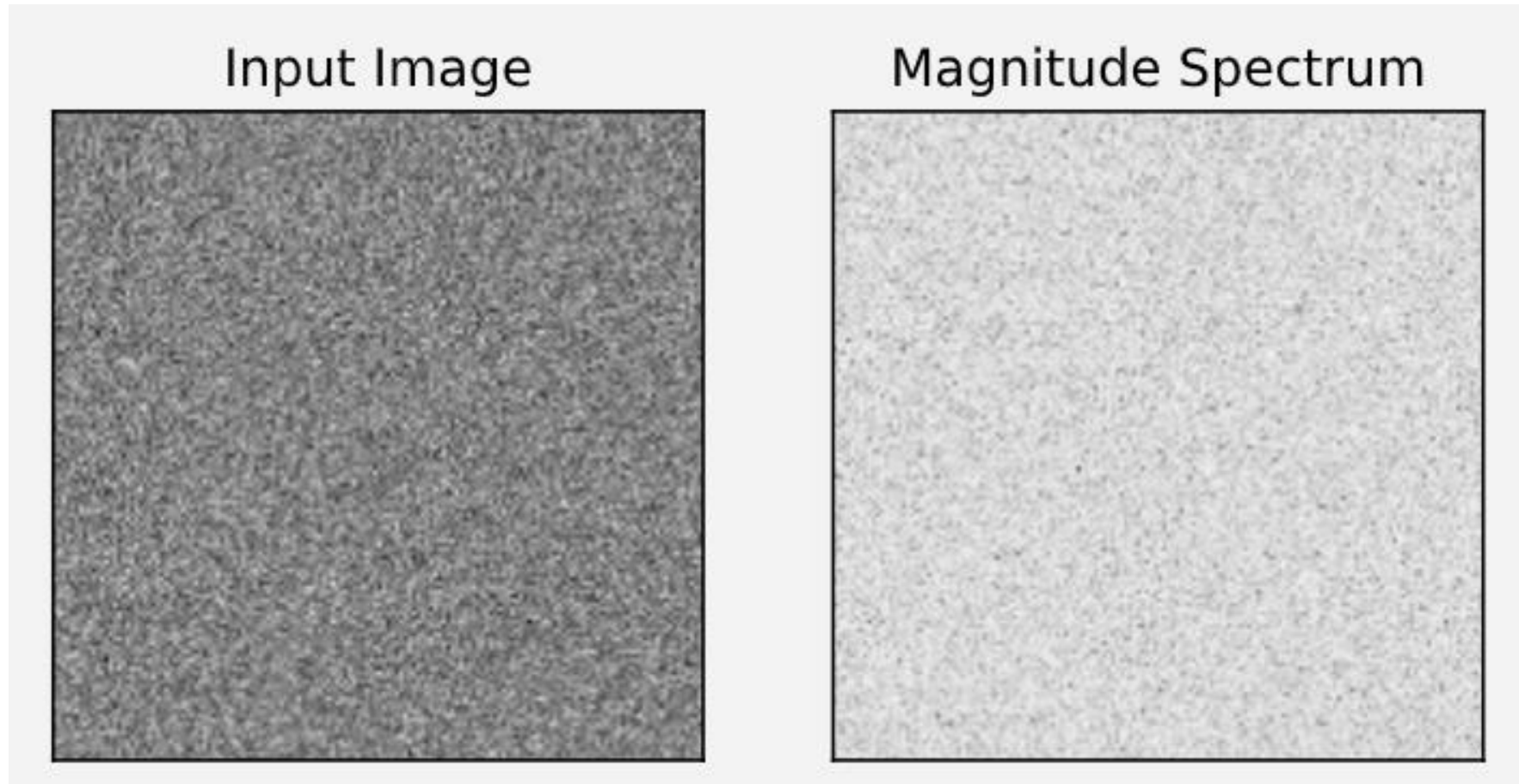


# LP example



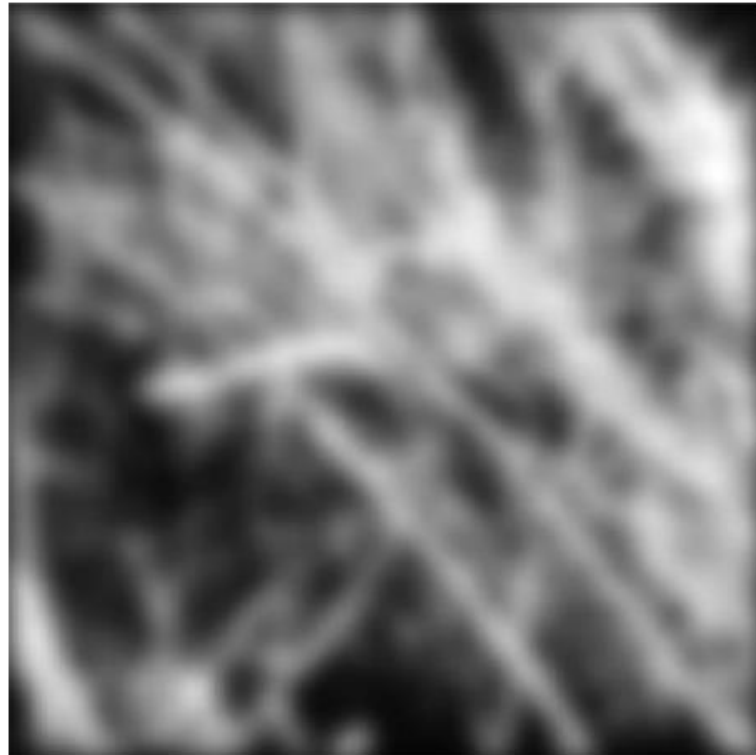
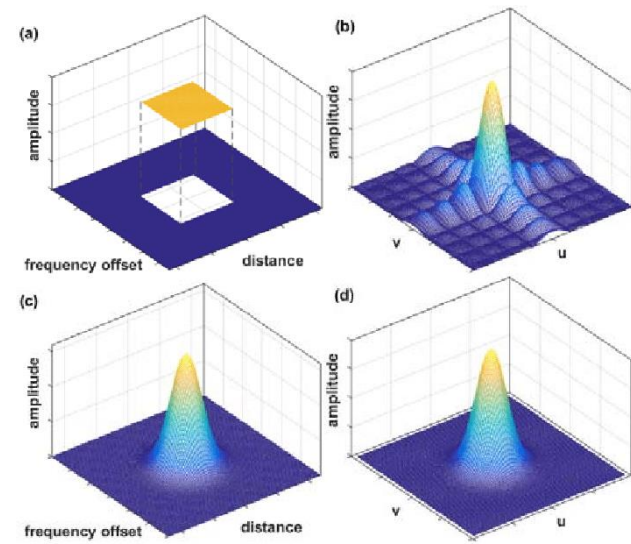
# FFT of gaussian noise

- Since gaussian noise (AWGN) is distributed along all frequencies, LP filter reduce this kind of noise significantly.

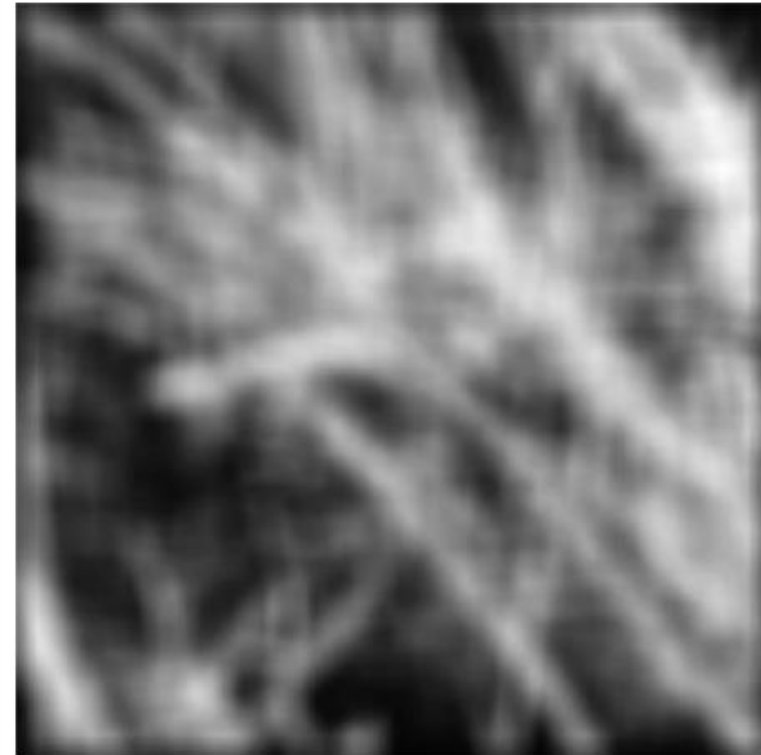
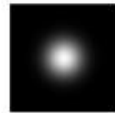


# Mean vs. Gaussian filter

- Since Mean filter has higher values in the higher frequencies, edge artifacts sometimes remains.



Gaussian  
filter



Box  
filter





# contents

- Image representation
- Pixel-wise operations
- Noise and filtering
- Frequency representation
- **Morphology operators**
- Connected components

# Morphology

- Handy tool whenever needed to clean up binary images.
- Each morphology operator is constructed as such:
  1. Select some kind of structure element (binary kernel)

$$s = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

# Morphology

- Handy tool whenever needed to clean up binary images.

- Each morphology operator is constructed as such:

1. Select some kind of structure element (binary kernel)

2. Convolve with input binary image  $g = f * s$

$$s = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

# Morphology

- Handy tool whenever needed to clean up binary images.

- Each morphology operator is constructed as such:

1. Select some kind of structure element (binary kernel)

2. Convolve with input binary image  $g = f * s$

3. Threshold the output

$$\theta_{TH}(x, t) = \begin{cases} 1 & \text{if } x \geq t, \\ 0 & \text{else} \end{cases}$$

$$s = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

# Morphology

- Handy tool whenever needed to clean up binary images.

- Each morphology operator is constructed as such:

1. Select some kind of structure element (binary kernel)

$$s = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

2. Convolve with input binary image  $g = f * s$

3. Threshold the output

$$\theta_{TH}(x, t) = \begin{cases} 1 & \text{if } x \geq t, \\ 0 & \text{else} \end{cases}$$

- Overall morphologic operation should look like so:

$$k = \theta_{TH}(f * s, t)$$



# Dilation

1. Select some kind of structure element (binary kernel)

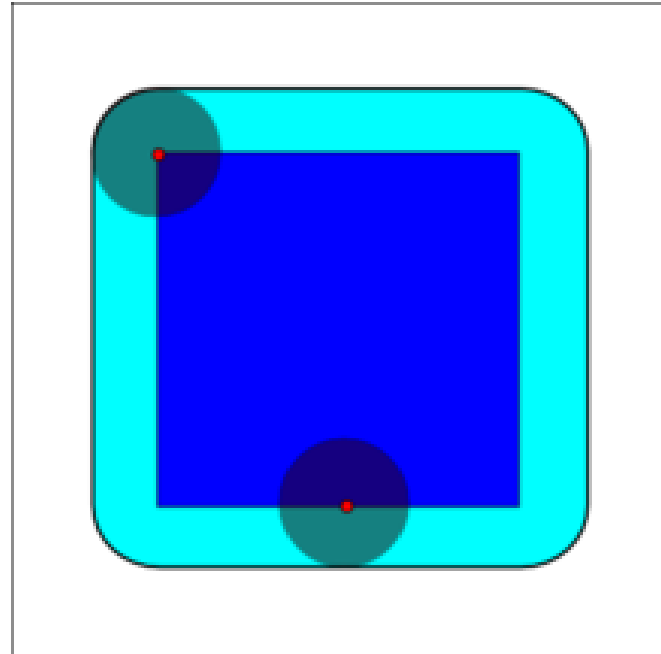
2. Convolve with input binary image  $g = f * s$

3. Threshold the output

$$\theta_{TH}(x, t) = \begin{cases} 1 & \text{if } x \geq t, \\ 0 & \text{else} \end{cases}$$

$$s = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

- Dilation:  $t = 1$ 
  - Skinny lines will get thicker



# Erosion

1. Select some kind of structure element (binary kernel)

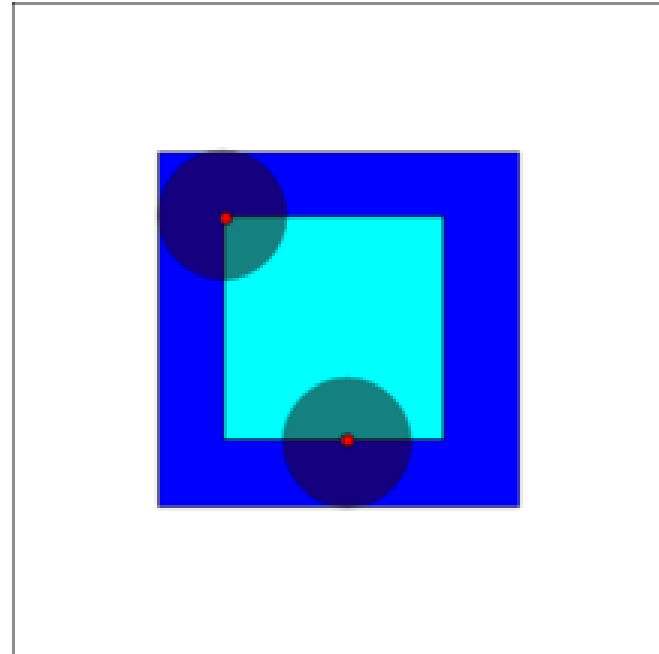
2. Convolve with input binary image  $g = f * s$

3. Threshold the output

$$\theta_{TH}(x, t) = \begin{cases} 1 & \text{if } x \geq t, \\ 0 & \text{else} \end{cases}$$

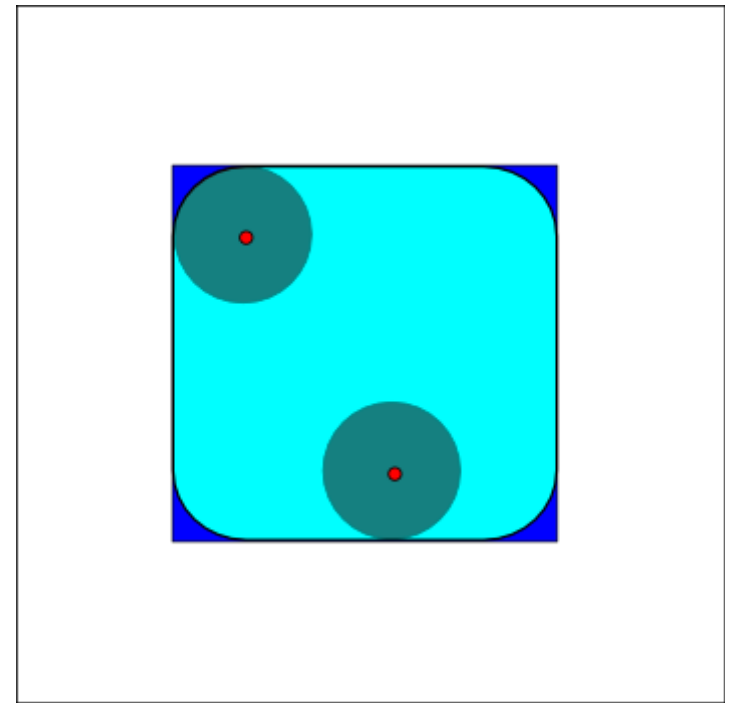
$$s = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

- Erosion:  $t = \text{sum}(s)$ 
  - Thicker lines will get skinny



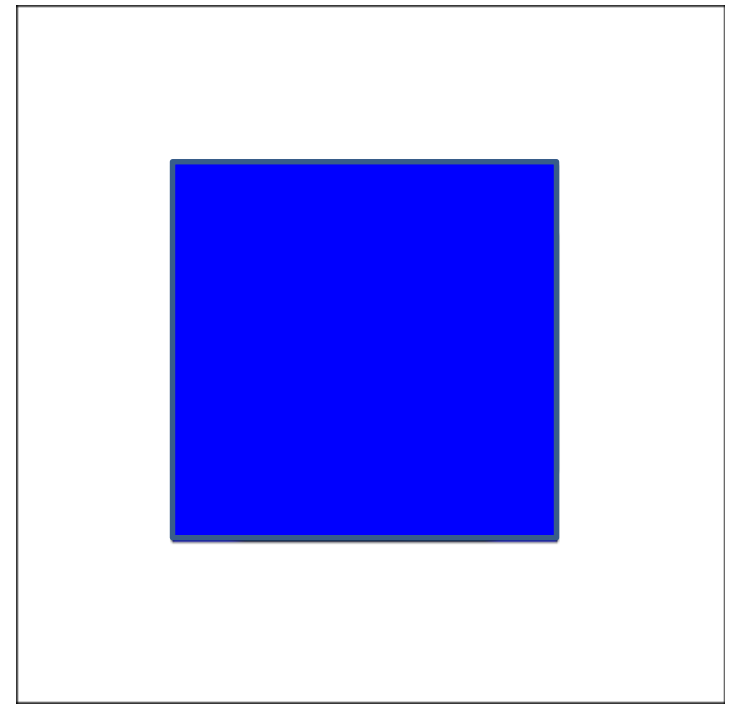
# Opening

- Erosion followed by dilation.
  - The effect is of rounding off sharp edges.



# Closing

- Dilation followed by erosion.
  - The effect is of closing of narrow gaps and holes.



# contents

- Image representation
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- **Connected components**

# Connected components

- Defined as regions of adjacent pixels that have the same value.
- Commonly used with binary images to find stand alone objects.
  - e.g.: letters in a document.

