Digital Image Processing

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Image Enhancement

Objectives of Image Enhacement

- Image enhancement means enhancement for **visual interpretation**
- This covers a **wide variety of processing methods** (e.g., making details better visible, improving contrast, making images sharper,…)
- The evaluation of the results is **higly subjective** (hence no general theory of image enhancement)
- The main objective of image enhancement is to process an image such that the result is more suitable for a **specific application**.
- Image enhancement trechniques are highly **problem oriented** (e.g., a method that enhances well an X-ray image may be unsuitable for a satellite image)
- A possible broad categorization:
  - **Spatial domain** enhancement techniques
  - **Frequency domain** enhancement techniques

Spatial Domain Enhancement

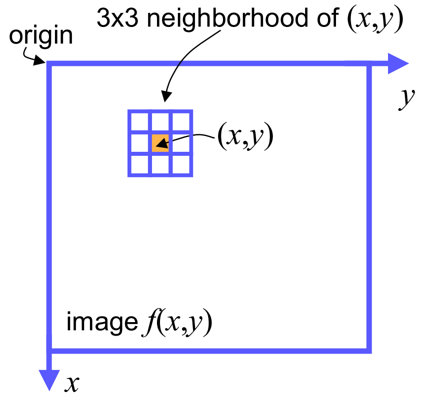
Spatial domain –
- aggregation of image pixels

$$g(x,y) = T(\,f(x,y)\,)$$

$f(x,y)$ – input image

$f(x,y)$ – output image

T – operator on f defined over some neighborhood of (x,y)

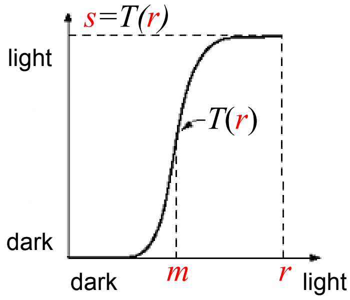


Simplest case: neighborhoud of size 1x1 (a single pixel)
In this case T is **intensity transformation**

$$s = T(\,r\,)$$

r and s – grey values of f and g, resp., at any position (x,y)

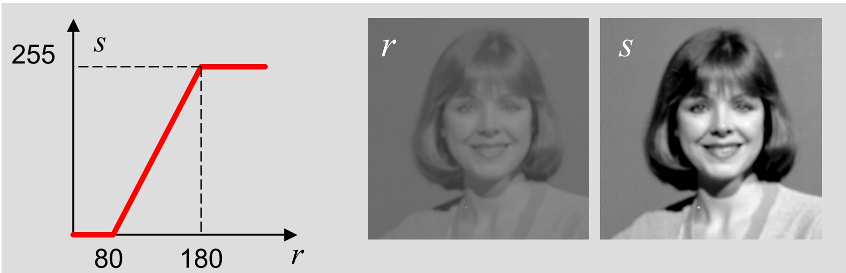
Intensity transformation



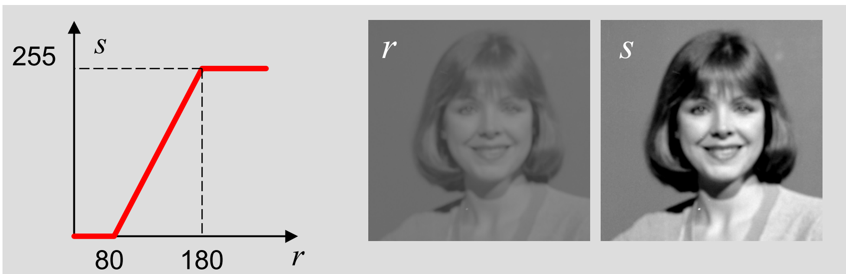
Contrast enhancement

The values of r below m are compressed into a narrow range of s towards black. The opposite efect for values above m.

Also: a narrow intensity range around m is transformed into a wider intensity range.

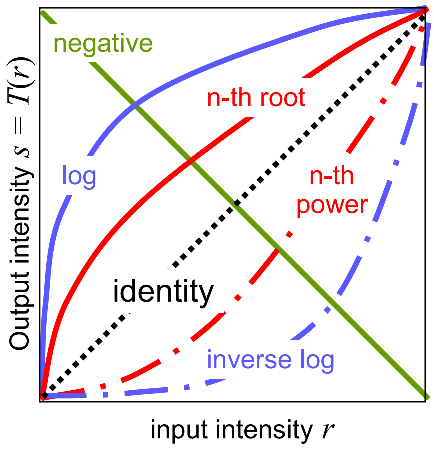


Contrast enhancement



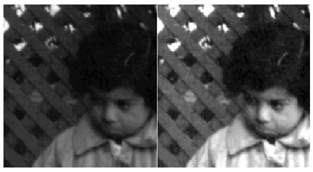
limiting case: thresholding

Basic gray-level transformations



Values of the transformation function are typically stored in a one dimensional array.

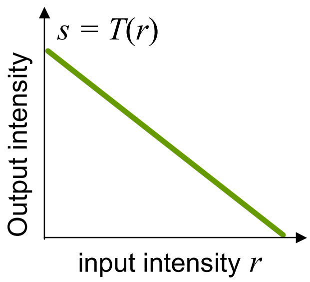
The mapping from r to s is implemented as a **look-up-table**

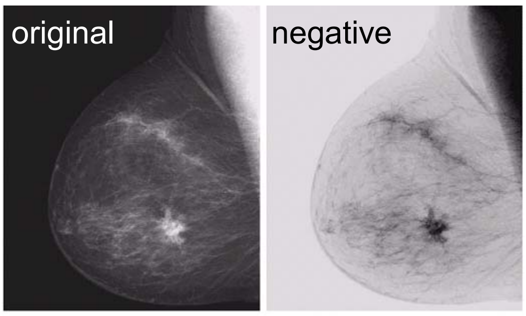


Which transformation produces this enhancement?

Image negative

Example: enhancement of digital mammograms



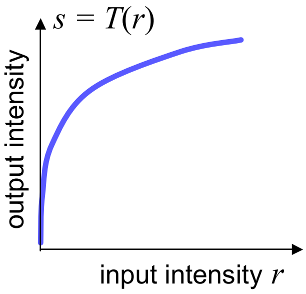


$s = L\text{-}1\text{-}r$

r and s – grey values of input and output image, resp., at any position

Input (and output) gray levels are in the range $[0, L\text{-}1]$

Log transformations



A narow range of low gray-level values in the input image is mapped to a wider range of output values. The opposite is true for higher gray values.

Expands the values of dark pixels.
Compresses the values of bright pixels.

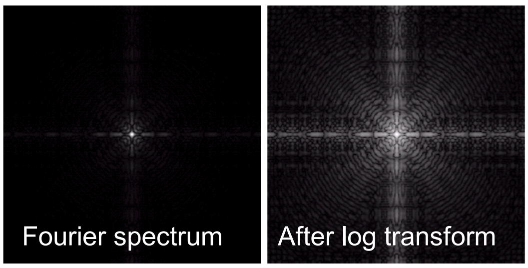
Compresses the overall dynamic range.
Allows visualisation of images with a large range of pixel values!

$$s = c\,log(1+r)$$

r and s – grey values of input and output image, resp., at any position

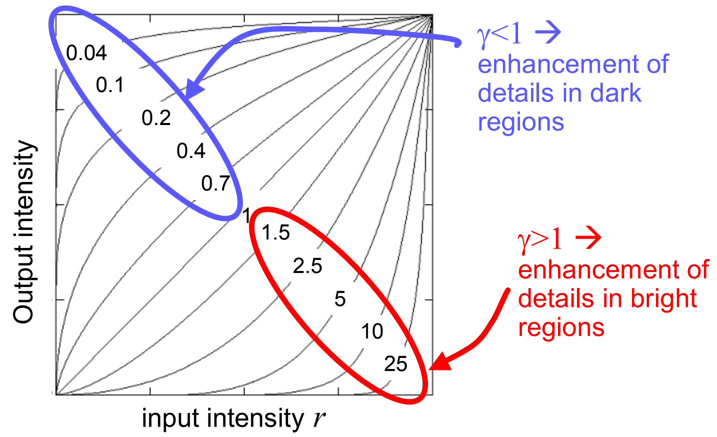
Assuming r ≥0 (gray levels are in the range $[0, L\text{-}1]$)

Visualisation by Log transform



Log transform is commonly used for visualisation of data that have a big dynamic range, such as
- Fourier spectra
- Ultrasound data
- Optical Coherence Tomography (OCT) data
- Radar images
- …

Power low transformations

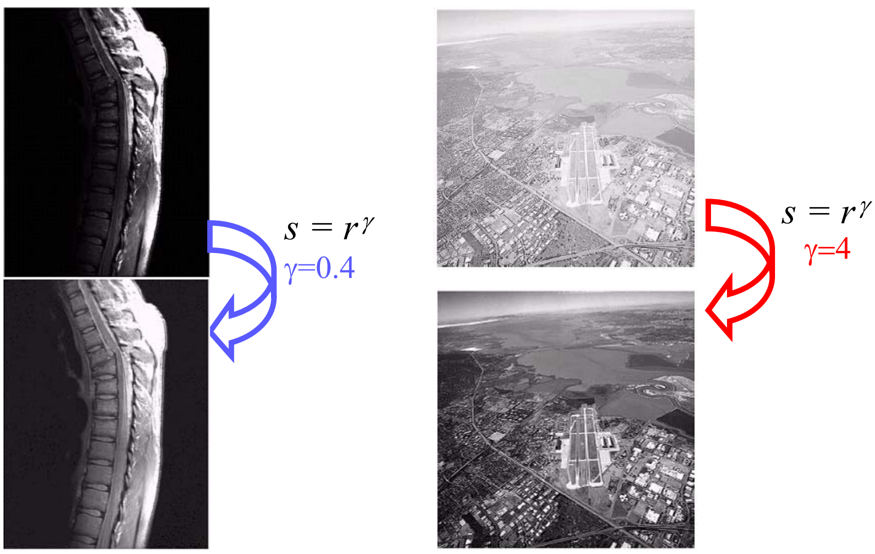


$s = c\, r^{\gamma}$

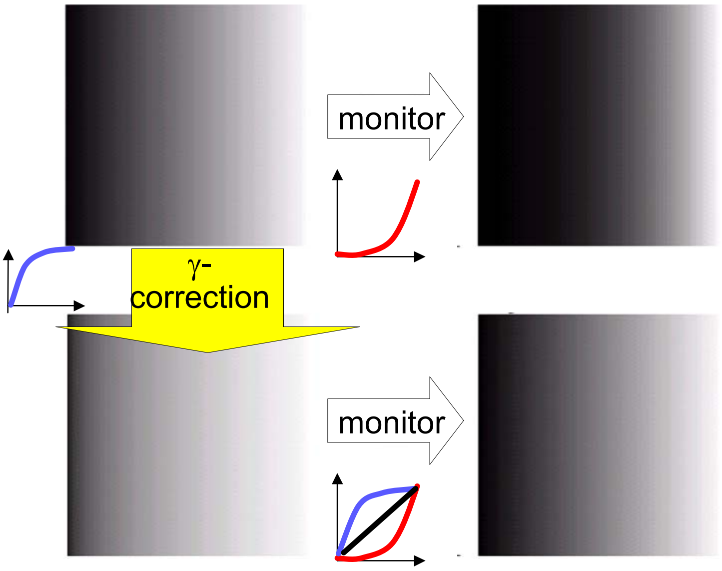
r and s – grey values of input and output image, resp., at any position

c, γ - positive constants

…Power low transformations…

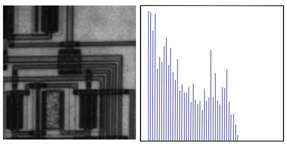


…Power low transformations



Histogram processing

$h(r_k) = n_k$



r_k : k-th grey level in the image

n_k : number of pixels having gray level r_k

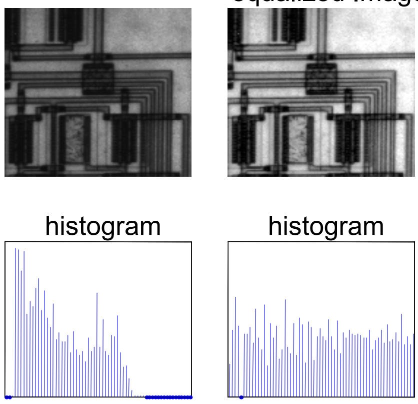
Normalized histogram

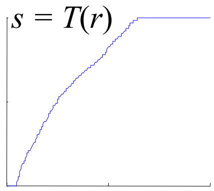
$p(r_k) = n_k / n$, n: number of image pixels

$p(r_k)$ is an estimate of probability of occurence of gray level r_k

- Histograms are simple to calculate in software and hardware
- Provide image statistics
- Useful in image compression, denoising, analysis

Histogram equalization



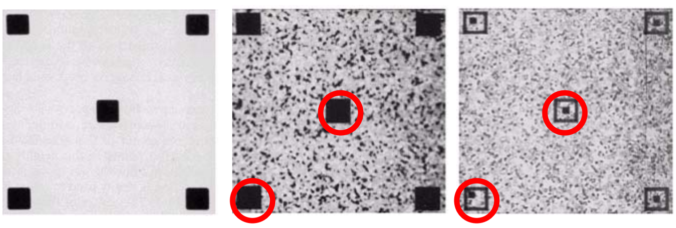


$$s_k = T(r_k) = \sum_{j=0}^{k} p(r_j) = \sum_{j=0}^{k} \frac{n_j}{n}$$

This mapping is cumulative histogram

Conclusion: to flatten (equalize) the histogram, transform the image with its cumulative histogram!

Local processing



original image | global histogram equalization | local histogram equalization (7x7windows)

It is often useful to apply intensity transformations locally (within local windows)

In some cases such processing creates artifacts! (e.g., can create non-existing structures in an almost flat background)

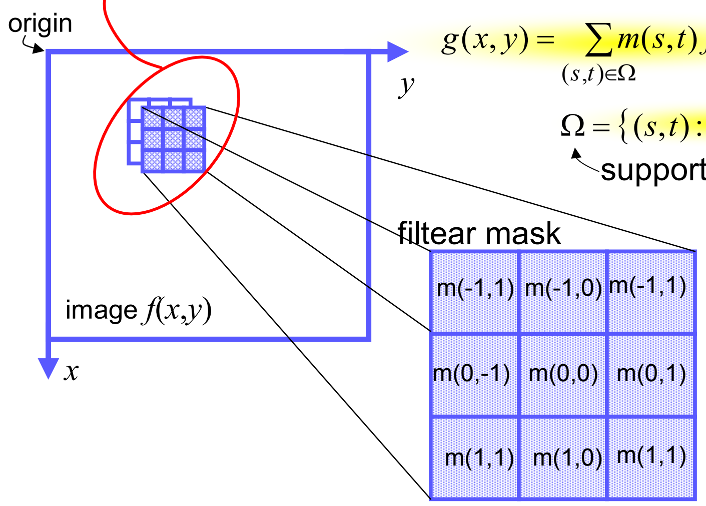
Basics of spatial filtering

$$g(x,y) = m(-1,-1)f(x-1,y-1) + ... + m(1,1)f(x+1,y+1)$$

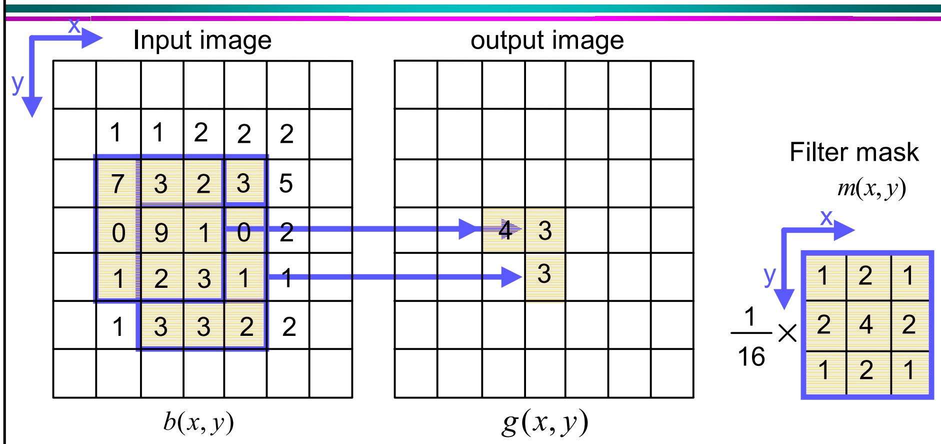
$$g(x,y) = \sum_{(s,t)\in\Omega} m(s,t)f(x+s,y+t)$$

$$\Omega = \{(s,t) : s,t = -1, 0, 1\}$$

support of the mask



Smoothing spatial filters



Correlation!: $g(x,y) = \sum_{(s,t)\in\Omega} g(s+x,t+y)m(s,t)$

$2\#\Omega-1$ calculations per pixel!

De index set Ω is the support of m

$\Omega = \{(x,y) : x,y = -1, 0, 1\}$ Ω includes usually (0,0) but not always!

Example: mean filter

This filter partly suppresses noise but blurs the edges

Note: this filter is separable

$$M = \frac{1}{25}\begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{pmatrix}$$

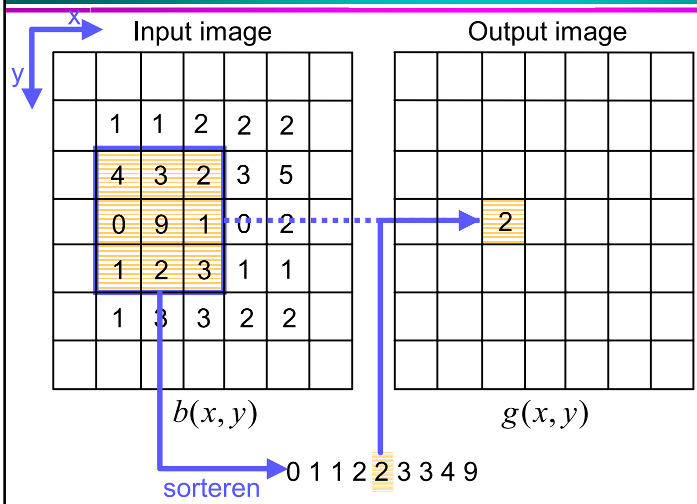
Order statistics filters

Order statistics filters are nonlinear spatial filters.

Operation: (1) perform ordering (ranking) the pixels within a filter mask.
(2) replace the value of the center pixel by the ranking result

Best known example in this class: median filter

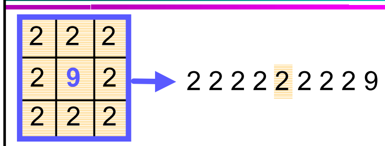
Order statistics filters: Median filter



Basic idea: remove “outliers”

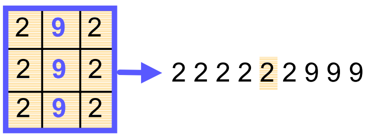
The median is a more robust statistical measure than mean

Properties of the median filter...

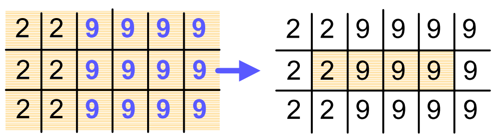


+removes isolated pulses

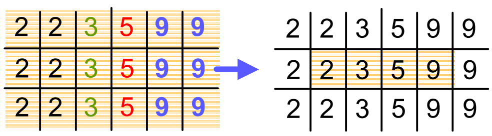
+preserves uniform areas



-removes thin vertical, horizontal, diagonal lines



+preserves sharp horizontal and vertical edges



+preserves “soft” horizontal and vertical edges

... Properties of the median filter...

2	9	9	9	9	9
2	2	9	9	9	9
2	2	2	9	9	9
2	2	2	2	9	9

→

2	9	9	9
2	2	9	9

+preserves sharp diagonal edges

2	3	5	9	9	9
2	2	3	5	9	9
2	2	2	3	5	9
2	2	2	2	3	5

→

2	3	5	9
2	2	3	5

+preserves "soft" diagonal edges

2	2	2	2	2	2
2	2	2	2	2	2
2	2	3	3	3	3
2	2	3	3	3	3

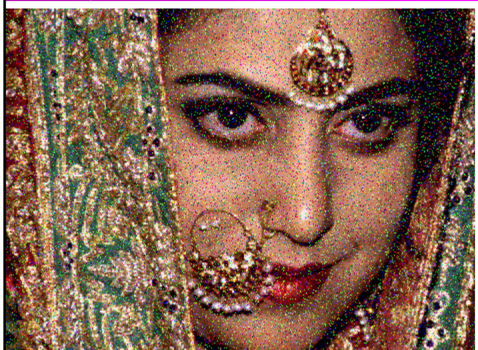
→

2	2	2	2
2	2	3	3
2	3	3	3

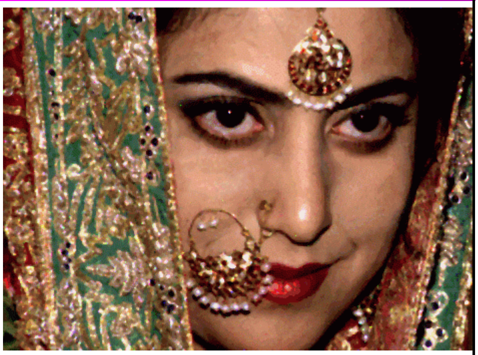
-damages corners

Some of these problems can be avoided by choosing not-rectangular windows

Removal of impuls noise



Impuls noise



median over 3x3

Median filter removes isolated noise peaks, without blurring the image

... Reduction of impuls noise …

Noise-free original

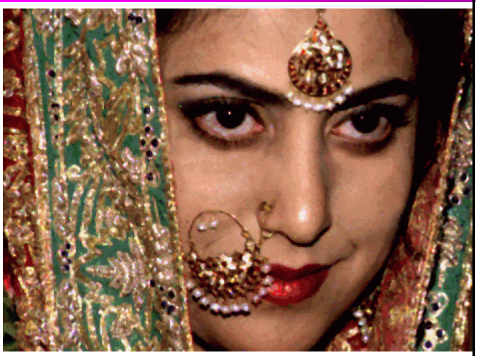
median over 3x3

Median filter removes isolated noise peaks,
without blurring the image

version: 30/11/2006

... Reduction of impulse noise

mean over 3x3



median over 3x3

Linear filters do not take into account impulsive (isolated) character of the noise and blur the image

The median filter performs in this case much better than the linear filters

Median filter and reduction of white noise

original

median over 3x3

For not-isolated noise peaks (e.g., white Gaussian noise) median filter is not very efficient.

Repeated application of the median filter

median over 3x3

median over 3x3, 8x applied

Iterating median filter can remove noise better, but flat blobs appear in the image

Sharpening spatial filters

- Principal objective: highlight fine detail or enhance image detail
- Often based on the first-order and second-order derivatives
- The derivatives of digital functions are defined in terms of differences

$$\frac{\partial f}{\partial x} \approx f(x+1) - f(x)$$

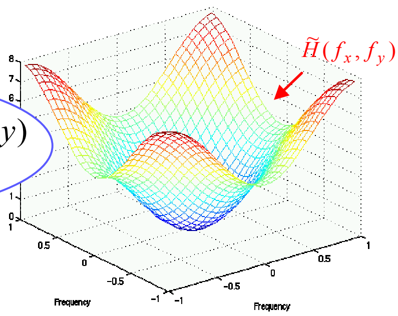
$$\frac{\partial^2 f}{\partial^2 x} \approx f(x+1) + f(x-1) - 2f(x)$$

- In most applications second-order derivative is better suited for image enhancement
- First-order derivatives are used for edge extraction but also have important use in image enhancement

Second order derivatives: Laplaciaan…

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

$$\approx f(x-\mathbf{1}, y) - \mathbf{4} f(x, y) + f(x+\mathbf{1}, y) + f(x, y-\mathbf{1}) + f(x, y+\mathbf{1})$$



digital implementation

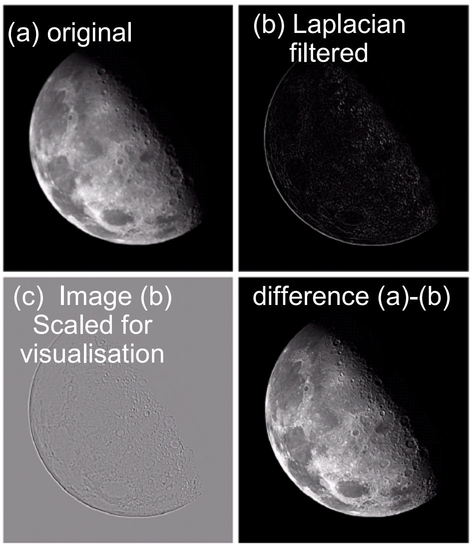
lineair filter with filter mask

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Enhancement:

$$g(x, y) = f(x, y) - \nabla^2 f(x, y)$$

… Second order derivatives: Laplaciaan



Enhancement:

$$g(x,y) = f(x,y) - \nabla^2 f(x,y)$$

Unsharp masking

Subtract a blurred version of an image from image itself

$$f_s(x,y) = f(x,y) - \bar{f}(x,y)$$

blurred version of $f(x,y)$

A generalization: **high-boost filtering**

$$f_{hb}(x,y) = Af(x,y) - \bar{f}(x,y)$$

This can be re-written as

$$f_{hb}(x,y) = (A-1)f(x,y) + f(x,y) - \bar{f}(x,y) =$$
$$= (A-1)f(x,y) + f_s(x,y)$$

If we choose that the sharp image *as*: $f_s(x,y) = -\nabla^2 f(x,y)$

$$f_{hb}(x,y) = Af(x,y) - \nabla^2 f(x,y)$$

"Unsharp masking" – a usual formulation

Unsharp masking : approximate inverse filter for Gaussian PSF with parameter σ:

$$g(x,y) = f(x,y) - \frac{\sigma^2}{2}\nabla^2 f(x,y)$$

Filter mask:

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} - z_0 \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \text{with } z_0 = \sigma^2/2$$

This filter amplifies noise. The noise amplification increases when z_0 increases

Note: if the noise amplification is a problem, choose $z_0 < \sigma^2/2$

⇒ blurring increases but not necessarily excessively

⇒ less noise amplification

Unsharp masking: example

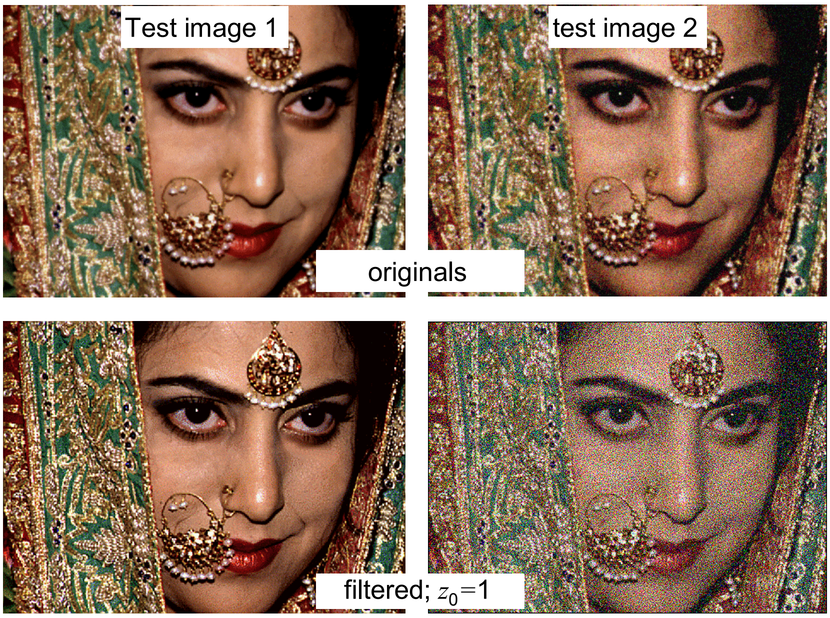
Gaussian filtered (z_0=0.5)

Gaussian filtered (z_0=0.5) +ruis

Unsharp masking $\Rightarrow \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} - z_0 \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$ with z_0=0.5

If z_0 is bigger (e.g. z_0=1) the resulting image is extra sharp

Unsharp masking and noise



sharper

→ noisier

Homomorphic filtering

Homomorfische filtering

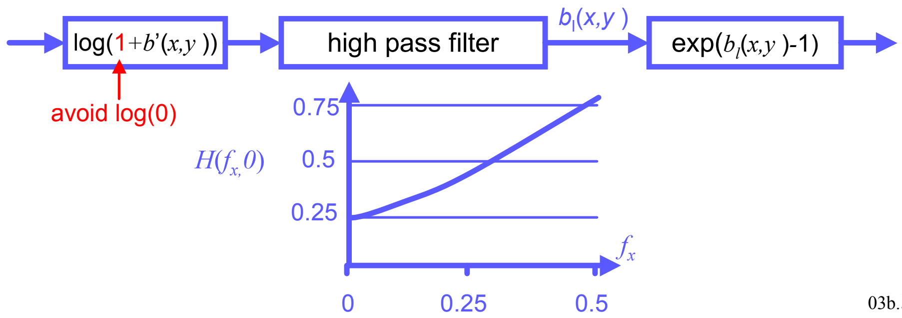
Goal: local contrast enhancement: compensation of spatially varying illumination

Illumination model: $b'(x,y)=b(x,y)I(x,y)$ met $b(x,y)$ the ideal image and $I(x,y)$ the not-uniform lighting

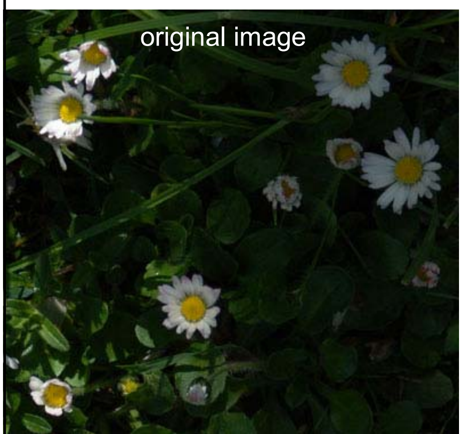
$\Rightarrow \log(b'(x,y))=\log(b(x,y))+\log(I(x,y))$

Assumption: $\log(I(x,y))$ varies slowly w.r.t $\log(b(x,y))$

$\Rightarrow$ remove $\log(I(x,y))$ by high pass filtering $\log(b'(x,y))$



Example: homomorphic filter

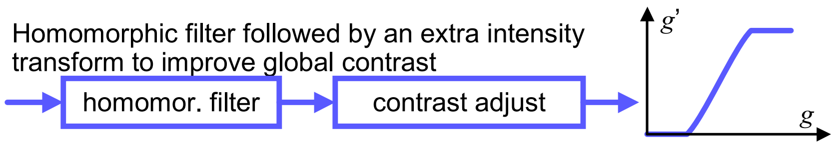


Remark:

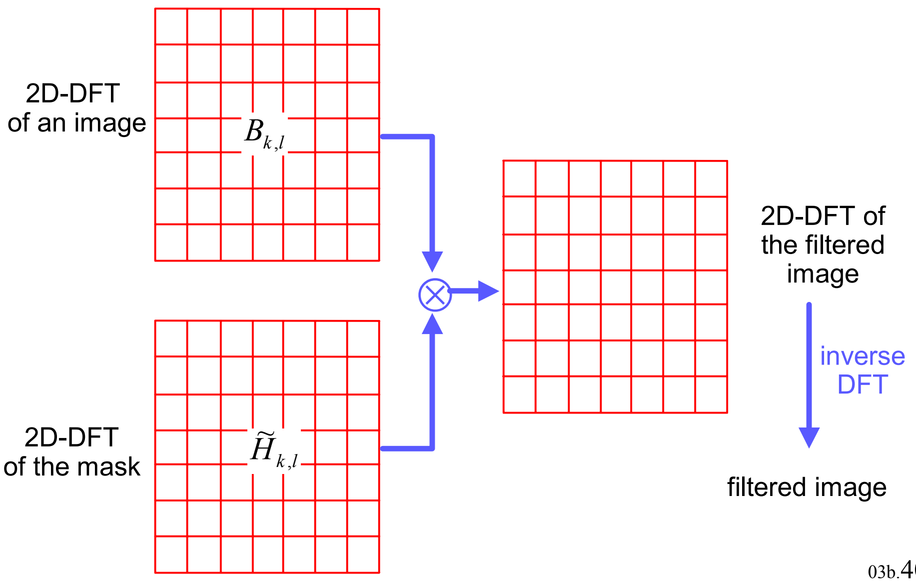
- Homomorphic filter is here applied to Y-component; U and V were not changed
- Truncation of RGB-values <0 en >255

Example: homomorphic filter

Homomorphic filter followed by an extra intensity transform to improve global contrast



Filtering in the Fourier domain



Vergelijking van het aantal berekeningen

Filteren van een $N \times N$ beeld met een $n \times n$ masker:

- Via convolutie/correlatie:
  - scheidbaar filter: $4n$-2 bewerkingen/pixel
  - niet-scheidbaar filter: $2n^2$-1 bewerkingen/pixel

- Via de DFT (als we de DFT van het masker al kennen):

$$\frac{4N^2 \log_2 N + N^2}{N^2} = 4\log_2 N + 1 \quad \text{bewerkingen/pixel}$$

Vermenigvuldiging in frequentiedomein

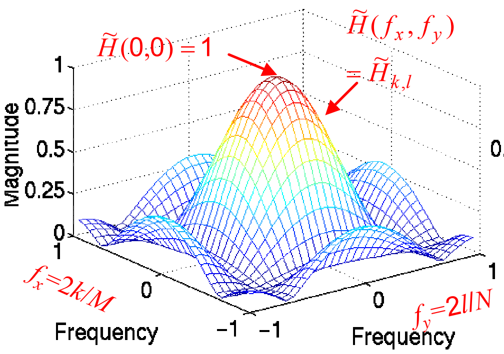
Voorwaartse en inverse DFT (via FFT)

De DFT-implementatie is voordeliger voor grote maskers

- Break-even punt (niet-scheidbaar): $n \approx \sqrt{2\log_2 N}$ (b.v. N=256 $\Rightarrow$ n=4)

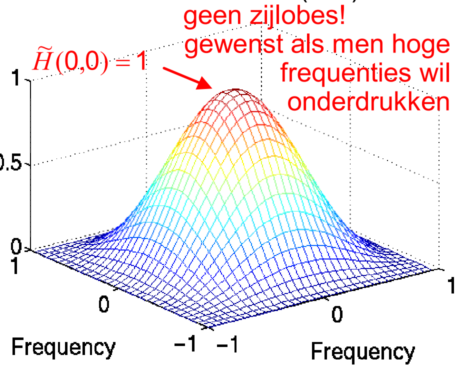
Voorbeelden: laagdoorlaatfilters

Uitmiddeling over 3x3 omgeving



Binomiaal-filter (3x3)

geen zijlobes!
gewenst als men hoge frequenties wil onderdrukken

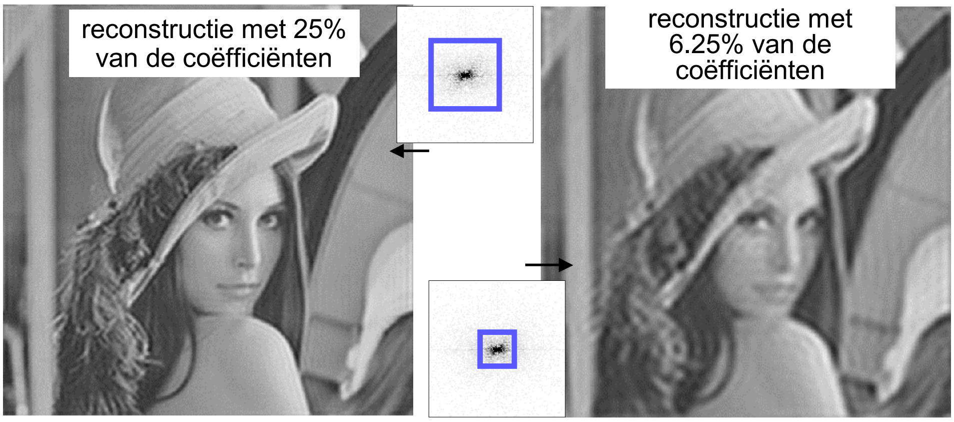


$$\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} = \frac{1}{9}\begin{bmatrix}1\\1\\1\end{bmatrix}\begin{bmatrix}1&1&1\end{bmatrix}$$

$$\frac{1}{16}\begin{bmatrix}1&2&1\\2&4&2\\1&2&1\end{bmatrix} = \frac{1}{16}\begin{bmatrix}1\\2\\1\end{bmatrix}\begin{bmatrix}1&2&1\end{bmatrix}$$

zorgt ervoor dat $\tilde{H}(0,0)=1$ $\Rightarrow$behoudt gemiddelde grijswaarde

Filter in het fourierdomein: voorbeeld



Filter: $\widetilde{H}_{k,l} = 1$ binnen het blauw vierkant en 0 erbuiten

Dit komt erop neer de fouriercoëfficiënten bij hoge spatiale frequenties nul te maken ⇒laagdoorlaatfilter

Invloed op het beeld:
- "Ringing" (rimpels)
- "Blurring" (wazig maken)