

# Medical Image Processing

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# Introduction

Medical imaging is the technique and process used to create images of the human body for clinical purposes or medical science.

Non-invasive visualization of internal organs, tissue, etc.

Medical imaging refers to several different technologies that are used to view the human body in order to diagnose, monitor, or treat medical conditions.

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# Major Modalities

Projection X-ray (Radiography)

X-ray Computed Tomography (CT)

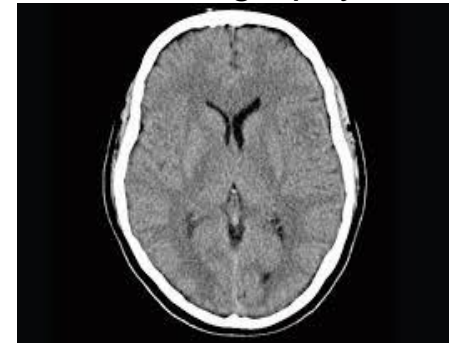
Medical Ultrasonography (US)

Magnetic Resonance Imaging (MRI)

Nuclear Medicine (SPECT, PET)



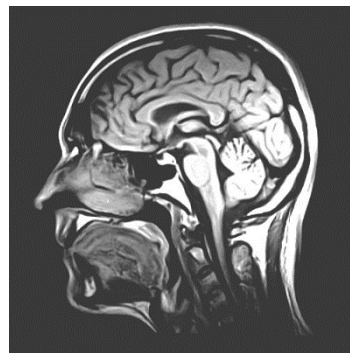
Radiography



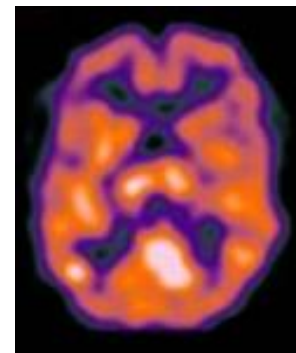
CT



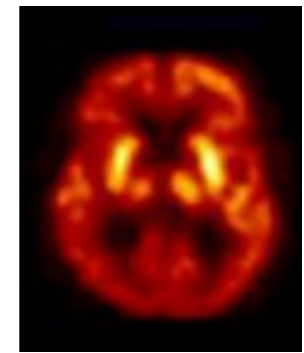
US



MRI



SPECT



PET

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# What is a digital image?

A digital image can be considered as a 2D light intensity function  $f(i,j)$ , where  $(i,j)$  denote spatial coordinates.

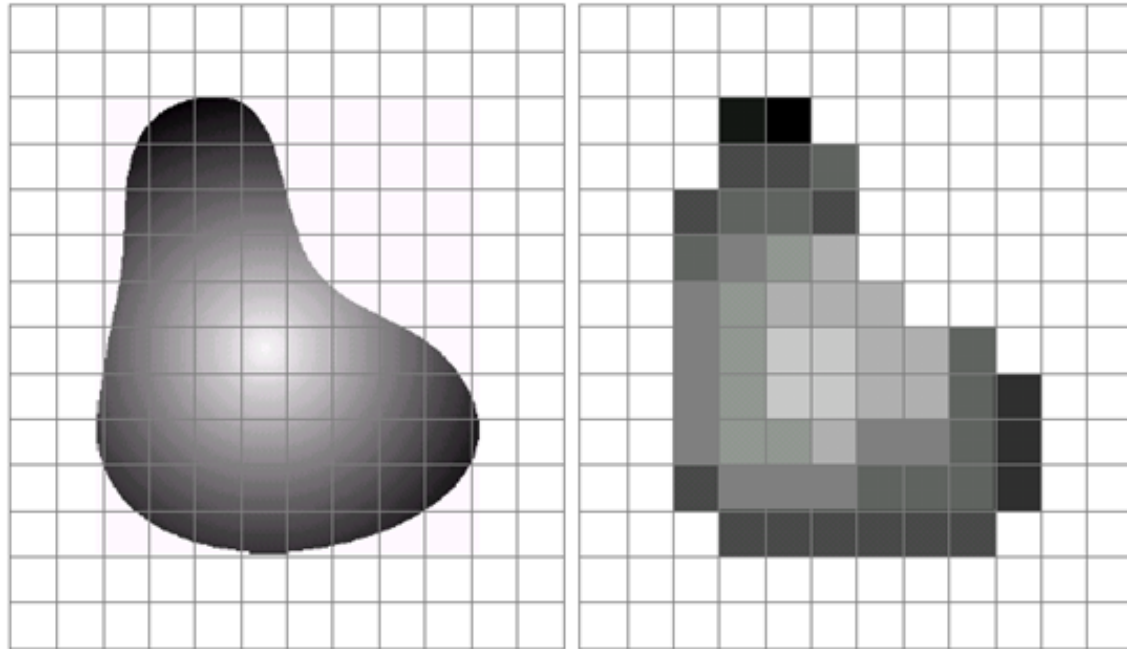
The value of  $f$  at any point  $(i,j)$  is proportional to the brightness of the image at that point.

A digital image is an image  $f(i,j)$  that has been discretized both in spatial coordinates (image sampling) and brightness (gray-level quantization).

The elements of digital image are called pixels.

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# Sampling and Quantization



Continuous image

Result of image sampling  
and quantization

Gonzalez & Woods, Digital Image Processing

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# Image Enhancement

The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application.

Image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods.

There is no general theory of image enhancement.

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# Image Enhancement

Spatial domain methods are procedures that operate directly on pixels.

Spatial domain processes will be denoted by the expression:

$$G(i, j) = T(F(i, j))$$

where  $F(i, j)$  is the input image,  $g(i, j)$  is the processed image, and  $T$  is an operator on  $F$ , defined over some neighborhood of  $(i, j)$ .

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# Contrast Stretching

One of the simplest linear functions is a contrast-stretching transformation.

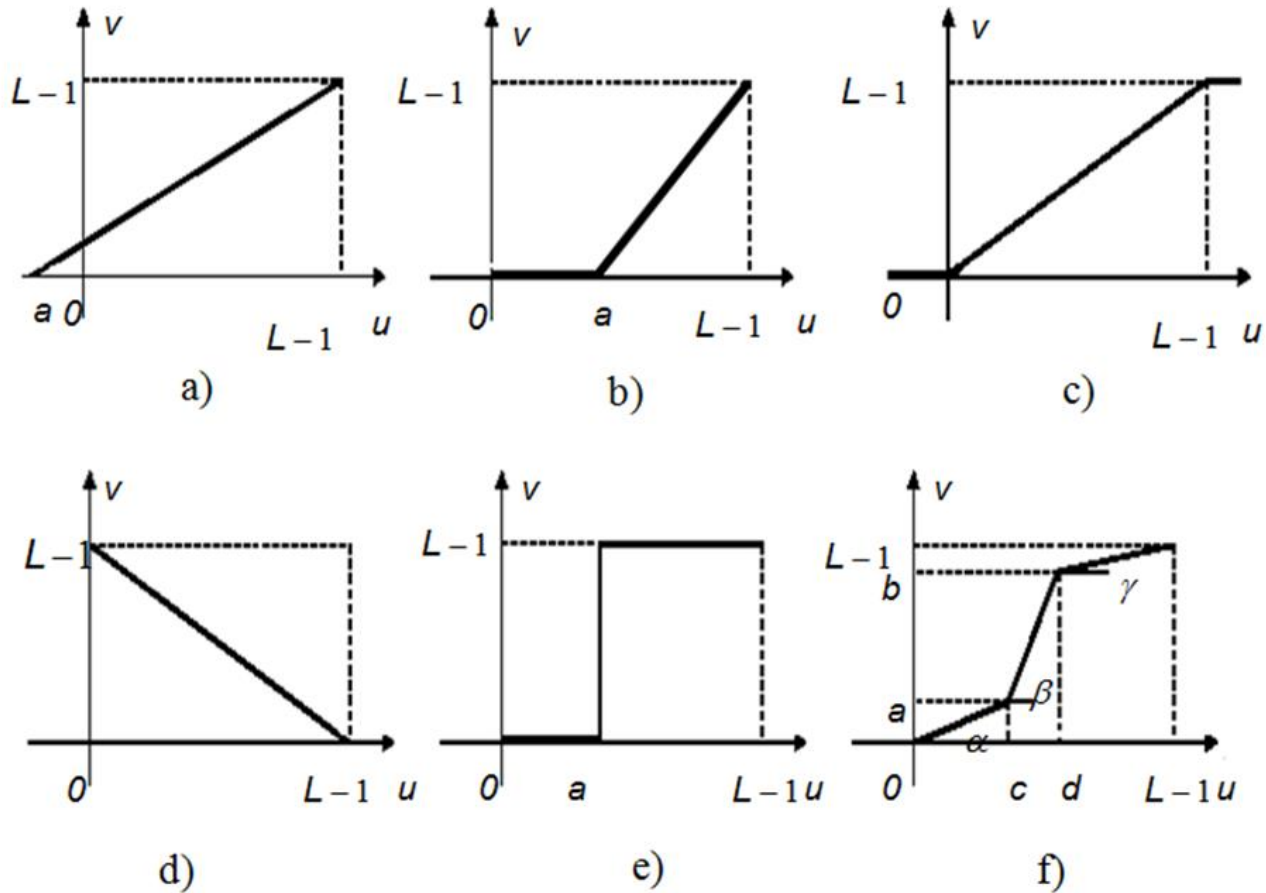
Low-contrast images can result from poor illumination, lack of dynamic range in the imaging sensor, or even wrong setting of a lens aperture during image acquisition.

The idea behind contrast stretching is to increase the dynamic range of the gray levels in the image being processed.

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# Contrast Stretching



Contrast-modification transformation

# Contrast Stretching

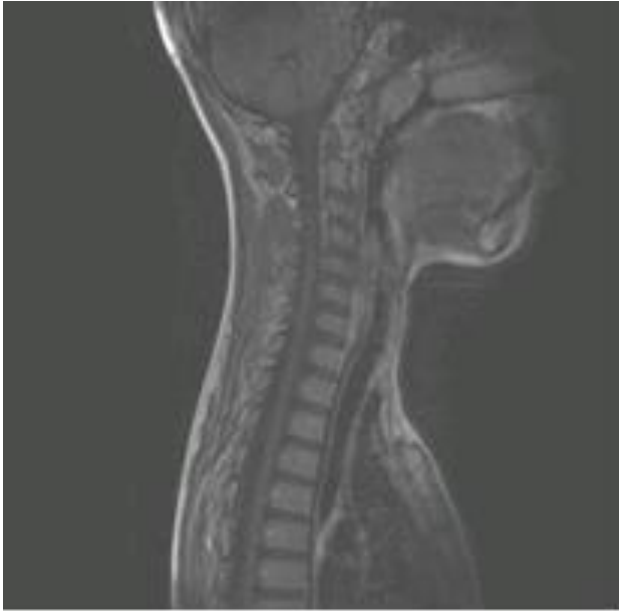


Original image



Inverted image

# Contrast Stretching

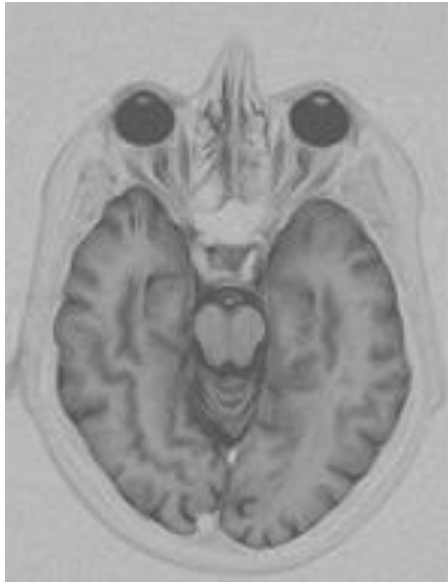


The low-contrast image



Result of contrast stretching

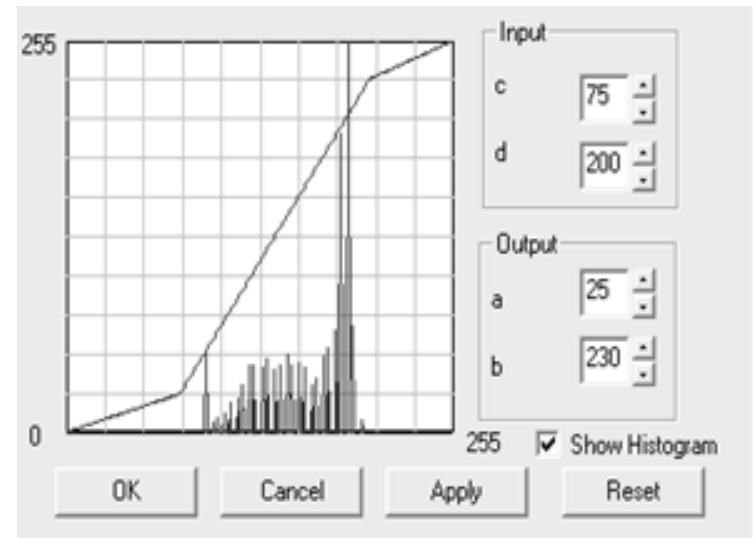
# Contrast Stretching



Low-contrast  
image



Enhanced image



Transformation function

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# Intensity Histogram

The histogram of an image normally refers to a histogram of the pixel intensity values.

This histogram is a graph showing the number of pixels in an image at each different intensity value found in that image.

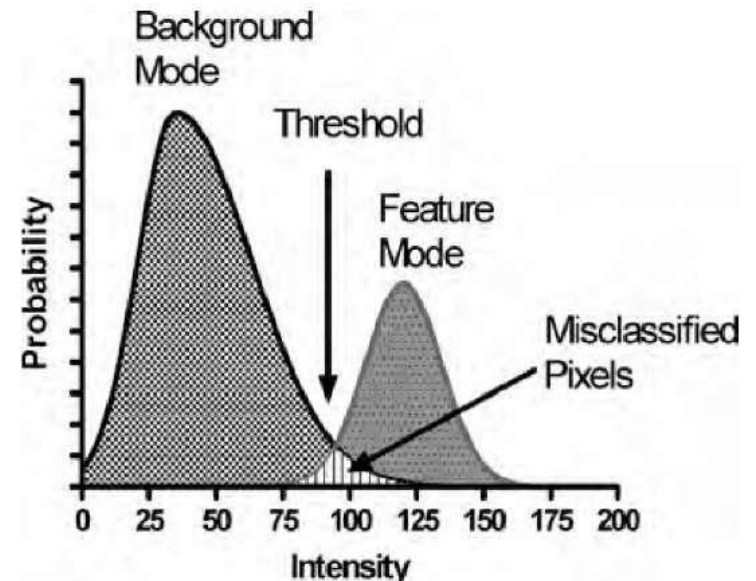
For an 8-bit grayscale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values.

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# Intensity Histogram

Histogram may be used to decide what value of threshold to use when converting a grayscale image to a binary one by thresholding.

If the image is suitable for thresholding then the histogram will be bi-modal, the pixel intensities will be clustered around two well-separated values.



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# Intensity Histogram

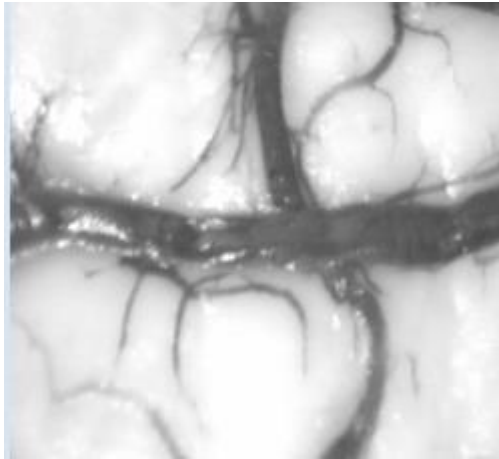
The histogram of a digital image with gray levels in the range  $[0, L-1]$  is a discrete function  $H(r_k) = n_k$ .

It is common practice to normalize a histogram by dividing each of its values by the total number of pixels in the image.

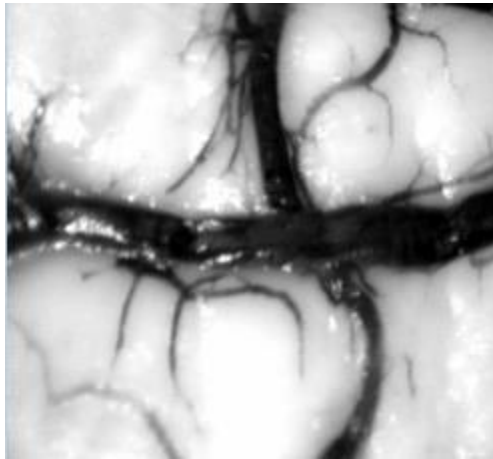
Thus, a normalized histogram is given by  $P(r_k) = n_k/n$ , for  $k=0, 1, \dots, L-1$ .

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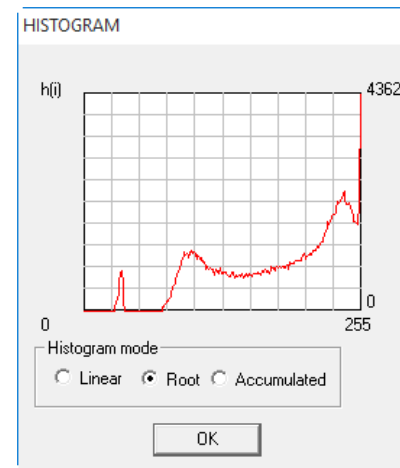
# Intensity Histogram



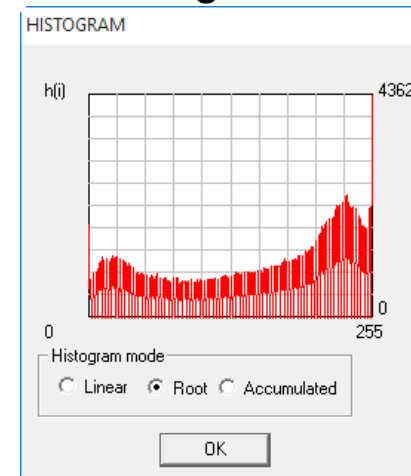
Original image



Enhanced Image



Histogram

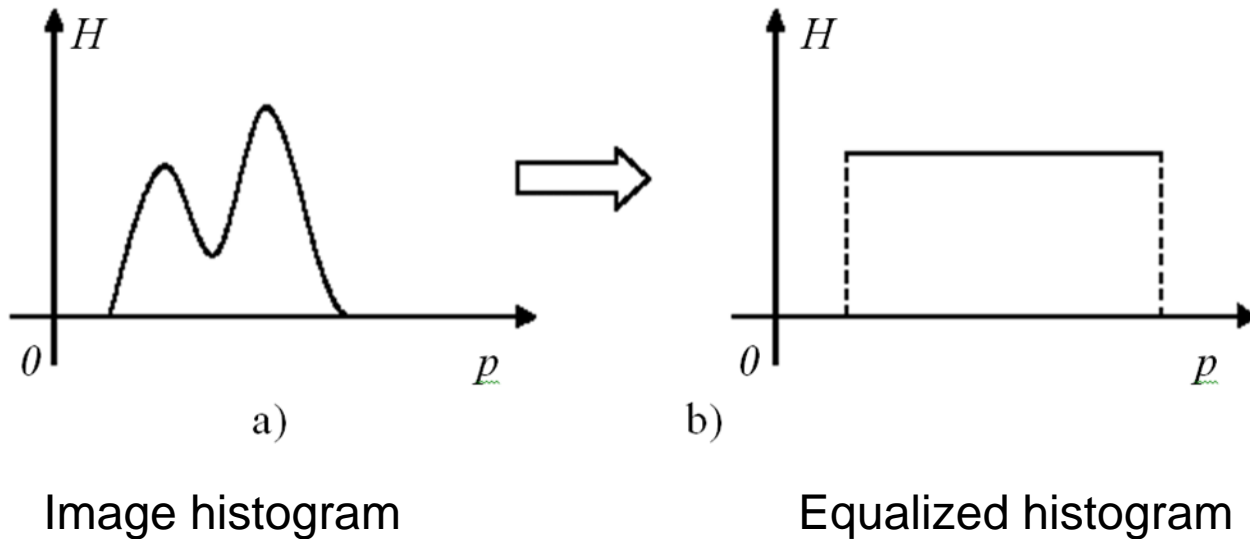


Modified histogram

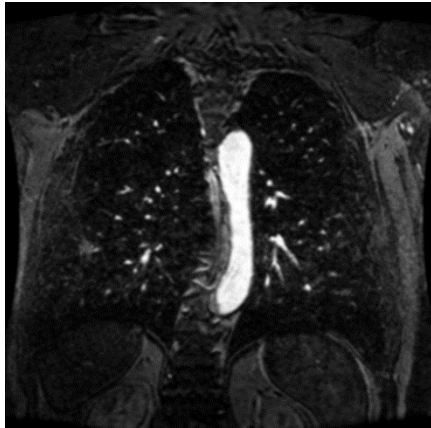


# Histogram Equalization

Histogram equalization employs a monotonic, non-linear mapping which re-assigns the intensity values of pixels in the input image in a way that the output image contains a uniform distribution of intensities.

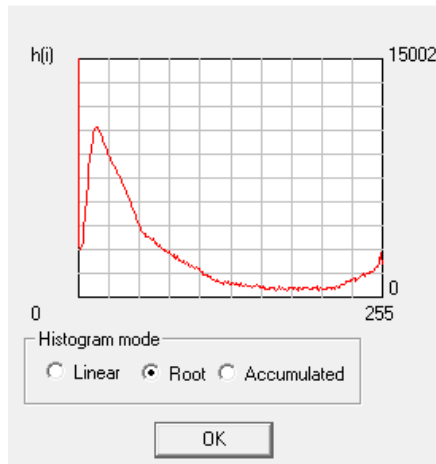


# Histogram Equalization



Original image

HISTOGRAM

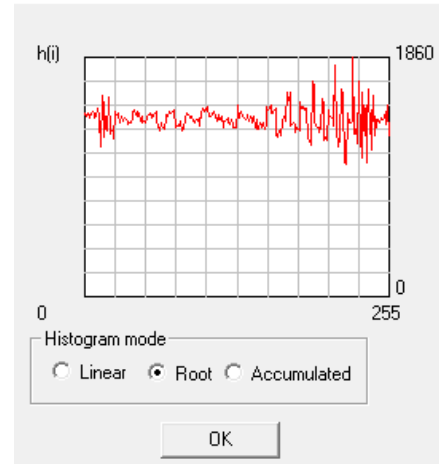


Histogram



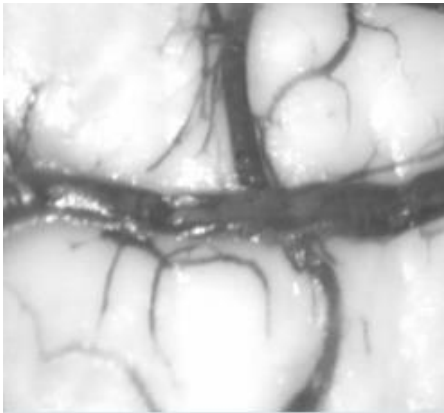
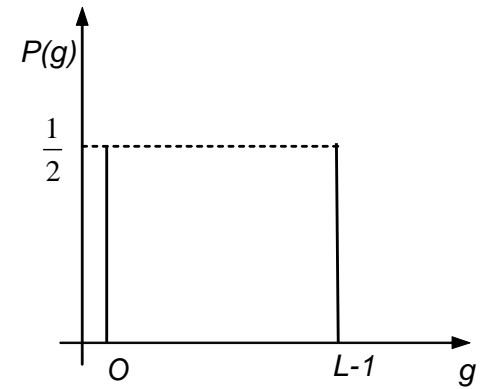
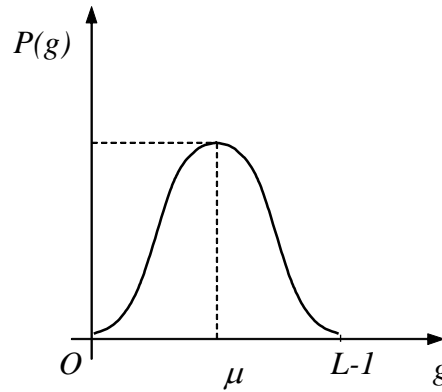
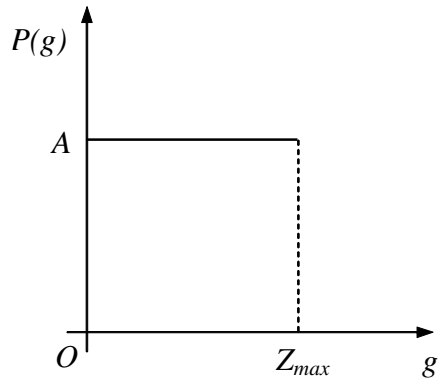
Enhanced image

HISTOGRAM

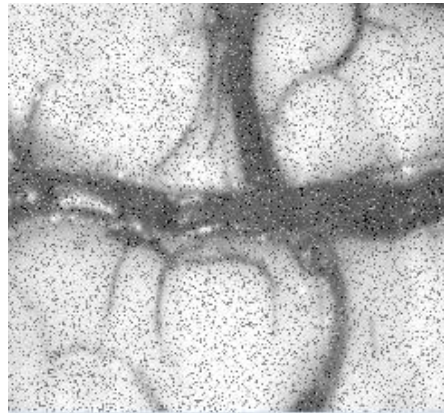


Equalized histogram

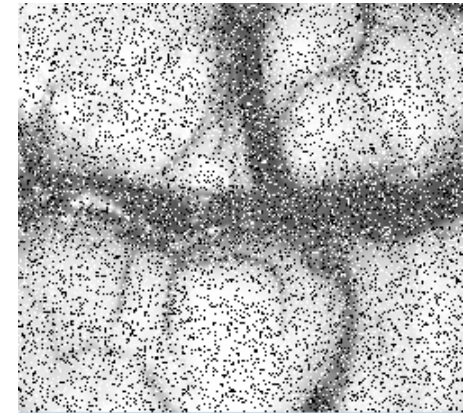
# Noise in Images



Original image



Uniform noise



Impulse Valued Noise

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# Digital Filters

Filters are mainly used to suppress either:

- the high frequencies in the image by smoothing the image;
- the low frequencies in the image (enhancing or detecting edges).

An image can be filtered either in the frequency or in the spatial domain.

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# Digital Filters – Mean Filter

The idea of mean filtering is to replace each pixel value with the average value of its neighbors, reducing the amount of intensity variation between the consecutive pixels.

$$G(i, j) = \frac{1}{M} \sum_{(n,m) \in V} F(n, m),$$

where  $F(n, m)$  are pixels from the neighborhood  $V$ ,  $M$  is the number of all pixels in the neighborhood, and  $G(i, j)$  is the result.

# Digital Filters – Mean Filter

$$H_1 = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$H_2 = \frac{1}{5} \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$H_3 = \frac{1}{10} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

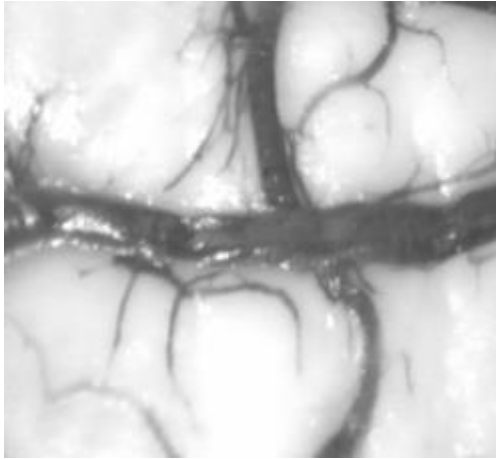
$$H_4 = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

$$H_5 = \left[ \frac{1}{a+2} \right]^2 \begin{bmatrix} 1 & a & 1 \\ a & a^2 & a \\ 1 & a & 1 \end{bmatrix}$$

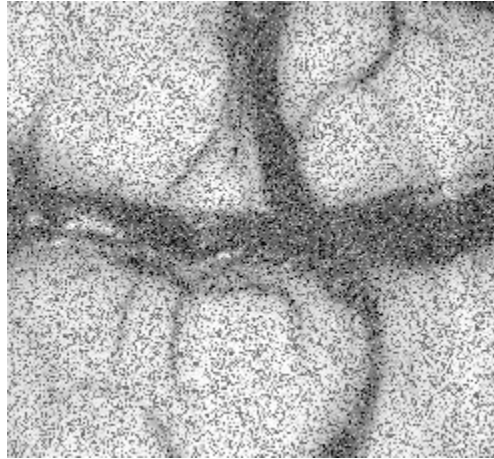
$$H_6 = \frac{1}{b+8a} \begin{bmatrix} a & a & a \\ a & b & a \\ a & a & a \end{bmatrix}$$

Various 3×3 averaging kernels

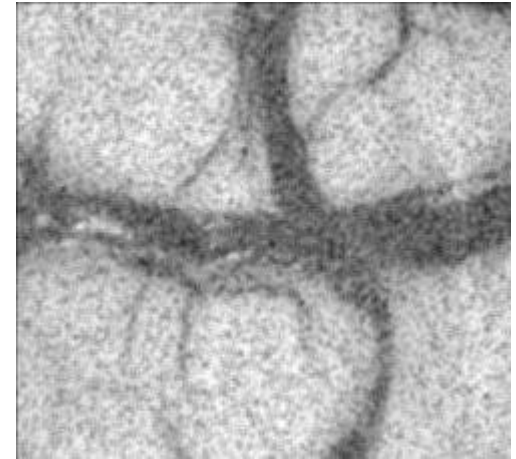
# Digital Filters – Mean Filter



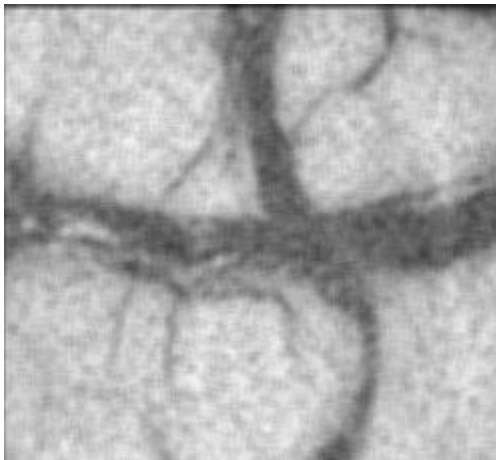
Original image



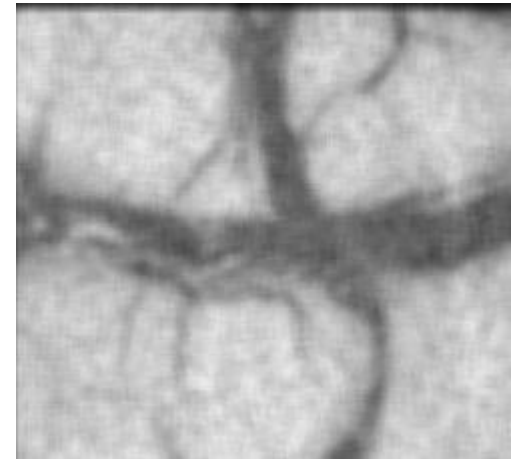
Uniform noise



Filtered 3x3



Filtered 5x5



Filtered 7x7

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# Digital Filters – Median Filter

The median filter replace the pixel value with the median of neighboring pixel values.

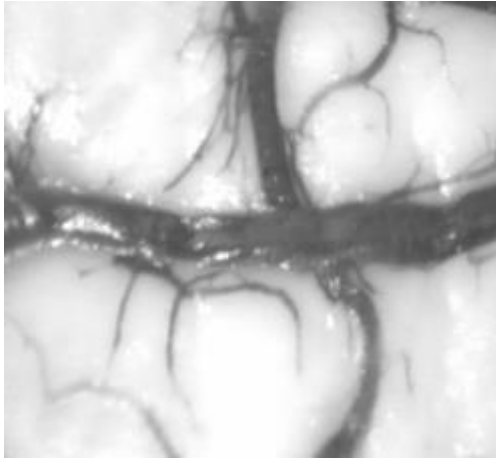
The median is calculated by first sorting all the pixel values from the neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

The median filter is much better at preserving sharp edges in the image than the mean filter.

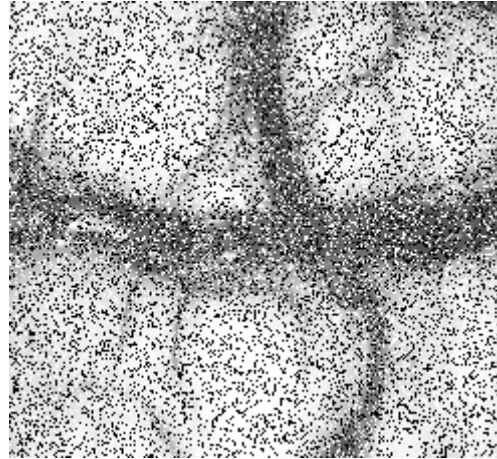
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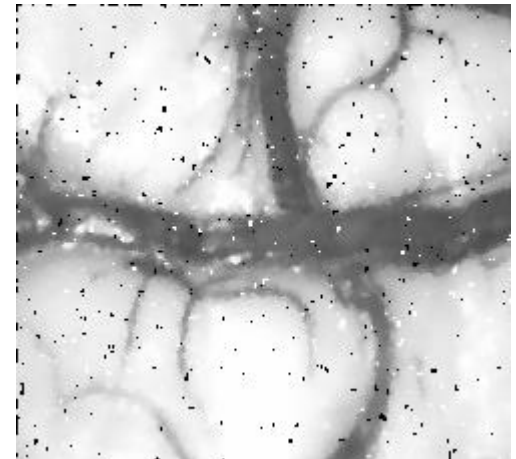
# Digital Filters – Median Filter



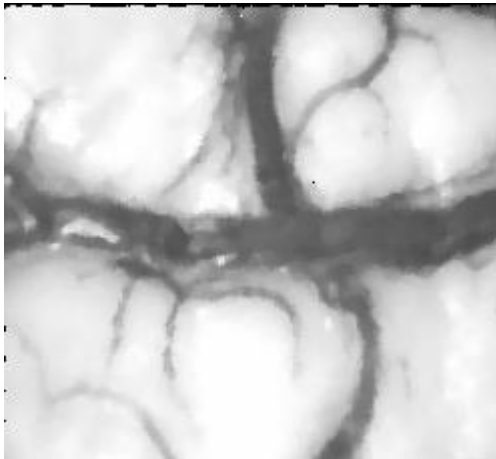
Original image



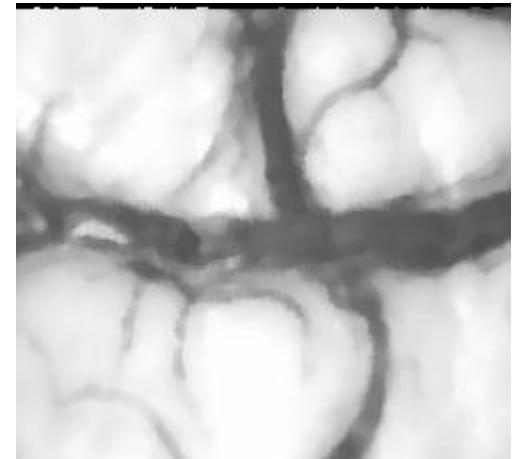
Impulsive noise



Filtered 3x3



Filtered 5x5



Filtered 7x7

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# Digital Filters – Median Filter

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# REFERENCES

## **Books:**

1. Digital Image Processing, 2nd Edition by Gonzalez and Woods, Prentice Hall
2. Image Processing, Analysis, 4th Edition, and Machine Vision, by M. Sonka, V. Hlavac, and R. Boyle
3. A. Marion, An Introduction to Image Processing, Chapman and Hall, 1991.
4. M. Ekstrom (ed.) Digital Image Processing Techniques, Academic Press, 1984.

[http://homepages.inf.ed.ac.uk/rbf/HIPR2/hipr\\_top.htm](http://homepages.inf.ed.ac.uk/rbf/HIPR2/hipr_top.htm)

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