7.- IMAGE ENHANCEMENT TECHNIQUES

This chapter is divided in three main groups of techniques: point operators, histogram modelization techniques, and spatial operators.

7.1.- Point operators

They modify each pixel on the image as a function of its intensity value, independently of the rest of the image. The application is based on transformation functions, and in practice is carried out using **LUT**'s *(Look Up Tables)* , where to the input grey level of each pixel is assigned a fixed output value. The LUT's allow the storage of a transformation just by saving a simple table, it not being necessary to store the complete resulting image.

We will name *f(x,y)* the input image, and *g(x,y)* the output image after applying the transformation:

$$f(x,y) \xrightarrow{T} g(x,y)$$

Example: *The "negative image" transformation is*

$$g(x,y) = (L - 1) – f(x,y)$$

where L represents the grey levels range of the image. (See images in figure 7.1).

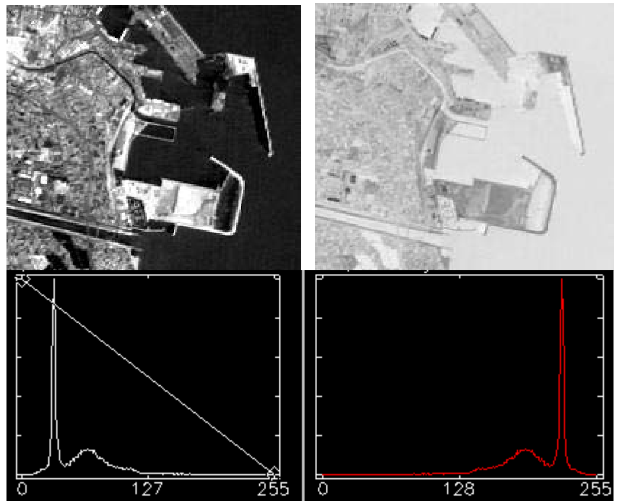


Figure 7.1.- Transformation that produces the "negative" of an image.

Linear transformations: They are defined by a linear function. Here are some examples:

a) *Modification of gain and offset*:

$$g(x,y) = a\, f(x,y) + b$$

where *a* controls the contrast and *b* controls the overall brightness of an image. It can be applied to correct the two calibration parameters of a sensor.

b) *Radiometric normalization based on mean and standard deviation*:

The mean (μ) and standard deviation (σ) of the input and output (reference) image *g(x,y)* needed. Thus, parameters *a* and *b* are expressed as a function of them:

$$a = \sigma_g / \sigma_f \quad ; \quad b = \mu_g - a\, \mu_f$$

This transformation is used:

- To correct erroneous detectors of a sensor (*striping*).
- To adjust the different images composing a mosaic (figure 7.2).
- To normalize images acquired on different dates before applying an analysis method for change detection.

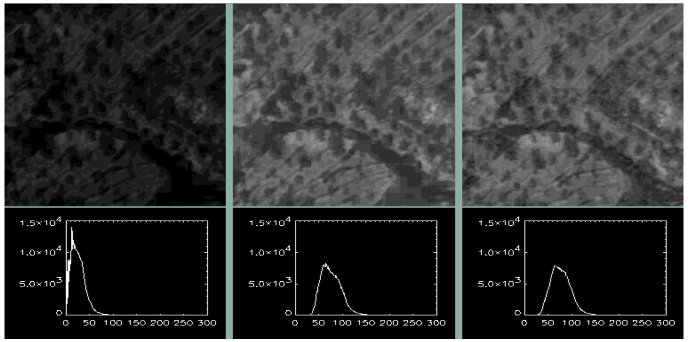


Figure 7.2.- Example of radiometric normalization to create a mosaic of images. The histogram of an image (left) has been adjusted (center) taking the other image (right) as a reference.

c) *Contrast enhancement*:

The ***histogram*** of a digital image is the graphic representation of the frequencies of the different intensity values on the image.

The linear transformation methods to enhance the contrast are based on ***histogram stretching***. Two intensity values are selected on the X-axis of the histogram and then, a linear transformation is defined to stretch or amplify the contrast inside this interval. The effect shown in figure 7.3, where the transformation linear stretching function is drawn on the histogram.

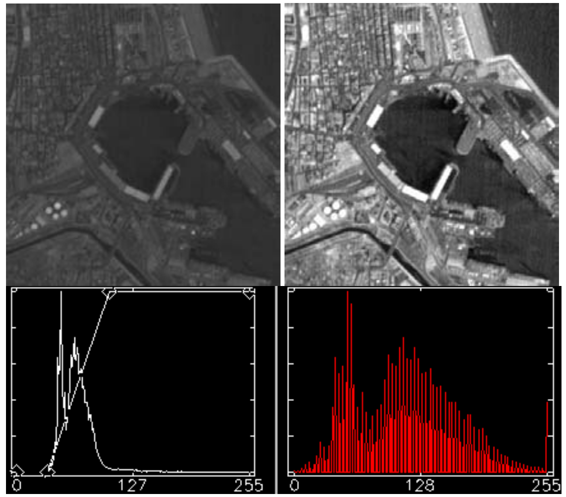


Figure 7.3.- Linear histogram stretching to enhance the contrast

d) *Linear piecewise transformations*:

The input intensity range is divided in several sections, and a different transformation function is applied on each of them (figure 7.4). For example:

$$g = \begin{cases} \alpha f & 0 <= f <= a \\ \beta(f - a) + g_a & a < f <= b \\ \gamma (f - b) + g_b & b < f <= L \end{cases}$$

Values of $\alpha, \beta, \gamma > 1$ have the effect of increasing the contrast, while values of $\alpha, \beta, \gamma < 1$ reduce the contrast.

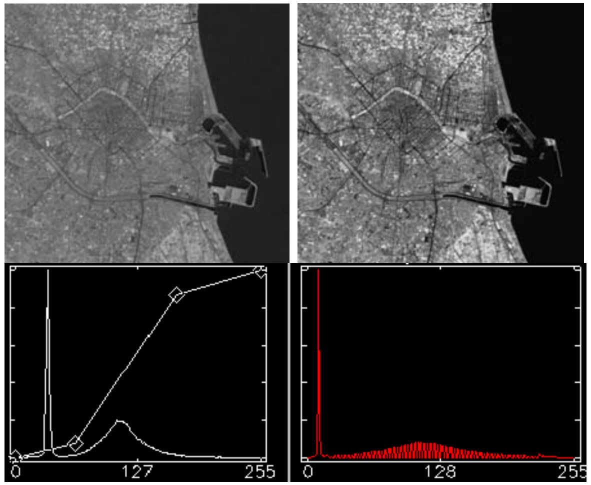


Figure 7.4.- Linear piecewise transformation. Contrast is increased in intermediate grey levels, and decreased in the extremes.

e) *Thresholding and density slicing:* The simplest expression is the *binarization*, where a threshold is defined and the values under it are recoded to zero, while values over the threshold are given the maximum value (figure 7.5).

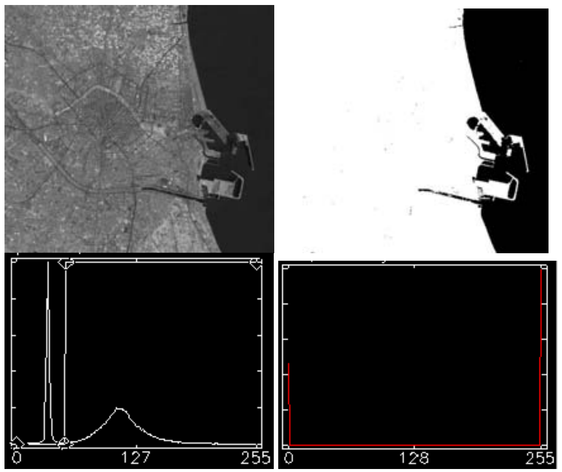


Figura 7.5.- Binarization of an image using a threshold equal to 50.

Variations of this method are multiple thresholding, or density slicing (figure 7.6)

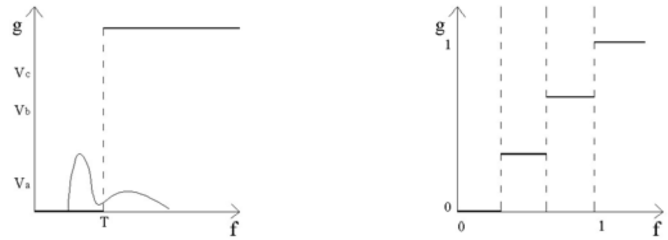


Figure 7.6.- Simple thresholding (left) and density slicing transformation (right)

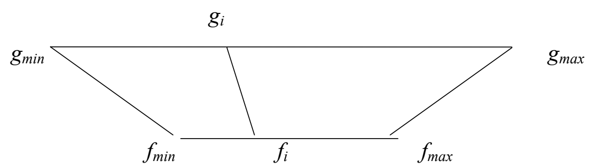
f) *Intensity level autoscaling* : Conversion from an intensity dynamic range to another by a linear transformation.

If $f_{mín}$ and $f_{máx}$ are the minimum and maximum possible input values, $g_{mín}$ and $g_{máx}$ the same for the output image, and f_i and g_i two generic values of both images, the compute of g_i in the output image is obtained as

$$\frac{f_i - f_{min}}{f_{max} - f_{min}} = \frac{g_i - g_{min}}{g_{max} - g_{min}}$$

operating

$$g_i = g_{min} + \frac{f - f_{min}}{f_{max} - f_{min}} \times (g_{max} - g_{min})$$



Non linear transformations:

a) *Logarithmic*: Used to compress the dynamic range:

$$g(x,y) = k \log(1 + |f(x,y)|) \quad ; \quad \text{k = scale constant}$$

This transformation also stretches the low values and reduces the contrast in high intensity values (figure 7.7).

b) *Exponential*: It has the opposite effect, increasing the contrast in the higher values and reducing the contrast in the lower values (figure 7.7):

$$g(x,y) = k\,(e^{|f(x,y)|}-1)$$

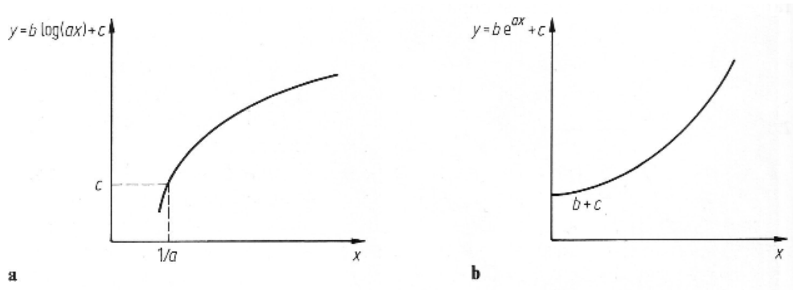


Figure 7.7.- Logarithmic (a) and exponential (b) transformations (Richards, 1993)

7.2.- Histogram modelization techniques

1.- *Equalization*

With the purpose of obtaining a histogram flat as possible, the intensity values of the image are homogeneously distributed on the intensity range (figure 7.8).

CHAPTER 7: Image enhancement techniques

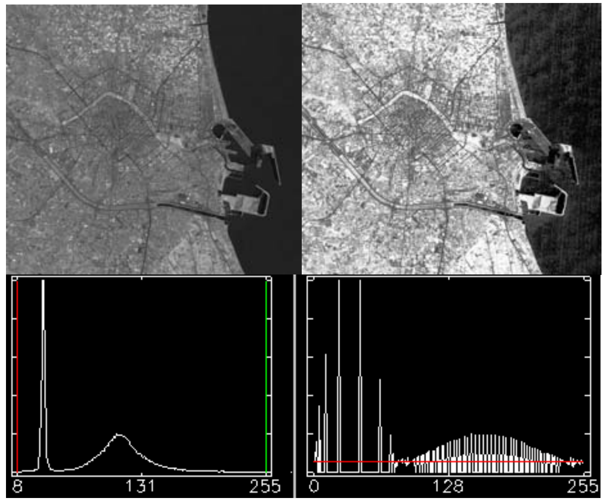


Figura 7.8.- Histogram equalization

2.- *Histogram specification*

This method, also named *histogram matching*, is analogous to the equalization but here, instead of having a flat histogram as a reference, another reference histogram is chosen. The aim is to obtain a histogram as close as possible to other. This technique can be applied, like the radiometric normalization based on mean and standard deviation of the histograms, when images of the same area that have been taken on different dates or by different sensors are being compared. This is common when analyzing changes or evolutions.

7.3.- Spatial operators

The ***noise*** of a digital image is that part of the information from the intensity values that does not come from the object or natural scene, but it has been introduced by external factors (atmosphere, sensor system).

The ***spatial frequency*** of an image is proportional to the number and magnitude of changes in the intensity level per distance unit.

The spatial operators modify the value of each pixel depending on the values of pixels in its neighbourhood. They are applied by masks or filters, and the spatial operation is called convolution:

$$g(x,y) = \sum_{(i,j)\in W}\sum f_{ij}(x,y).h(i,j)$$

where *g(x,y)* is the value of a pixel *(x,y)* , *W* is the neighbourhood, and *h(i,j)* is the function of weights or filter.

Applying a generic 3x3 filter over a generic pixel *(x,y)* , its resulting vaule on the filtered image is given by the expression

$$\begin{aligned} g(x,y) = {} & w_1 f(x-1,y-1) + w_2 f(x,y-1) + w_3 f(x+1,y-1) + \\ & + w_4 f(x-1,y) + w_5\ f(x,y) + w_6 f(x+1,y) + \\ & + w_7 f(x-1,y+1) + w_8 f(x,y+1) + w_9 f(x+1,y+1) \end{aligned}$$

The complete filtered image is obtained by moving the filter along the image. Figure 7.9 shows a diagram of the process.

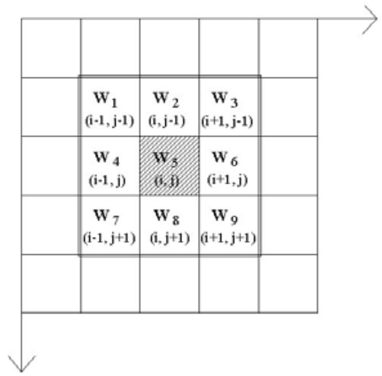


Figure 7.9- Application of a 3x3 filter over a pixel.

<u>*Classification of the spatial operators*</u>

- Smoothing filters (***low-pass***)

- High frequency enhancement filters (***high-pass***)

- ***Edge detection*** filters

a) **Smoothing filters**

They are used to reduce noise on images. The most common are:

- <u>*Mean filter*</u>: Each pixel value is substituted by the mean value of the neighbouring pixels:

$$g(x,y) = \frac{1}{N_W}\sum_{(i,j)\in W}\sum f_{ij}(x,y) \qquad \begin{bmatrix} \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \end{bmatrix}$$

- *<u>Median filter</u>*: Each pixel value is substituted by the median value of the neighbouring pixels. It is efficient in eliminating binary (*salt and pepper*) noise.

- *<u>Mode filter</u>*: Each pixel value is substituted by the most repeated value of the neighbourhood. Useful in filtering classified (thematic) images.

Figure 7.10 shows some examples of smoothing filters.

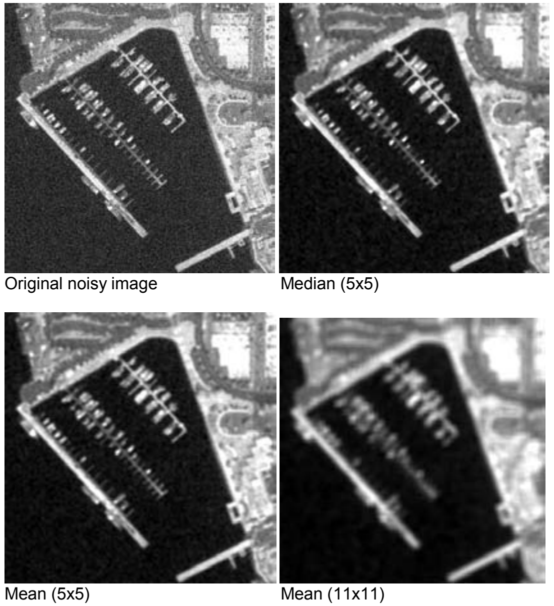


Figure 7.10.- Image with gaussian noise and the result of application of 3 low-pass filters.

<u>Example</u>: *What would be the result of applying a (3x3)mean filter over the 9 central pixels of the 5x5 image shown below? And the result of applying a (3x3) median filter? What is the difference between both results?*

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 10 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Mean*: In the 9 pixels, the results will be: [(8 x 1) + 10]/9 =* ***2***

Median*: In the 9 pixels, the median value of the series 1,1,1,1,1,1,1,1,10 is* ***1***

$$Media: \begin{bmatrix} 2 & 2 & 2 \\ 2 & 2 & 2 \\ 2 & 2 & 2 \end{bmatrix} \qquad Mediana: \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

The mean <u>reduces</u> the noise effect of the central pixel, but the median <u>eliminates</u> its effect. This is a typical case of the suitability of median filtering to eliminate binary noise.

b) **High frequency enhancement filters**

They have an opposite effect from the smoothing filters: they enhance the high frequency values on images, which are related to spatial details, but also to noise. The high-pass coefficients for a 3x3 mask are:

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

After the application of a high-pass filter, usually a scaling of the intensity range is needed for visualization purposes. Image 7.11 shows an example of the application.


Original image High-pass (3x3) Sobel (3x3)

Figure 7.11.- Application of a high-pass filter (center) and a *Sobel* filter (right).

A generalization of these filters are known as ***High-boost*** filters, which are defined by multiplying the original image by an amplification factor (A):

High-Boost = A x Original – Lowpass =
= (A - 1) original + original - Lowpass =
= (A - 1) original + Highpass.

Thus, the original image is partially added to its high-pass version, obtaining an effect of high frequency (detail) enhancement of the original image (figure 7.12).

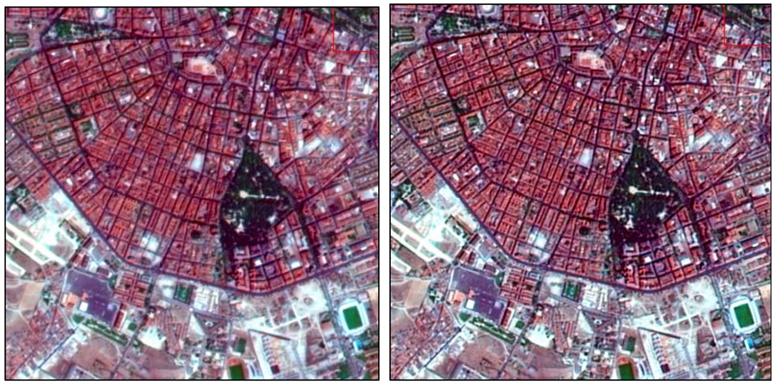


Figure 7.12.- Example of application of a *High boost* filter. There is a subtle increase of spatial detail (high frequencies) in the filtered image (right).

c) **Edge detection filters**

The most common edge detection filter is based on the ***gradient*** operator, that is based on the first derivative of the image function *f(x,y)*. The gradient vector is defined by:

$$\nabla f = \begin{pmatrix} G_X \\ G_Y \end{pmatrix} = \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix}$$

and its magnitude:

$$\nabla f = \sqrt{(G_X^2 + G_Y^2} = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

a practical approximation is:

$$\nabla f \approx |G_X| + |G_Y|$$

The direction of the gradient vector at the point *(x,y)* is given by the angle α:

$$\alpha = \operatorname{arctg}\left(\frac{G_Y}{G_X}\right)$$

measured with respect to the *X* axis.

In digital images, differences are used to obtain derivatives, so the first derivatives on directions X and Y in a generic point are:

$$\Delta f_x = f(x,y) - f(x-1,y)$$
$$\Delta f_y = f(x,y) - f(x,y-1)$$

and their associated masks:

$$\Delta_x = \begin{bmatrix} 0 & 0 \\ -1 & 1 \end{bmatrix} \qquad \Delta_y = \begin{bmatrix} 0 & -1 \\ 0 & 1 \end{bmatrix}$$

Other gradient operators are:

- *Roberts*: 2x2 cross operator, examines diagonal directions

$$\Delta_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \qquad \Delta_y = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

- *Prewitt*: 3x3 operator:

$$\Delta_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad \Delta_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

- *Kirsch directional operators:* represented by the masks (on the four principal directions):

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

- *Sobel*: (Figure 7.11). It is defined by:

$$\Delta_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \Delta_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

The **Laplacian** of a bidimensional function *f(x,y)* is obtained from the second derivatives::

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

In a digital image, and for a 3x3 region:

$$\nabla^2 f = 4f(x,y) - \left[f(x,y-1) + f(x-1,y) + f(x+1,y) + f(x,y+1) \right]$$

If the first derivative on the direction X is:

$$\Delta f_x = f(x,y) - f(x-1,y)$$

the second derivative in the same direction is obtained by derivation of the previous expression:

$$\begin{aligned} &\Delta f_{xx} = \Delta f_{xq}\left[f(x,y) - f(x-1,y) \right] = \\ &\left[f(x,y) - f(x-1,y) \right] - \left[f(x-1,y) - f(x-2,y \right] = \\ &f(x,y) - 2f(x-1,y) + f(x-2,y) \end{aligned}$$

This is equivalent to a linear mask (1 -2 1). Changing signs and extending the mask to two directions

$$\nabla^2 f = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

7.4.- Filtering in the frequency domain

The convolution operations over an image can be applied in the frequency domain, using the concept of the *Fourier transform*.

FOURIER TRANSFORM *(equations)*

	TRANSFORM	INVERSE TRANSFORM	COMPONENTS
CONTINUOUS FUNCTION 1-D	$F(u)=\int_{-\infty}^{\infty} f(x)\cdot e^{-j2\pi ux}dx$	$f(x)=\int_{-\infty}^{\infty} F(u)\cdot e^{j2\pi ux}du$ **F(u) = R(u) + j I(u)** $F(u)=\lvert F(u)\rvert\cdot e^{-j\phi(u)}$ $e^{j2\pi ux}=\cos 2\pi ux + j\,\mathrm{sen}\,2\pi ux$	$\lvert F(u)\rvert=\sqrt{R^2(u)+I^2(u)}$ $\phi(u)=\mathrm{arctg}\left[\frac{I(u)}{R(u)}\right]$
CONTINUOUS FUNCTION 2-D	$F(u,v)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\cdot e^{-j2\pi(ux+vy)}dxdy$	$f(x,y)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} F(u,v)\cdot e^{j2\pi(ux+vy)}dudv$	
DISCRETE FUNCTION 2-D	$F(u,v)=\frac{1}{M\cdot N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\cdot e^{-j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}$	$f(x,y)=\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} F(u,v)\cdot e^{j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)}$	

The convolution theorem

The convolution of a digital image *f(x,y)* by a filtering function *h(x,y)*, on a neighbourhood *W* is given by the expression

$$f(x,y)*h(x,y)=g(x,y)=\sum_{i,j\in W}\sum f_{ij}(x,y)\cdot h(i,j)$$

If *F(u,v)* is the Fourier transform of *f(x,y),* and *H(u,v)* is the Fourier transform of *h(x,y)*, then the Fourier transform of *f(x,y)*h(x,y)* is *F(u,v).H(u,v)*. That is,

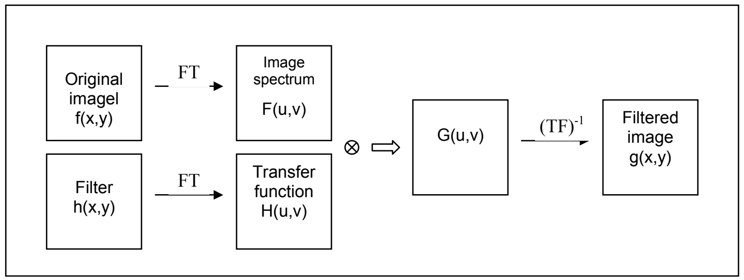
$$f(x,y)*h(x,y)\Leftrightarrow F(u,v)\cdot H(u,v)$$

And also the inverse is valid:

$$f(x,y)\cdot h(x,y)\Leftrightarrow F(u,v)*H(u,v)$$

The practical importance of this theorem is that any convolution of an image can be obtained as a product of two images in the frequency domain. The advantages are that large masks on the spatial domain can be easily performed in the frequency domain, and that is easier to filter the periodic noise in this domain.

<u>Steps of filtering</u>



Examples

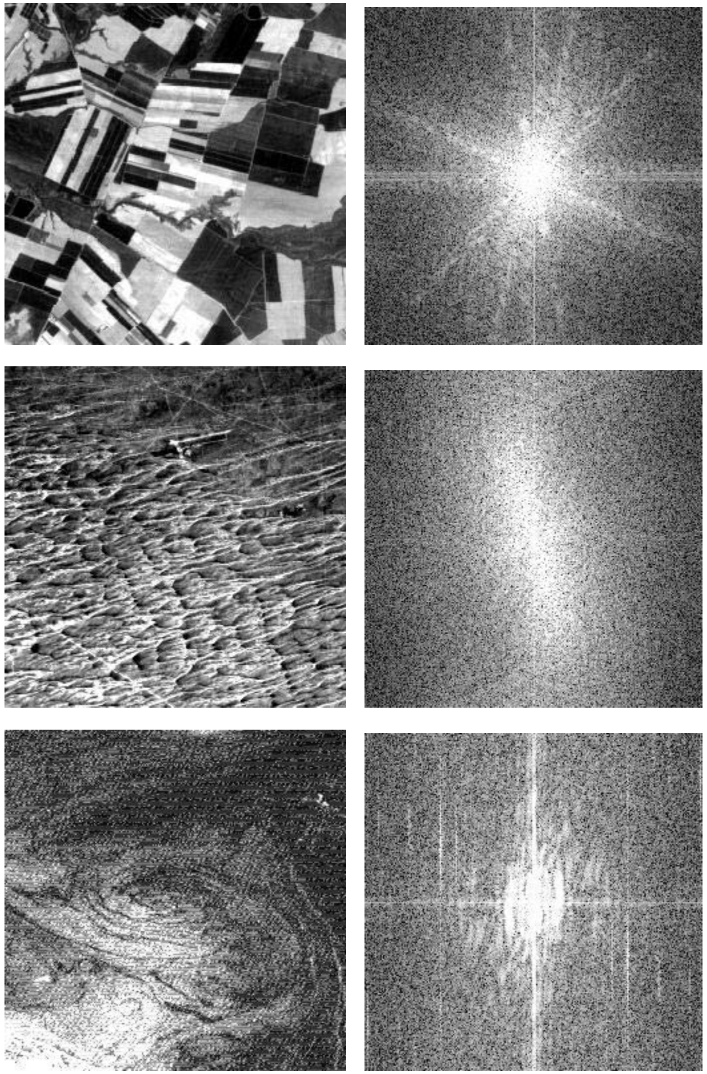


Figure 7.12.- Three images (left) and their respective Fourier transforms (right).

Low-pass filtering

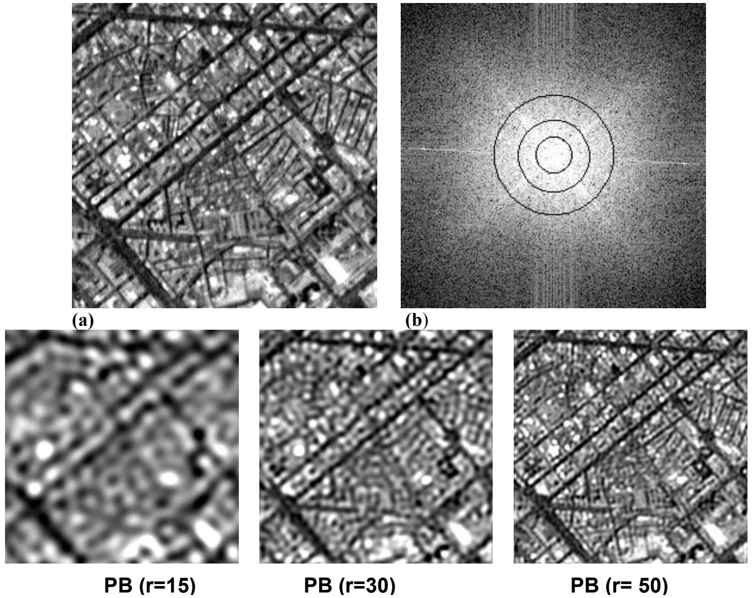


Figure 7.13.- Low-pass filtering in the frequency domain

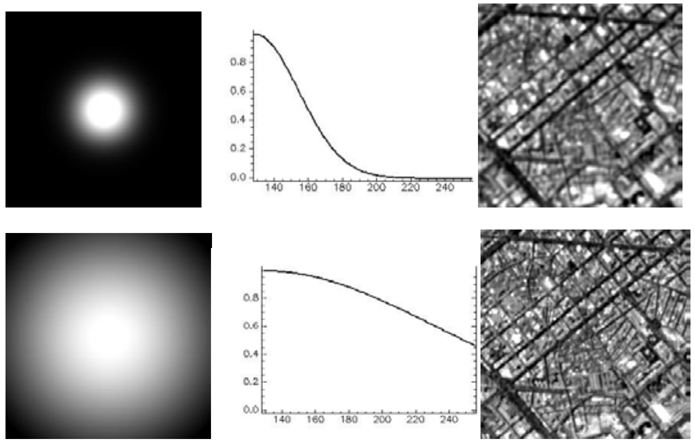
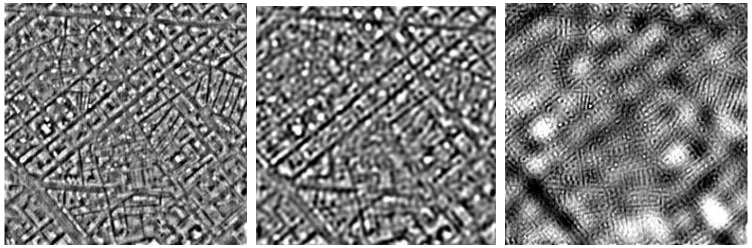


Figure 7.14.- Transfer functions (left) defined by two gaussian functions, σ=0,2 (above) and σ=0,8 (below). Semi-profiles of the transfer functions (center). Filtered images(right).

High-pass filtering



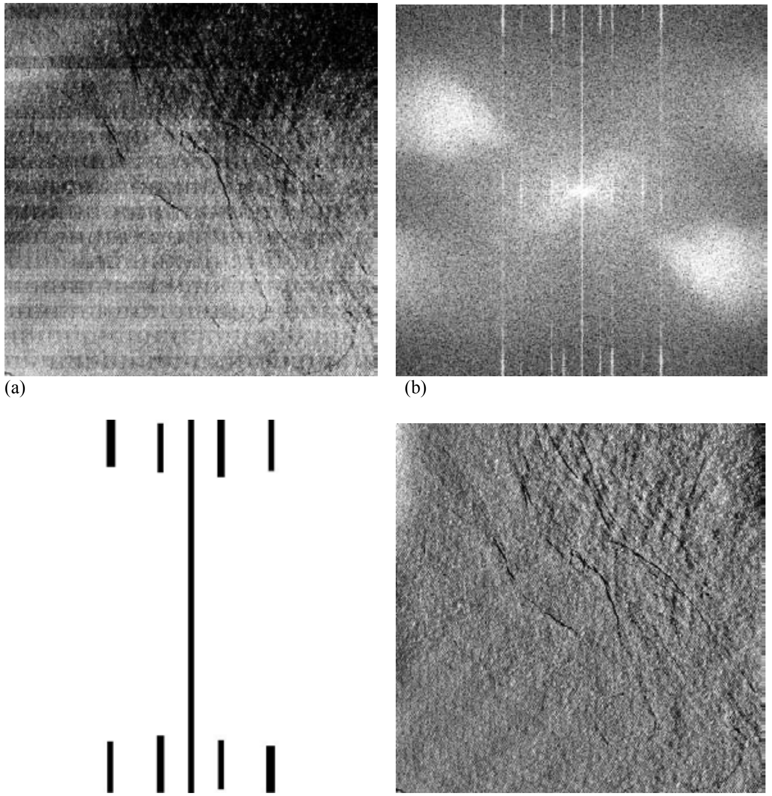
(a) (b) (c)

Figure 7.15.- Examples of three images filtered in the frequency domain using: (a) High-pass circular filter (radius=15); (b) Band-pass circular filter (ring between 10 and 40); and (c) the same with extremes frequencies.

Periodic noise filtering

Some descriptive relationships between the spatial and spatial frequency domains (Schowengerdt, 1997):

Spatial domain.	Spatial frequency domain.
Periodic patterns.	High amplitude "spikes", localized at the frequencies of the patterns.
Linear, quasi-periodic features.	High amplitude line through the origin, oriented orthogonal to the spatial patterns.
Non-linear, non-periodic features.	High amplitude "cloud", primarily at lower frequencies.



(a) (b) (c) (d)

Figure 7.16.- Periodic noise elimination: (a) Original image; (b) Fourier spectrum; (c) specific binary filter (transfer function); (d) image result of filtering.

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