



# **MMAT 5390: Mathematical Imaging**

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## **Lecture 7: Even Discrete Cosine Transform & Image enhancement in the frequency domain**

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# Even Discrete Cosine Transform

## 1D and 2D Even Discrete Cosine Transform:

**1D:** The 1D EDCT (for a signal  $f$  of size  $M$ ) is given by

$$\hat{f}_{ec}(m) = \frac{1}{2M} \sum_{k=-M}^{M-1} f(k) \cos \frac{\pi m(2k+1)}{2M}$$

where  $0 \leq m \leq 2M - 1$ .

**2D:** Let  $f$  be an  $M \times N$  image. Reflect it about its left and top border to get a  $2M \times 2N$  image. (indices are shifted by  $\frac{1}{2}$ )

The EDCT of  $f$  is given by

$$\hat{f}_{ec}(m, n) = \frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} f(k, l) \cos \left[ \frac{m\pi}{M} \left( k + \frac{1}{2} \right) \right] \cos \left[ \frac{n\pi}{N} \left( l + \frac{1}{2} \right) \right]$$

with  $0 \leq m \leq 2M - 1, 0 \leq n \leq 2N - 1$

**For details, please refer to Lecture Note Chapter 2**

# Inverse Even Discrete Cosine Transform

## Inverse Even Discrete Cosine Transform:

2D:

$$f(k, l) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} C(m)C(n) \hat{f}_{ec}(m, n) \cos \frac{\pi m(2k+1)}{2M} \cos \frac{\pi n(2l+1)}{2N}$$

for  $C(0) = 1, C(m) = C(n) = 2$  for  $m, n \neq 0$

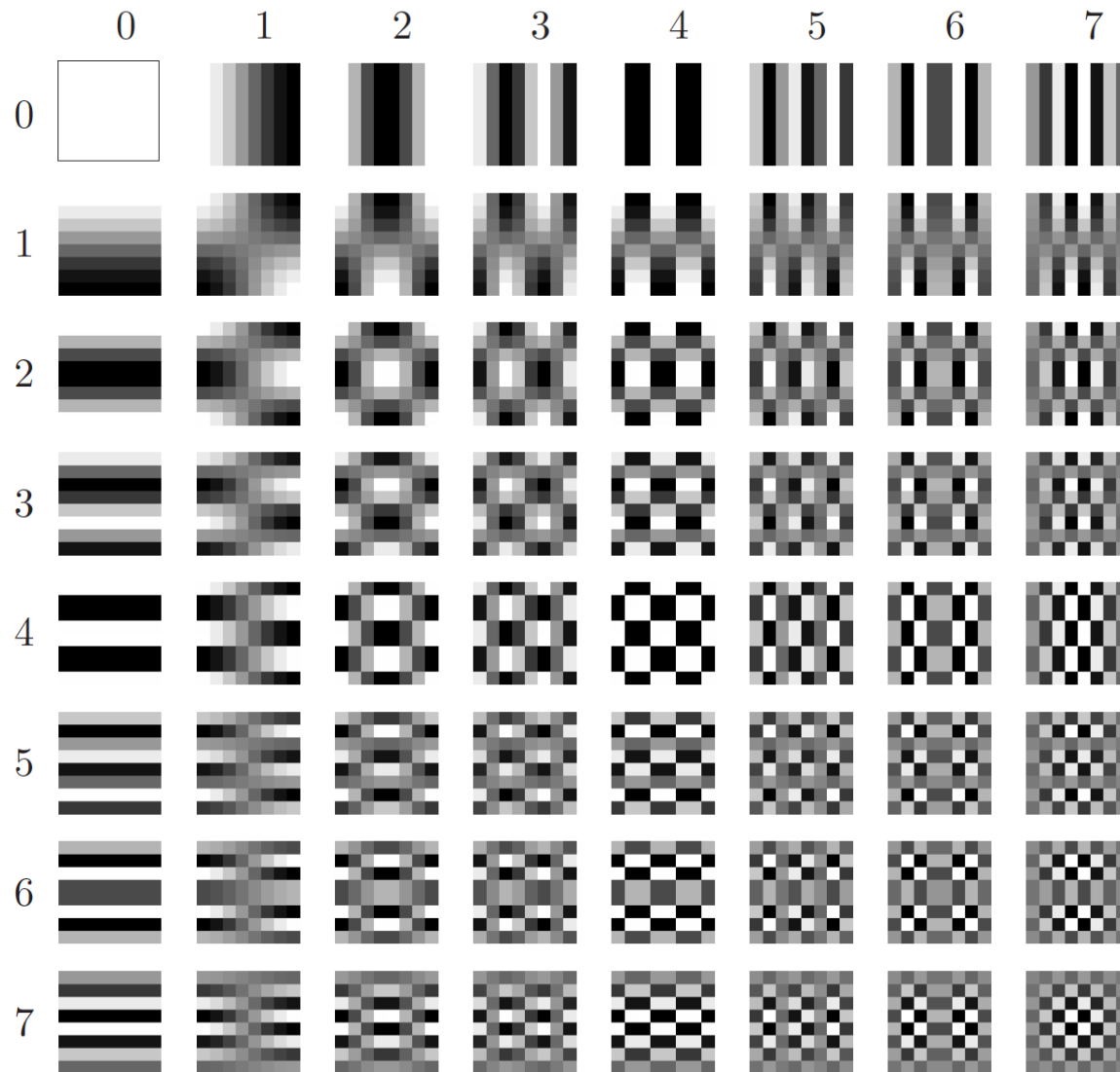
## Image Decomposition

$$f = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \hat{f}_{ec}(m, n) \vec{T}_m \vec{T}_n^T$$

$$\text{where: } \vec{T}_m = \begin{pmatrix} T_m(0) \\ T_m(1) \\ \vdots \\ T_m(M-1) \end{pmatrix}, \vec{T}_n^T = \begin{pmatrix} T'_n(0) \\ T'_n(1) \\ \vdots \\ T'_n(N-1) \end{pmatrix} \text{ with } T_m(k) = C(m) \cos \frac{\pi m(2k+1)}{2M}$$

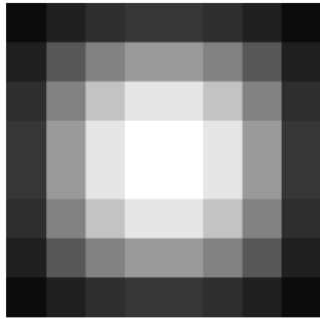
$$\text{and } T'_n(k) = C(n) \cos \frac{\pi n(2k+1)}{2N}.$$

# Elementary images of EDCT decomposition

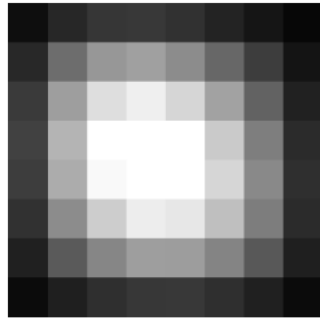


The basis images in terms of which any  $8 \times 8$  image is expanded by EDCT.

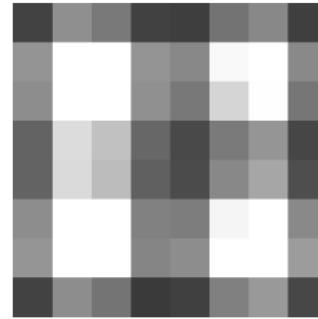
# Reconstruction w/ EDCT decomposition



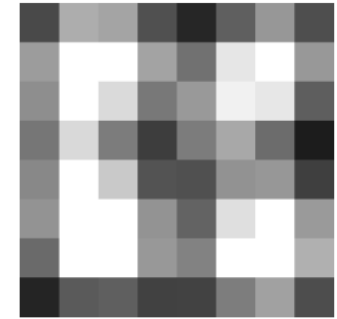
(a)



(b)



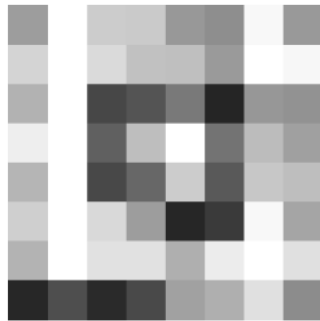
(c)



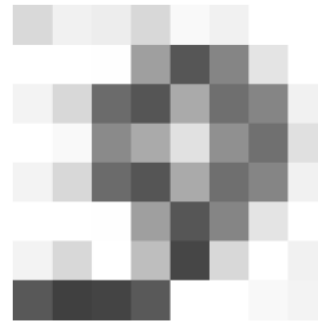
(d)



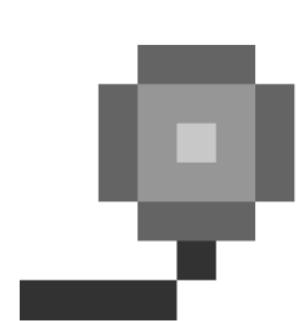
(e)



(f)



(g)



(h)

- (a) = using 1x1 elementary images (first 1 row and first 1 column elementary images);
- (b) = using 2x2 elementary images (first 2 rows and first 2 column elementary images...and so on...

## Other similar transforms

### Odd Discrete Cosine Transform:

$$\hat{f}_{oc}(m, n) \equiv \frac{1}{(2M-1)(2N-1)} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} C(k)C(l)f(k, l) \cos \frac{2\pi mk}{2M-1} \cos \frac{2\pi nl}{2N-1}$$

### Even Discrete Sine Transform:

$$\hat{f}_{es}(m, n) \equiv -\frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} f(k, l) \sin \frac{\pi m(2k+1)}{2M} \sin \frac{\pi n(2l+1)}{2N}$$

### Odd Discrete Sine Transform:

$$\hat{f}_{os}(m, n) \equiv -\frac{4}{(2M+1)(2N+1)} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} f(k, l) \sin \frac{2\pi m(k+1)}{2M+1} \sin \frac{2\pi n(l+1)}{2N+1}$$

All of them have explicit formula for their inverses.  
(For details, please refer to Lecture Note Chapter 2)

## Other similar transforms

### Inverse Odd Discrete Cosine Transform:

$$f(k, l) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} C(m)C(n) \hat{f}_{oc}(m, n) \cos \frac{2\pi mk}{2M-1} \cos \frac{2\pi nl}{2N-1}$$

where  $C(0) = 1, C(m) = C(n) = 2$  if  $m, n \neq 0$

### Inverse Even Discrete Sine Transform:

$$f(k, l) = - \sum_{m=1}^M \sum_{n=1}^N S(m)S(n) \hat{f}_{es}(m, n) \sin \frac{\pi m(2k+1)}{2M} \sin \frac{\pi n(2l+1)}{2N}$$

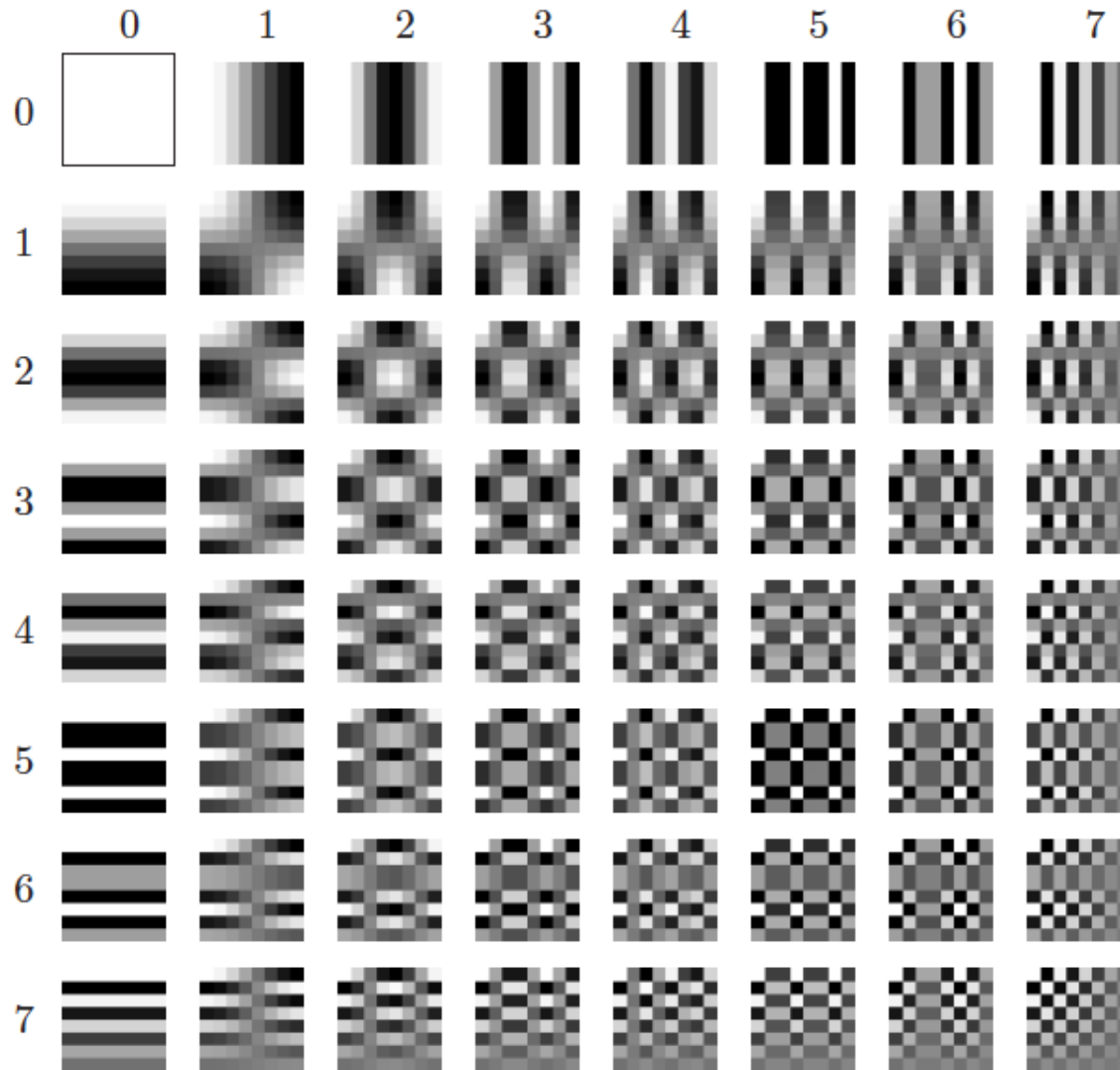
where  $S(M) = S(N) = 1, S(m) = S(n) = 2$  for  $m \neq M, n \neq N$ .

### Inverse Odd Discrete Sine Transform:

$$f(k, l) = -16 \sum_{m=1}^M \sum_{n=1}^N \hat{f}_{os}(m, n) \sin \frac{2\pi m(k+1)}{2M+1} \sin \frac{2\pi n(l+1)}{2N+1}$$

(For details, please refer to Lecture Note Chapter 2)

# Elementary images of ODCT decomposition



The basis images in terms of which any  $8 \times 8$  image is expanded by EDCT.



# Reconstruction w/ ODCT decomposition



(a)



(b)



(c)



(d)



(e)



(f)



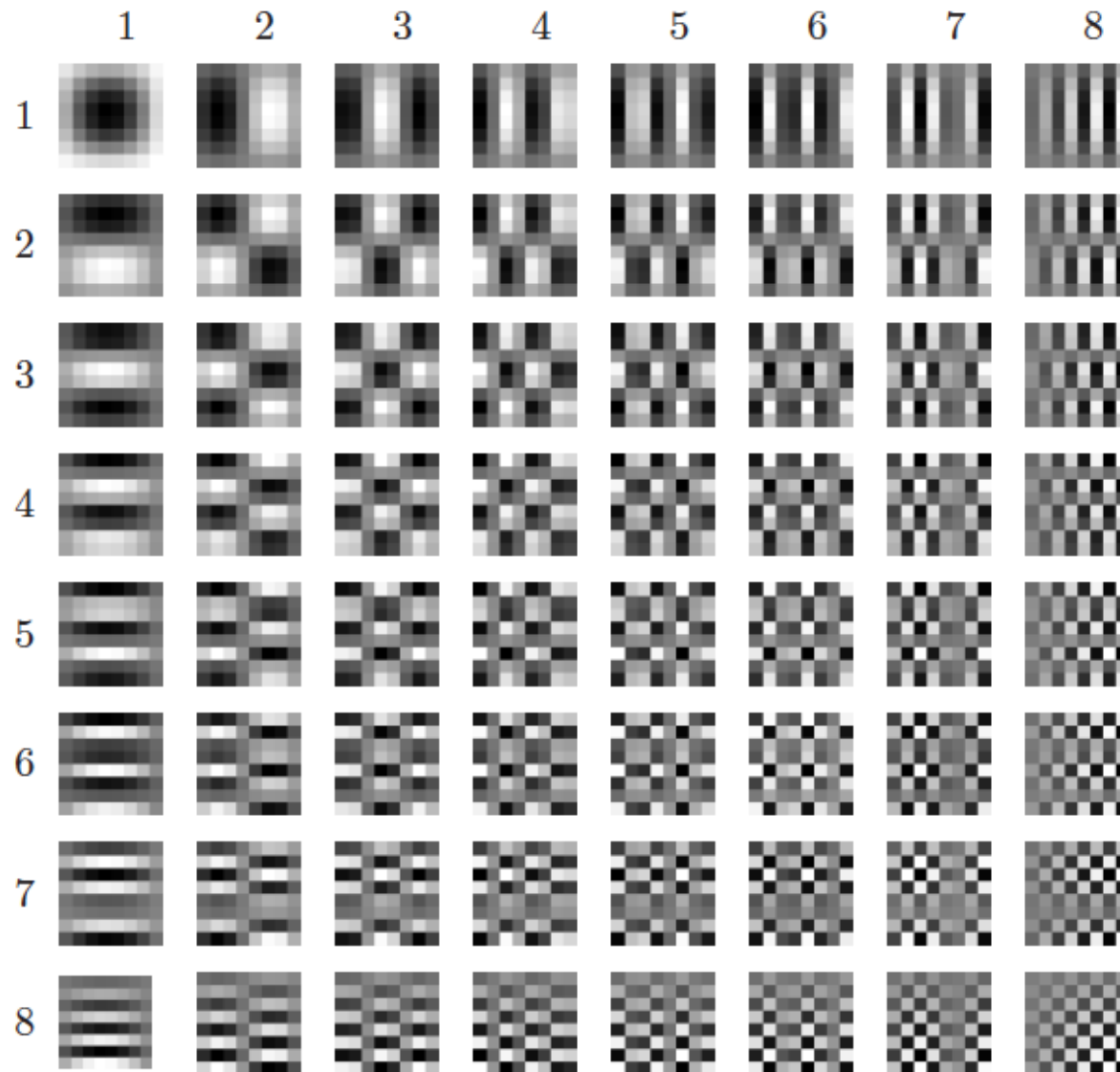
(g)



(h)

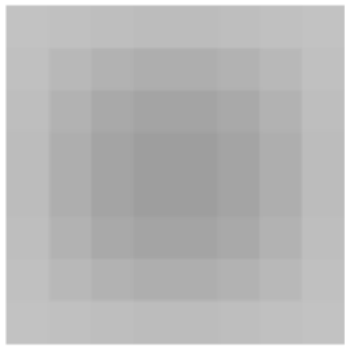
- (a) = using 1x1 elementary images (first 1 row and first 1 column elementary images);
- (b) = using 2x2 elementary images (first 2 rows and first 2 column elementary images...and so on...

# Elementary images of EDST decomposition



The basis images in terms of which any  $8 \times 8$  image is expanded by EDCT.

# Reconstruction w/ EDST decomposition



(a)



(b)



(c)



(d)



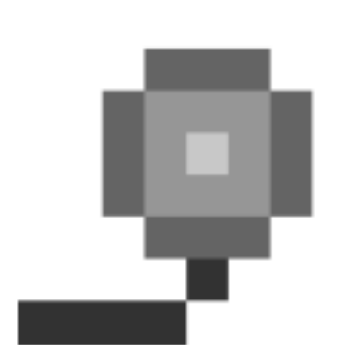
(e)



(f)



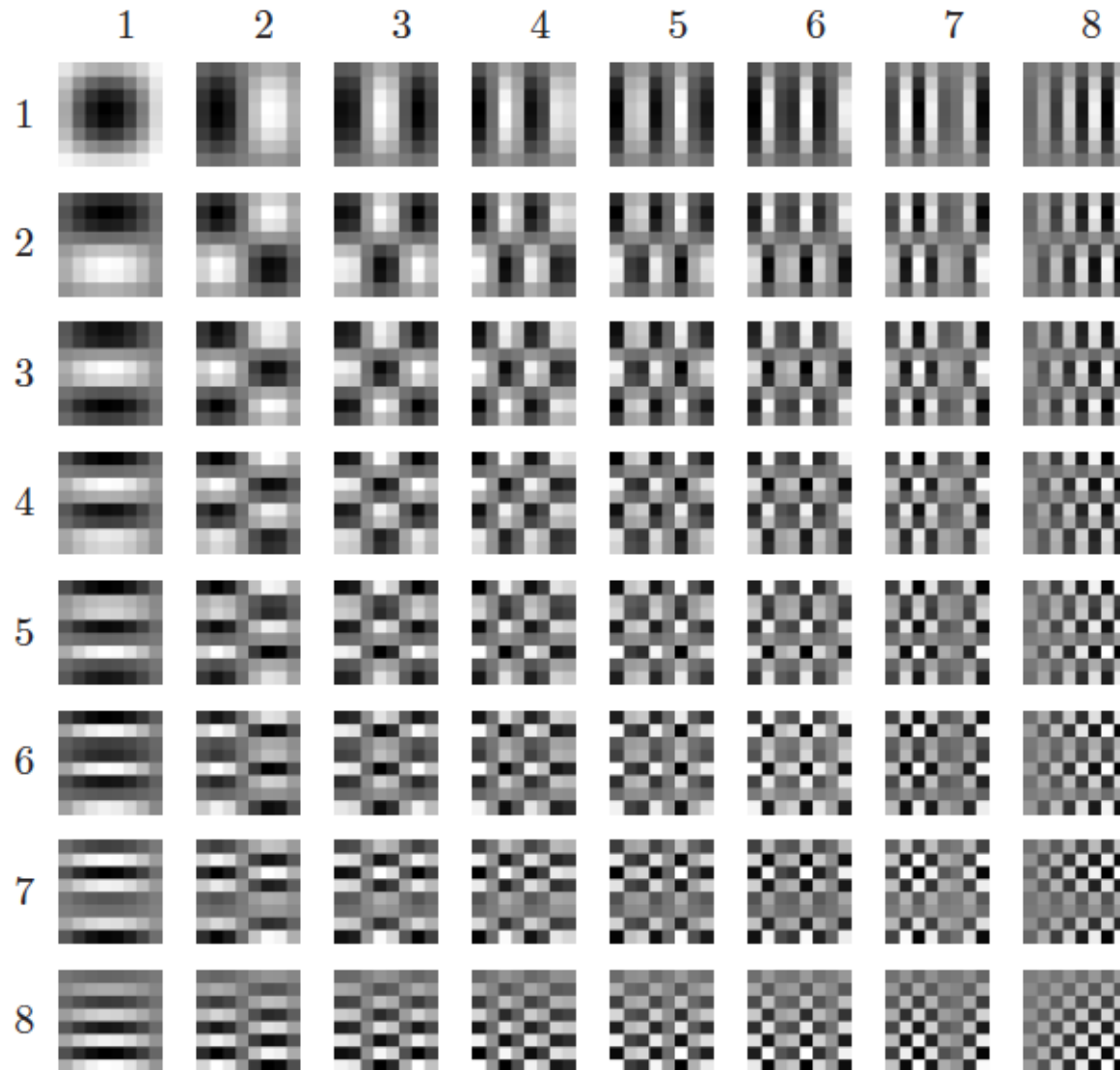
(g)



(h)

- (a) = using 1x1 elementary images (first 1 row and first 1 column elementary images);
- (b) = using 2x2 elementary images (first 2 rows and first 2 column elementary images...and so on...

# Elementary images of ODST decomposition



The basis images in terms of which any  $8 \times 8$  image is expanded by EDCT.

# Reconstruction w/ ODST decomposition



(a)



(b)



(c)



(d)



(e)



(f)



(g)



(h)

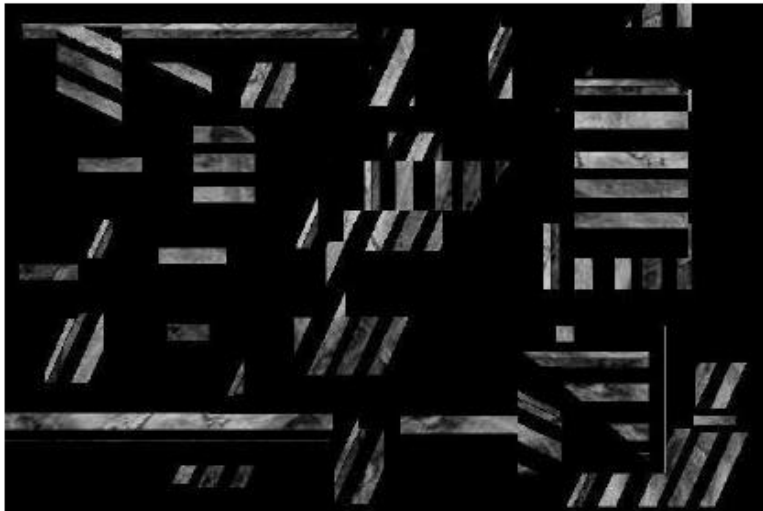
- (a) = using 1x1 elementary images (first 1 row and first 1 column elementary images);
- (b) = using 2x2 elementary images (first 2 rows and first 2 column elementary images...and so on...

## Comparison of errors

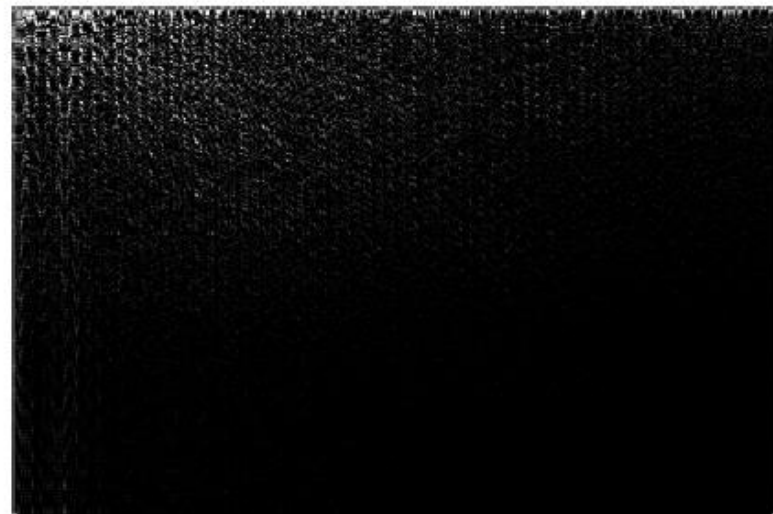
The flower example:

	0	1	2	3	4	5	6
SVD	230033	118412	46673	11882			
Haar	366394	356192	291740	222550	192518	174625	141100
Walsh	366394	356190	262206	222550	148029	92078	55905
DFT	366394	285895	234539	189508	141481	119612	71908
EDCT	366394	338683	216608	173305	104094	49179	35662
ODCT	368946	342507	221297	175046	96924	55351	39293
EDST	341243	328602	259157	206923	153927	101778	55905
ODST	350896	326264	254763	205803	159056	109829	67374

## More example on DCT decomposition



(a)

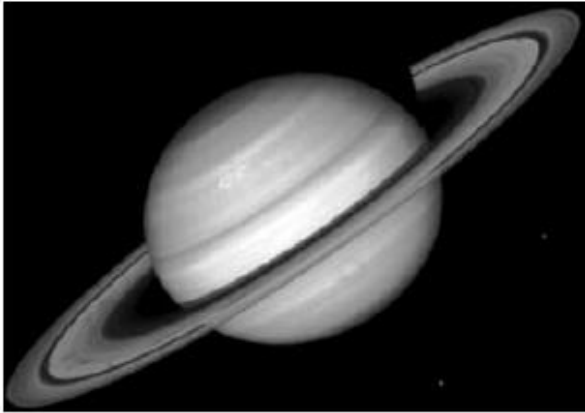


(b)

(a) Uncorrelated image and its DCT; (b) Correlated image and its DCT.

# More example on DCT decomposition

Original image



DCT



(a)

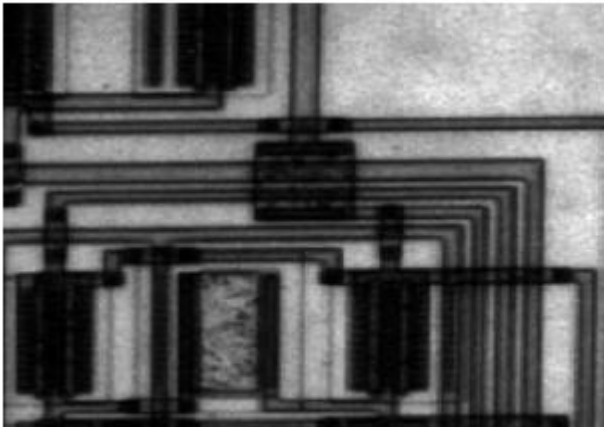


(b)



# More example on DCT decomposition

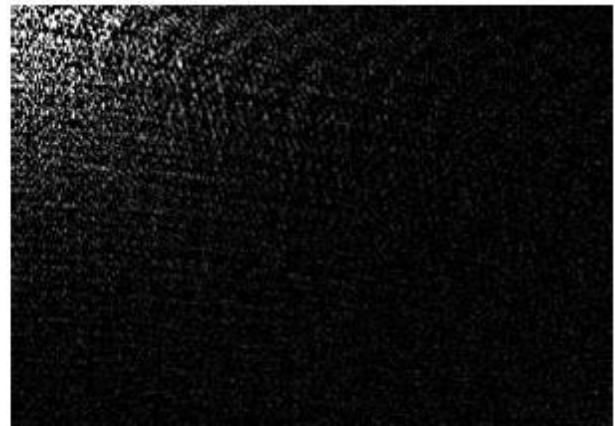
Original image



DCT



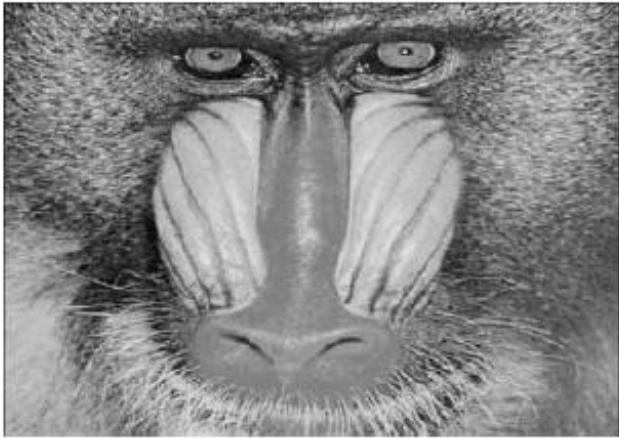
(c)



(d)

# More example on DCT decomposition

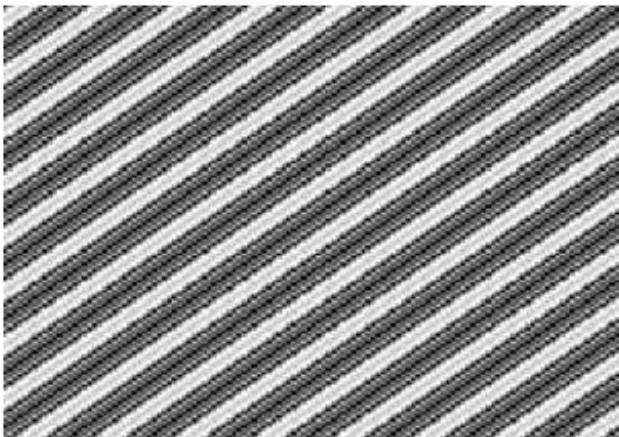
Original image



DCT



(e)



(f)

# More example on DCT decomposition



(a)



(b)



(c)



(d)

**Inverse DCT of Saturn; (a) DCT(100%); (b) DCT(75%); (c) DCT(50%); (d) DCT(25%).**

# More example on DCT decomposition



(a)



(b)



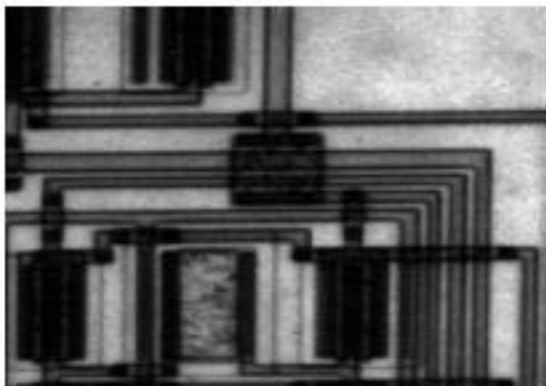
(c)



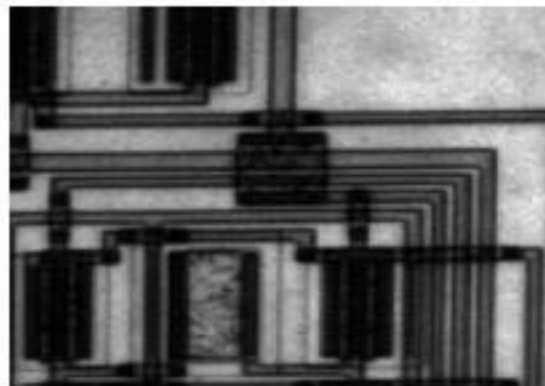
(d)

**Inverse DCT of Child; (a) DCT(100%); (b) DCT(75%); (c) DCT(50%);  
(d) DCT(25%).**

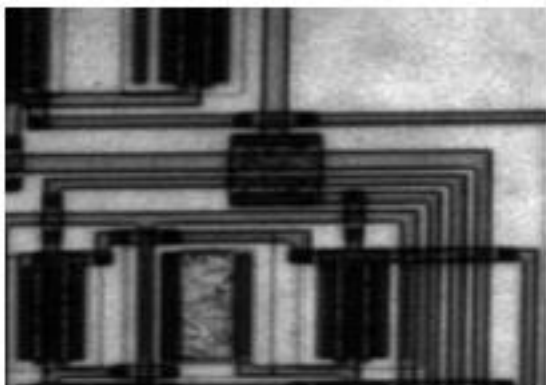
# More example on DCT decomposition



(a)



(b)



(c)



(d)

**Inverse DCT of Circuit; (a) DCT(100%); (b) DCT(75%); (c) DCT(50%);  
(d) DCT(25%).**

# More example on DCT decomposition



(a)



(b)



(c)

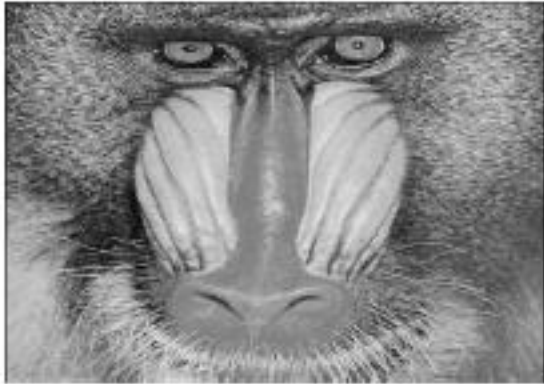


(d)

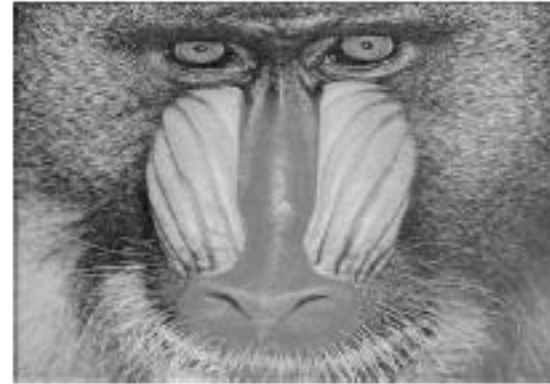
**Inverse DCT of Trees; (a) DCT(100%); (b) DCT(75%); (c) DCT(50%);  
(d) DCT(25%).**



# More example on DCT decomposition



(a)



(b)



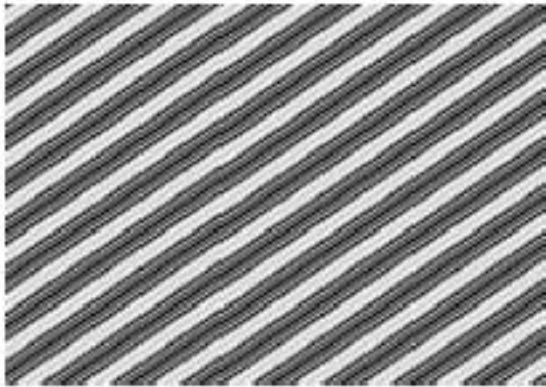
(c)



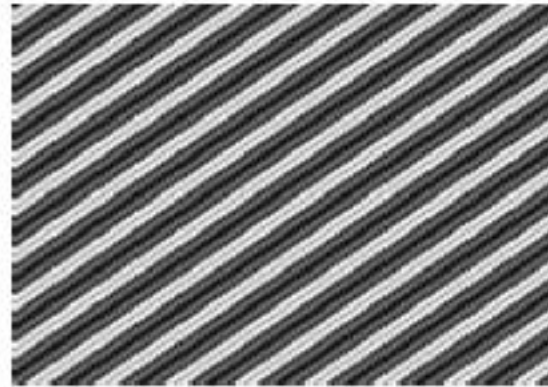
(d)

**. Inverse DCT of Baboon; (a) DCT(100%); (b) DCT(75%); (c) DCT(50%);  
(d) DCT(25%).**

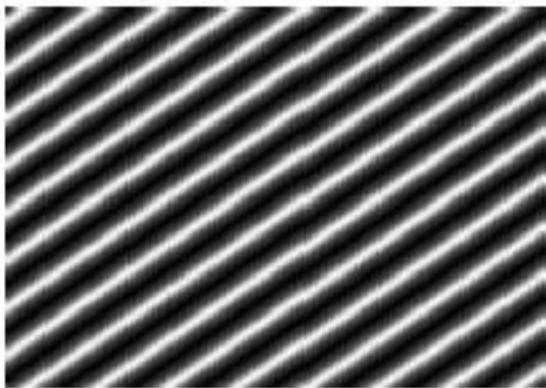
# More example on DCT decomposition



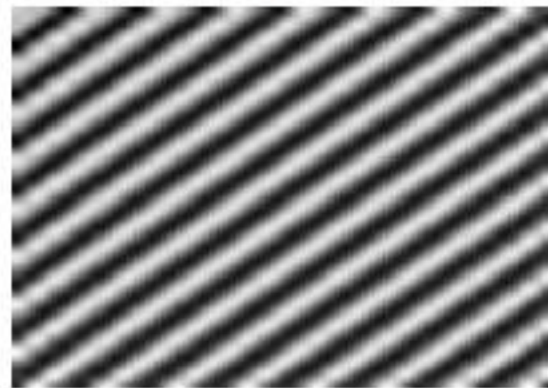
(a)



(b)



(c)



(d)

**Inverse DCT of sine wave; (a) DCT(100%); (b) DCT(75%); (c) DCT(50%);  
(d) DCT(25%).**



# Image Enhancement

## ■ What is image enhancement?

- Image enhancement is the process by which we improve an image so that it looks subjectively better.

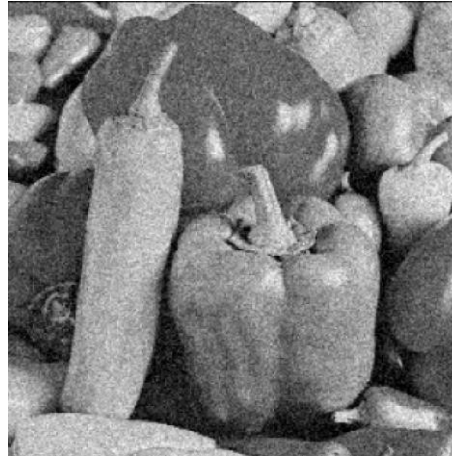
## ■ How?

- An image is enhanced when we:
  - remove additive noise and interference;
  - remove multiplicative interference;
  - increase its contrast;
  - decrease its blurring.
- Some standard methods:
  - smoothing or low pass filtering;
  - sharpening or high pass filtering;
  - histogram manipulation and
  - algorithms that remove noise while avoid blurring the image.

# Image Enhancement

- **We will consider two image enhancement problems:**

- Image denoising



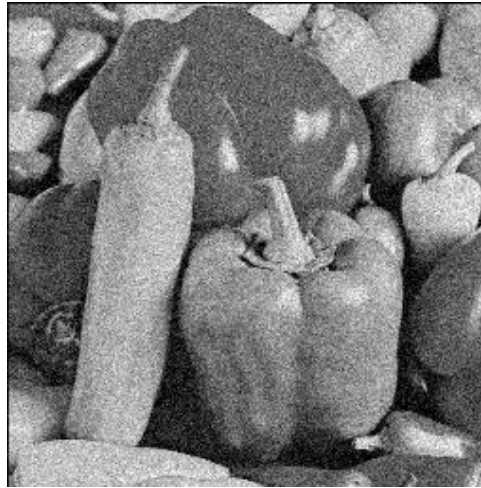
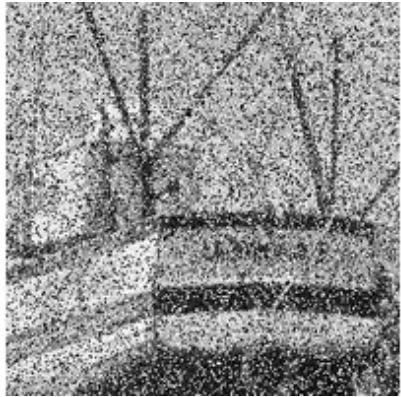
- Image deblurring



# Image Enhancement

- **We will consider two image enhancement problems:**

- Image denoising



- Image deblurring



# Image Enhancement

- **Linear filtering:**
  - Modifying a pixel value (in the spatial domain) by a linear combination of neighborhood values.
- **Operations in spatial domain v.s. operations in frequency domains:**
  - Linear filtering (matrix multiplication in spatial domain) = discrete convolution
  - In the frequency domain, it is equivalent to multiplying the Fourier transform of the image with a certain function that “kills” or modifies certain frequency components

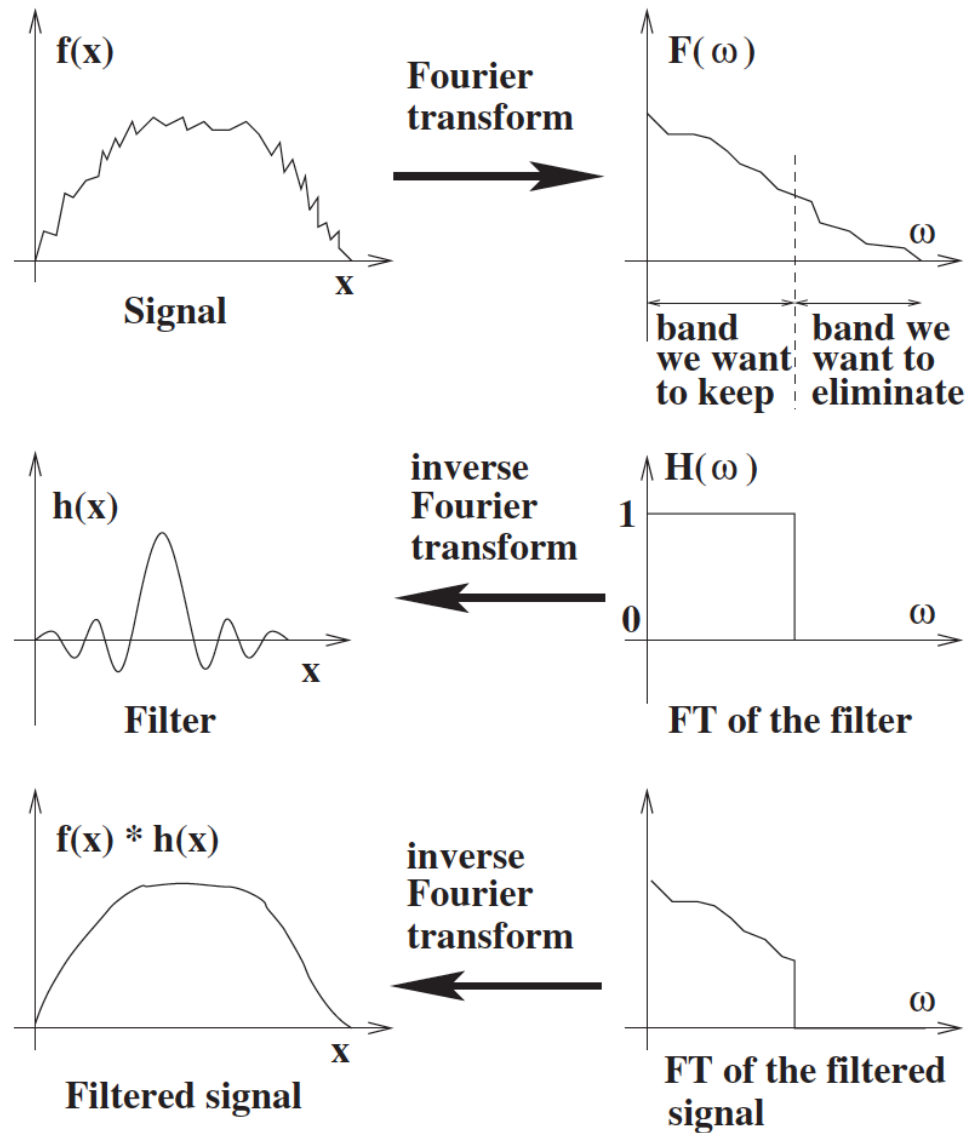
# Spatial transform v.s. frequency transform

- **Discrete convolution:**

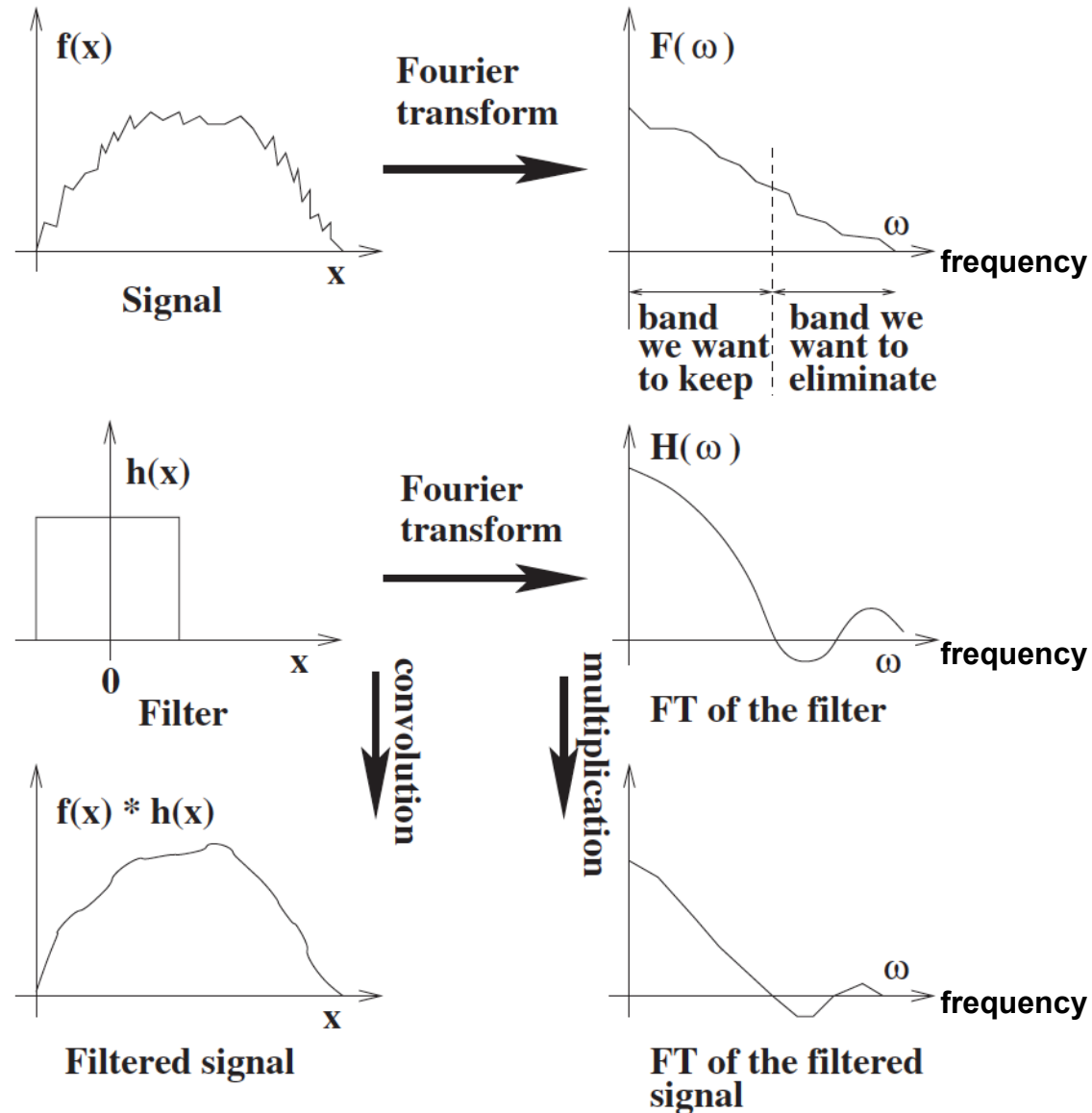
$$v(n, m) = \sum_{n'=0}^{N-1} \sum_{m'=0}^{M-1} g(n - n', m - m') w(n', m')$$

- **DFT of Discrete convolution: Product of fourier transform**
- **DFT(convolution of f and w) = C\*DFT(f)\*DFT(w)**
- Multiplying the Fourier transform of the image with a certain function that “kills” or modifies certain frequency components

# Spatial transform v.s. frequency transform



# Spatial transform v.s. frequency transform



# Gaussian noise

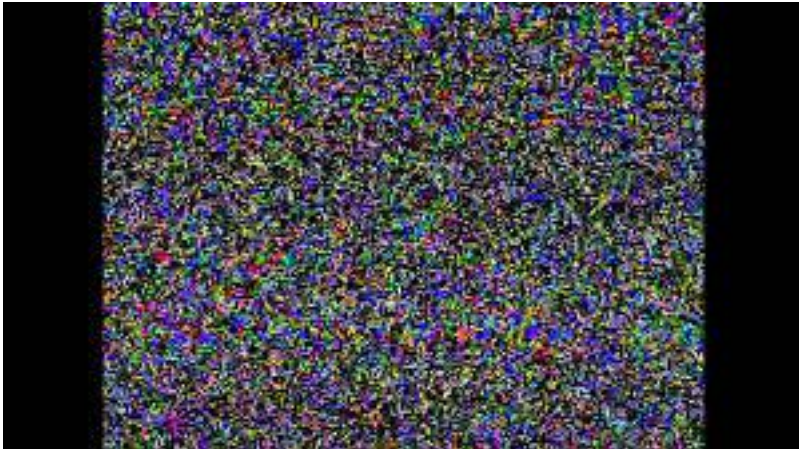
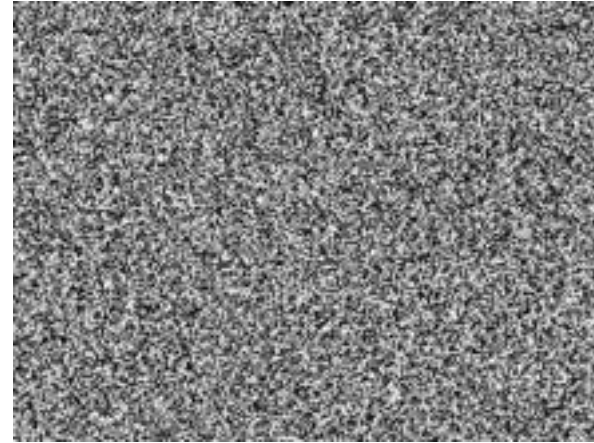
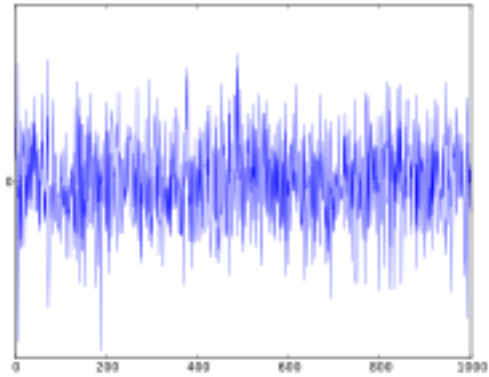
- Example of Gaussian noises:





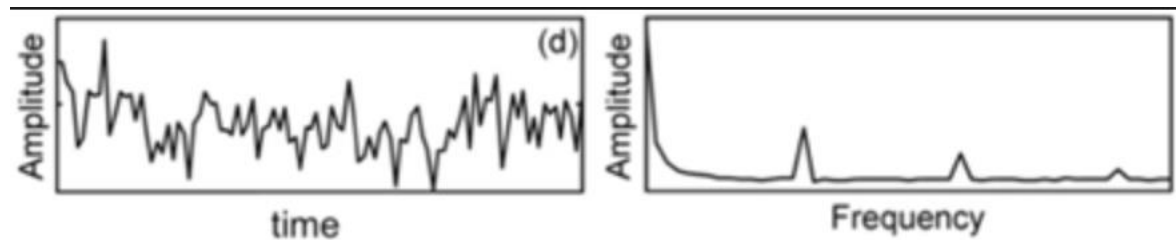
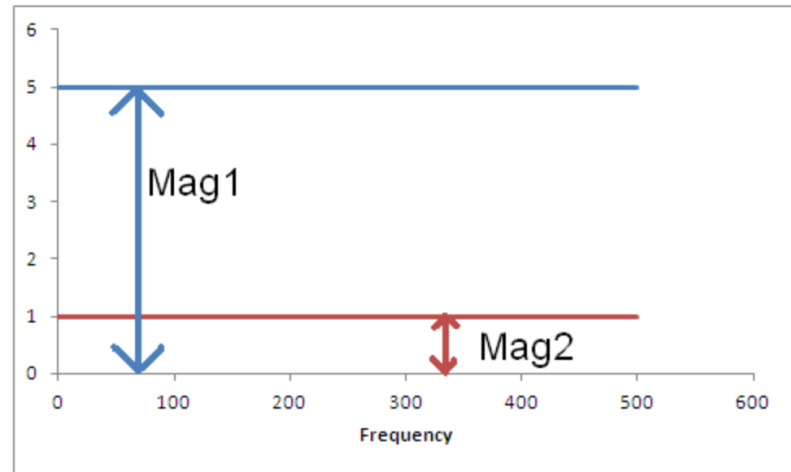
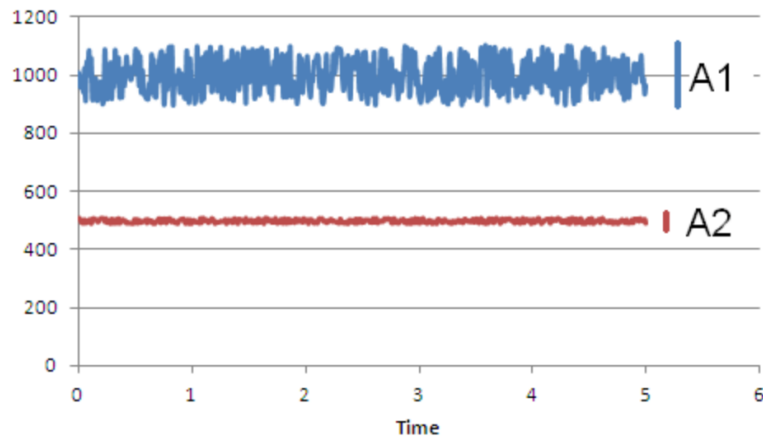
# White noise

- Example of white noises:



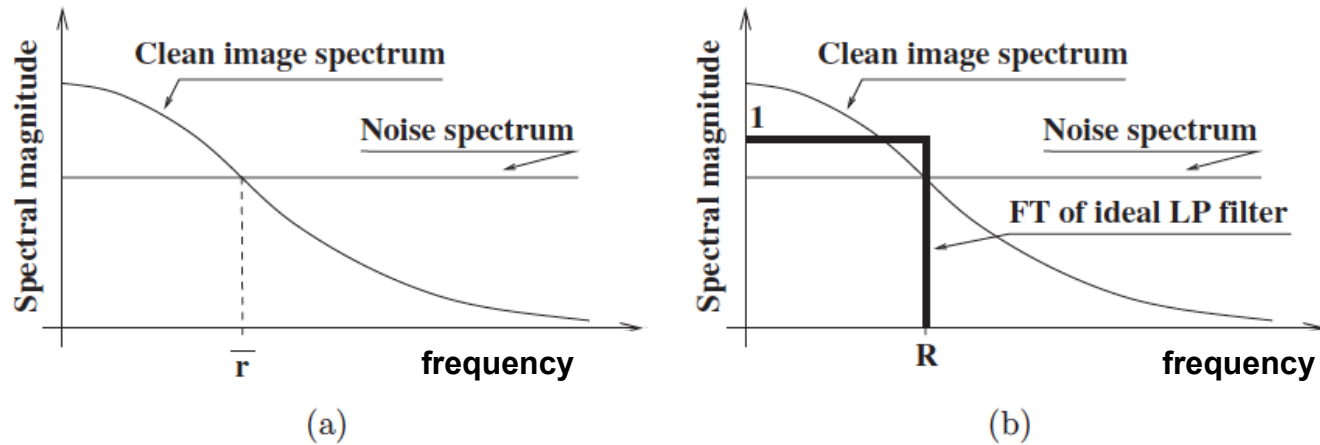
# White noise

## ■ Example of white noises:



# Noises as high frequency component

Why noises are often considered as high frequency component?



- (a) Clean image spectrum and Noise spectrum (Noise dominates the high-frequency component);
- (b) Filtering of high-frequency component

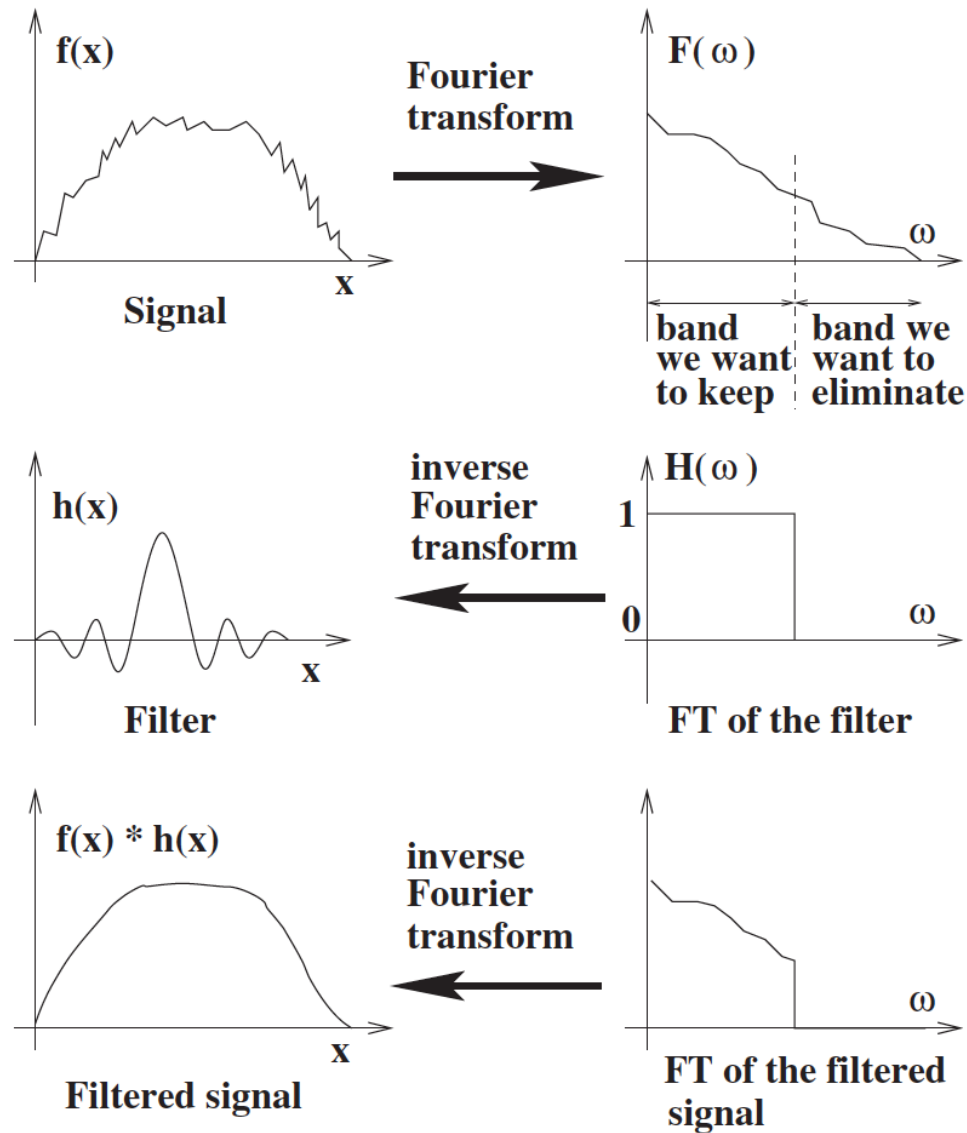
# Spatial transform v.s. frequency transform

- **Discrete convolution:**

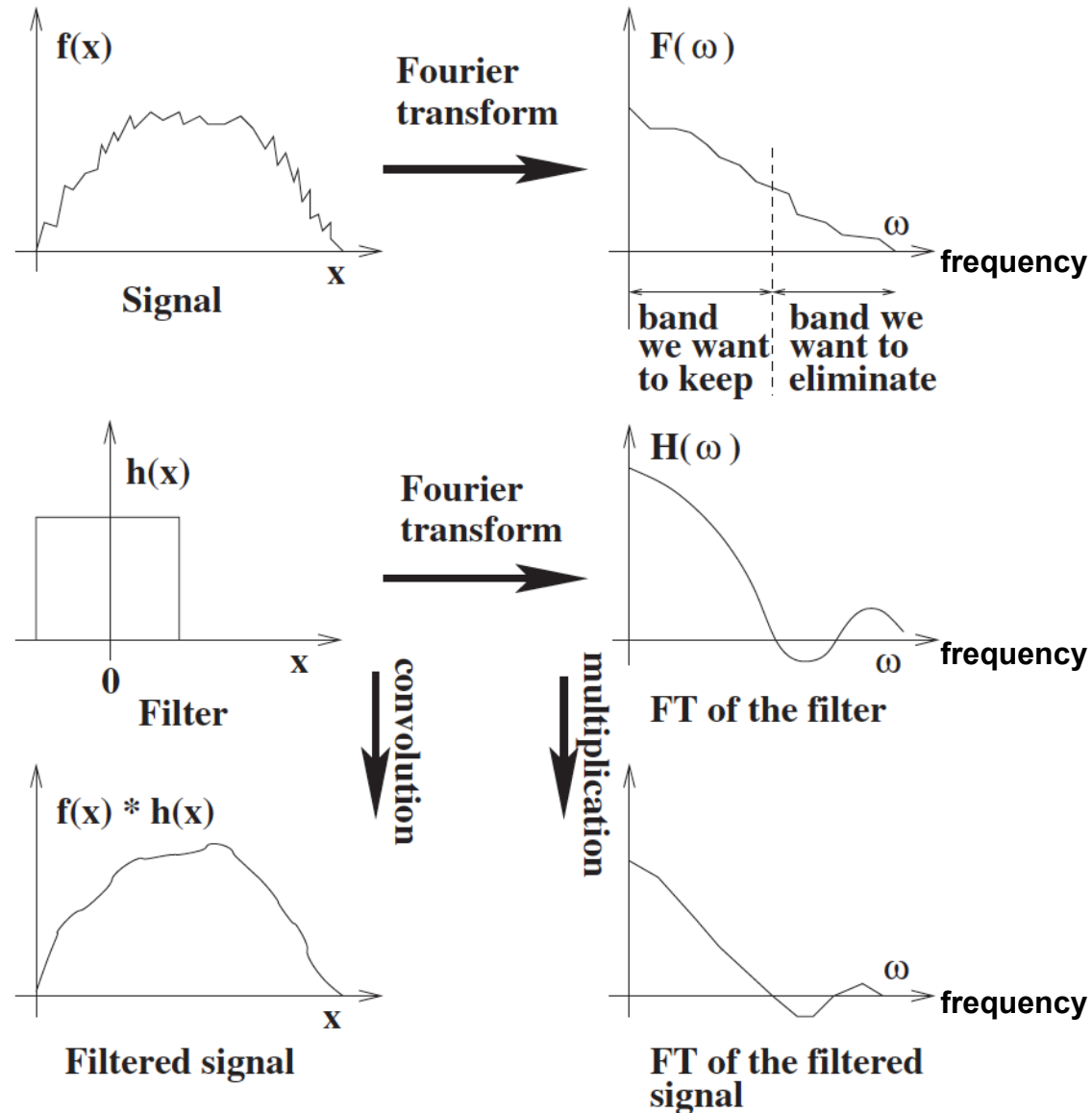
$$v(n, m) = \sum_{n'=0}^{N-1} \sum_{m'=0}^{M-1} g(n - n', m - m') w(n', m')$$

- **DFT of Discrete convolution: Product of fourier transform**
- **DFT(convolution of f and w) = C\*DFT(f)\*DFT(w)**
- Multiplying the Fourier transform of the image with a certain function that “kills” or modifies certain frequency components

# Spatial transform v.s. frequency transform

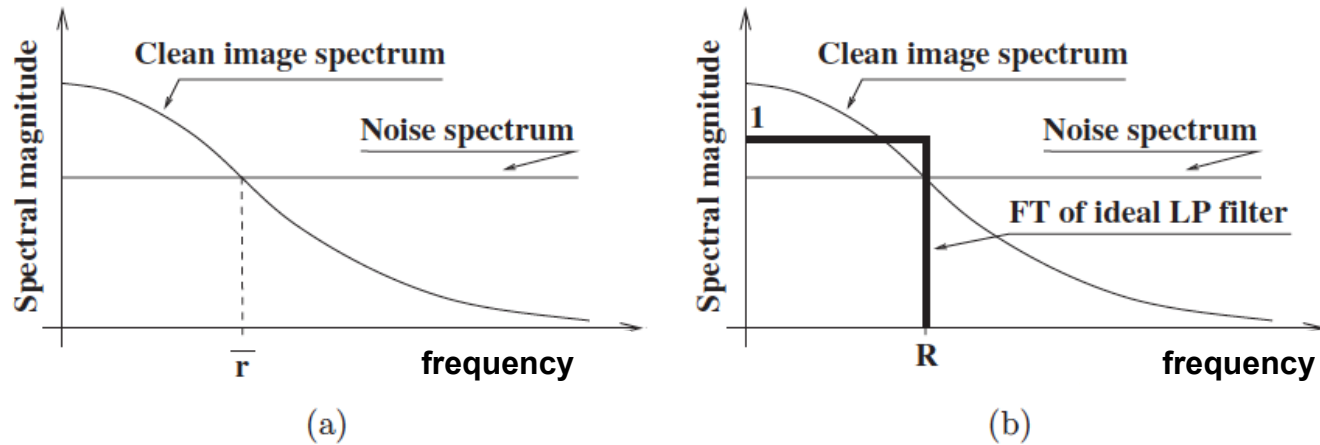


# Spatial transform v.s. frequency transform



# Noises as high frequency component

Why noises are often considered as high frequency component?

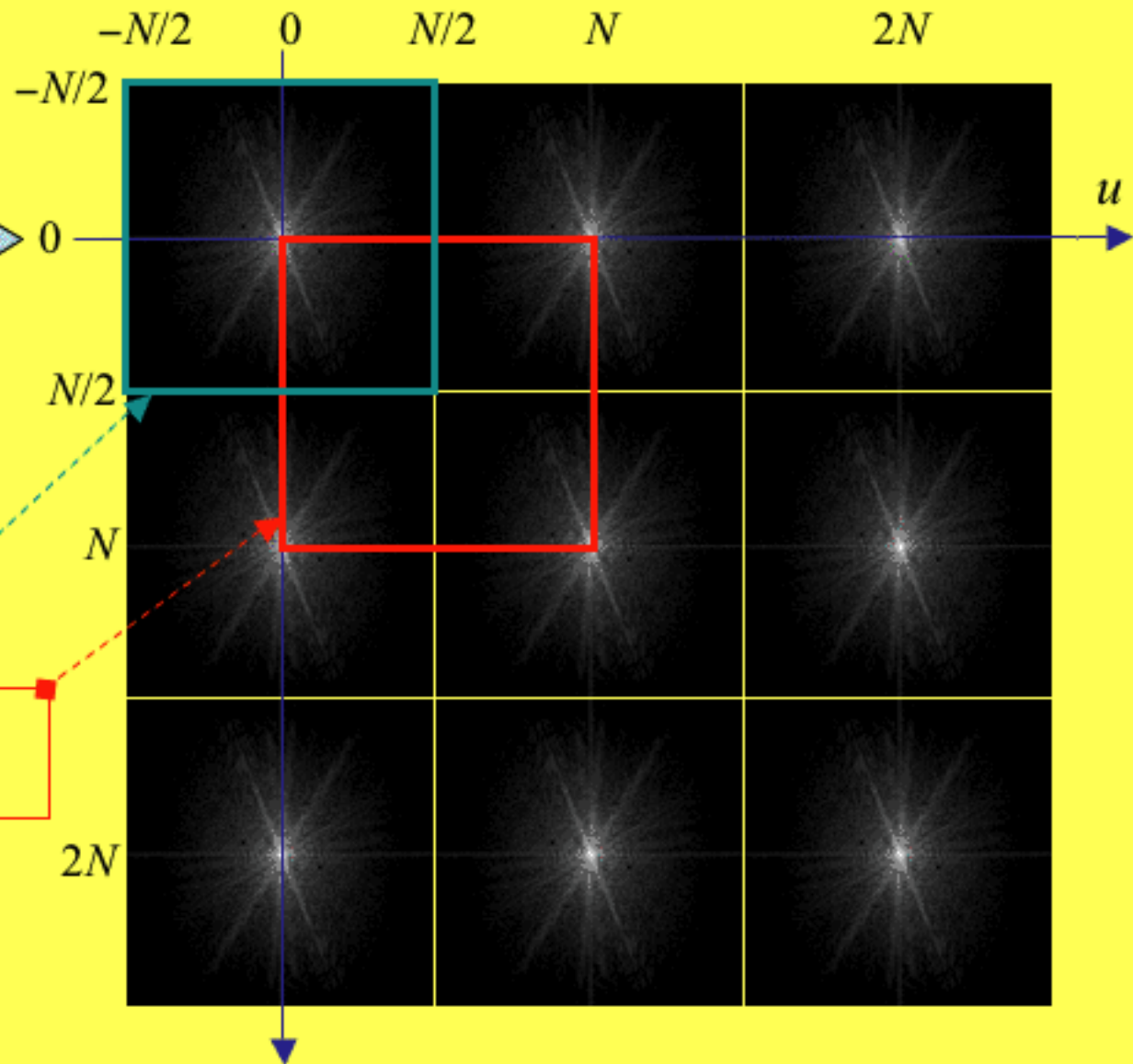


- (a) Clean image spectrum and Noise spectrum (Noise dominates the high-frequency component);
- (b) Filtering of high-frequency component

# Frequency spectrum of an image



DFT



Representation of spectra  
being easier to interpret

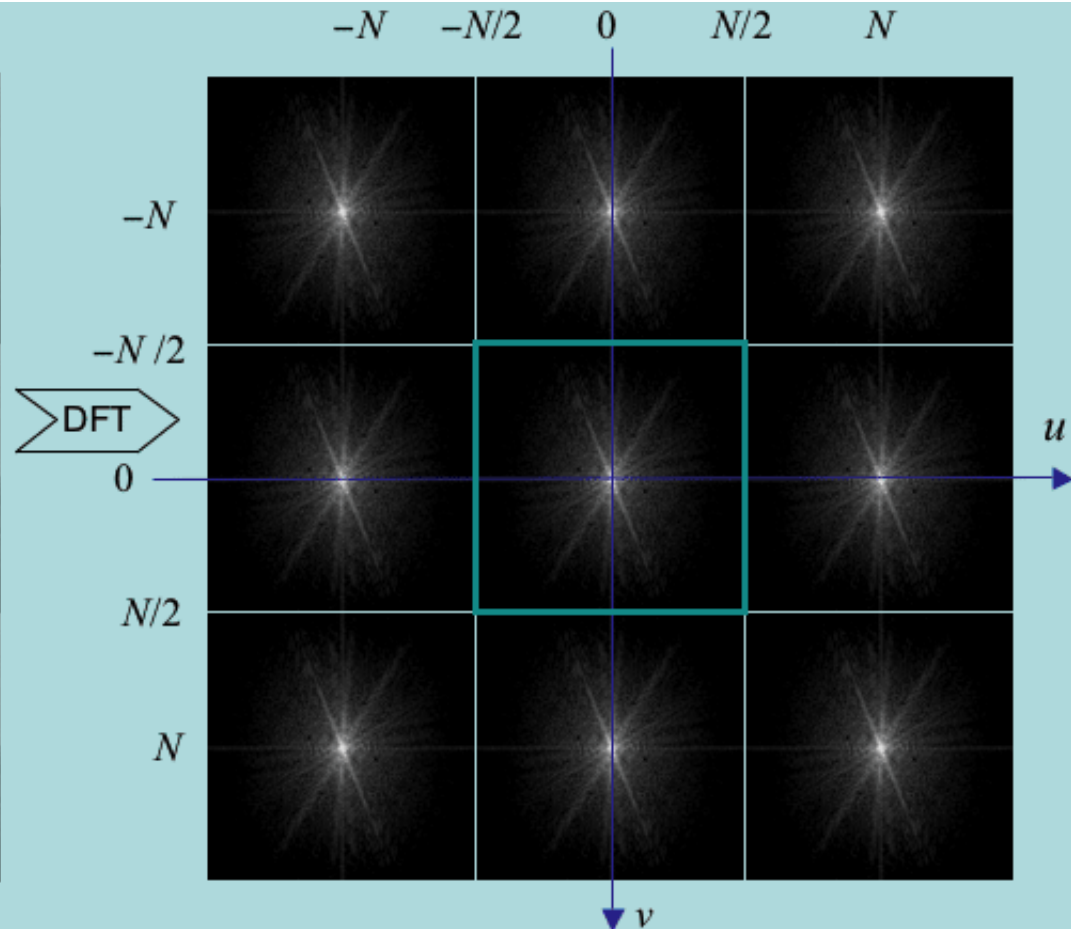
Single period of the spectrum  
computed by a DFT



# Frequency spectrum of an image



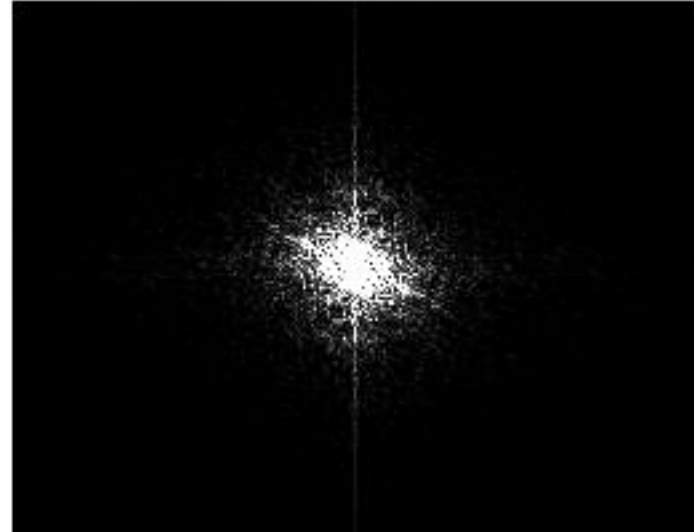
Spatial discontinuities caused by considering an image to be periodic



# Frequency spectrum of an image

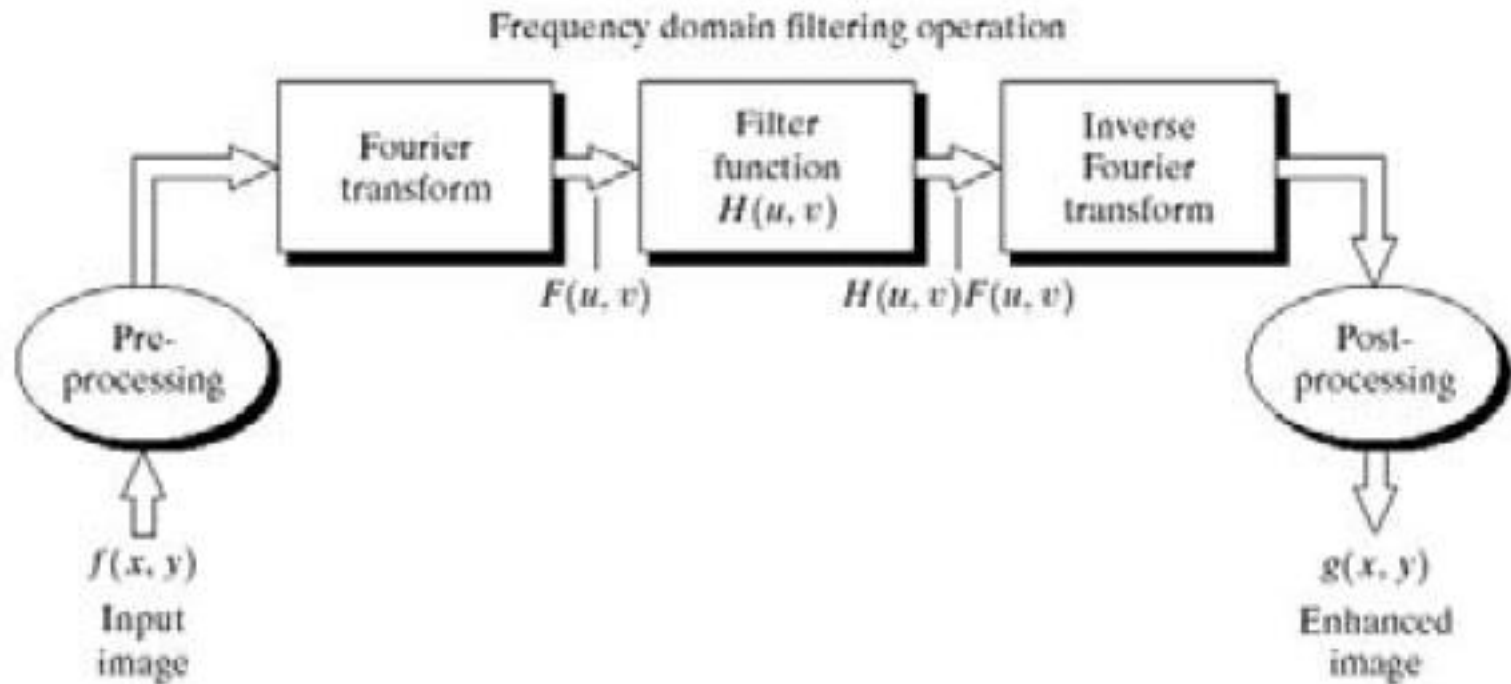


**Original image**

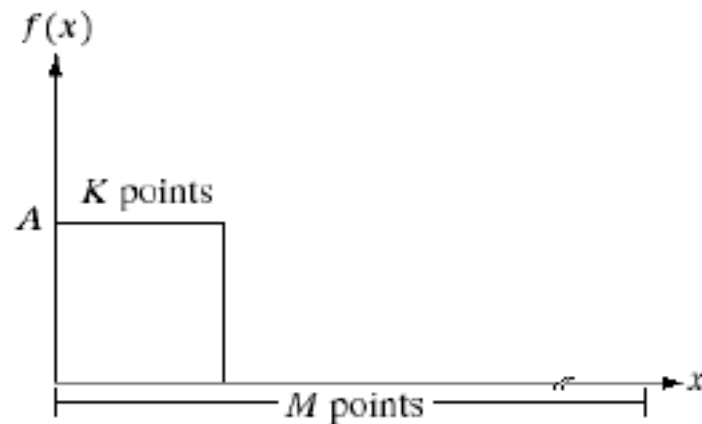


**Spectrum**

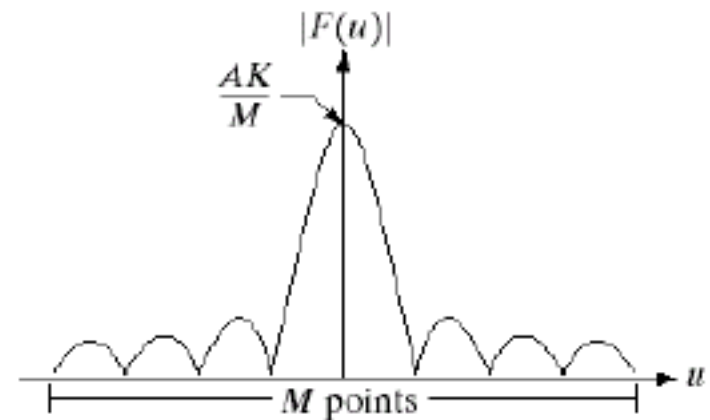
# Key steps for image enhancement in the frequency domain



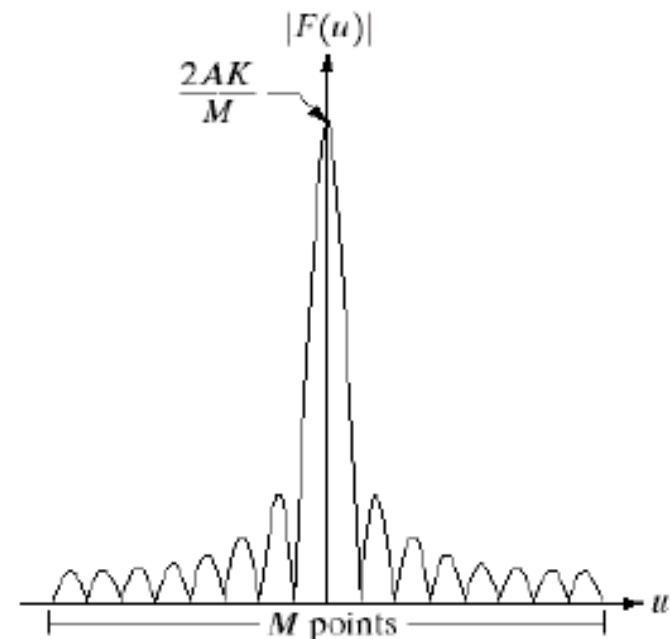
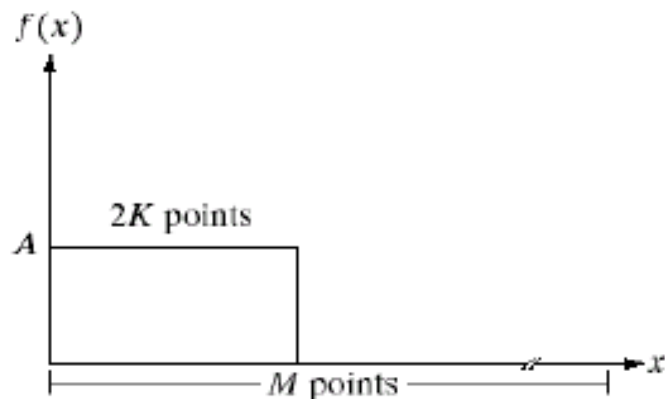
# Relationship between spatial and frequency domain



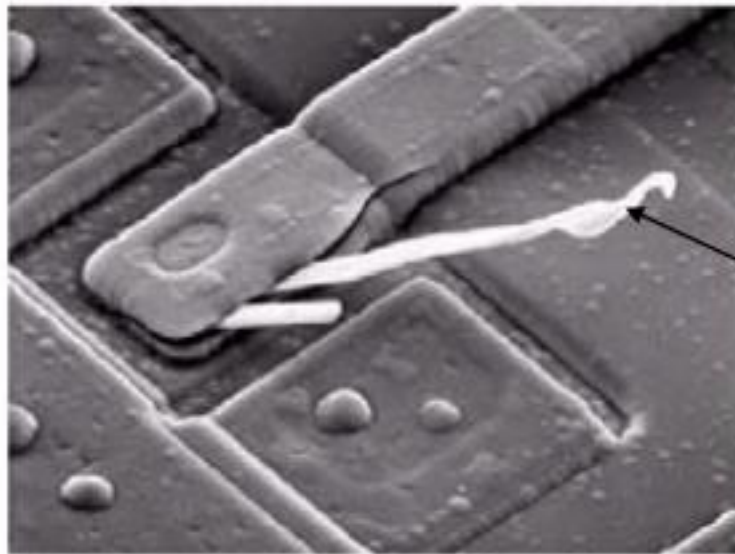
**Flat filter**



**Low pass filtering**



# Spatial and frequency domain



protrusions

SEM: scanning electron  
Microscope

(a) SEM image of a damaged integrated circuit.  
(b) Fourier spectrum of (a).  
(Original image courtesy of Dr. J. M. Hudak, Brockhouse Institute for Materials Research, McMaster University, Hamilton, Ontario, Canada.)

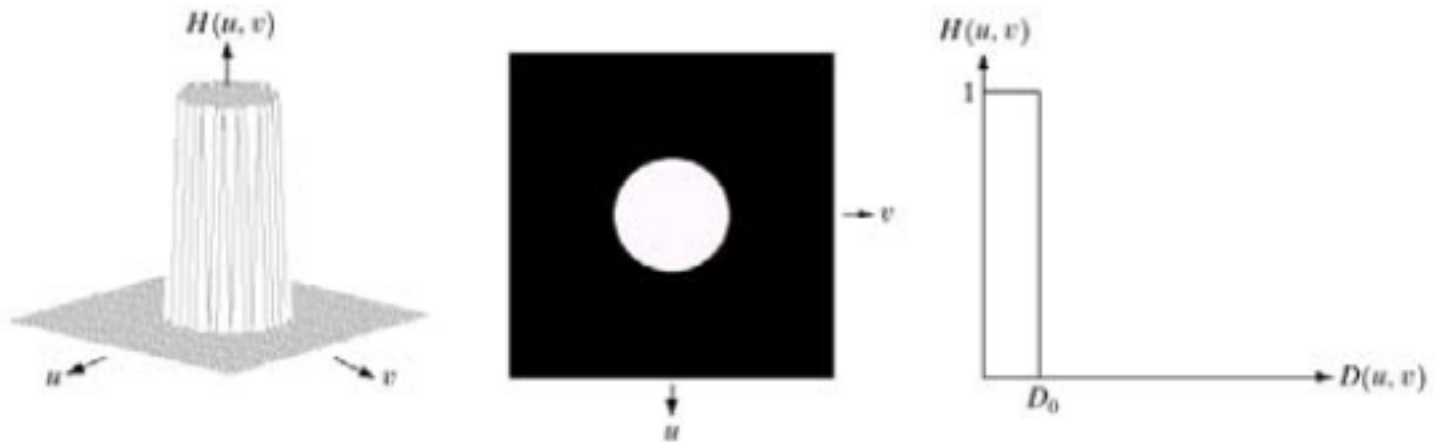
notice the  $\pm 45^\circ$  components and the vertical component which is slightly off-axis to the left! It corresponds to the protrusion caused by thermal failure above. 4.29

# Ideal Low Pass Filter

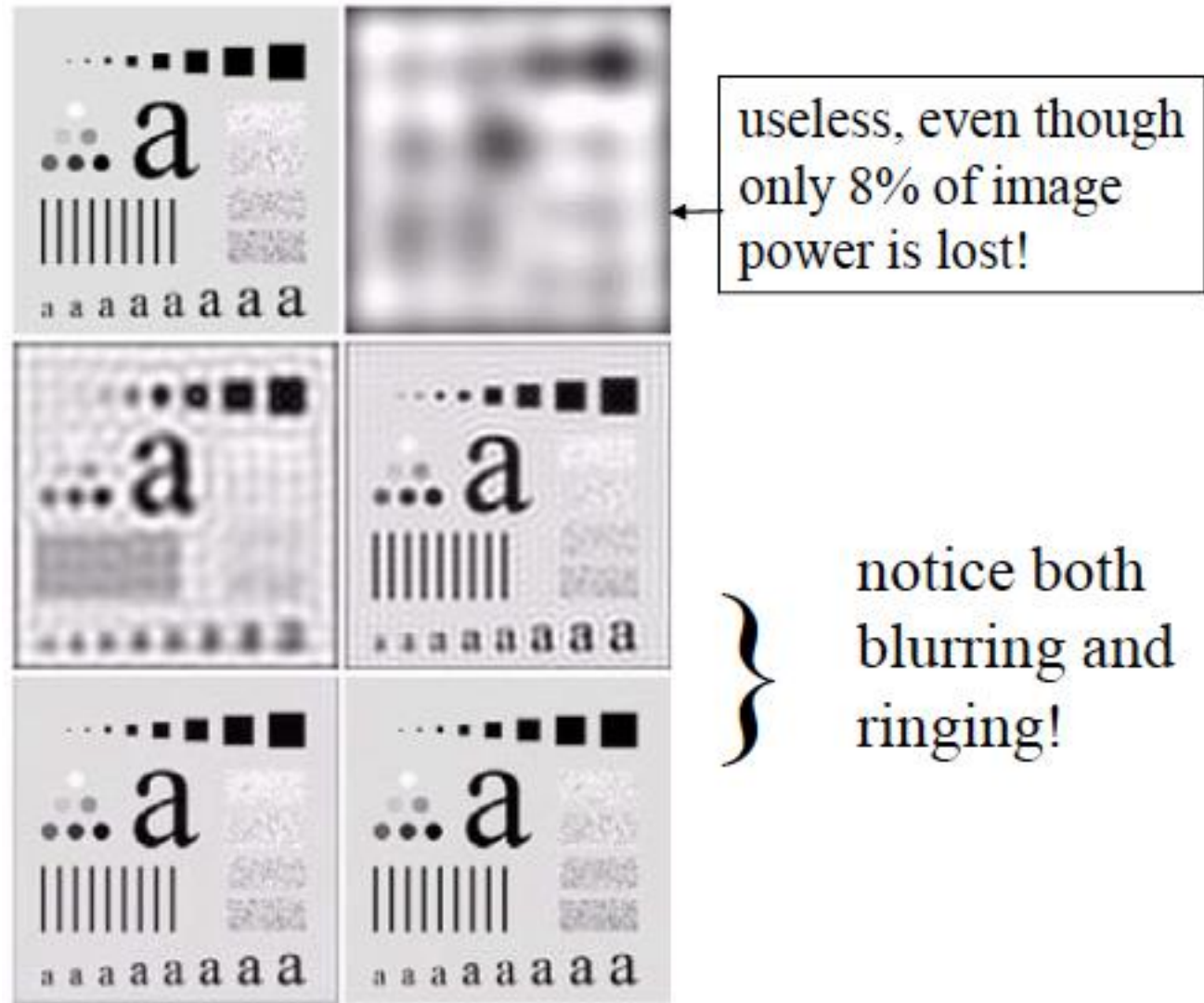
Ideal low-pass filter

$$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \leq D_0 \\ 0 & \text{if } D(u, v) > D_0 \end{cases}$$

$D_0$  is the cutoff frequency and  $D(u, v)$  is the distance between  $(u, v)$  and the frequency origin.

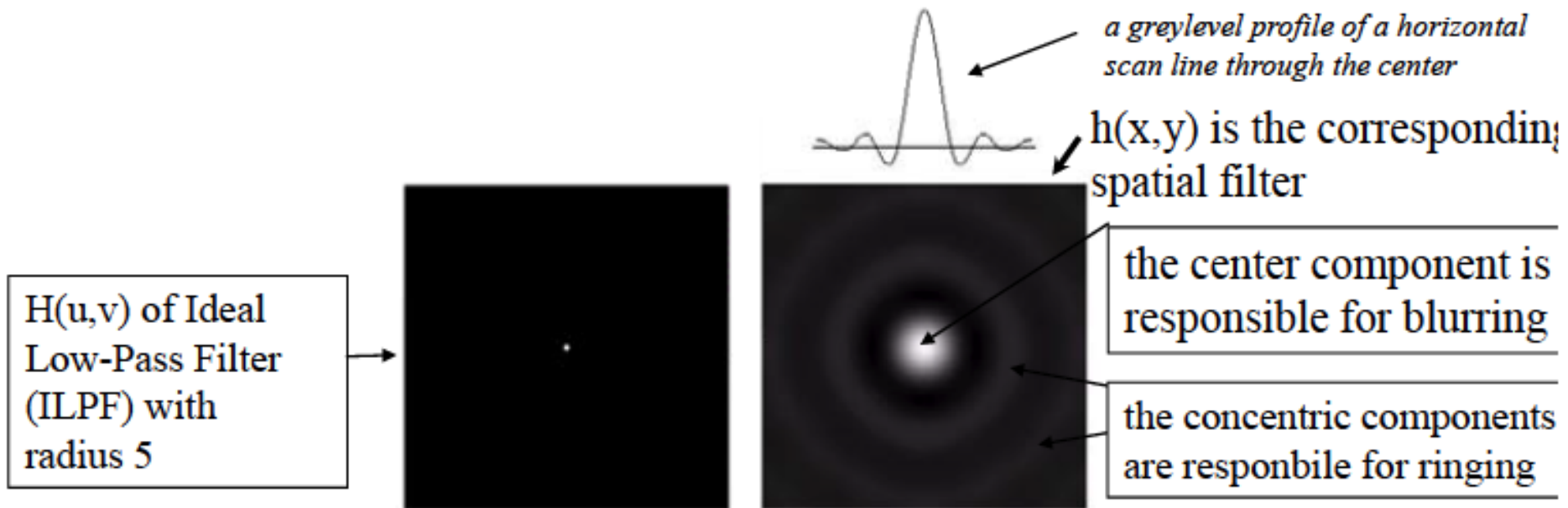


# Ideal Low Pass Filter



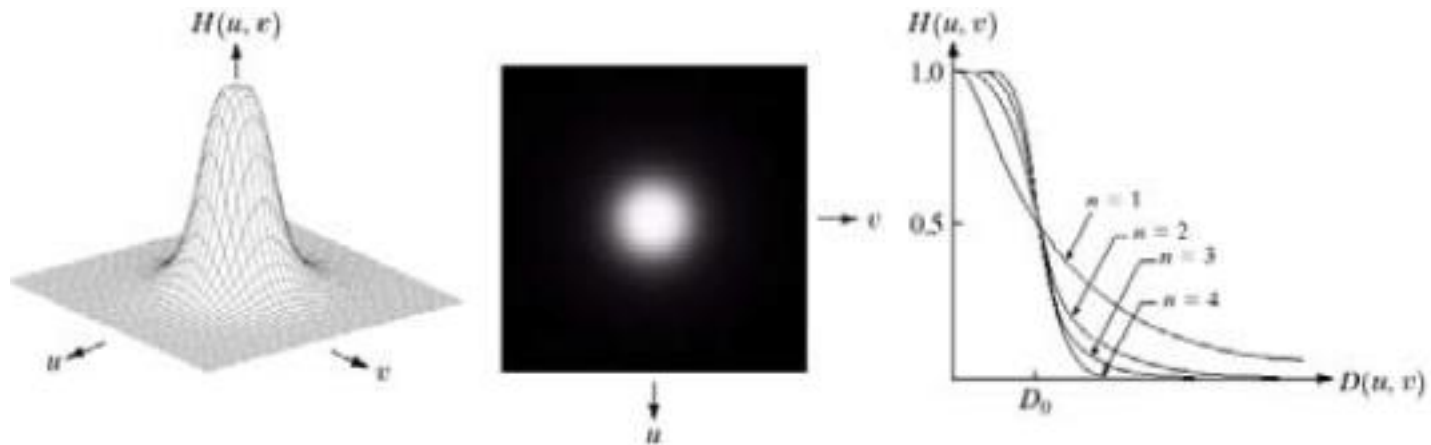
**Ideal Low Pass Filter with larger and larger radii  $D_0$**

# Explanation of ringing effect

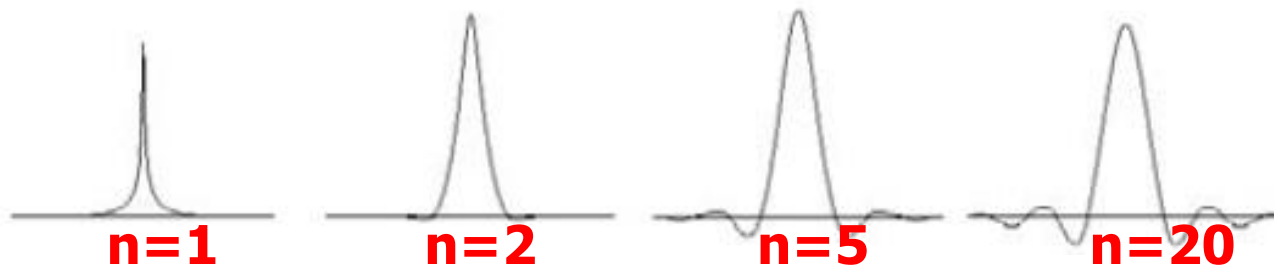
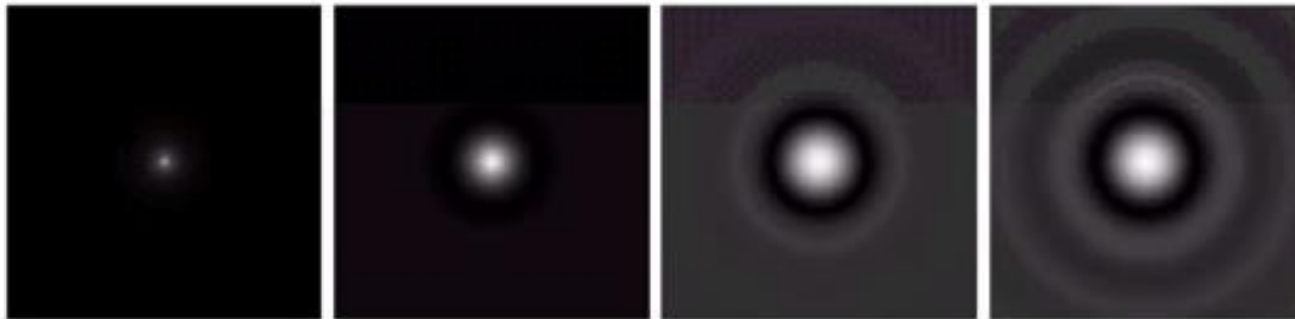




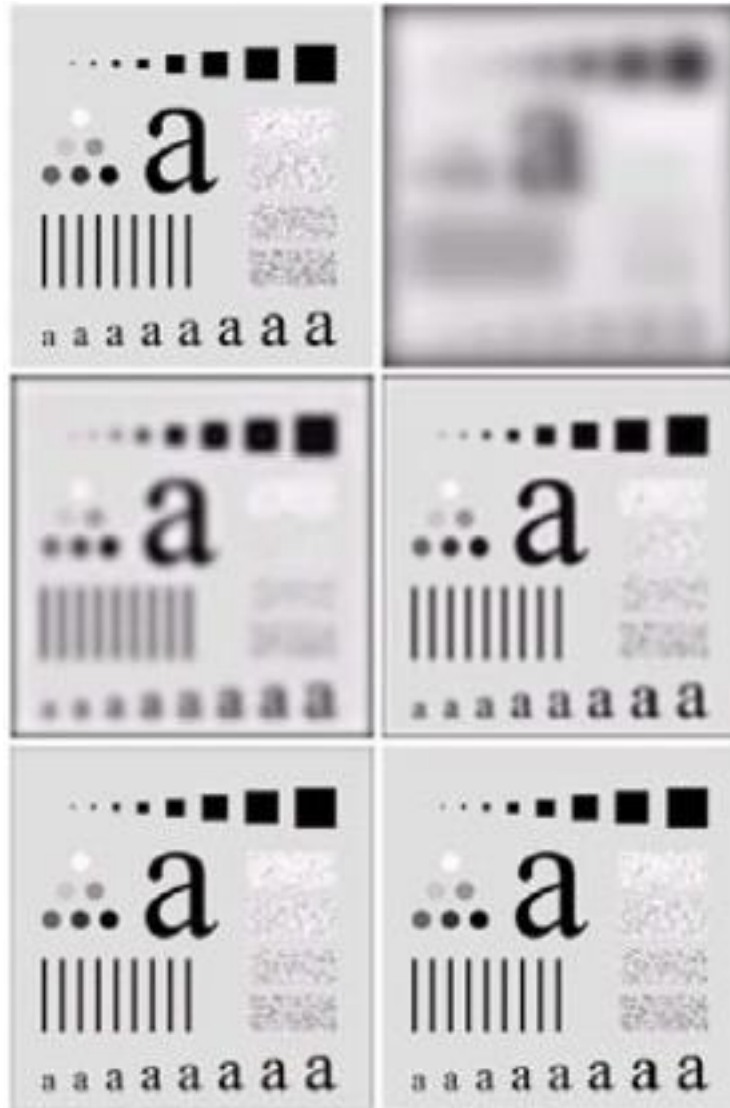
# Butterworth Low Pass Filter



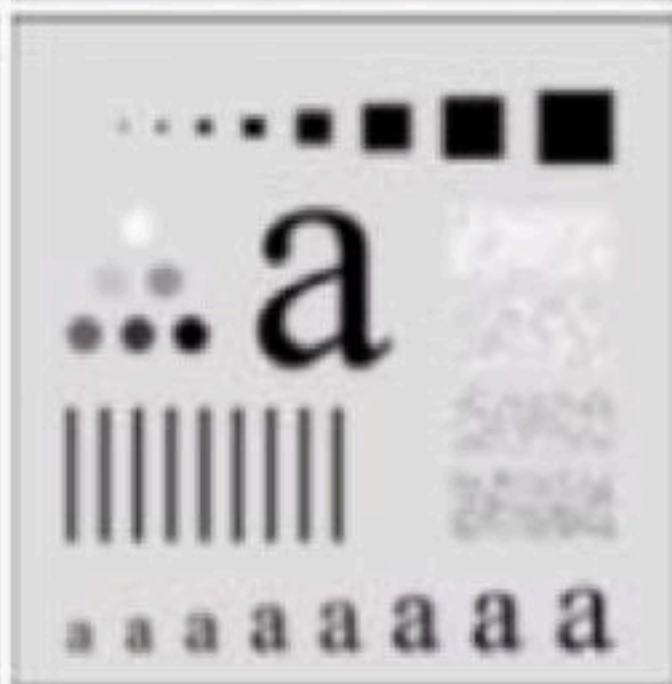
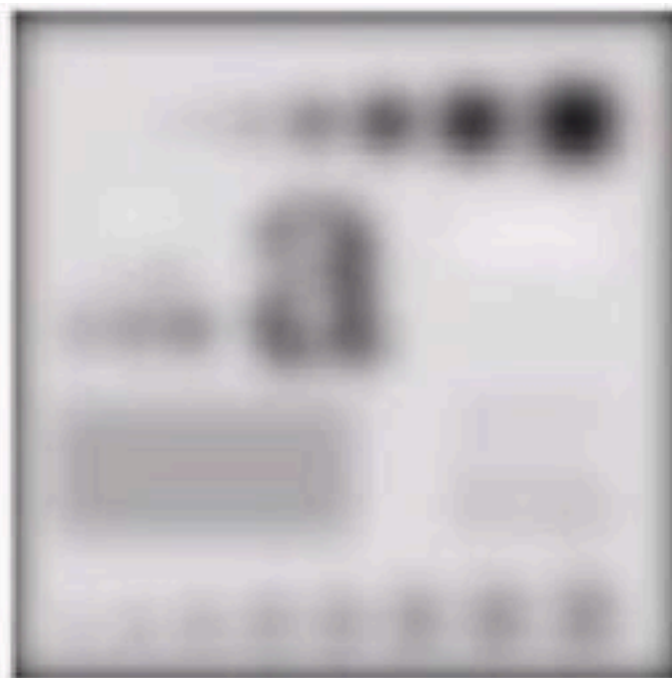
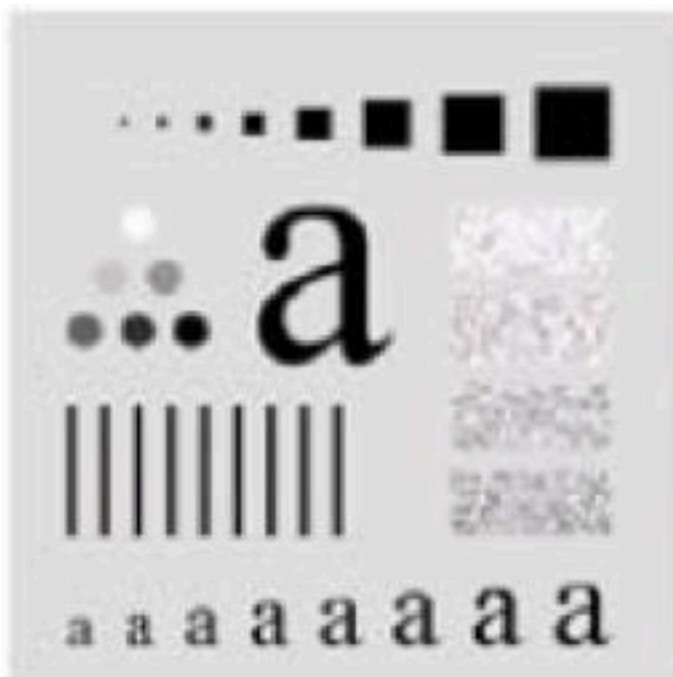
$$H(u, v) = \frac{1}{1 + [D(u, v) / D_0]^n}$$



# Butterworth Low Pass Filter



**Butterworth Low Pass Filter with larger and larger radii D0**



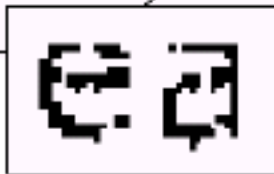
Gal

)

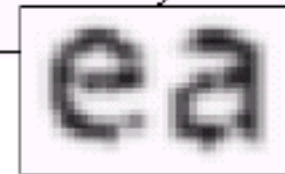
# Gaussian Low Pass Filter

**Applications:** fax transmission, duplicated documents and old records.

Historically, certain computer programs were written using only two digits rather than four to define the applicable year. Accordingly, the company's software may recognize a date using "00" as 1900 rather than the year 2000.



Historically, certain computer programs were written using only two digits rather than four to define the applicable year. Accordingly, the company's software may recognize a date using "00" as 1900 rather than the year 2000.



GLPF with  $D_0=80$  is used.

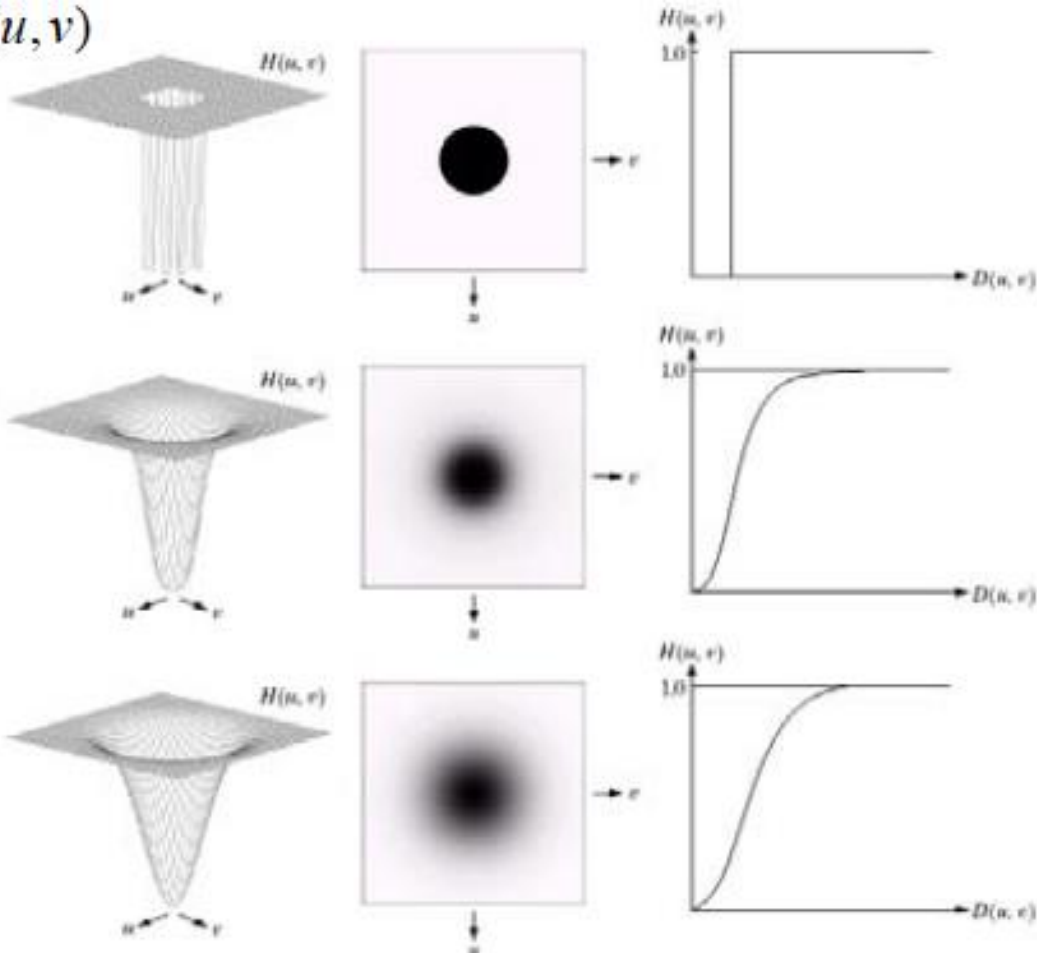
## Application: Low Pass Filter

A LPF is also used in printing, e.g. to smooth fine skin lines in faces.



# High Pass Filter

$$H_{hp}(u, v) = 1 - H_{lp}(u, v)$$

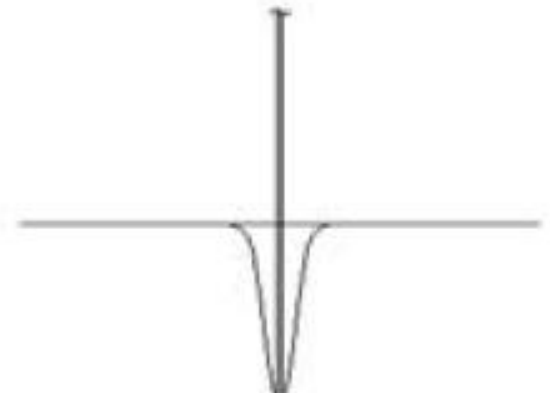
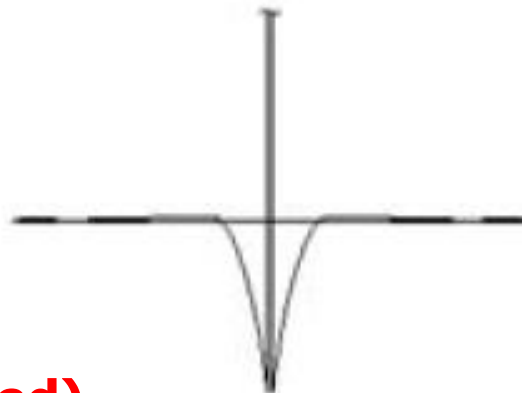
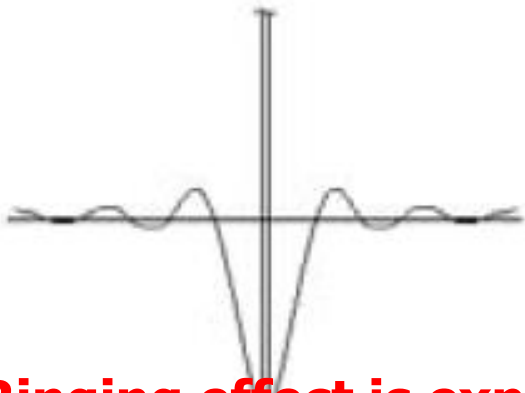
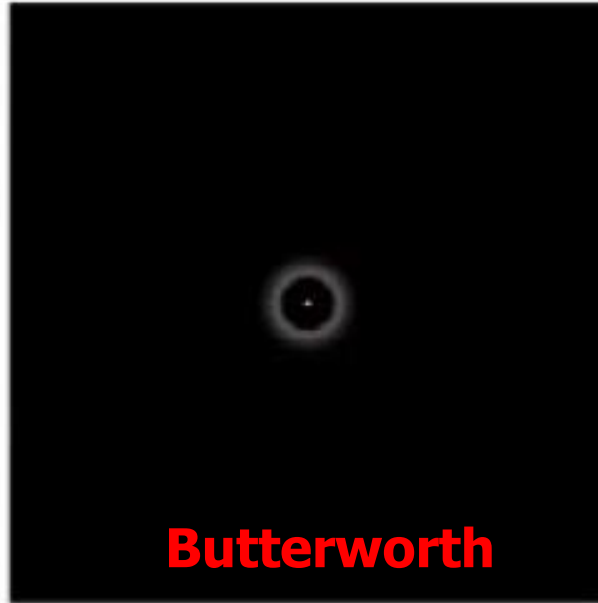
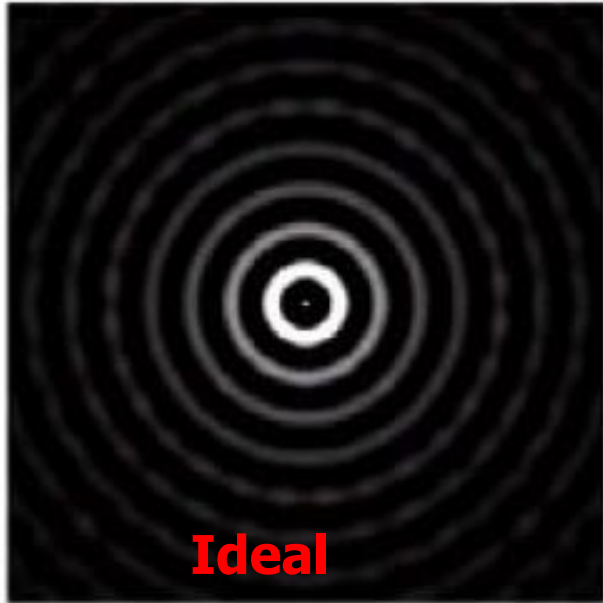


ideal high-pass  
filter

Butterworth  
high-pass

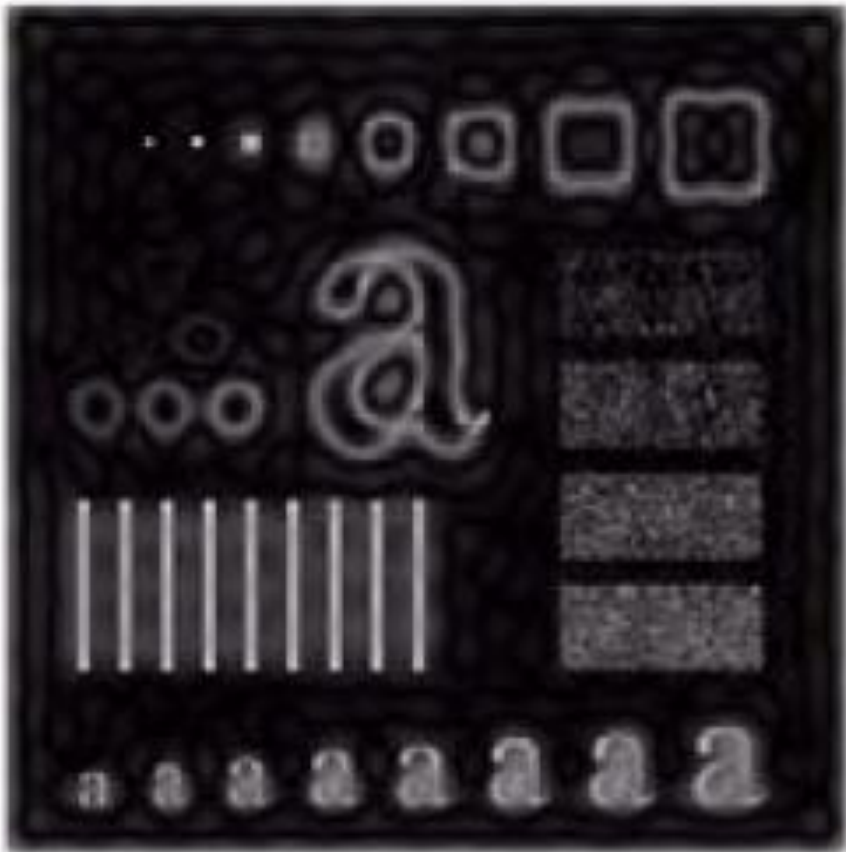
Gaussian  
high-pass

# Spatial representation of High Pass Filter

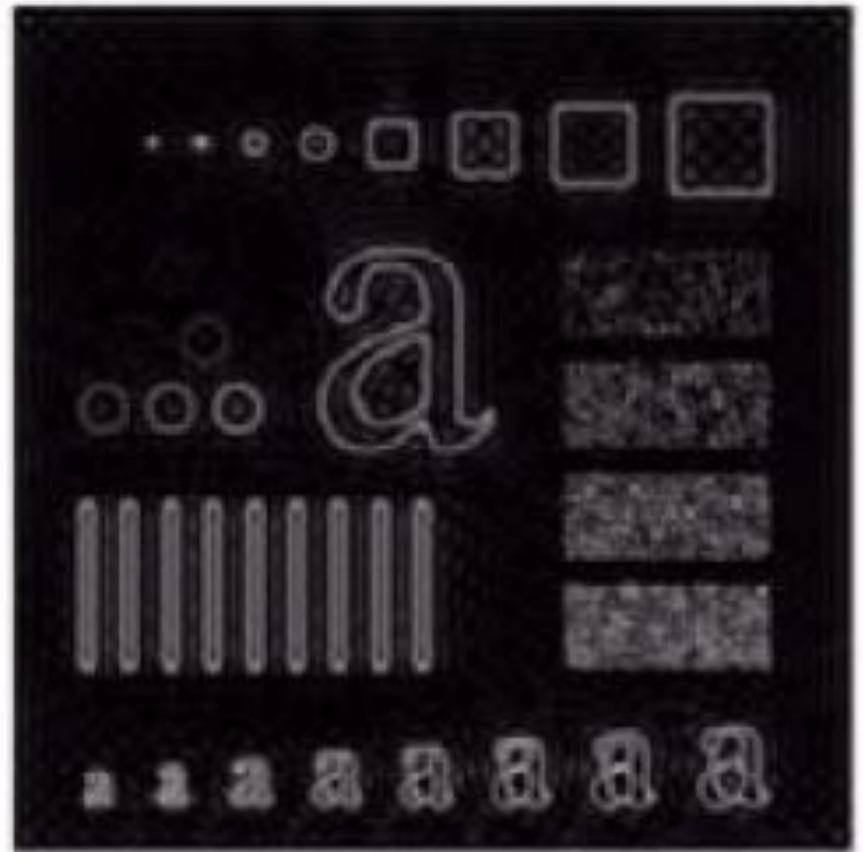


**(Ringing effect is expected)**

# Ideal High Pass Filter



**$D_0 = 15$**

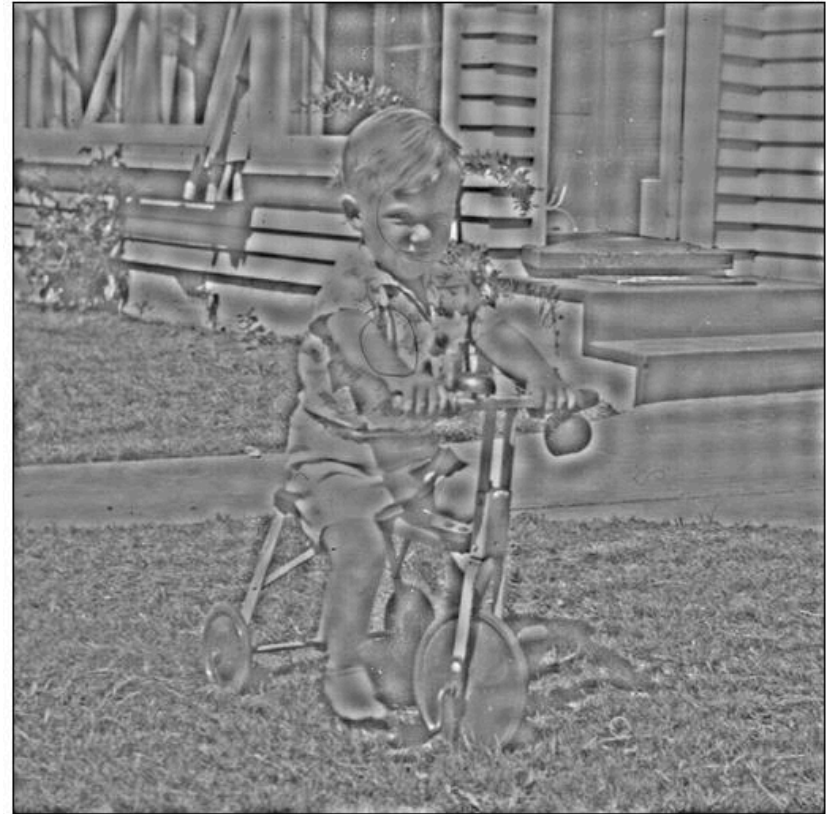


**$D_0 = 30$**

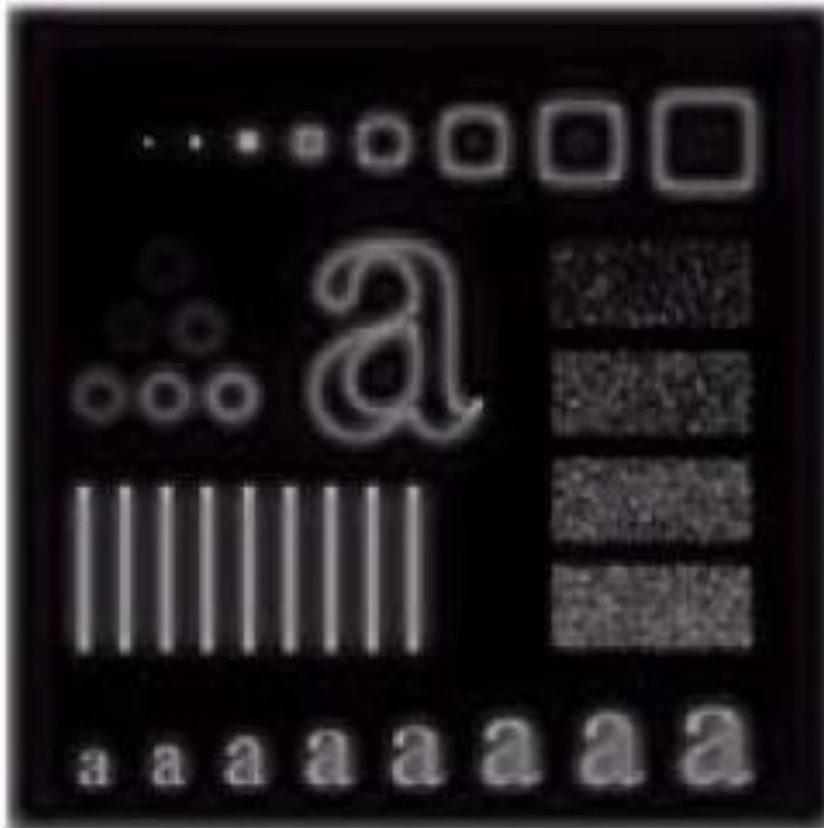
**(Ringing effect is observed)**



# Ideal High Pass Filter



# Butterworth High Pass Filter



**$D_0 = 15$**



**$D_0 = 30$**

## Comparison: High Pass Filter



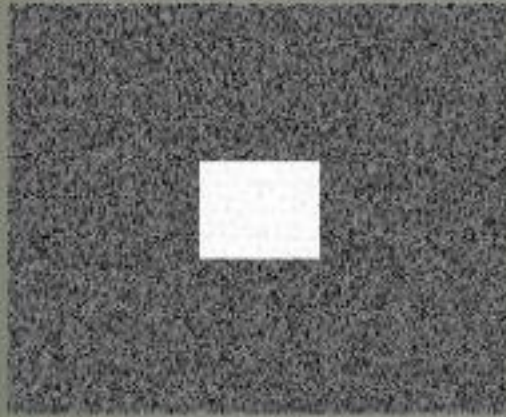
**High-pass filtering**



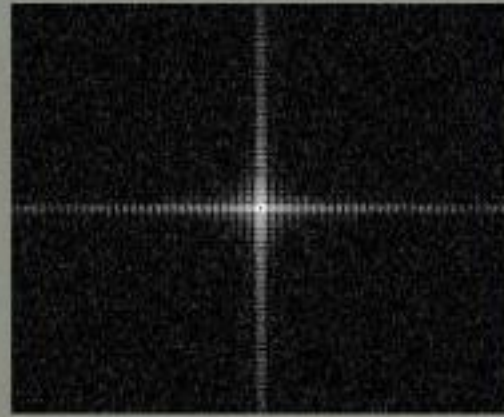
**Low-pass filtering**

# Image denoising examples

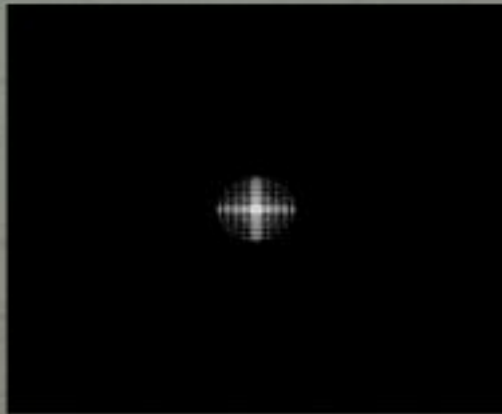
## Ideal filtering



Original Image



Fourier Transform



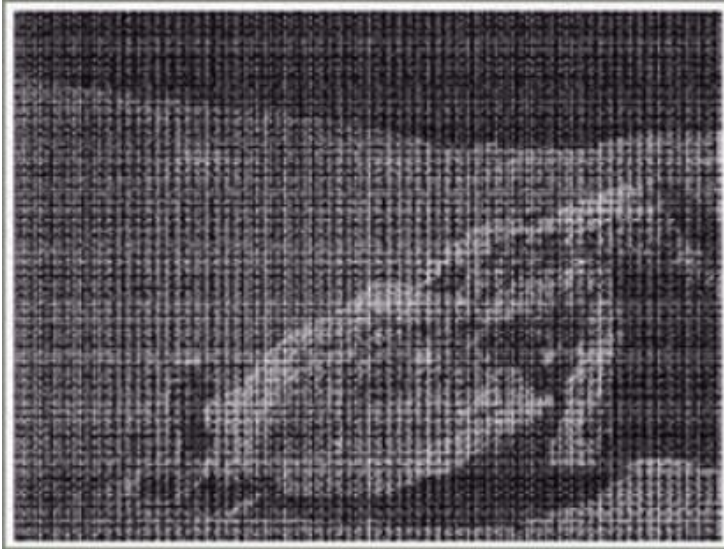
Apply LPF on FT



Inverse Fourier Transform

# Image denoising examples

## Ideal filtering



**Noisy image**



**Frequency domain**



**Denoised**



# Image denoising examples

## Butterworth filtering



**Noisy**

# Image denoising examples

## Butterworth filtering



**Denoised**

# Image denoising examples

## Gaussian filtering

noisy



denoised



$(\sigma=1)$

denoised



$(\sigma=1.5)$



# Image denoising examples

