Physics Department

Image processing lecture

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INTRODUCTION AND OVERVIEW

❖History of Digital Image Processing

- Early 1920s: One of the first digital imaging applications was in the newspaper industry. Images were transferred by submarine cable between London and New York.
  – Pictures were coded for cable transfer and reconstructed at the receiving end on a telegraph printer

- 1960s: Improvements in computing technology and the onset of the space race led to a surge of work in digital image processing.
  1964: Computers improved the quality of images of the moon taken by the Ranger 7 probe. Such techniques were also used in other space missions, including the Apollo landings.

Image Processing

Liftoff of Ranger 7 on July 28, 1964

from Cape Kennedy at Launch Complex 12

The first image of the moon ever taken

. A U.S. spacecraft Ranger 7 sent this back
on July 31, 1964, about 17 minutes before slamming

into the lunar surface

1980s - Today: The use of digital image processing techniques has exploded and they are now used for all kinds of tasks in all kinds of areas

– Image enhancement/restoration

– Artistic effects

– Medical visualization

– Industrial inspection

– Law enforcement

– Human-computer interfaces.

Image Processing

1.1 MOTIVATION الدافع

The need to extract information from images and interpret their contents has been one of the driving factors in the development of image processing1 and computer vision during the past decades.

Image processing applications cover a wide range of human activities, such as the following:

❖ Medical Applications: Diagnostic imaging modalities such as digital radiography, PET (positron emission tomography), CAT (Computerized Axial Tomography), MRI (Magnetic Resonance Imaging), and fMRI (Functional Magnetic Resonance Imaging), among others, have been adopted by the medical community on a large scale.

Industrial Applications: Image processing systems have been successfully used in manufacturing systems for many tasks, such as safety systems, quality control, and control of automated guided vehicles (AGVs).

Military Applications: Some of the most challenging and performance-critical scenarios for image processing solutions have been developed for military needs, ranging from the detection of soldiers or vehicles to missile guidance and object recognition and reconnaissance tasks using unmanned aerial vehicles (UAVs). In addition, military applications often require the use of different imaging sensors, such as range cameras and thermographic forward-looking infrared (FLIR) cameras.

❖ Law Enforcement and Security: Surveillance applications have become one of the most intensely researched areas within the video processing community.

Biometric techniques (e.g., fingerprint, face, iris, and hand recognition), which have been the subject of image processing research for more than a decade, have recently become commercially available.

1.2 BASIC CONCEPTS AND TERMINOLOGY

In this section, we define the terms most used in this course, although there is no universal agreement on the terminology used in this field, it is the most common definition used in our study of this course.

➢ *What is an Image?*

An *image* is a visual representation of an object, a person, or a scene produced by an optical device such as a mirror, a lens, or a camera. This representation is two-dimensional (2D), although it corresponds to one of the infinitely many projections of a real-world, three-dimensional (3D) object or scene.

Or:-

An image is nothing more than a two-dimensional signal. The mathematical function defines it $f(x, y)$ where x and y are the two coordinates horizontally and vertically and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. The image is called a digital image when x, y and the amplitude values of f are all finite discrete quantities. The field of digital image processing refers to the processing of digital images using a digital computer. It is a way of recording and presenting information visually.

Image Processing

➢ *What is a Digital Image?*

A digital image is a representation of a two-dimensional image using a finite number of points, usually referred to as *picture elements*, *pels*, or *pixels*. Each pixel is represented by one or more numerical values: for monochrome (grayscale) images, a single value representing the intensity of the pixel (usually in a [0, 255] range) is enough; for color images, three values (e.g., representing the amount of red (R), green (G), and blue (B)) are usually required. Alternative ways of representing color images, such as the *indexed color image* representation.

Pixels (Pictures of elements) are the building blocks of every digital image. Clearly defined squares of light and color data are stacked up next to one another both horizontally and vertically. Each picture element (pixel for short) has a dark-to-light value from 0 (solid black) to 255 (pure white). There are 256 defined values. A gradient is the gradual transition from one value to another in sequence.

➢ *What is Digital Image Processing?*

Image processing is computer imaging where application involves a human being in the visual loop. In other words, the image is to be examined and acted upon by people.

❖ **The major topics within the field of image processing include:**

1. Image acquisition. 2. Image enhancement. 3. Image restoration.

4. Image compression. 5. Image segmentation

6. Image representation and description. 7. Image recognition.

1.2.1. Image acquisition

is the first process that gives some hints regarding the origin of digital images. It could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling.

1.2.2 Image Enhancement

Involves taking an image and improving it visually and bringing out detail that is obscured, or simply highlights certain features of interest in an image. One of the simplest enhancement techniques is increasing the contrast of an image. Enhancement methods tend to be problem-specific. For example, a method that is used to enhance satellite images may not be suitable for enhancing medical images.

Although enhancement and restoration are similar in aim, to make an image look better. They differ in how they approach the problem. The restoration method attempts to model the distortion to the image and reverse the degradation, whereas enhancement methods use knowledge of the human visual systems responses to improve an image visually, as Fig. (1).

a **b**

Fig. (1.1) Image Enhancement, an image with poor contrast, b- Image enhancement by contrast stretching

1.2.3 Image Restoration

Is the process of taking an image with some known, or estimated degradation, and attempting to reconstruct or restore it to its original appearance, using a priori knowledge of the degradation phenomenon as in fig. (2). Image restoration is often used in the field of photography or publishing.

a b

Figure (1.2) Image Restoration a. Image with distortion b. Restored image

1.2.4 Image Compression

This is done by eliminating visually unnecessary data and by taking advantage of the redundancy that is inherent in most images. Where it deals with techniques for reducing the storage required to save an image, or the bandwidth required to transmit it.

Image data can be reduced 10 to 50 times, and motion image data (video) can be reduced by factors of 100 or even 200.

It has two major approaches:

a) ***Lossless Compression:*** **- This compression is called lossless because no data are lost, and the original image can be recreated**

exactly from the compressed data. For simple images such as text-only images.

There are two methods of lossless comparison:

1- Huffman Coding 2- Run-Length Coding

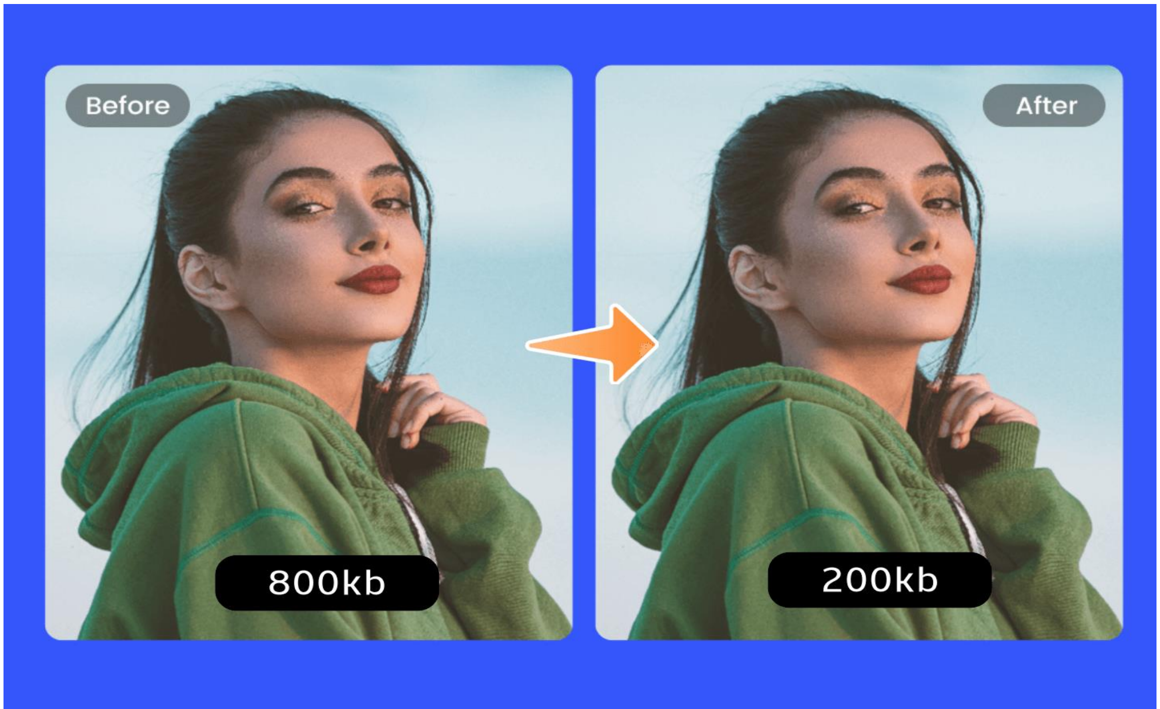
b) ***Lossy Compression: -*** **These compression methods are called Lossy because they allow a loss because they allow a loss in actual image data, so the original uncompressed image cannot be created exactly from the compressed file. For complex images these techniques can achieve compression ratios of 100 0r 200 and still retain in high – quality visual information. For simple images or lower-quality results compression ratios as high as 100 to 200 can be attained, as shown in Fig. (1.3).**

- **The ratio of the original (uncompressed) image file and the compressed file is referred to as the compression ratio C_R :-**

$$CR=\frac{U\ \text{size}}{C\ \text{size}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1.1)$$

Where: - U size is Uncompressed File Size =M*N*K

C size is Compressed File Size



a b

Fig. (1.3) Image Compression, a- Image before compression (80 KB),

b- Image after compression (200 KB).

Example: The original image is 256x256 pixels, 8 bits per pixel. After compression, the image file size is 6554 bytes. Find the compression ratio?

Sol.

U size= M*N*K =(256x256x8)/8 = 65536 bytes

$$CR = \frac{U\ size}{C\ size} = 65536/6554 = 9.999 = 10.$$

This can also be written as (10:1). This means that the original image has 10 bytes for every 1 byte in the compressed image.

1.2.5 Image Segmentation

Is concerned with procedures that partition an image into its constituent parts or objects.

1.2.6 Image Representation

refers to the methods and techniques used to digitally encode and interpret images. It involves converting visual information, such as a photograph or video frame, into a format that a computer can process.

After an image is segmented into regions, the regions are represented and described in a form suitable for computer processing (descriptors).

• Representing a region:

1. In terms of its external characteristics (boundary)

2. In terms of its internal characteristics

Exp: A region might be represented by the length of its boundary.

- **External representations are used when the focus is on the shape of the region.**
- **Internal representations are used when the focus is on color and texture.**

1.2.7 Image Recognition

Is the process that assigns a label to an object based on its descriptions.

1.3 Digital image processing applications

Image processing is used in a wide range of applications for example:

a. **Security (e.g. fingerprint, face, and iris recognition)**

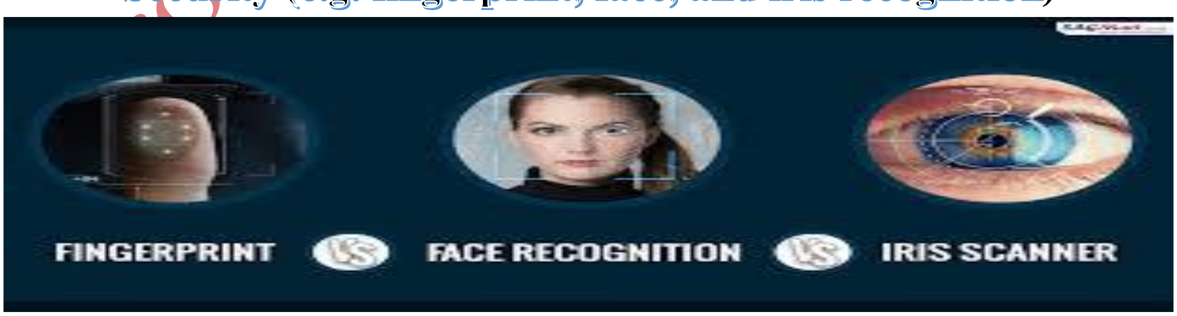


Fig. (1.4) Recognition system for the personal digital assistant (PDA)

b. Surveillance (e.g. car number plate recognition).

Fig. (1.5) Automatic Number Plate Recognition System

C. Medical applications.

1.4 Elements of Visual Perception

Although the field of digital image processing is built on a foundation of mathematical and probabilistic formulations, human intuition and analysis play a central role in the choice of one technique versus another, and this choice often is made based on subjective, visual judgments. Thus, developing a basic understanding of human visual perception as the first step in this course of study is appropriate, to the elementary mechanics of how images are formed and perceived by humans

1.5 The Human Visual System

The Human Visual System (HVS) has two primary components:

1. Eye. 2. Brian.

* The structure that we know the most about is the image-receiving sensors (the human eye).

* The brain can be thought of as being an information processing unit analogous to the computer in our computer imaging system. These two are connected by the optic nerve, which is a bundle of nerves that contains the pathways for visual information to travel from the receiving sensor (the eye) to the processor (the brain).

1.6 Structure of the Human Eye

The figure below shows a simplified horizontal cross-section of the human eye. The eye is nearly a sphere, with an average diameter of approximately 20 mm. Three membranes enclose the eye:

1- The *cornea* and *sclera* outer cover

2- The *choroid: - It has two parts: - a) Iris Diaphragms b) Ciliary body.*

3- The *retina*: - The two major classes of receptors: -

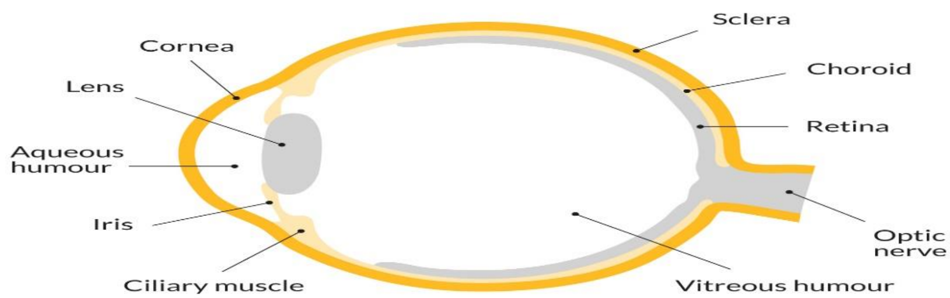


Fig. (1.6) A simplified diagram cross-section of the human

1. **Cones: - are tiny cells in the back of the eye that are sensitive to light and help you see. A problem with the chemicals in the cones, or if some color cones are missing, can cause color blindness (when someone has trouble telling the difference between red and green or between blue and yellow). Cones require a lot lighter and they are used to see color. We have three types of cones: blue, green, and red. The human eye only has about (6-7) million cones.**
2. **Rods:- are a type of photoreceptor cell in the retina. They are sensitive to light levels and help give us good vision in low light. They are concentrated in the outer areas of the retina and give us peripheral vision. Rods are 500 to 1000 times more sensitive to light than cones. The retina has approximately (75-150) million rods.**

Q- Can the human eye sense all wavelengths or only visible light?

Yes, the eye can sense all wavelengths, but the lens of the eye absorbs ultraviolet and infrared rays

1.7 IMAGE FORMATION IN THE EYE

The major in an ordinary photographic camera, the lens has a fixed focal length. Focusing at various distances is achieved by varying the distance between the lens and the imaging plane, where the film (or imaging chip in the case of a digital camera) is located. In the human eye, the converse is true; the distance between the center of the lens and the imaging sensor (the retina) is fixed, and the focal length needed to achieve proper focus is obtained by varying the shape of the lens. The fibers in the ciliary body accomplish this by flattening or thickening the lens for distant or near objects, respectively. The distance between the center of the lens and the retina along the visual axis is approximately 17 mm. The range of focal lengths is approximately 14 mm to 17 mm, the latter taking place when the eye is relaxed and focused at distances greater than about 3 m. The geometry in Fig. (1.7) illustrates how to obtain the dimensions of an image formed on the retina. For example, suppose that a person is looking at a tree 15 m high at a distance of 100 m. Letting h denote the height of that object in the retinal image, the geometry of Fig. (1.7) yields (15/ 100) = h /17 or h = 2.5 mm. The retinal image is focused primarily on the region of the fovea. Perception then takes place by the relative excitation of

light receptors, which transform radiant energy into electrical impulses that ultimately are decoded by the brain.

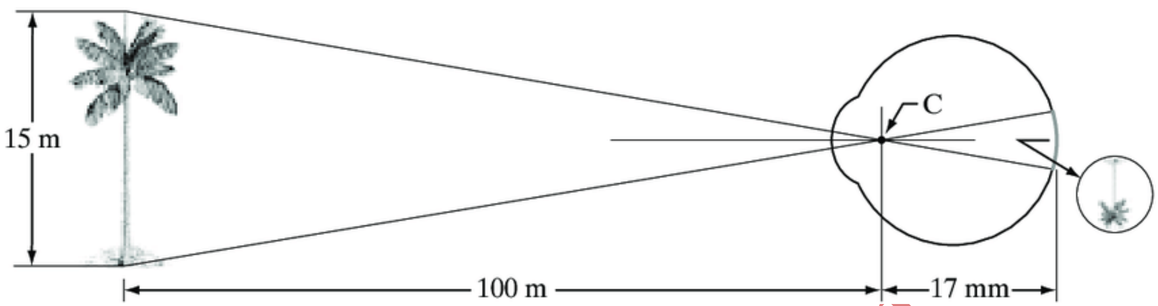


Fig. (1.7) Graphical representation of the eye looking at a palm tree. Point C is the focal center of the lens.

1.8 BRIGHTNESS ADAPTATION AND DISCRIMINATION

Digital images are displayed as sets of discrete intensities. The range of light intensity levels to which the human visual system can adopt is enormous (on order 10^{6}) from the scotopic threshold to the glare limit. Experimental evidence indicates that subjective brightness is a logarithmic function of the light intensity incident on the eye. Fig (1.8) illustrates a plot of light intensity versus subjective brightness.

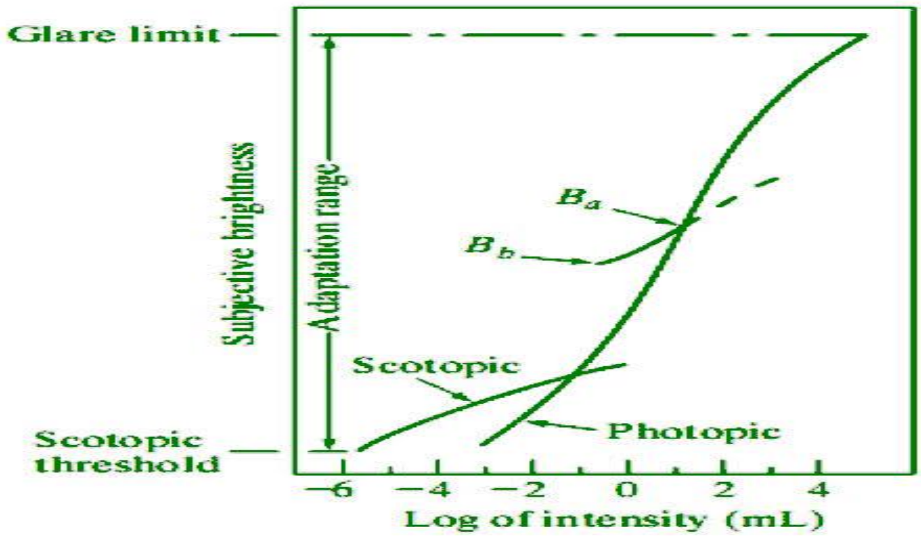


Fig.(1.8) Range of subjective brightness sensations showing a particular adaptation level, B_a

illustrates this characteristic to the glare limit. The long solid curve represents the range of intensities to which the visual system can adapt.

In photopic vision alone, the range is about 10^6. The transition from scotopic to photopic vision is gradual over the approximate range from 0.001 to 0.1 millilambert (–3 to –1 mL in the log scale), as the double branches of the adaptation curve in this range show.

The essential point in interpreting the impressive dynamic range depicted in Fig.1.8 is that the visual system cannot operate over such a range simultaneously. Rather, it accomplishes this large variation by changes in its overall sensitivity, a phenomenon known as brightness adaptation. The total range of distinct intensity levels it can discriminate simultaneously is rather small when compared with the total adaptation range

Subjective brightness: - means intensity as perceived by the human visual system.

Brightness adaptation: - means the human visual system can operate only from scotopic to glare limit. It can’t operate over the range simultaneously. It accomplishes this large variation by changes in its overall intensity.

- Brightness is the intensity of light in simple words. Adaptation basically is "getting used to" and being comfortable with it. So conceptually brightness adaption is basically "getting used to changes in brightness/ changes intensity of light". A simple example is when you go out into the light from darkness you take some time to "get used" to the brightness outside and feel comfortable. This is what exactly is brightness adaption.
  In an image, we observe many brightness levels and the vision system can adapt to a wide range. If the **mean value** of the pixels inside the image is around Zero gray level, then the brightness is low and the images dark but for mean value near 255 then the image is light. If fewer gray levels are used, we observe false contours منحني bogus lines resulting from gradually changing light intensity not being accurately represented.

Two phenomena demonstrate that perceived brightness is not a simple function of intensity. The first is based on the fact that the visual system tends to undershoot or overshoot around the boundary of regions of different intensities. Figure 1.9 a) shows a striking example of this phenomenon. Although the intensity of the stripes is constant, we perceive a strongly scalloped brightness pattern, especially near the boundaries [Fig.1.9 (b)]. These seemingly scalloped bands are called Mach bands after Ernst Mach, who first described the phenomenon in 1865. The second phenomenon, called simultaneous contrast, is that a region's perceived brightness does not depend simply on its intensity, as Fig. (1.10) demonstrates. All the center squares have the same intensity.

Mach band: - are one of the many visual phenomena which occur when two gray images are placed adjacent to each other differing only in illumination.

Or Mach bands are an optical illusion named after the physicist Ernst Mach. It exaggerates the contrast between edges of the slightly differing shades of gray, as soon as they contact one another, by triggering edge-detection in the human visual system.

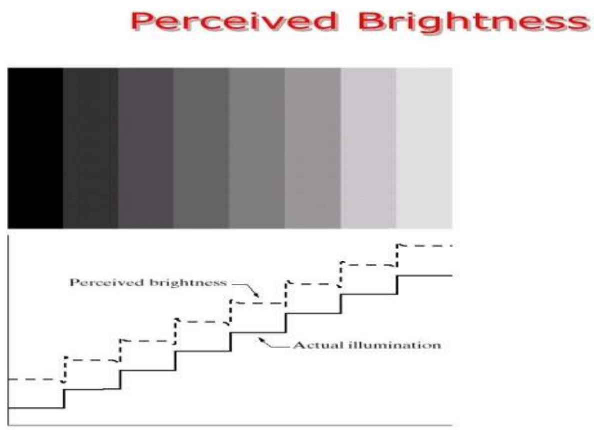


Fig. 1.9 (a) An example showing that perceived brightness is not a simple function of intensity. The relative vertical positions between the two profiles in (b) have no special significance; they were chosen for clarity.

However, they appear to the eye to become darker as the background gets lighter. A more familiar example is a piece of paper that seems white when lying on a desk but can appear black when used to shield the eyes while looking directly at a bright sky.

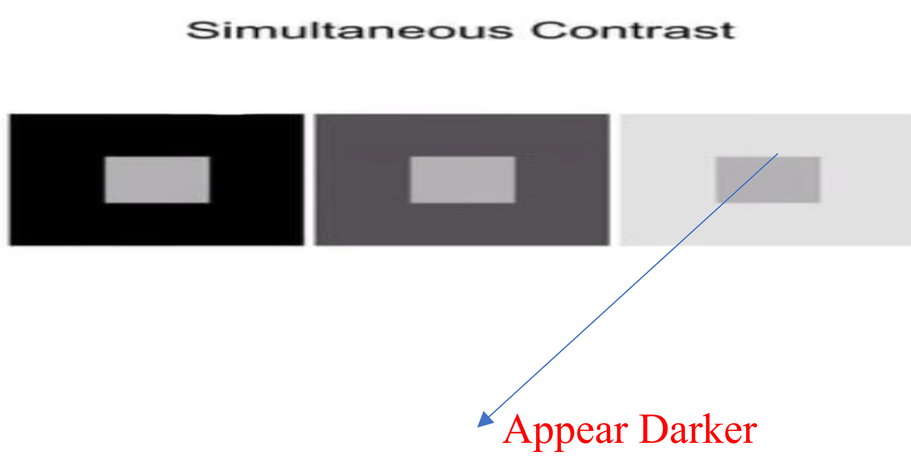


Fig. (1.10) Examples of simultaneous contrast. All the inner squares have the same intensity, but they appear progressively darker as the background becomes lighter.

1.9 Light and Electromagnetic Spectrum

Light can be described in terms of electromagnetic waves or particles, called photons. A photon is a tiny packet of vibrating electromagnetic energy that can be characterized by its wavelength or frequency. Wavelength is usually measured in meters (and its multiples and submultiples). Frequency is measured in hertz (Hz) and its multiples. Wavelength (λ) and frequency (f) are related to each other by the following expression:

$$\lambda = v / f. \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(1-1)}$$

where (v) is the velocity at which the wave travels, usually approximated to be equal to the speed of light (c): 2.998 × 108 m/s

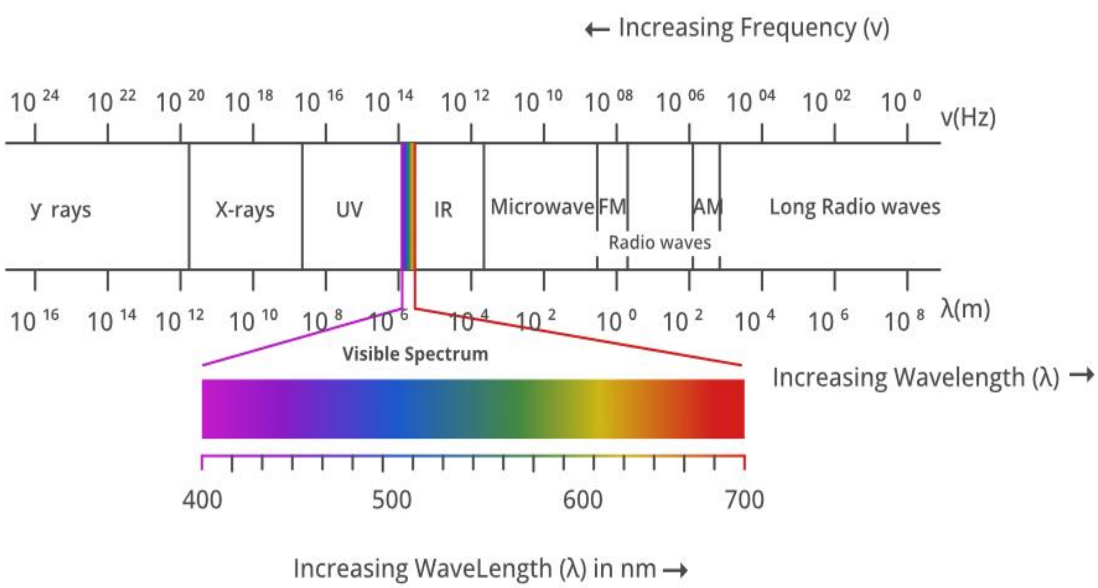


Fig. (1.11) Electromagnetic Spectrum

Light travels in waves, much like the waves you find in the ocean. As a wave, light has several basic properties that describe it. One is frequency, which counts the number of waves that pass by a given point in one second.

Another is wavelength, the distance from the peak of one wave to the peak of the next. These properties are closely and inversely related: The larger the frequency, the smaller the wavelength — and vice versa. A third is energy, which is similar to frequency in that the higher the frequency of the light wave, the more energy it carries. Your eyes detect electromagnetic waves that are roughly the size of a virus. Your brain interprets the various energies of visible light as different colors, ranging from red to violet. Red has the lowest energy and violet has the highest.

Beyond red and violet are many other kinds of light our human eyes can't see, much like there are sounds our ears can't hear. On one end of the electromagnetic spectrum are radio waves, which have wavelengths billions of times longer than those of visible light. On the other end of the spectrum are gamma rays, with wavelengths billions of times smaller than those of visible light.

The energy of the various components of the electromagnetic spectrum is given by the expression

$$E = h\,f \quad \ldots\ldots\ldots\ldots\ldots\ldots (1\text{-}2)$$

where h is Planck's constant. The units of wavelength are meters, with the term's *microns* (denoted mm and equal to 10^{-6} m) and *nanometers* (denoted nm and equal to 10^{-9} m) being used just as frequently. Frequency f is measured in *Hertz* (Hz), with one Hz being equal to one cycle of a sinusoidal wave per second. A commonly used unit of energy is the *electron volt*.

Electromagnetic waves can be visualized as propagating sinusoidal waves with wavelength see fig. (1.12) or they can be thought of as a stream of massless particles, each traveling in a wavelike pattern and moving at the speed of light. Each massless particle contains a certain amount (or bundle) of energy, called a *photon*. We see from Eq. (2-2) that energy is proportional to frequency, so the higher-frequency (shorter wavelength) electromagnetic phenomena carry more energy per photon. Thus, radio waves have photons with low energies, microwaves have more energy than radio waves, infrared still more, then visible, ultraviolet, X-rays, and finally gamma rays, the most energetic of all. High-energy electromagnetic radiation, especially in the X-ray and gamma-ray bands, is particularly harmful to living organisms.

Light is a type of electromagnetic radiation that can be sensed by the eye. The visible (color) spectrum is shown expanded in Fig. 1.11. The visible band of the electromagnetic spectrum spans the range from approximately 0.43 mm (violet) to about 0.79 mm (red). For convenience, the color spectrum is divided into six broad regions: violet, blue, green, yellow, orange, and red. No color (or other component of the electromagnetic spectrum) ends abruptly; rather, each range blends smoothly into the next, as Fig. 1 .11 shows.

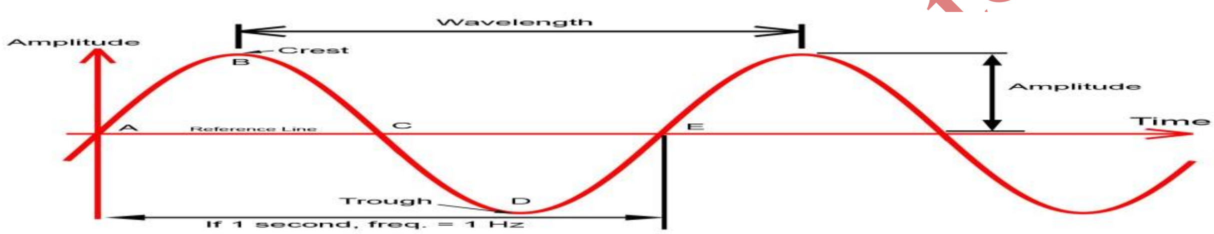


Fig. (1.12) ***Sine Wave***

The colors perceived in an object are determined by the nature of the light *reflected* by the object. A body that reflects light relatively balanced in all visible wavelengths appears white to the observer. However, a body that favors reflectance in a limited range of the visible spectrum exhibits some shades of color. For example, green objects reflect light with wavelengths primarily in the 500 to 570 nm range, while absorbing most of the energy at other wavelengths.

Light that is void of color is called *monochromatic* (or *achromatic*) light. The only attribute of monochromatic light is its intensity. Because the intensity of monochromatic light is perceived to vary from black to gray and finally to white, the term *gray level* is used commonly to denote monochromatic intensity.

The range of values of monochromatic light from black to white is usually called ***grayscale***, and monochromatic images are frequently referred to as *grayscale images*.

Chromatic (color) light spans the electromagnetic energy spectrum from approximately 0.43 to 0.79 mm, as noted previously. In addition to frequency, three other quantities are used to describe a chromatic light source: radiance, luminance, and brightness. *Radiance* is the total amount of energy that flows from the light source, and it is usually measured in watts (W).

Luminance, measured in lumens (lm), gives a measure of the amount of energy an observer *perceives* from a light source. For example, light emitted from a source operating in the far infrared region of the spectrum could have significant energy (radiance), but an observer would hardly perceive it; its luminance would be almost zero.

brightness is a subjective descriptor of light perception that is practically impossible to measure. It embodies the achromatic notion of intensity and is one of the key factors in describing color sensation.

In principle, if a sensor can be developed that is capable of detecting energy radiated in a band of the electromagnetic spectrum, we can image events of interest in that band. Note, however, that the wavelength of an electromagnetic wave required to “see” an object must be of the same size as, or smaller than, the object.

For example, a water molecule has a diameter on the order of $\mathbf{10^{-10}}$ m. Thus, to study these molecules, we would need a source capable of emitting energy in the far (high-energy) ultraviolet band or soft (low-energy) X-ray bands.

1.10 The sources of images

1- Electromagnetic wave radiation 2- Acoustic 3- Ultrasonic wave

4- Electron beams for electron microscopy 5- synthetic images produced by computer software and used in graphics and visualization.

1.11 Conventional Physical Measurement

Physics experiments are usually performed by reading and recording calculations of the finite physical parameters. For example, it can measure the intensity of light as a function of distance. Where the light intensity is measured as a function of the distance between the light source and the detector (i.e., represented by the 1D signal) see Figure (1.13). Therefore, limited data can be recorded which can be easily manipulated and can be drawn on graph paper easily and directly. This occurs in most traditional physics experiments and research

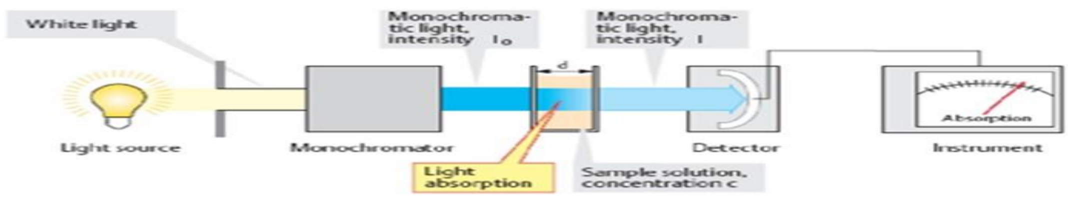


Fig. (1.13) light detector

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The process of recording or capturing photos (2D signal) is a process usually requires a light source within a specific spectral range that is used to illuminate a scene and then take a picture of this scene using the camera, where the camera represents an optical system. That used to record or capture images, according to the concepts of optics. Here the image is formed on a light-sensitive surface 2D plane that records light intensity coming from the scene objects. This plane surface is a light intensity detector. It consists of two light-intensity detector types:

1. The first type is the chemical photosensitive films that were popular before the advent of digital cameras in recent decades.
2. The second type is two-dimensional (2D) electronic sensors that record the optical density and create a digital matrix representing the detected optical density, which can be saved or sent over various digital communication networks in the form of two-dimensional arrays and can be displayed as a matrix image on the screens of special devices such as mobile phones, digital cameras, computers and others.

Digital images usually contain huge numbers of data that have been measured and recorded for a specific physical state. The vast amount of this data cannot be handled easily by hand and the information cannot be extracted easily and cannot be drawn manually. Therefore, the processing and extracting information from it requires using the computer and adopted mathematical physics.

Also, it is not possible to dispense with mathematical statistics to analysis image information, Figure (1.14) shows that the 2D image formation process for a 3D scene view and the process of converting it to digital image f(x,y) or I(x,y)

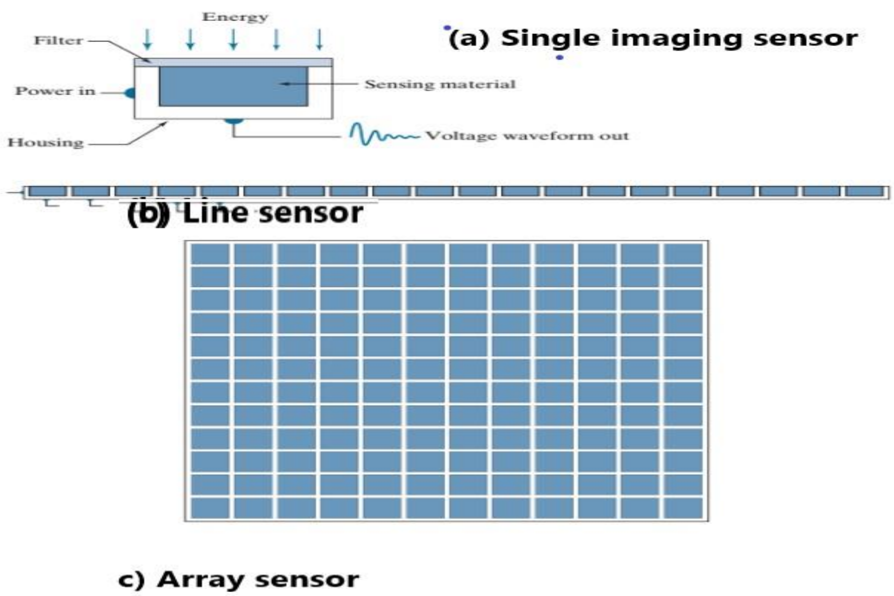


Fig. (1.14): 2D image formation process for a 3D scene view and the process of converting it to a digital image

1.12 Image Formations and Analysis

Images are represented by two-dimensional functions called f(x,y). The magnitude of at spatial coordinates (x, y) is a positive scalar quantity, and its physical significance is determined by the image source, as shown in Figure (1.15). Image intensity values resulting from a physical process are directly proportional to the energy radiated by a physical source, such as electromagnetic waves

The f(x,y) or I(x,y) values must finite; that is **[37]**:

$$0 \leq f(x,y) < \infty \quad \text{..........(1-3)}$$

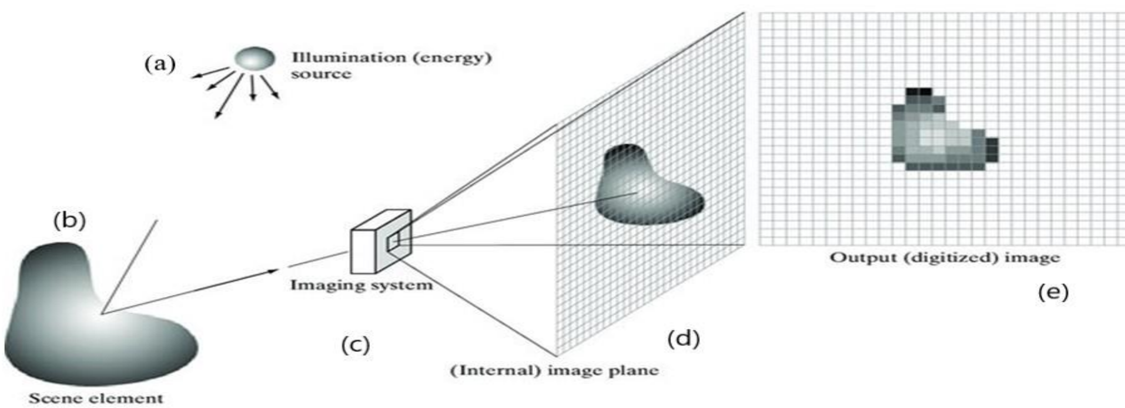


Fig. (1.15): An example of the digital image acquisition process. (a) Energy ("illumination") source. (b) An element of a scene. (c) Imaging system. (d) Projection of the scene onto the image plane. (e) Digitized image

The function f(x,y) can be defined by two distinct components:
1. The level of the lighting source reaching the observation location.
2. Identify the level of illumination reflected by objects within the scene.

The components denoted by i(x,y) and r(x,y) are generally known as the illumination and reflection components, respectively. When the two functions are combined, they produce the product f(x,y):

$$f(x, y) = i(x, y)\, r(x, y) \quad \ldots\ldots(1\text{-}4)$$

where

$$0 \le i(x, y) < \infty \quad \ldots\ldots(1\text{-}5)$$

and

$$0 \le r(x, y) \le 1 \quad \ldots\ldots(1\text{-}6)$$

The last formula states that the reflectance is bounded between 0 (representing total absorption) and 1 (representing total reflection). The determination of i(x,y) depends on the light source, while r(x,y) depends on the characteristics of the objects depicted.

Real illumination in real scene represent function of i(x,y,z,λ), and the object points reflectivity r(x,y,z,λ) in 3D space world converted into 2D space in image world f(x,y) or I(x,y). The third-dimension z will be reduced to the image space as its effect is transformed into an effect on the recorded intensity of the image element. As for the wavelength) λ (or the spectral beam used to illuminate the scene, it has been neglected in the mathematical formula of the resulting image because each spectral beam will have its own sensor to record this spectral image.

1.13 Understanding the Color Models

Color is visual as well as connected to the emotional and even cultural perspectives of individuals. When you cite color in terms of science, physics In physics terminology, color is a way used to refer to the wavelengths in the spectrum. When it comes to colors, most of the time they are referred to with RGB terminologies.

Q/ What Is a Color Model?

A color model can be defined as a system that makes use of the three primary colors (RGB) to produce a vast range of colors. There are many color models used in the technology sector and each of them is different and has a certain purpose. The range of colors that can be produced by deploying any particular color model is referred to technically as a color space.
The different color models are:

1. RGB and CMY color models 2. HSV color model 3. YUV color model

1.13.1 RGB Color Model and CMY Color Model

RGB is the standard for the primary colors, and, whenever you talk or hear about the color models, RGB comes first. Primary colors are used to produce the secondary colors as and when required. Before dwelling deeper, one should understand that there are two classifications of color models: additive and subtractive models.

Q-1 / What Is an Additive Color Model?

The RGB color model is the finest example of an additive color model, as red, green, and blue are added and brought together to produce a broad range of other colors. Going back to the RGB color model, using the primary colors R, G, and B in several combinations with different levels of intensity, one can derive various colors, naturally. One simple instance is how the color white is derived from the RGB color model. If the light contains the combination of (additive) red, green, and blue at equal strength, we get the color white (Figure 1.16).
To make it more technical, additive colors are all about adding individual wavelengths. Various colors are derived through this process.

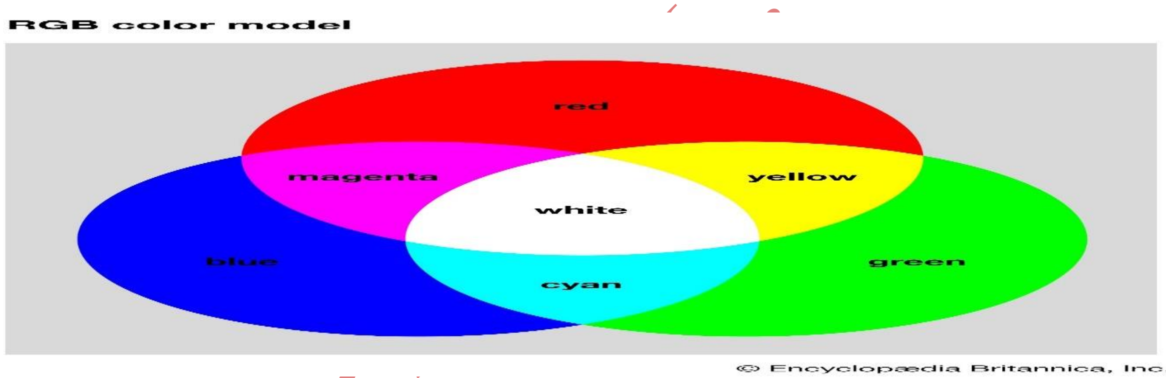
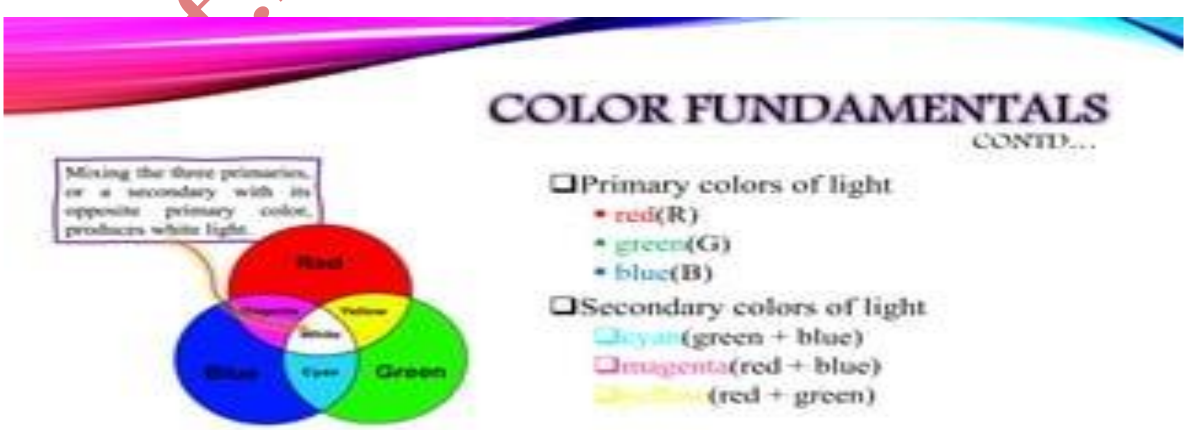


Fig. (1.16) RGB color model



Q-2 What Is a Subtractive Primary Color?

Subtractive colors are about the absorption or subtraction of certain wavelengths from white light, which acts as the input source. When two of the three pure additive colors are combined, a new color is produced and it is referred to as a subtractive primary color. Using (Figure 1.16)، one can visualize when R and B are combined, it forms magenta; while R and G upon combining gives yellow; and finally, B and G when combined begets cyan (Figure 1.17). Cyan (C), magenta (M), and yellow (Y) are termed as subtractive primaries. They are also referred to as the CMY model.

To go further, magenta and yellow upon combination produces red, combining cyan and yellow gets you green, and cyan and magenta produces blue. Interestingly, Cyan + Magenta + Yellow = Black!

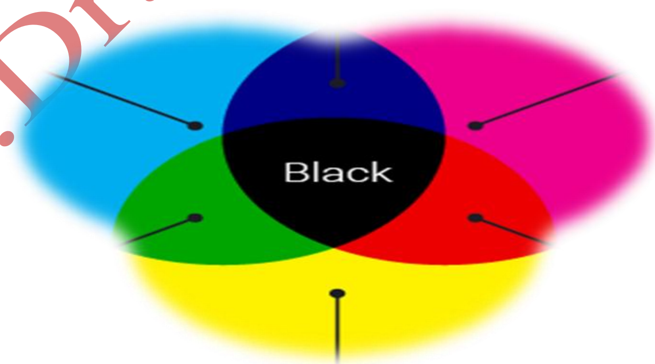
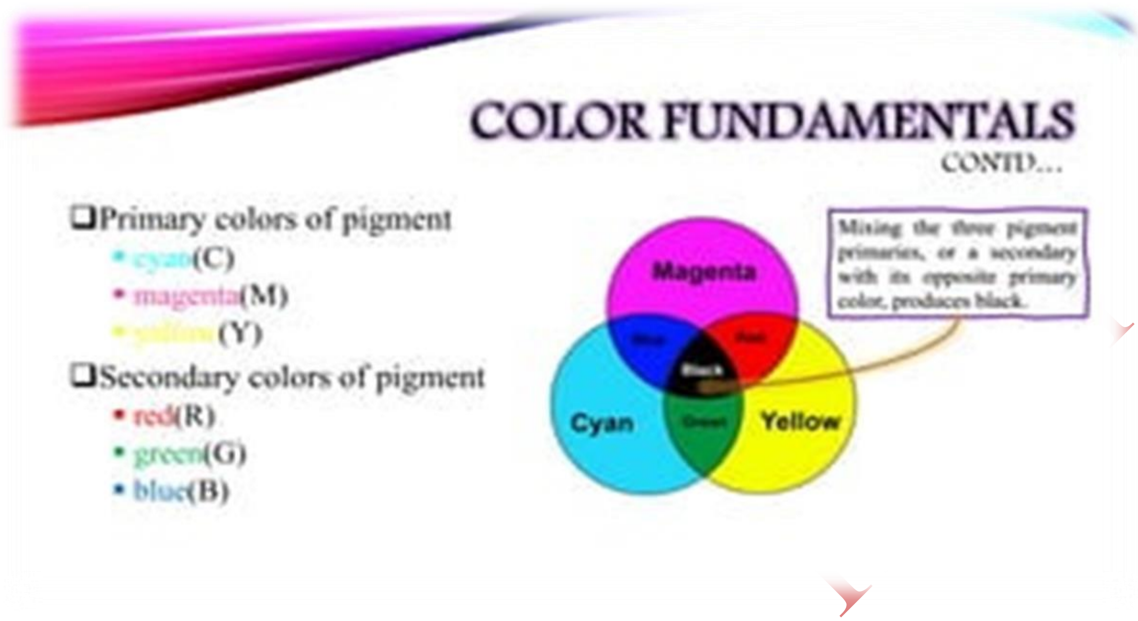


Fig. (1.17) The CMY model



FOOD FOR THOUGHT

Can you name one application where these primitive and derived colors are used intensively?

All monitor and television displays use this concept

Fig. (1.18) Hue scale.

1.13.2 HSV Color Model

HSV corresponds to hue, saturation, and value. Some people call this HSB, which corresponds to hue, saturation, and brightness. Just like RGB, the HSV color model is fundamentally composed of three components. They are as follows:

1. Hue – This is the color. It can be signified as a point in a 360-degree color circle (Figure 1.18).
2. Saturation – This is directly connected to the intensity of the color (range of gray in the color space). It is normally represented in terms of percentage ranging from 0% to 100%. If it is100%, it signifies an intense color presence.
3. Value – This can also be called brightness and just like saturation, it is represented as percentage. The range is from 0% to 100%. Zero represents black and 100 represents the brightest.

The hue scale is presented in Figure 1.18 and it ranges from 0 to 360 degrees (also see Figure 2.19).

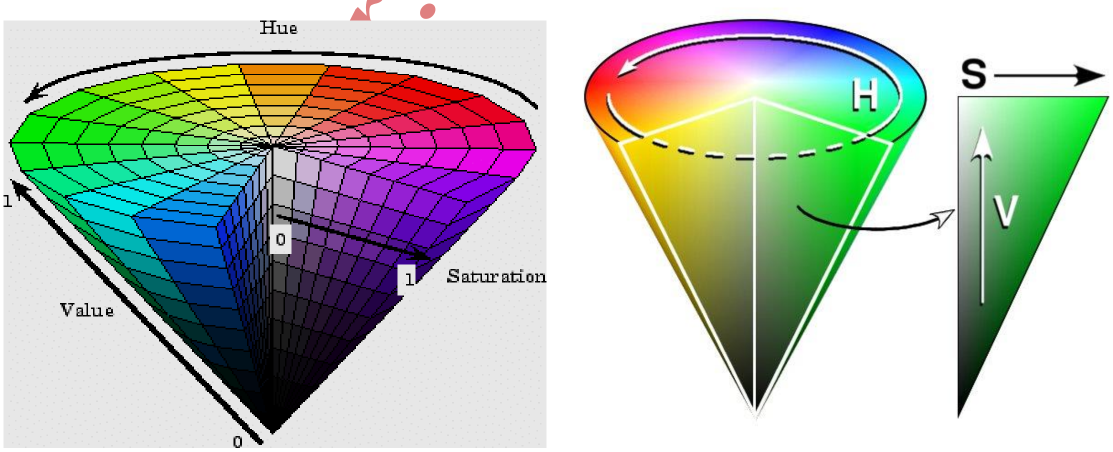


Fig. (1.19) The HSV triangle.

1.13.3 YUV Color Model

YUV is one of the color encoding systems and is mostly used in the color image pipeline (i.e., components used between an image source [for example, a camera] and image renderer [any display device]). YUV is an alternate option for the traditional RGB in display systems and is one of the efficient options in an image processing application where displays are involved. In this color encoding scheme, the transmission errors are said to be reduced compared to the traditional RGB scheme. YUV standards have been globally accepted and products in the market almost are mostly in favor of YUV standards. Hence, this color model overtakes the rest of the schemes. Here, it is important for readers to also understand two terms:

1. Luminance – This refers to the brightness.
2. Chrominance – This refers to the color.

In YUV, Y represents the luminance. U and V are connected to the chrominance, which refers to the color. Thus, people also refer to this color model as the luminance/chrominance color system. In this model, the luminosity of the given color is detached and the hue (color) is determined. The luminosity data goes into the Y channel, whereas U and V carries different content. The U channel is created after subtracting the Y from the amount of blue in the given image.

Concerning V, this channel is created by subtracting the amount of red from Y.

From RGB to YUV

$Y = W_R\ R + W_G\ G + W_B\ B$, where R is red, G is green, B is blue.
$U = 0.492\ (B - Y)$, where B is blue, Y is yellow. …… (1-7)
$V = 0.877\ (R - Y)$, where R is red, Y is yellow.

$W_{R} = 0.299, \quad W_{G} = 1 - W_R = 0.587, \quad W_B = 0.114$

From YUV to RGB

$$R = Y + 1.140V$$
$$G = Y - 0.395U - 0.581V \qquad \ldots\ldots\ldots\ldots(1\text{-}8)$$
$$B = Y + 2.032U$$

The conversion from the RGB to the YUV happens in the way as represented in equations (1-7).

Is this done? No, we have more information to pay attention to. There is a concept called chroma subsampling. What is chroma subsampling? Chroma subsampling is a process that is connected to the lessening of color resolution of video signals. The reason behind this is very straightforward: to save the bandwidth. Chroma is also called color component information. One can lessen or reduce this by sampling and thereby comes the term chroma subsampling. It happens by sampling at a lower rate than the brightness. As we know, brightness is all about luminance. But, when the color information is reduced, won't it be detected by human eyes? The answer is interesting. Human eyes are more sensitive to brightness variation than to color variations and hence there is no problem!

1.14 Characteristics of Image Operations

There are two topics to be discussed under this roof. One is a type of operation and the other is a type of neighborhood. Not to panic! Both are understandable and are discussed in detail in the following sections.

1.14.1 Types of Operations

The actions one can carry out with an image to transform the input into an output are defined as the types of operations. There are three fundamentals' categories under these types of operations:

1. Point operation
2. Local operator
3. Global operator

1. **Point operations.** A pixel's grey value is changed without any knowledge of its surroundings.

Although point operations are the simplest, they contain some of the most powerful and widely used of all image processing operations. They are especially useful in image *pre-processing*, where an image is required to be modified before the main job is attempted.

First, let's understand the point operation (Figure 1.20). Here, the output value at a specific coordinate is dependent only on the input value at the same coordinate and nothing else. An example would be apt here. (See Figure 1.21).

The second operation to be understood is local. This is diagrammatically presented in Figure (1.22). In this approach, not just a pixel but the neighbors are considered and they are also in action. The output intensity level at a pixel not only depends on the corresponding pixel at the same coordinate but

also on the neighboring pixels (Figure 1.23).
The next topic in the queue is the global operation. What is it? Let's unfold the mystery! Here, the output value at a specific point is dependent on all the values in the input image. This is diagrammatically presented in Figure (1.24).
The next subject to be discussed is neighborhoods.

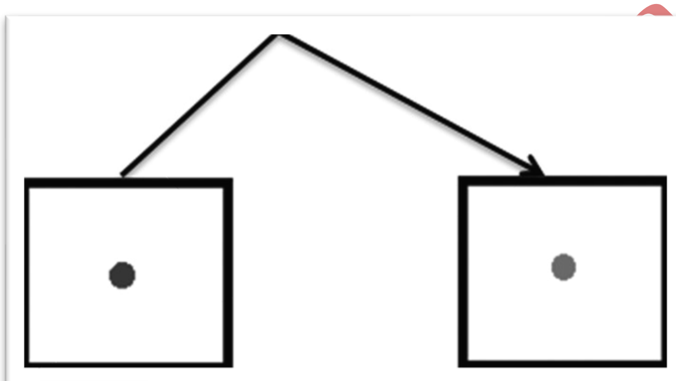


Fig. (1.20) Point operation

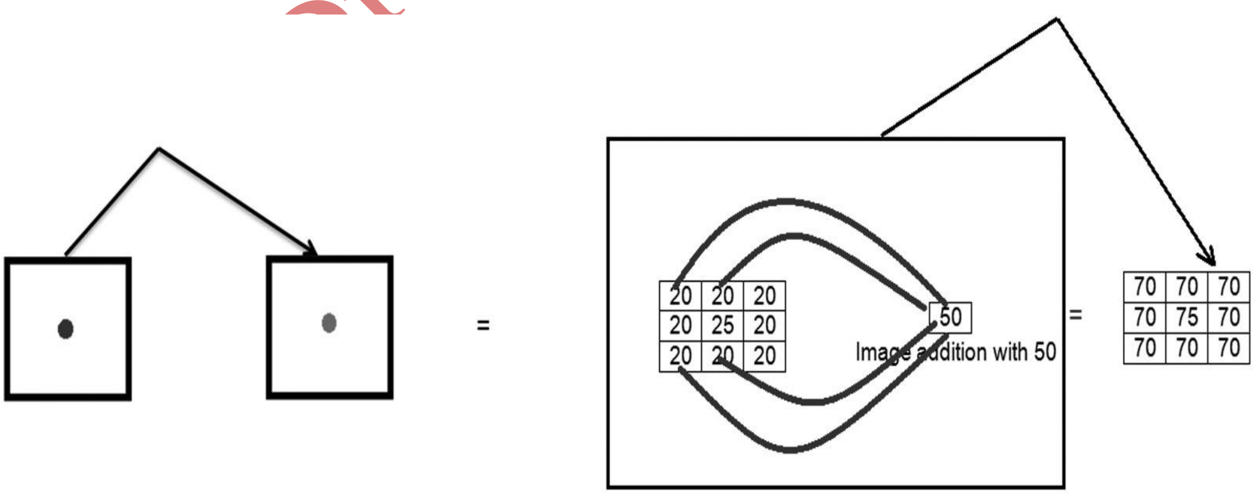


Fig. (1.21) A simple example of a Point operation

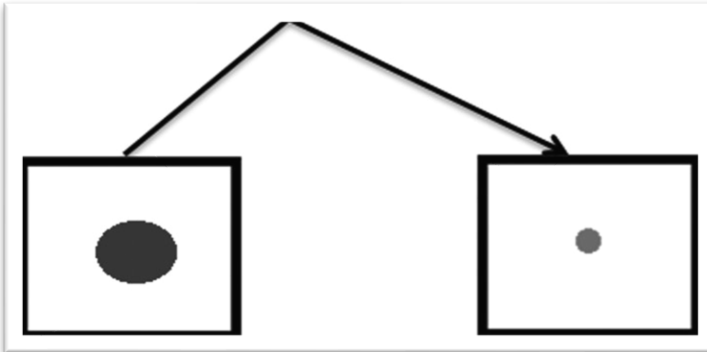


Fig. (1.22) Local operation.

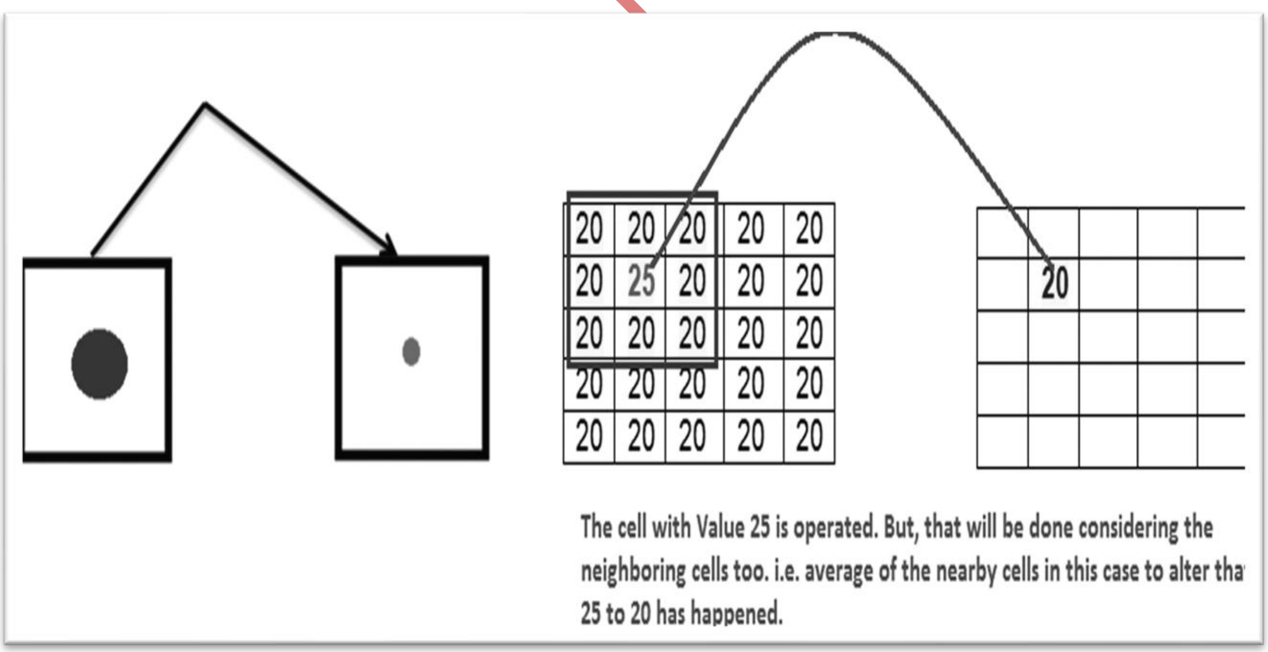


Fig. (1.23) Local operation with an implementation example

1.14.2 Types of Neighborhoods

As the name suggests, this concerns the neighboring pixels. Based on the Neighboring pixels, the value of the considered pixel is altered. There are Two types of neighborhoods are supported in modern-day image processing. They are:-

a) Rectangular sampling b) Hexagonal sampling

Fig. (1.24) Global operation.

Fig. (1.24) Neighborhoods.

Let us start with rectangular sampling. In this method, normally a rectangle is laid over the image matrix and operations are done accordingly on the local neighbor. There are two subclassifications in this: the 4-connected neighbor and 8-connected neighbor techniques (Figure 1.24). Hexagonal sampling is not used much and is to be dealt with separately.

1.15 Different Types of Image Formats

This is one of the topics that is part of any image processing book without fail because it carries much impact and importance.

- First, define what image format is all about. It is a predefined and standard way of organizing a digital image. Also, the image format is connected to how the image is stored. The format can be compressed or uncompressed and the same will be discussed in depth as follows for each image type.

1.15.1 TIFF (Tag Image File Format)

TIFF is expanded as Tag Image File Format. It is normally referred to as a huge file format, meaning if an image is stored as a TIFF, it is expected to be huge in size. As we know, when an image gets larger, it has a lot of data and content in it. TIFF images are also classified as an uncompressed image format type. A TIFF is preferred where flexibility is paramount in terms of colors. TIFF can support grayscale, CMY, RGB, and more. TIFF is mostly preferred by graphic designers and photographers as it supports vast color options. People also refer to TIFF as a lossless file format.
To understand TIFF better, the following pros and cons should be considered.

Pros: - 1-Very versatile, and can support multiple colors and options such as CMY and RGB.

2- Quality is not compromised and it ensures perfect and complete quality.

Cons:- Its very large size is a concern.

1.15.2 JPEG (Joint Photographic Experts Group)

Lots of people would have heard and may even be more familiar with the JPEG image type. Yes, it is very popular among all of us. Let us understand the technicalities of it.

The JPEG is extremely popular for many reasons. It is a compressed storage technique. Much information can be stored in a smaller sized file and hence it can save a lot of space. Your digital camera's default image type is likely JPEG as it gets better storage-related results.

Whereas the TIFF is lossless, the JPEG is lossy. It loses some information when compressed. The biggest concern with the JPEG image is the ability for the user to re-edit it. You will not get the best quality when the JPEG image is edited; that is, the quality of the image will be degraded. However, wherever the size of the image should be small (as in webpages) and needs to load faster, JPEG is the obvious choice.

Let's analyze the pros and cons of JPEGs:

Pros

- Small size and reduced storage needs.
- Default image type in digital cameras, which enables more photos to be stored.
- Apt for the websites and digital documents, as the image loads faster.
- Compatible with most operating systems and is widely accepted. This image type is indeed very popular.

Cons

- The discarded data is a huge concern. This could affect the content and quality.
- May create room for false observations because of artifacts.
- Transparency is hurt when this kind of image is used.

1.15.3 GIF (Graphics Interchange Format)

GIF has been expanded to a graphics interchange format. It is a fantastic and efficient image format. It has both the features of a JPEG and TIFF. Like the TIFF, GIF retains the quality, and like JPEG, it has a reduced storage scenario. Yes, the GIF is a lossless compression technique-based image. It compresses the image but with no loss. Hence, the size of the image is as small as a JPEG while the quality is retained.

But there is a negative aspect to the GIF. It comes with a very limited color range, meaning it may not support as many colors as desired. The compression happens by reducing the number of colors. To understand this better, if there are five shades of red, GIF would make it one shade of red.

The pros and cons are discussed next:

Pros 1- Reduced size for file storage. 2- Quality retainment.

3- Suitable for images where multiple color shades are not required.

Cons Very limited color options.

1.15.4 PNG (Portable Network Graphic)

The PNG solves some of the negative aspects identified with the GIF. The colors supported tend to be the major challenge in the GIF and they are addressed with a PNG. The complete range of colors is supported in a PNG. Even then, the competitor JPEG is in the introduction, because a PNG is a larger file when compared to JPEG hence the preference for JPEG. A PNG is classified as a lossless, compression-based image.

Pros

- Improved color range support compared to GIF.
- Increased transparency.
- Smaller file size than GIF.

Cons File size is still not smaller than JPEG.

1.15.5 RAW Format

People refer to a “raw” format for many reasons. Raw image content is not processed and can’t be used directly. Raw images are the format of the images immediately after creation, i.e., when you click a photo, before processing, it would be a raw image. Also, since it is not processed, a raw image cannot be printed. A RAW file is an uncompressed format, and since there has been no processing, the size of the file is very high.

There are many types of RAW formats available on the market. They include CR2 and CRW (both created by Canon), NEF (created by Nikon Cameras), and PEF (created by Pentax Digital Cameras).

(2-1) Image Statistics

- Image mean & local mean
- Image variance and local variance
- Image histogram and histogram equalization.
- Image contrast and local contrast

(2-2) The Statistical Image Properties.

The statistical properties of an image provide useful information, such as the pixel values' total, mean, standard deviation, and variance. The analysis of the statistical properties of images is dictated by the concern of adapting secondary treatments such as filtering, restoring, coding, and shape recognition to the image signal. Several image properties can be calculated from image data, the most imported.

Properties (mean μ, standard deviation σ or variance σ^2, contrast and Image histogram) of the image or image local regions.

(2-2-1) Image Mean (μ)

Image means brightness is known as the mean brightness for the image Elements (or sub-image or local image region) and determined from the Following relationship:

$$\textbf{Mean}=\frac{1}{M\times N}\sum_{x=1}^{M}\sum_{y=1}^{N}f(x,y)\ \ldots\ldots\ldots\ldots \quad \textbf{(2-1)}$$

Where **M** and **N** denote the height and the width of the image (or sub-image or local image region), the multiplication of them equals the Number of image or sub-image elements.

(2-2-2) Standard Deviation (STD or σ)

The standard deviation σ represents the mean of variations of the image (or local or sub-image region) element values to its mean and it is determined from the following relationship:

$$\mathbf{STD} = \sqrt{\frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} (I(x,y) - \mathbf{Mean})^2} \quad \ldots \quad \mathbf{(2\text{-}2)}$$

The variance $\boldsymbol{\sigma}^2$ represents the square value of the standard deviation.

(2-2-3) Image histogram and histogram equalization

Histograms plot how many times (frequency or occurrence) each intensity value in the image occurs. An image histogram is a graph that shows the number of pixels in each image pixel intensity level (pixel value) or each index of the indexed color image. The image histogram contains the information needed for image equalization, as image pixels are extended to give reasonable contrast.

- **Graph and grayscale:** We can get the image histogram by Drawing the pixel value distribution across the full grayscale range.

Hist. of pixel(n)= (numb. of pixels of value=n)/ total numb. of pixels

Example: Produce a histogram given the following image (a matrix filled with integers) with the grayscale value ranging from 0 to 7, that is, With each pixel encoded into 3 bits.

I=[0,1,2,2,6,2,1,1,2,1,1,3,4,3,3,0,2,5,1,1]

Or given by :-

$$I = \begin{bmatrix} 0 & 1 & 2 & 2 & 6 \\ 2 & 1 & 1 & 2 & 1 \\ 1 & 3 & 4 & 3 & 3 \\ 0 & 2 & 5 & 1 & 1 \end{bmatrix}$$

Solution:

Since the image (I) of many pixels (N*M=20) is encoded using 3 bits for each pixel, we have the pixel value ranging from 0 to 7. The count for each grayscale is listed in the Table below.

Image pixel level value (v)	Number of pixels (occurrence) Oc(v)	Probability of v P(v)=Oc(v)/(N*M)	Cumulative Probability Cp(v) P(V) +Cp(v) before
0	2	0.1	0.1
1	7	0.35	0.45
2	5	0.25	0.70
3	3	0.15	0.85
4	1	0.05	0.90
5	1	0.05	0.95
6	1	0.05	1.00
7	0	0.00	1.00

Based on the grayscale distribution counts, the histogram is created as shown below:

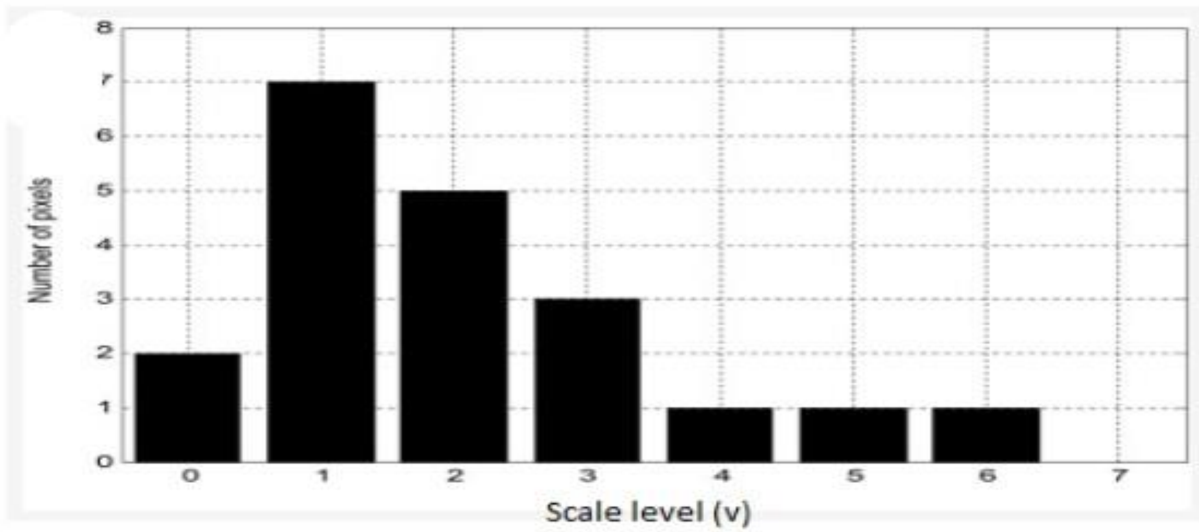


Fig. (2.1) The histogram of the Number of pixels (occurrence) Oc(v)

As we can see, the image has pixels whose levels are more concentrated in the dark scale in this example

H.w: - plot Cp(v)?

Example:

The following Fig (2.2) shows the data (i) and its histogram h(i).

Histograms

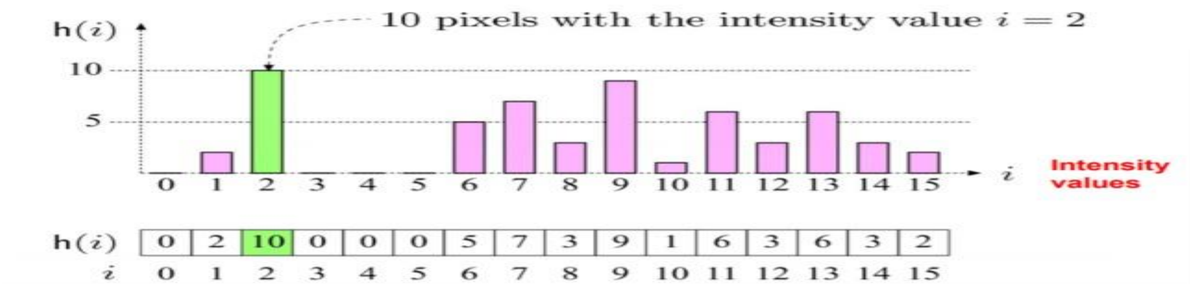


Fig. (2.2) Example of Histograms (h(i))

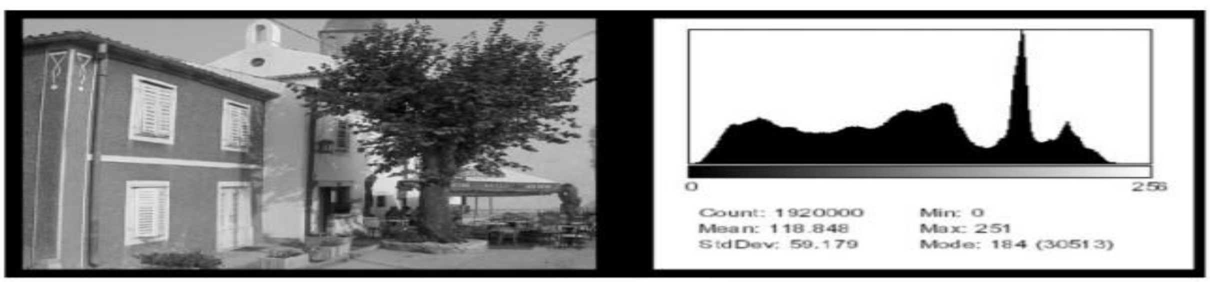


Fig. (2.3) Real example of the left image and its histogram.

Different images can have the same histogram; the three images fig (2-4) has the same histogram:

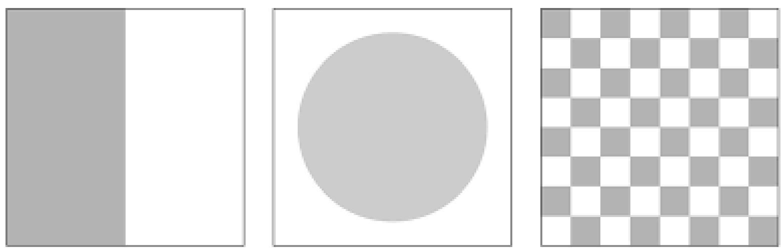


Fig (2-4)

Half of the pixels are gray, half are white, The Same histogram means same statistics. The Distribution of intensities could be different in the image plane.

Q- Can we reconstruct an image from a histogram? No

Histograms help detect image acquisition issues. ***Problems with image can be identified on histogram (over and under exposure, brightness, contrast, & dynamic range).***

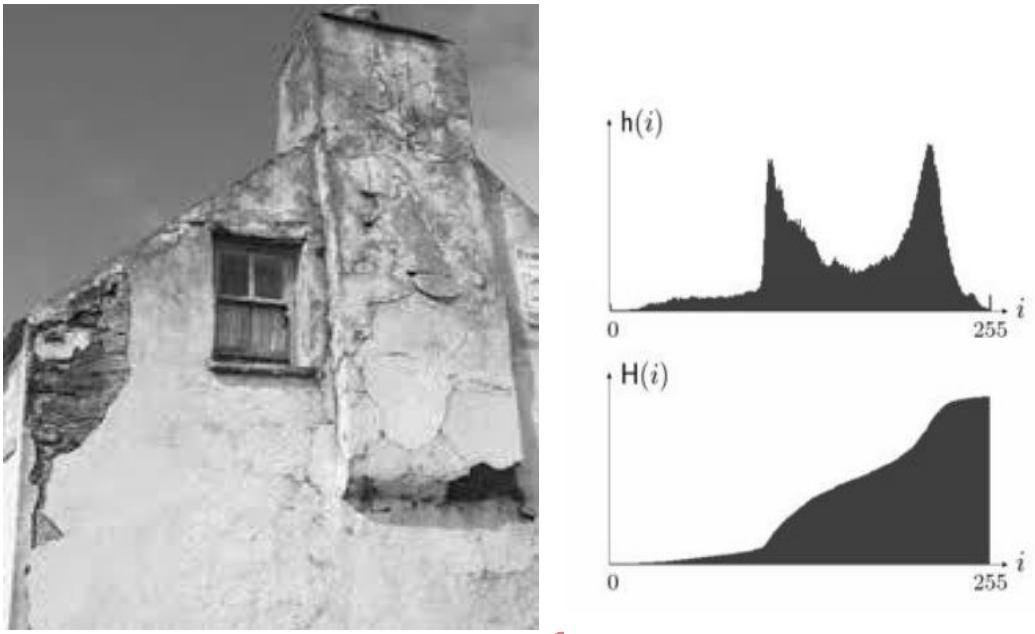
With the histogram, the equalization technique can be developed. Equalization stretches the scale range of the pixel levels to the full range to give an improved contrast for the given image. To do so, the the equalized new pixel value is redefined as:

$$J = \text{Round integer}\,(C_p\,(I) * L) \text{ --------} \qquad (2\text{-}3)$$

Where (J) represents the new contrast enhancement image and (L) is the maximum scale pixel value in the image (I). Since the accumulated counts can range from 0 up to 1, and the equalized pixel value can vary from 0 to the maximum scale level (L) i.e. integer value (0 to L). It is due to the accumulation procedure that the pixel values are spread over the whole range from 0 to the maximum scale level (L).

following **Fig (2-5)** shows the image and its histogram and cumulative histogram

Image histogram



Cumulative image histogram

Fig (2-5) Image histogram and Cumulative image histogram

The cumulative histogram is a variation of the histogram in which the vertical axis represents not just the counts for a single gray level but denotes the counts for the intensity in consideration, plus all values less than that intensity.

Image Histogram Equalization

Histogram equalization is a method to process images to adjust the contrast of an image by modifying the intensity distribution of the histogram see **Fig (2-6)**. The objective of this technique is to give a linear trend to the cumulative probability function associated with the image.

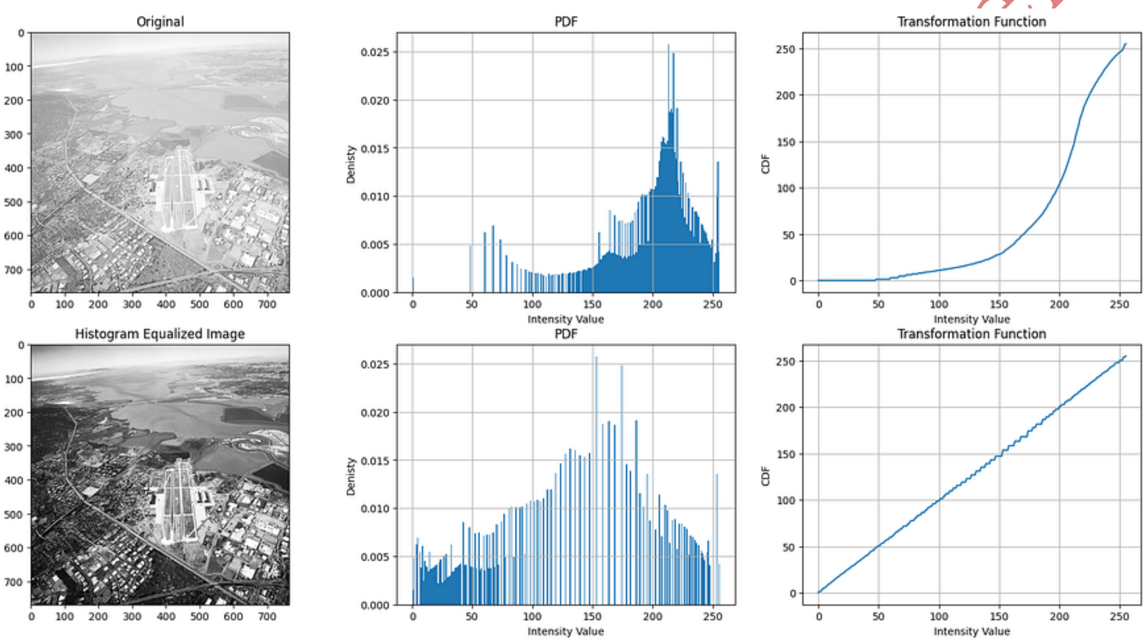


Fig. (2-6) Effect of Histogram Equalization

Example:

Given the following image (matrix filled with integers) with a grayscale value ranging from 0 to 7, that is, with each pixel encoded in 3 bits,

$$I = \begin{bmatrix} 0 & 1 & 2 & 2 & 6 \\ 2 & 1 & 1 & 2 & 1 \\ 1 & 3 & 4 & 3 & 3 \\ 0 & 2 & 5 & 1 & 1 \end{bmatrix}$$

Perform equalization using the histogram and plot the histogram for the equalized image.

Solution:

Based on the histogram result in the Table below, we can compute an accumulative probability Cp(v) for each grayscale level (v), as shown in the Table below.
The maximum scale value is L=7 and the total number of image elements is N*M=20. The equalized pixel level (nv) using Eq. (2-1) is given in the last column.

Image pixel level value (v)	Number of pixels التكرار (occurrence) Oc(v)	Probability of v P(v)=Oc(v)(/N*M)	Cumulative Probability Cp(v)	New Image pixel level value (Equalized pixel Level) (nv) = CP(v) * 7
0	2	0.1	0.1	1
1	7	0.35	0.45	3
2	5	0.25	0.70	5
3	3	0.15	0.85	6
4	1	0.05	0.90	6
5	1	0.05	0.95	7
6	1	0.05	1.00	7
7	0	0.00	1.00	7

To see how the old pixel-level
I **(x, y) = 4 is equalized to the new pixel level J(x, y) = 6, which we apply above Eq(2-1). Where Cp (4) =0.90**
then: The new value:
n v=Round integer (Cp(4)*7)=Round integer(0.90*7)=
Round integer (6.3)=6.
So, the equalized image using the above Table is finally obtained by replacing each old pixel value(v) in the old image (I) with its corresponding equalized new pixel value (n v) in the enhanced image (J) that given by

$$J = \begin{bmatrix} 1 & 3 & 5 & 5 & 7 \\ 5 & 3 & 3 & 5 & 3 \\ 3 & 6 & 6 & 6 & 6 \\ 1 & 5 & 7 & 3 & 3 \end{bmatrix}$$

To see how the histogram is changed see Fig (2-7), we compute the pixel level counts according to the equalized image. The result is given in the Table below, and the new histogram for the equalized image is below.

Image pixel level value (v)	Number of pixels (occurrence) Oc(nv)	Probability of v P(v)=Oc(nv)/N * M	Cumulative Probability Cp(nv)
0	0	0.0	0.0
1	2	0.1	0.1
2	0	0.0	0.1
3	7	0.35	0.45
4	0	0.0	0.45
5	5	0.25	0.70
6	4	0.2	0.90
7	2	0.1	1.00

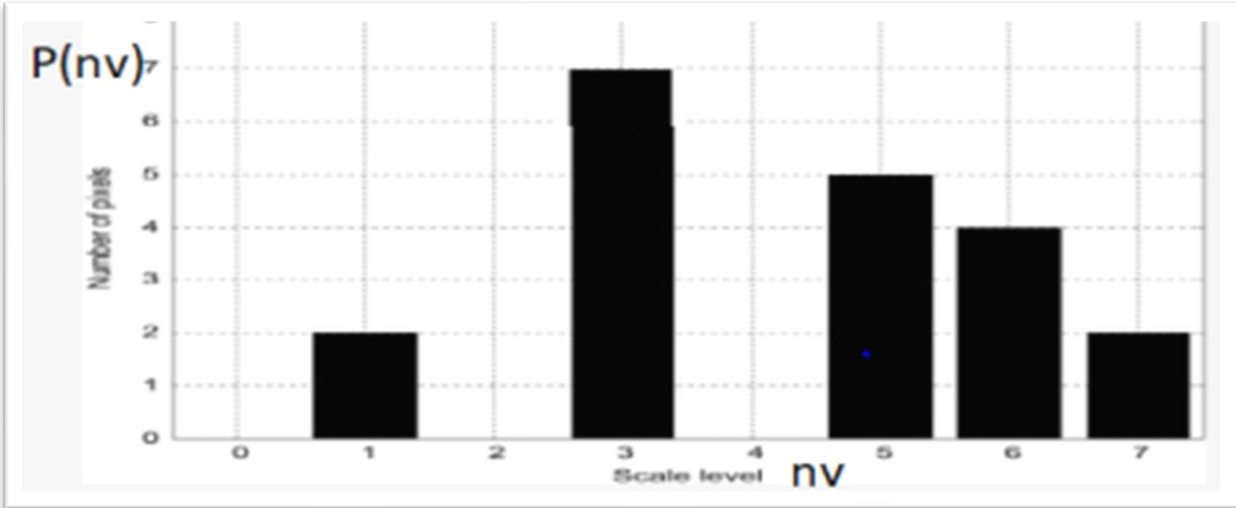


Fig. (2-7)

Next, we apply the image histogram equalization to enhance an image and its histogram in Fig (2-8) below. We see that there are many pixel counts residing at the lower scales in the histogram. Hence, the image looks rather dark and may be underexposed.

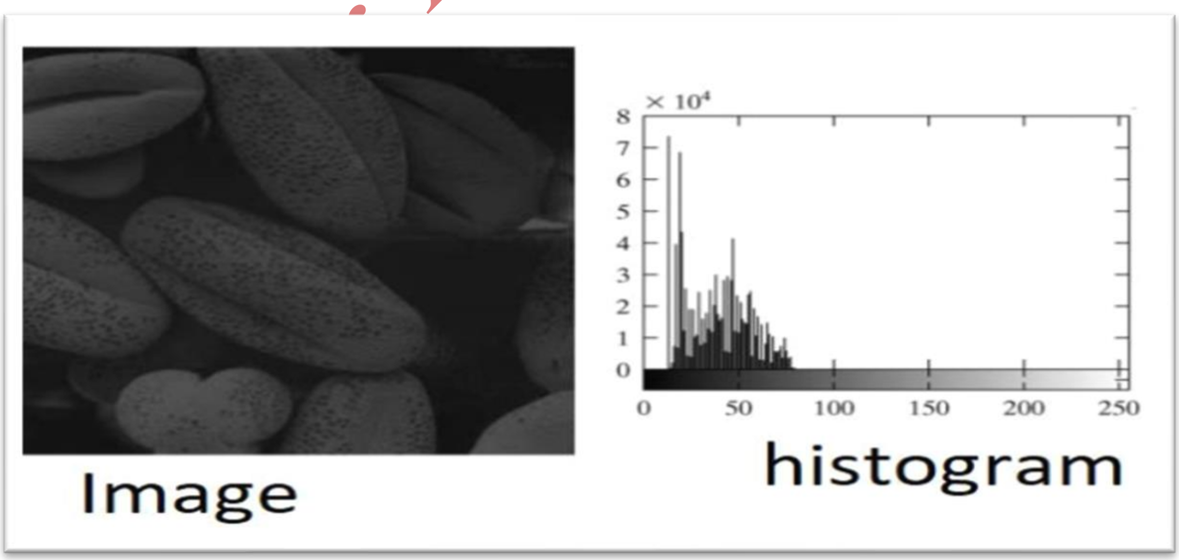


Fig. (2-8) Original grayscale image, & its Histogram.

Figure (2-9) below: show the equalized grayscale image for an image in fig (2-8) above using the histogram equalization method and its histogram. As shown in the histogram, the equalized pixels reside more on the larger scale, and hence the equalized image has improved contrast.

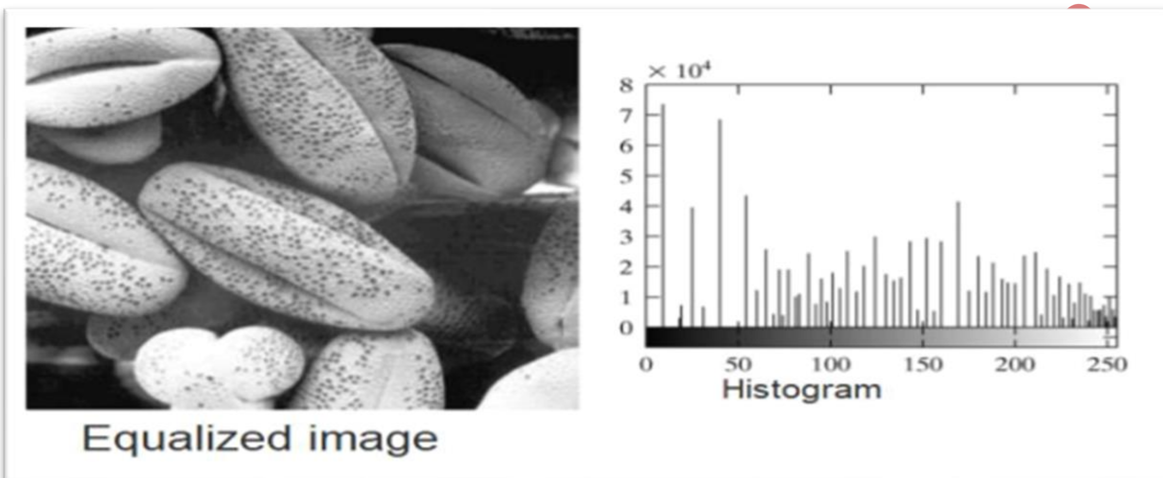


Fig. (2-9) equalized grayscale image, & its Histogram.

(2-2-4) Image Contrast

The contrast of a grayscale image indicates how easily objects in the image can be distinguished. High-contrast images have many distinct intensity values. The low-contrast image uses few intensity values.

Histograms and Contrast: Low contrast, Normal contrast, and High contrast images and their histograms are shown in

Fig (2-10)

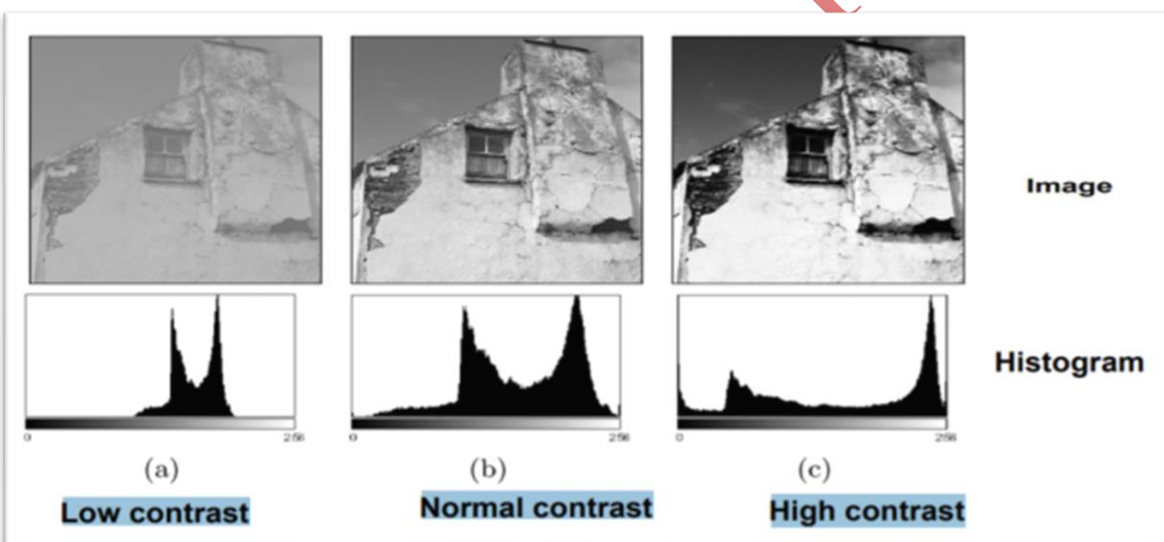


Fig. (2-10) Type of Contrast of an Image and Histogram

Good or High Contrast? Widely spread intensity values + large difference between min and max intensity values in the above image.

Image Contrast (Luminance Contrast): is the relationship between the *luminance* of a brighter area of interest and that of an adjacent darker area.

- **Weber Contrast: - One of the oldest luminance contrast statistics, Weber Contrast, is also often used for these patterns (small, sharp-edged graphic objects like symbols and text characters on larger uniform backgrounds):**

Weber Contrast equation is given by:

$$C_W = \frac{Imax - Imin}{Imin} \quad \text{……….} \quad (2\text{-}4)$$

Where I max and I $_{\min}$ represents the maximum and minimum luminance of the image or local image values respectively.

- **Michelson contrast:**

Michalson contrast measures the relation between the spread and the sum of the two luminances. Also known as *visibility* is commonly used for patterns where both bright and dark features are equivalent and take up similar fractions of the area (e.g. sine-wave gratings).(Its value is between zero and one.) The Michelson contrast is defined as

$$C_M = \frac{Imax - Imin}{Imax + I\ min} \text{……….} (2\text{-}5)$$

Where Imax and I min represent the maximum and minimum luminance of the image or local image values respectively.

Example: Find the two contrast values for the center pixel of the the following mask using the adjacent points.

2	2	100
3	16	250
4	10	251

Solution

Imax in the 3*3 mask is 251, and I min =2, so the contrast values are as follow:

1. Weber Contrast: Cw = (251-2)/2 = 124.5

2. Michelson contrast: C_M

= (251-2) / (251+2) = 0.9841

Notes: -

1- **Contrast is the sharpness in the details. There is good sharpness, but if the camera contains aberrations, the sharpness decreases.**
2- **The cause of blur or lack of clarity in the image is either diffraction or aberration.**
3- **The most important information in the image is located in the edge area, so when the edge is lost in the image, we lose most of the important information.**
4- **If the edges are present in large numbers, the Contrast is large, Conversely, if the number of edges is small, the contrast will be small.**
5- **Another type of contrast is statistical contrast, which depends on the standard deviation and the means.**

$$Cs = \frac{\sigma}{\mu} \quad \ldots\ldots\ldots\ldots\ldots\ldots(2\text{- }6)$$

SNR or signal-to-noise ratio

is the ratio between the desired information or the power of a signal and the undesired signal or the power of the background noise.

$$\text{SNR} = \frac{\mu}{\sigma} \quad \ldots\ldots\ldots\ldots(2\text{-}7)$$

Chapter -3 Digital Image Noise

Noise is defined as unwanted information that can appear in the signal and lead to its distortion.

- Signal types: -

a- Electrical signal b-Audio signal

c- Two-dimensional signal (image)

(3-1) Noise Models

The presence of noise in images distorts them, which makes analyzing them a difficult process. Therefore, studying noise helps a lot in knowing its effect on images or determining the optimal methods for removing it from images and recovering information about the image with minimal losses.

The types of noise can be classified mathematically as follows: -

1- Additive Noise 2- Multiplicative Noise 3- Salt and Pepper Noise 4- Sinusoidal Noise 5- Periodic Noise.

(3-1-1) Additive Noise

It is random noise that does not depend on the signal (That is, its causes are external factors that have no relation to the real signal) and its characteristics are as follows: -

1- It is white noise whose spectral intensity is constant throughout the image.

2- Statistical approximations of the additive noise distribution usually approach the Gaussian or uniform distribution.

3- Additive linearization in which the image obtained is an original image plus noise, and is given by the following relationship:-

$$I(x, y) = R(x, y) + n(x, y) \quad \ldots\ldots\ldots\ldots (2\text{-}8)$$

الضوضاء المضافة
ناتجة استطارة او حرارة
ومعدلها صفر وقيمتها بين ($-\infty \longrightarrow \infty$)

(صفر الى 255)
خالية من الضوضاء

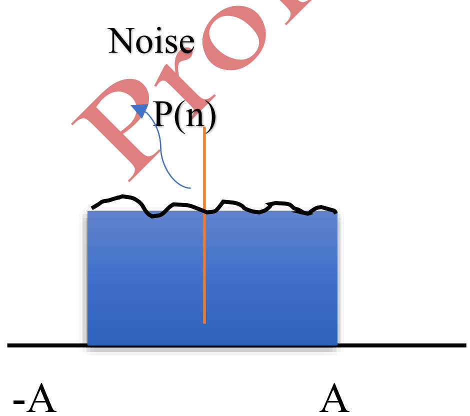
الصورة المشوهة

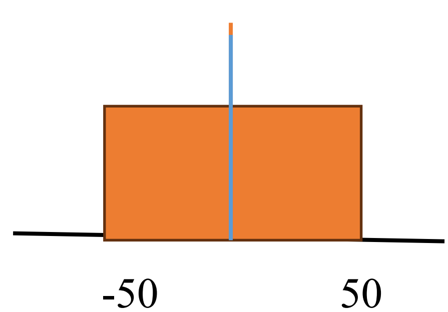
ملاحظة: - الضوضاء إذا نحن عملناها بالصورة تسمى محاكاة (Simulation)

There are two mathematical models for additive noise that can be represented as follows: -

a-Uniform Noise: -

This noise is caused by distorted signals with random values with regular frequencies and representing a distribution with equal probability for each value of the noise (n).





Each element has the same probability, and if the range of noise increases, the image distortions also increase. Uniform noise has a mean of zero but has a standard deviation. This noise may appear in the television signal.

$$\sigma = \sqrt{\sum V\, P(V) - \left(\sum V\, P(V)\right)^2} \quad ....(2\text{-}9)$$

R

50	51	49	200
52	50	53	201
50	49	202	200
200	203	200	220

+(-50)

0	1	-1	150
2	0	3	151
0	-1	152	150
150	153	150	170

ملاحظة: ـ التكرارات في التوزيع المنتظم لها نفس القيمة (أي لها نفس التكرار لكن توزيعها عشوائي)
أي ان تكرار العنصر لنفسه لكثافة العناصر .

ويستخدم مرشح (الفلتر) local Mean لإزالته.

$$\bar{I} = (\bar{R} + \bar{n}) \quad ..(2\text{-}10)$$

b -Gaussian Noise: -

This noise occurs due to the dispersion of electromagnetic waves in different directions, due to the presence of dust particles or particles of relatively small diameters present in the air. This noise is subject to Gaussian distribution.

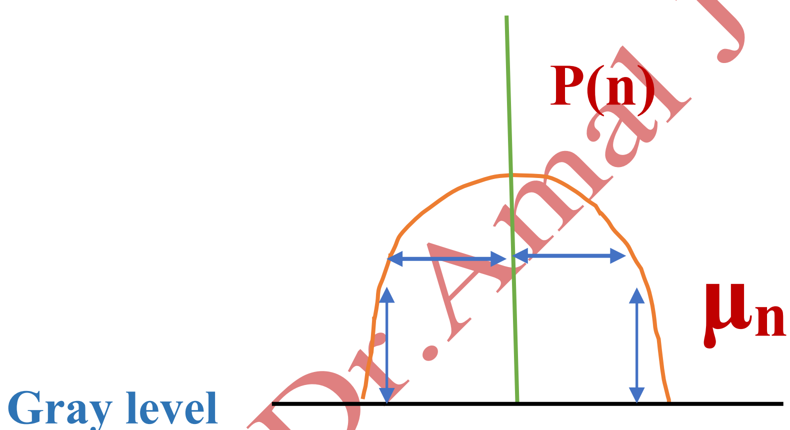
$$P(n) = \frac{1}{\sqrt{2\pi\,\sigma_n^2}}\; e^{\frac{-(n-\mu_n)^2}{2n\,\sigma_n^2}} \qquad \text{............ (2- 11)}$$

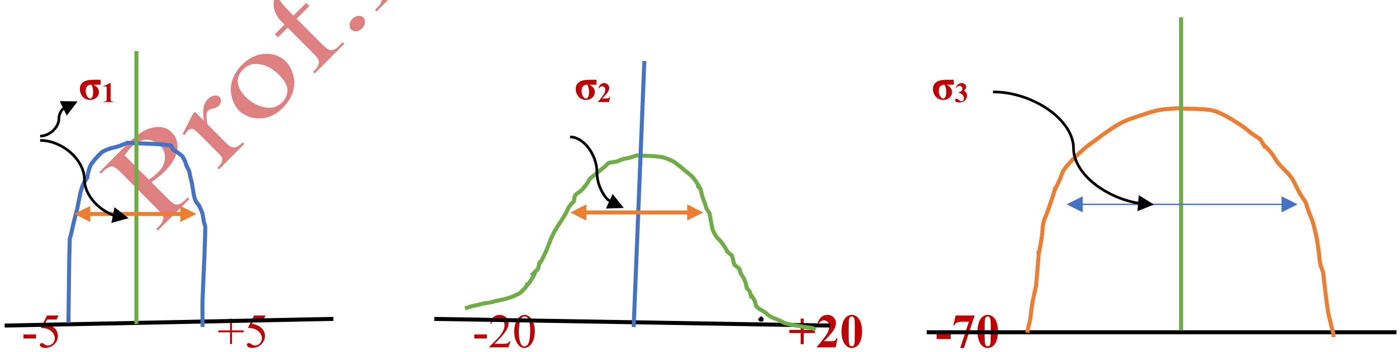
where: -

n: - Random variable

μ_n: - The rate value of a random variable.

σ^2_n:- Covariance of the random variable





Small distortion **high distortion** **very high distortion**

- **Notice: - 1- When the standard deviation of noise increases, the distortion in the image increases.**
  2- Gaussian noise is irregular, when we approach zero the frequency increases.

(3-1-2) Multiplicative Noise: refers to an unwanted random signal that gets multiplied into some relevant signal during capture, transmission, or other processing.

or

It is random noise that depends on the signal, meaning that the bright areas in the image are high noise, and the lower the light intensity, the less noise. This means that the relationship between the amount of noise and intensity is smooth (linear) and this noise is characterized by: -

1- Estimates of the distribution of multiplicative noise often approach a chi-square distribution or a Poisson distribution.

2- The resulting images are an original image(R) multiplied by noise (F), as shown in the following mathematical formula: -

$$I= R+ n(R)$$

$$I(x ,y) = R(x ,y) .F(x ,y) \quad = R(x ,y) + n\, R(x ,y)$$

if it was $n\, R\, (x, y) = K\, (x, y) \Longrightarrow = \text{constant}$

$$\therefore I\, (x, y) = R\, (x, y) + K\, (R\, (x, y))$$

$$I(x, y) = R(x,y)\, (1+ K)$$

يعتمد على الموقع فقط لا يعتمد على الإشارة

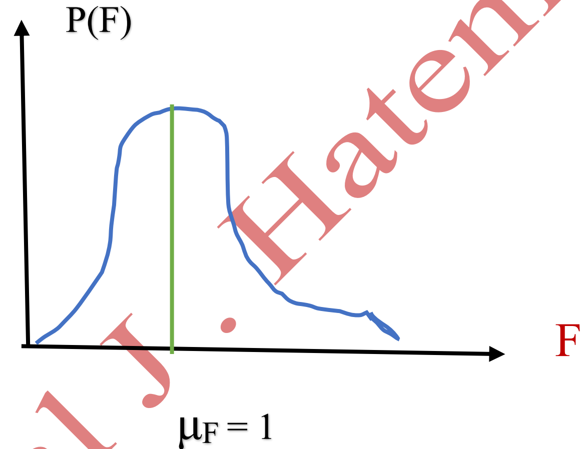
بينما الضوضاء (KR) تعتمد على الإشارة (K=0)

F (x ,y) = متغير عشوائي لا يعتمد على الإشارة

$\mu_F = 1$, $\dot{F} = 1$ المعدل

في بعض المصادر يسمى F (x, y) بالضوضاء لكنه متغير يعتمد على الموقع ولا يعتمد على الإشارة.

(F (x, y) > 1) تعتبر ضوضاء إيجابية لأنها تكبر الإشارة.



There are two types of Multiplicative noise: -

a- Poisson Noise: -

Its reason is due to the quantum nature of photons, so it is sometimes called quantum noise or photonic noise. This noise distorts images taken with **photonic imaging systems** such as X-ray imaging and is also present in **low illuminance**.

b- Speckle noise (النقطية البقعية، الرقطية،) (Distribution Square – Chi., X^2)

is a form of noise that commonly occurs in images acquired through coherent imaging techniques such as ultrasound imaging, synthetic aperture radar (SAR), and Laser imaging systems hologram systems are systems that produce low-quality images due to speckle noise. Unlike Gaussian noise or salt and pepper noise, which manifest as additive disturbances, speckle noise is multiplicative.

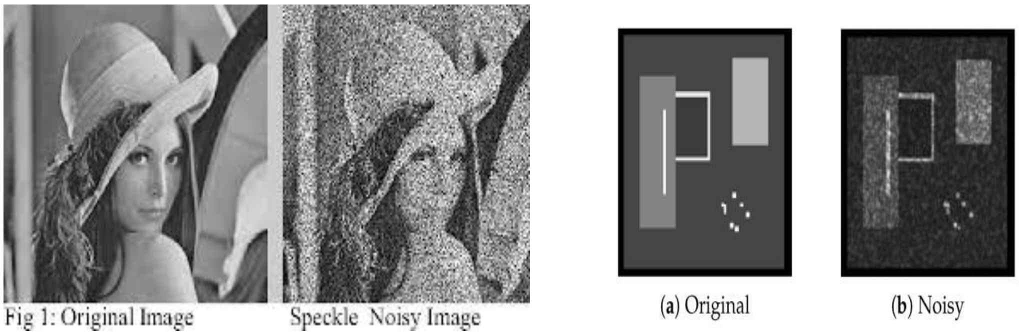


Fig. (3-1) Original image and simulated noisy image.

This noise is normalized by the cosine function (cos)

I (x, y) = 255 cos (π/2 * I (x, y)/255)

……………………………………………………

The difference between additive and multiplicative noise

5	100
41	101

+

-5	4
10	-11

→

0	104
51	90

R + n → I 255

5	100
41	101

2	4
10	2

→

0	400
410	202

R * F → I 255

ملاحظة مهمة: - لا يوجد F بقيمة سالبة.

F = 0 → 255 , the mean of F = 1

R(x,y) = 0 → 255

ملاحظة:- في بعض الأحيان بدلا من تحويل القراءة لاي قيمة اعلى من 255 الى 255 بأخذ الجذر التربيعي لان اعلى قيمة ل $(255)^2$ هي 255 .

$$\boxed{0 \mid 10 \mid 0} \; + \; \boxed{5} \; = \; \boxed{5 \mid 15 \mid 5}$$

يلاحظ ان الضوضاء الجمعية هي ضوضاء بيضاء يظهر تأثيرها المنظم في جميع المناطق.

$$\boxed{0 \mid 10 \mid 200} \; * \; \boxed{5} \; = \; \boxed{0 \mid 50 \mid 1000}$$

$$n(R_i) = I - R_i \; = \; \begin{array}{ccc} n(R_0) & n(R_1) & n(R_2) \\ \boxed{0} & \boxed{40} & \boxed{800} \end{array}$$

∴ **الضوضاء الضربية في مناطق الشدة الواطئة تكون قليلة، اما في مناطق الشدة العالية تكون عالية.**

(3-1-3) Salt and Pepper Noise: -

In some imaging or image scanning systems, a change in intensity and location occurs, which distorts the resulting image, and this distortion is in the form of points randomly distributed across the image plane. This noise is of two types: -

Salt Noise: represented by white points. A= 255

Pepper Noise: represented by black points. A= 0

The main reason for generating this noise is the presence of large particles located in the distance between the light source and the imaging or image-scanning device.

The best way to remove this noise is to use the median and mode method.

This noise is sometimes called **Replacement Noise.**

(3-1-4) Periodic noise

It falls within the multiplicative noise and is not random. It occurs when scanning the image (scanner) due to irregularity in the intensity distribution of illumination when scanning, as in electrical devices.

(3-1-5) Sinusoidal noise

The image contains two types of noise, one of which depends on the signal (multiplicative noise) and the other does not depend on the signal (additive noise).

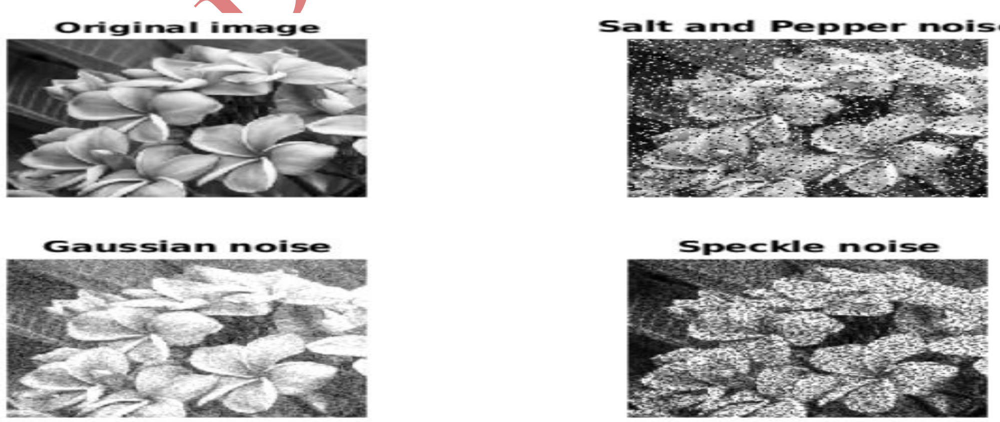


Fig. (3-2) Types of Noises

Chapter -4 Digital Smoothing Filter

(4-1) Filters: - **There are several types of filters, including**

1-Optical Filters 2- digital Filters
3- electronic Filters

(4-2) Digital Filters: - The filter needs time to be applied, which may be a second, an hour, or more.

- **Filters are used for**

1- Noise Removal Filters

2- Image enhancement Filters

In digital image processing, smoothing operations are used to remove noises. Image filtering is a most important part of the smoothing process

Filtering techniques enhance and modify digital images. They also blur and reduce noise, sharpen, and detect edges. Image filters are mainly used to suppress high (smoothing techniques) and low frequencies (image enhancement, edge detection). The classification of image filters is as follows.

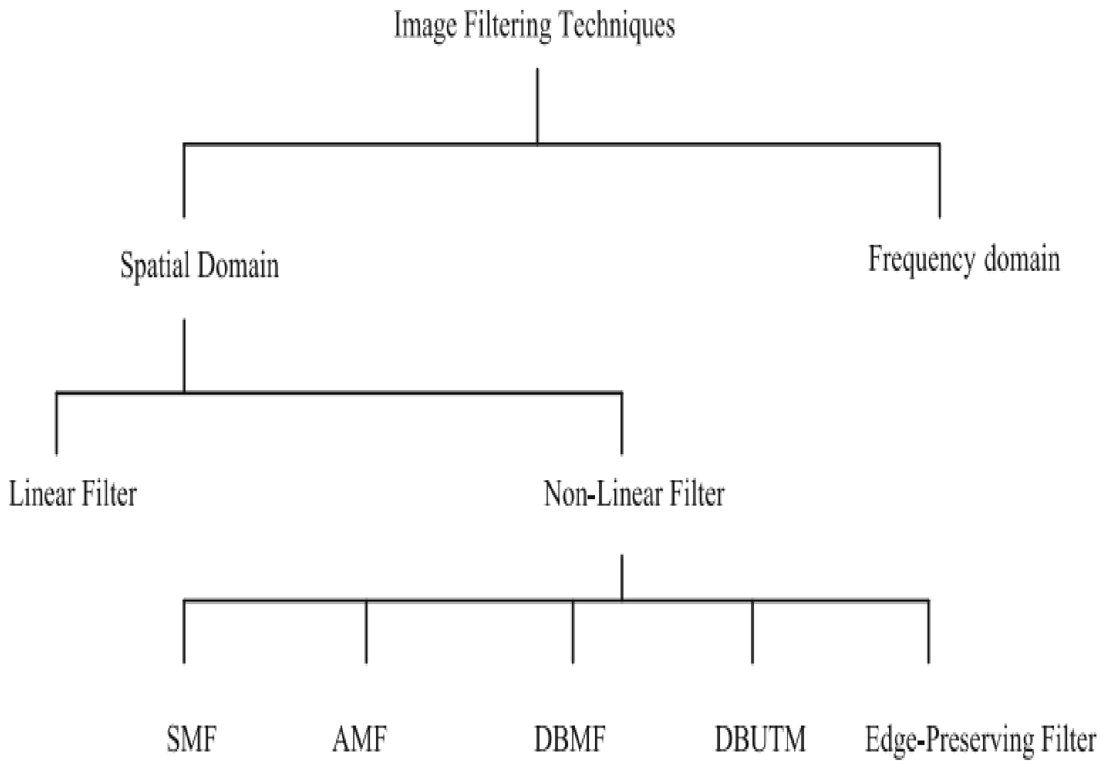


Fig (4-1) Classification of image filters (Simple Adaptive Median filter (AMF), Decision-Based Median Filter (DBMF), Decision-Based Untrimmed Median Filter (DBUTM))

According to this classification, image filters can be divided into two main categories. Spatial filtering is the traditional method of image filtering, it is used directly on the image pixels while Frequency domain filters are used to remove high and low frequencies and smoothing.

Nonlinear filters are used to detect edges. Those filtering techniques are more effective than linear filters. In linear filtering, image details and edges are tended to blur. Gaussian filter, Laplacian filter, and Neighborhood Average (Mean) filter can be identified as examples of linear filters. Median filters are nonlinear filters.

(4-2-1) Spatial domain: -

The spatial domain refers to image operators that change the gray value at any pixel (x, y) depending on the pixel values in a square neighborhood- centered at (x,y) using a fixed integer matrix of the same size. The integer matrix is called a filter, mask, kernel, or window.

The mechanism of spatial filtering shown in Fig (4-2), consists simply of moving the filter mask from pixel to pixel in an image. At each pixel (x,y), the response of the filter at that pixel is calculated using a predefined relationship (linear or nonlinear)

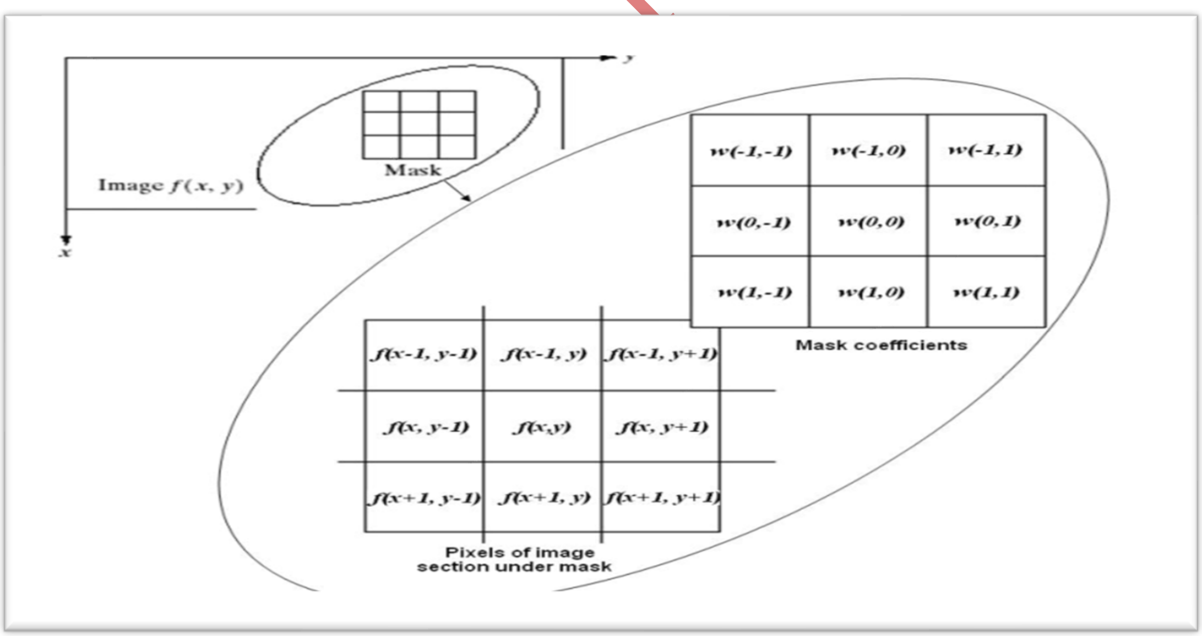


Fig. (4-2) The spatial filtering

(4-2-1-1) Traditional Filters

a-Neighborhood Average (mean, Box) Filters: -

This filter is also called a mean filter. In average filtering, pixel values will be replaced by average values of neighbor pixels. The calculation of the average value is as follows.

23	25	30	35	30
25	30	35	37	40
45	40	37	43	45
38	40	43	42	46
35	40	42	45	47

		39		

Value = (30 + 35+ 37+ 40 + 37+ 43+ 40+ 43+ 42) /9 = 38.55 = 39

Average Filter

$$I(x, y) = R(x, Y) + n(X, y)$$

$$M(x, y) = \frac{1}{BXB} \sum_{x=1}^{B} \sum_{y=1}^{B} I(x, y)$$

$$M(x, y) = \frac{1}{B2} \sum_{i=x-B/2}^{x+B/2} \sum_{j=y-\frac{B}{2}}^{y+B/2} I(i, j)$$

معادلة تحريك الفلتر

- **النوافذ قد تكون 3x3، 5x5، 7X7، 9X9، 11X11 .... يكون حجم الفلتر دائما فرديا وليس زوجيا؟**
- **لأنه لدينا حالة تناظر حول العنصر المركزي في حالة نافذة فردية وإذا كانت زوجية يحصل اضعاف للصورة الاصلية.**

ملاحظة مهمة جدا: -

اذا كان مجموع اوزان الفلتر = صفر الفلتر يستخدم للحافات (Edge)

اذا كان مجموع اوزان الفلتر = 1 الفلتر يستخدم للتجانس (Smoothing)

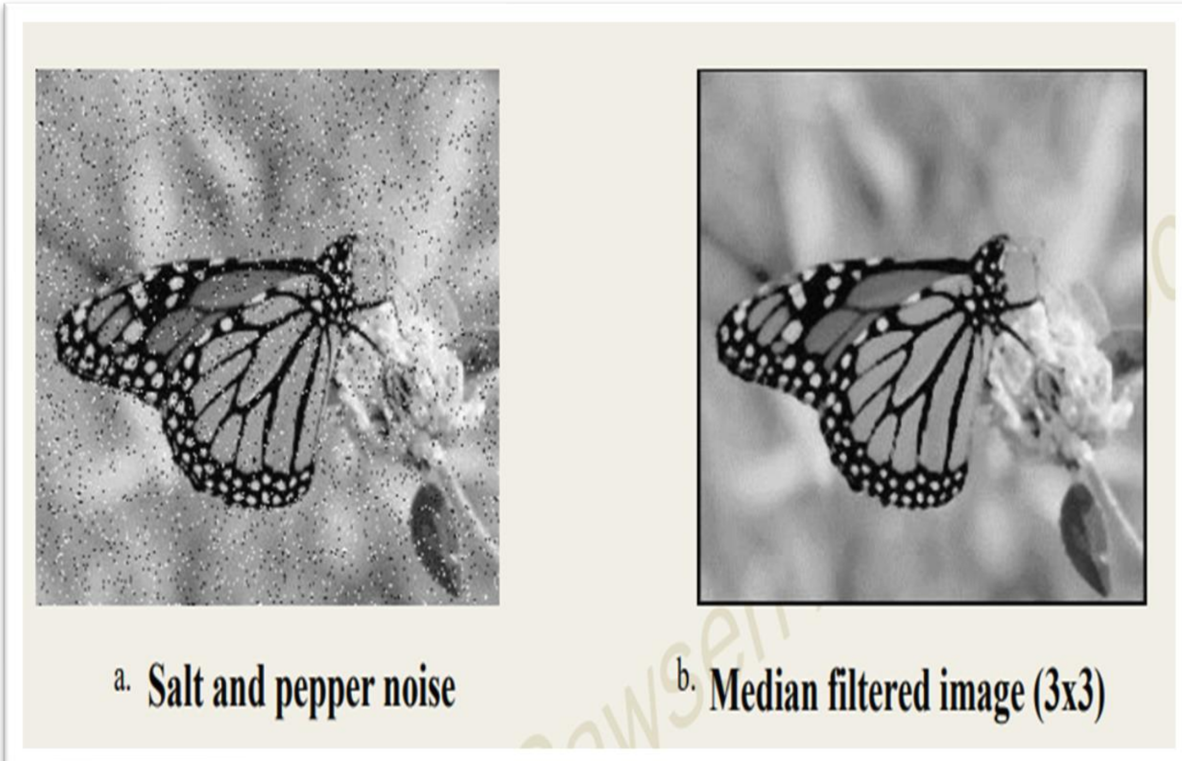
أذا كان مجموع اوزان الفلتر لا يساوي صفر او1 الفلتر يستخدم لحدة الصورة (Sharping)

b-Median Filter

The median filter is non-linear. Typically, these filters operate on a small sub-image, "Window," and replace the center pixel value (similar to the convolution process). It is considered the best filter because it is non-linear and simply calculates statistics. The median filter is used to preserve edge properties while reducing the noise in the image, and it's also an efficient way to remove salt-and-pepper noise.

Order statistics is a technique that arranges the entire pixels in sequential order, given an N×N window (W), the pixel values can be ordered from the smallest to the largest (ascending order). I1 <I2< I3< ....……< IN ^{2}

- **Where I_1, I_2, I_3 ...., I_N are the intensity values of pixels within the (NxN) window**



a. Salt and pepper noise b. Median filtered image (3x3)

The calculation of the median value is given below.

30	35	40	42	42
35	42	37	37	40
38	39	40	41	42
40	41	42	43	43
42	43	45	44	46

		41		

37, 37, 39, 40, **41**, 42, 42, 43

C- Mode: The most frequent value. In any given data set, there may be one mode or more than one mode, or there may be no mode and it is used for segmentation. The Mode filter is used to remove noise from an image by replacing pixels with the most frequently occurring pixel value selected from a certain window size.

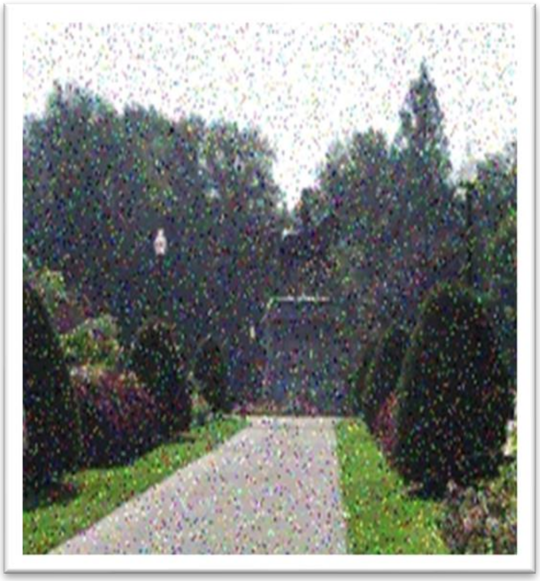
For example, given the grayscale 3x3 pixel window;

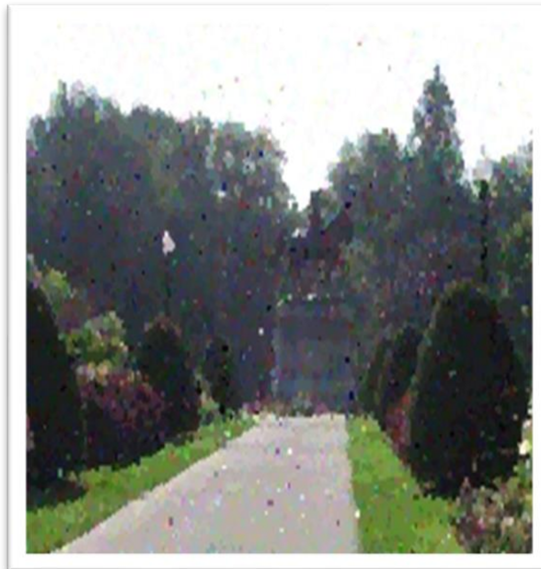
22	77	48
150	77	154
0	77	219

Thus, the center pixel would be at 77 since 77 is the most frequently occurring value in the list of pixels.

The mode filter (like the median filter) is very effective at removing noise while not destroying sharp edges in an image.

Origin image with Noise Mode Filter



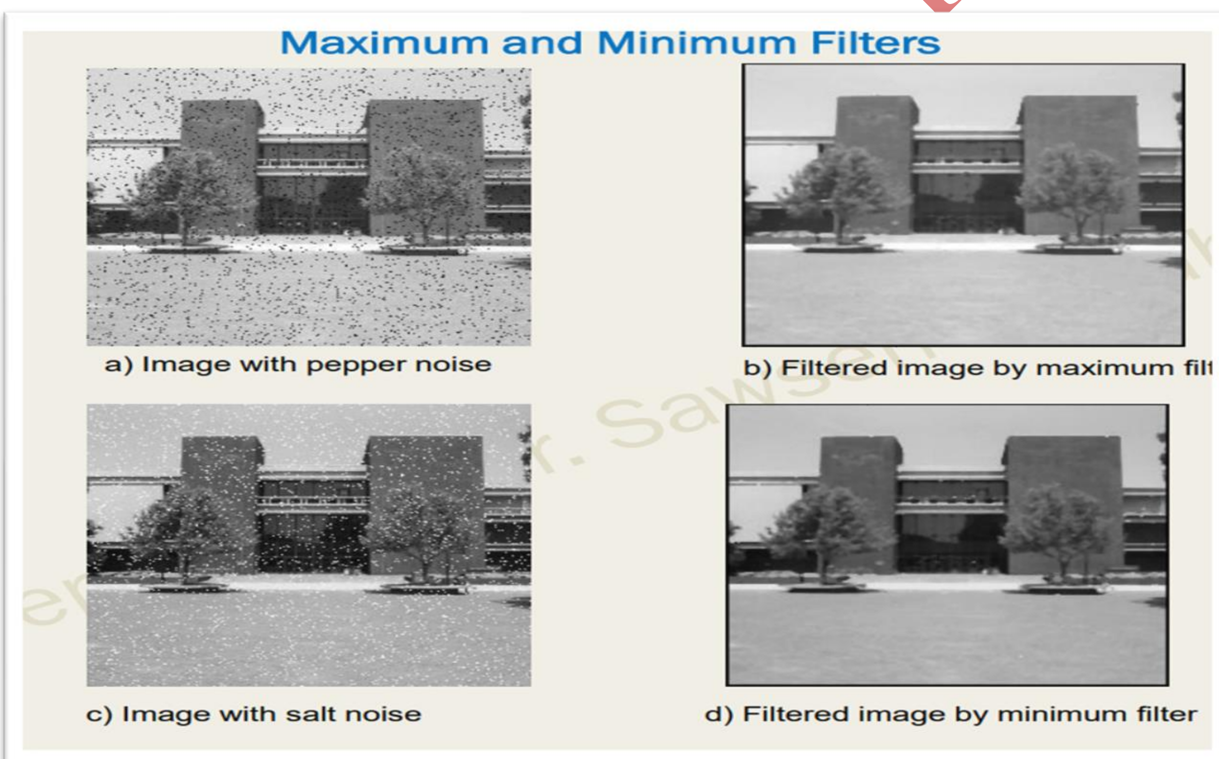


D- Min & Max: -

Maximum and Minimum Filters are two-order filters that can be used for the elimination of salt-and-pepper noise.

- **The maximum filter selects the largest value within an ordered window of pixel values and replaces the central pixel with the largest value (lightest one).**
- **Used to find the brightest points in an image.**
- **The maximum filters work best for removing pepper-type noise.**
- **The minimum filter selects the smallest value within an ordered window of pixel values and replaces the central pixel with the smallest value (darkest one) in the ordered window.**

➤ **The minimum filters work best for removing salt-type noise, NOTE: - a minimum or low-rank filter will tend to darken an image and a maximum or high-rank filter will tend to brighten an image.**



Example: - If Image

4	5	7	15	20
8	7	8	11	20
4	5	2	17	21
15	25	30	32	10

Apply Traditional filters on 17 no.

1-Mean filter. 2- Median filter. 3-Mode.

4- (Min, Max) filter.

Solution: -

1-Mean Filter = 1/9 (8+11+20+2+17+21+30+32+10)

= 16.7 = Cint (16.7) = 17 the mean

2-Median = 2,8,10,11,17,20,21,30.3

3-Mode → **Don't find element**

4-Min = 2 يعمل الصورة اكثر سوادا لأنه

يتخلص من النقاط البيضاء في الصورة **Salt**

5- Max =32 يعمل الصورة اكثر بياضا لأنه

يتخلص من النقاط السوداء (**Pepper**)

H.W: - Apply Traditional filters on (8, 5) no.

1-Mean filter. 2- Median filter. 3-Mode.

4- (Min, Max) filter: -

4	5	8	15
8	7	8	11
4	5	2	17
15	25	30	32

E- Laplacian Filter…

The Laplace smoothing technique is mainly used to detect image edges. It highlights gray-level discontinuities. It is based on the second spatial derivation of an image. The equation below has been used to define the Laplacian operator.

$$Laplace(f) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

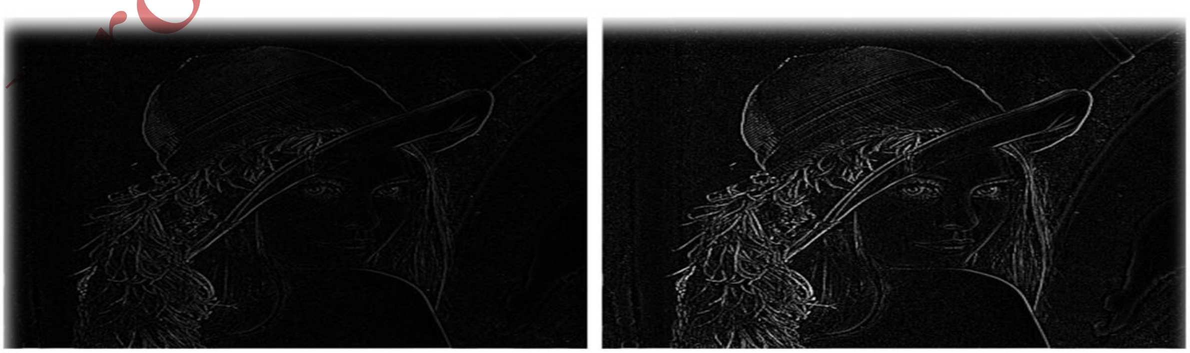
Laplace edge detectors use only one kernel. To detect the edges of an image, this kernel detects 2nd-order derivatives of the image's intensity levels by using only a single pass. We can use "kernel 2" to detect edges with diagonals. It will give a better approximation. Also, the Laplace method gives faster calculations than others.

0	-1	0
-1	4	-1
0	-1	0

Kernel 1

-1	-1	-1
-1	8	-1
-1	-1	-1

Kernel 2

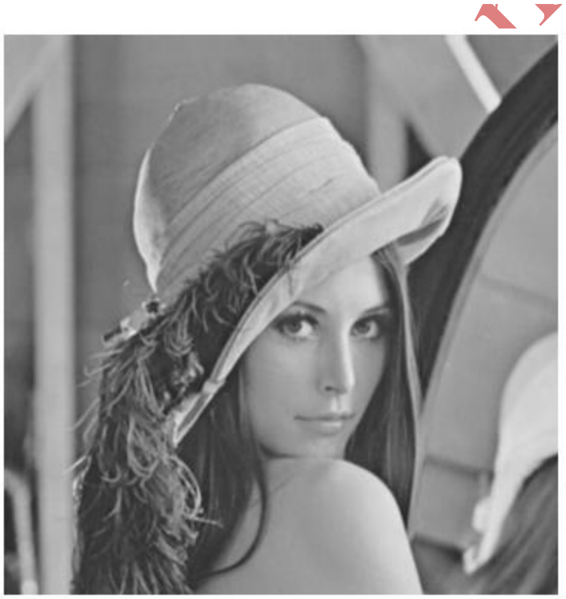


Kernel 1 Kernel 2

F- Gaussian Filter

This filter is a 2-D convolutional operator. It is used to blur images. Also, it removes details and noises. The Gaussian filter is similar to the mean filter. But the main difference is, that the Gaussian filter uses a kernel. That kernel has a shape of a Gaussian hump. Gaussian kernel weights pixels at its center much more strongly than its boundaries. There are different Gaussian kernels. Based on the kernel size, the output image will be different.

$$\frac{1}{16} \times \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \qquad \frac{1}{273} \times \begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$



3X3 Kernel

5x5 Kernel

(4-2-1-2) Adaptive Filters: -

These filters are based on the location statistics of the image and also on the mathematical model.

Adaptive filters are commonly used in image processing to enhance or restore data by removing noise without significantly blurring the structures in the image.

a- Lea and Kaun Filters.

b- Homomorphic filters. (**Powerful filters**)

a) Lea and Kaun Filters.

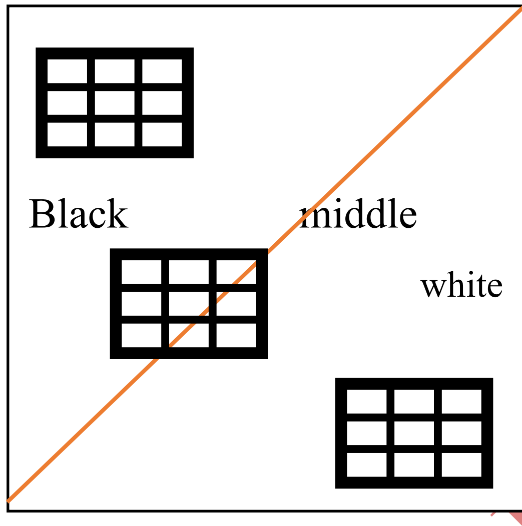
$$\bar{R}(x,y) = \underbrace{W\bar{I}}_{\text{Smoothing}} - \underbrace{(1 - W) I}_{\text{Edge}}$$

يعمل تنعيم كبير   يحافظ على الحافات

$$0 \leq W \leq 1$$

- A window has been placed on different image areas (black, white, and middle) to interpret each region?

Black and white	Middle
No edge	Edge Presence Edge and blurring
μ , σ = very small **≈ 0** تباين قليل لذلك تعمل تنعيم	**μ , σ = very high** تباين عالي (منطقة الحافة مهمة بسبب احتواءها على اغلب المعلومات فيجب المحافظة عليها)
W = 1 عامل التنعيم **R=I**	**W= different values وجود موديلين من الضوضاء الجمعية والضربية**
التنعيم بنسبة 100% (فلتر المعدل)	W= 0 **حافات قوية دون تشويه**



b-Homomorphic filters

1- It is one of the most powerful filters, but alone it is not powerful

If we have additive noise related to R.R^2, we take either the square root or the cube root of R.

$$R\,R^2 = \mathbf{R}\sqrt{\boldsymbol{R^2}}$$

2- If the noise is Multiplicative, then the situation is difficult here, take its logarithm

$$I = R.\,F$$

$$\text{Log}(I) = \log(R) + \log(F)$$

تم تحويل الموديل من الضرب الى جمع

$$\bar{\mathbf{I}} = (\bar{\mathbf{R}} + \bar{\mathbf{n}})$$

الان نستطيع المعالجة بالأساليب التقليدية.

(4-2-1-3) Edge Detection Filters (derivative Operator)

It plays an important role in many image processing applications and is very important in the process of analyzing the image and extracting useful information and features from it through the edge. The presence of the edge depends on the value of the point and its similarity to the values of its neighboring points. If the grayscale value of a particular point is similar to the values of its neighbors, it is not considered an edge. If the difference is large, then it represents an edge.

Its uses

1- To improve the edges in the image by increasing the contrast, that is, the sharpness of the details in the image. This is the opposite of smoothing, which weakens the edge.

2- Improve contrast 3- Image analysis, that is, extracting edges that represent details of the image or a feature of the body, and extracting edges with features that are different from each other.

- **Edge: -** A discontinuity in grayscale values, that is, a sudden change in the values of a point with its neighbors, as well as a change in color and texture.
- **Thresholding:** - It is a process that takes place after distinguishing and showing the contrast and the effect of the points that are part of an edge, after which the points are connected to form the boundaries that distinguish the components and separate them from the background of the image, and they are chosen intuitively.

$$T = \frac{\sum F(i,j)}{W x h} \quad \approx 0 \Rightarrow 1$$

➢ There are several derived filters, which are:

1- Robert's mask Filter: - Gx=

-1	0
0	1

, Gy=

0	-1
1	0

كشف الحافات الافقية **كشف الحافات العمودية**

2- Soble Mask: - Gx=¼

1	2	1
0	0	0
-1	-2	-1

كشف الحافات الافقية

Gy=¼

1	0	-1
2	0	-2
1	0	-1

3-Laplacian filter: - 1/4 ,

1	2	1
0	0	0
-1	-2	-1

1/8

1	1	1
1	-8	1
1	1	1

يستخدم لتحسين التفاصيل في جميع الاتجاهات وتكون الحافات واضحة في هذا الفلتر.

4-Laplacian + addition **يستخدم لتحسين الحافات لا تساوي صفر**

0	-1	0
-1	5	-1
0	-1	0

5-Convolution filter: - (مهم جدا) يعمل على التواء الصورة

Gx=

- 1	1

Gy=

1
-1

6- Sharping filter: -

من الفلاتر المهمة التي تعمل على أ- تقوية الحافات ب- زيادة التباين أي زيادة الحدة في التفاصيل ج- تنعيم الحافات.

عرفنا ان معدل فلاتر التنعيم = 1 معدل فلاتر الحافات = صفر

اما معدل فلاتر الحدة فلا يساوي صفر ولا واحد

1/8

1	1	1
1	-9	1
1	1	1

7- Uniform filter (average Mask)

1/9

1	1	1
1	1	1
1	1	1

Non-uniform filter

1/16

1	2	1
2	4	2
1	2	1

يفضل الفلتر غير المنتظم وذلك لأنه أكثر وزنا.

✓ **الفلاتر السابقة تعتمد على المشتقة**

اسود	بيضاء
x+1, y	x, y

1D

$\Delta x = 1 \qquad , \frac{\partial f}{\partial x} = f\ (x+1,y) - f(x,y)$

x, y+1	x, y

$\Delta y = 1 \qquad , \frac{\partial f}{\partial y} = f\ (x,y+1) - f(x,y)$

المشتقة الثانية

$$\frac{\partial^2 f}{\partial x^2} = f\ (x+1,y) + f(x-1,y) - 2\,f\ (x,y) \quad \ldots.(\ 4\text{-}1)$$

$$\frac{\partial^2 f}{\partial y^2} = f\ (x,y+1) + f(x,y-1) - 2\,f(x,y) \quad \ldots..(4\text{-}2)$$

The gradient

$$\nabla f = \frac{\partial f(x,y)}{\partial x} + \frac{\partial f(x,y)}{\partial y} = \frac{\partial f(x,y)}{\partial x\,\partial y}$$

➢Laplacian

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

بتعويض المعادلات (4-1)و(4-2) في المعادلة السابقة لنحصل على

$$\nabla^2 f = f\ (x+1,y) + f(x-1,y) + f\,(x,y+1) + f(x,y-1) - 4\,f(x,y) \quad \text{...........(4-3)}$$

هناك بعض المؤثرات تستعمل اكثر من دالة مثل لابلاس +الجمع وكالاتي :-

g(x,y) =

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

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

➢Laplacian + addition

$$g(x, y)= f(x, y) - [\ f(x+1,y) + f(x-1, y) + f(x, y+1) + f(x, y-1)\ ] + 4 f(x, y)$$

$$= 5 f(x, y) -[\ f(x+1,y) + f(x-1, y) + f(x, y+1) + f(x, y-1)\ ]$$

To calculate

$\nabla^2 f = |\ Gx^2 + Gy^2\ |$

$\nabla f = |\ Gx^2 + Gy^2\ |^{1/2}$ ……..(4-4)

To calculate the Roberts mask

C_1	C_2	C_3
C_4	C_5	C_6
C_7	C_8	C_9

$Gx = |\ C_9 - C_5|$

$Gy = |\ C_8 - C_6|$

$\nabla f = |\ Gx^2 + Gy^2\ |^{1/2}$

-1	0
0	1

0	-1
1	0

If g =max (Gx, Gy) ≥ threshold then edge point e (x, y) =255 else e (x, y) =0 (Smoothing)

To calculate the Soble Mask

$Gx = | C_7 + 2\,C_8 + C_9 | - | C_1 + 2\,C_2 + C_3 |$

$Gy = | C_3 + 2\,C_6 + C_9 | - | C_1 + 2\,C_4 + C_7 |$

$$\nabla f = \sqrt{| Gx^2 + Gy^2 |}$$

If $g = \max(Gx, Gy) = \frac{(Gx, Gy)}{2} \geq$ threshold

then edge point e (x, y) =255 else e (x, y) =0

Example: - Apply the Roberts mask on the image, where the threshold =25?

4	3	7	100	99
5	4	100	101	103
6	7	99	102	113
10	8	8	100	104

Solution: -

The Robert's mask

$$Gx = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}, \qquad Gy = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

1- V(4)= ?

Gx= -4 +4 = 0

Gy= -3 + 5= 2 $\longrightarrow$ $\nabla f = |0| + |2| = 2$

2< th $\therefore$ **v(4) = 0**

2- V (3) =?

Gx= -3+100 =97

Gy= -7+ 4 = -3 ⟶ **∇f= |97| +| -3| = 97+3=100**

100 > th **∴ v(3) = 255**

3- V(7) =?

Gx= -7+101= 94

Gy = 100-100=0 ⟹ **∇f= |94| +| 0| =94+0=94**

94 > th **∴ V(7) = 255**

4- V(100) = ?

Gx = -100 + 103 = 3 , Gy = -99 + 101 = 2

∇f =|3| +| 2| =5 **5 < th** **∴ V(100) = 0**

5- V(5) = ?

Gx= -5 +7 = 2 , Gy= -4+6= 2

∇f = |2| +| 2| =4 **4 < th** **∴ V(100) = 0**

4	3	7	100	99
5	4	100	101	103
6	7	99	102	113
10	8	8	100	104

0	255	255	0	0
0	255	0	0	0
0	255	255	0	0
0	0	0	0	0

Example: - Apply the Soble mask on the same image, where the threshold = 25?

Solution: -

Gx=1/4

1	2	1
0	0	0
-1	-2	-1

Gy =1/4

1	0	-1
2	0	-2
1	0	-1

4	3	7	100	99
5	4	100	101	103
6	7	99	102	113
10	8	8	100	104

1- V(4)= ?

Gx= ¼ | 4+6+7-6-14-99| =1/4 |-102|=1/4 *102 =102/4 = 25.5

Gy= ¼ | 4+10+6 -7-200-99 | = ¼ |-286|= 1/4 * 286 =286/4 = 71.5

g =(Gx+Gy) /2 = 48.5

g = max (Gx, Gy) > th. then e (x, y) = 255

2- V(100)= ?

Gx= ¼ | 3+14+100-7-198-102| = 1/4 |-190|

Gx = ¼ * 190 = 190/4 =47.5

Gy = ¼ | 3+8+7 -100-202-102|= ¼|-386|= 96.5

g =(Gx+Gy) /2 = 72

g = max (Gx, Gy) > th. then e (x, y) = 255

3- V(101)=?

Gx= ¼ | 7+ 200+99-33-204-113|= ¼|-110|

= 110/4= 27.5

Gy= ¼| 7+200+99-99-206-113|= ¼|-112|

= 112/4 = 28

g =(Gx+Gy) /2 = 55.5/2=27.75

g = max (Gx, Gy) > th. then e (x, y) = 255

وهكذا بقية البكسلات لتنتج الصورة الاتية

4	3	7	100	99
5	4	100	101	103
6	7	99	102	113
10	8	8	100	104

0	0	0	0	0
0	255	255	255	0
0	255	255	255	0
0	0	0	0	0

Example: - Apply the mask average (1) for the following matrix?

1/9

1	1	1
1	1	1
1	1	1

0	1	10	100	102	103
5	4	11	102	108	100
4	7	100	103	105	103
5	8	9	10	100	102
10	50	50	57	60	61
10	51	52	55	61	52

Sol.

Row 2

2-R (4) = 1/9 (0+1+10+5+4+11+4+7+100) = 142/9 =16

2-R (11) =1/9(1+10+100+4+11+102+7+100+103) =438/9=49

2-R(102)=1/9(10+100+102+11+102+108+100+103+105)=741/9= 82.3 =82

2-R(108)= 1/9(100+102+103+102+108+100+103+105+103)=926/9=102.8=103

Row 3

3-R (7) = 1/9(5+4+11+4+7+100+5+8+9)=153/9 = 17

3-R (100) = 1/9(4+11+102+7+100+103+8+9+10) = 354/9=39.3=39

3-R(103)= 1/9(11+102+108+100+103+105+9+10+100)=648/9=72

3-R(105)= 1/9(102+108+100+103+105+103+10+100+102)=833/9= 92.5=93

Row 4

4-R(8)= 1/9(4+7+100+5+8+9+10+50+50)=243/9 =27

4-R(9)= 1/9(7+100+103+8+9+10+50+50+57)= 394/9=43.7=44

4-R(10)=1/9(100+103+105+9+10+100+50+57+60)=594/9=66

4-R(100)=1/9(103+105+103+10+100+102+57+60+61)=701/9=77.8 =78

وهكذا للصف الخامس نقوم بنفس العمل
اما الصف الأول والسادس والعمود الاول والسادس فيتم تصفيرهم فتصبح المصفوفة كالاتي:-

0	1	10	100	102	103
5	4	11	102	108	100
4	7	100	103	105	103
5	8	9	10	100	102
10	50	50	57	60	61
10	51	52	55	61	52

→

0	0	0	0	0	0
0	16	49	82	103	0
0	17	39	72	93	0
0	27	44	66	78	0
0	27	38	50	62	0
0	0	0	0	0	0

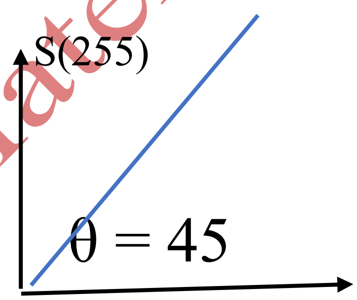
H.W: - Apply the mask average (2) for same matrix?

(4-3) Image Mapping (Gray level Transformation)

Enhancing an image provides better contrast and more detail than a non-enhanced image. Image enhancement has many applications. It is used to enhancement medical images, images captured in remote sensing, images from satellites e.t.c

The identity transformation function is given below

$S = r$



$S = T(r)$ ....(4- 5)

Where r =f (x, y) input image (الاصلية)

S= g (x, y) output image (المعالجة)

In the above equation, we note that there is no effect on the output image, and the angle between the input and output images is $\theta = 45^{\circ}$

➢Gray level transformation

There are three basic gray-level transformations

1- Identity

$S = r$ تم شرحها سابقا

Gray level = 0 ⟶ 255

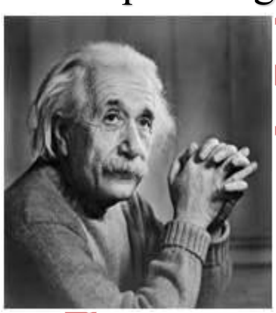
$S = g(x,y) / 255$, $r = f(x,y) / 255$

2-Image Negative

The second linear transformation is negative transformation, which is an invert of identity transformation. In negative transformation, each value of the input image is subtracted from the L-1 and mapped onto the output image.

The result is somewhat like this.

Input Image



Output Image

In this case, the following transition has been done.

$$S = (L - 1) - r \;\dots\dots\dots\dots\; (4\text{-}6)$$

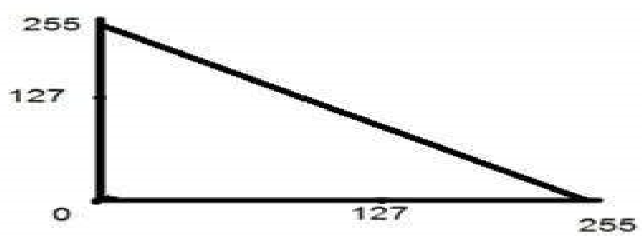
since the input image of Einstein is an 8 bpp (bit per pixel) image, the number of levels in this image is 256. Putting 256 in the equation, we get this

$S = 255 - r$ مستويات الصورة الداخلة**...(4-7)**

So, each value is subtracted by 255 and the resulting image is shown above. So, what happens is that the lighter pixels become dark and the darker picture becomes light. And it results in a image negative.

It has been shown in the graph below.

- ✓ **أذا كان المستويات الرمادية للصورة في المدى (0 , L-1)، L= 256**
  يقصد بالتحويل السالب إذا كان البكسل اسود يصبح ابيض وبالعكس.



3-Logarithmic transformations

Logarithmic transformation further contains two types of transformation. Log transformation and inverse log transformation.

a) Log Transformation: -

The log transformations can be defined by this formula

$$S = c \log (r + 1) \qquad \text{………..(4-8)}$$

Where s and r are the pixel values of the output and the input image and c is a constant. The value 1 is added to each of the pixel values of the input image because if there is a pixel intensity of 0 in the image, then log (0) is equal to infinity. So, 1 is added, to make the minimum value at least 1.

During log transformation, the dark pixels in an image are expanded as compared to the higher pixel values. The higher pixel values are kind of compressed in log transformation. This results in the following image enhancement.

The value of c in the log transform adjusts the kind of enhancement you are looking for.

b) Inverse Log transformation

The inverse log transform is opposite to log transform.
It is given by the following equation: -

$$S = C\,10^{r} \quad \ldots\ldots\ (4\text{-}9)$$

4- Power – low Transformation

There are further two transformations power law transformations, which include nth power and nth root transformation. The transformations can be given by the expression:

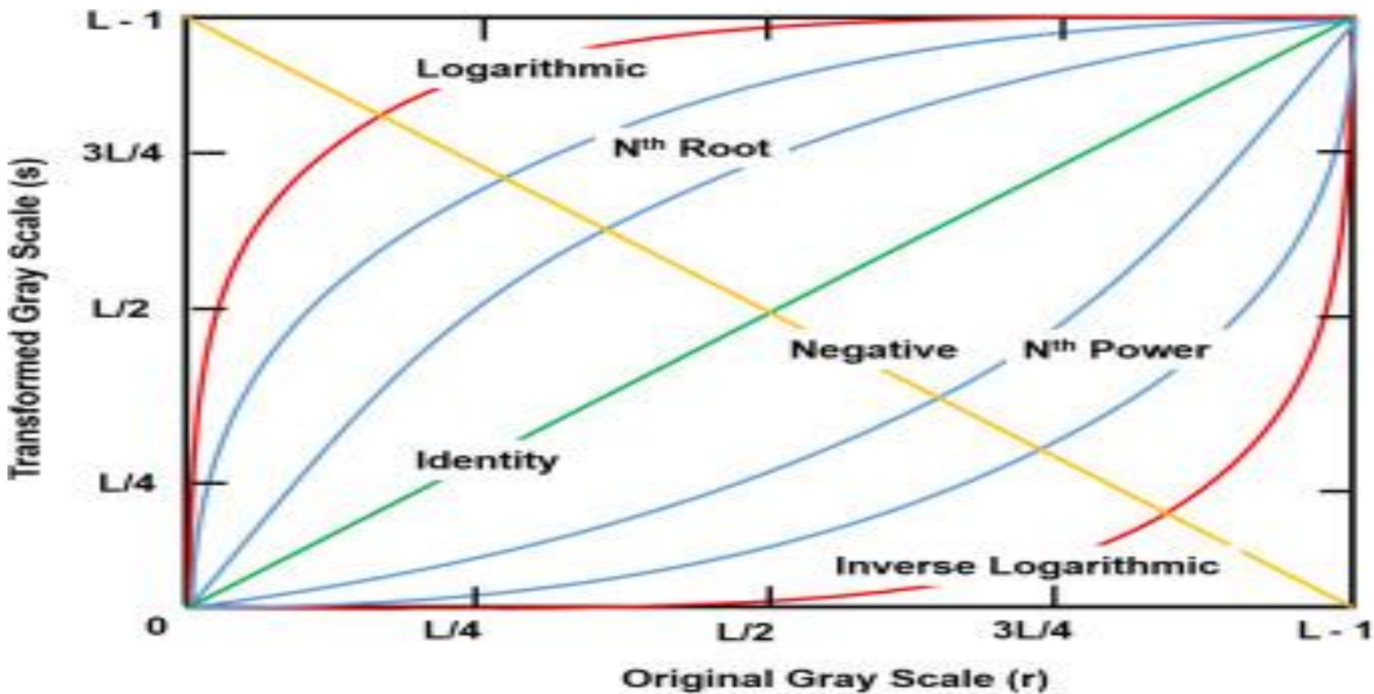
$$S = c\,r^{\gamma} \quad \ldots\ldots(4\text{-}10)\ \text{power}$$

$$S = C\,r^{1/\gamma} \quad \ldots\ldots(4\text{-}11)\ \text{root}$$

This symbol γ is called gamma, due to which this transformation is also known as gamma transformation.

Variation in the value of γ varies the enhancement of the images. Different display devices/monitors have their gamma correction, which is why they display their images at different intensities.

The following figure shows the types of transformations: -



Example: - Find a Negative image for the following image?

Sol.

Origin image

0	1	0	0
2	1	3	1
200	255	251	1
255	1	0	1

Negative image

255	254	255	255
253	254	252	254
5	0	1	254
0	254	255	254

كل ما تم شرحه سابقا هي الفلاتر (المرشحات) المكانية التي تعتمد على الموقع

المكاني. اما النوع الثاني فهي الفلاتر الترددية.

(4-2-2) Frequency domain: -

A frequency filter is an electrical circuit that sometimes changes the amplitude and phase of an electrical signal for frequency. Filters are used in many electronic and communications applications

It is another type of filter that converts the image from spatial coordinates (x, y) to frequency coordinates (u, v) by applying Fourier transforms.

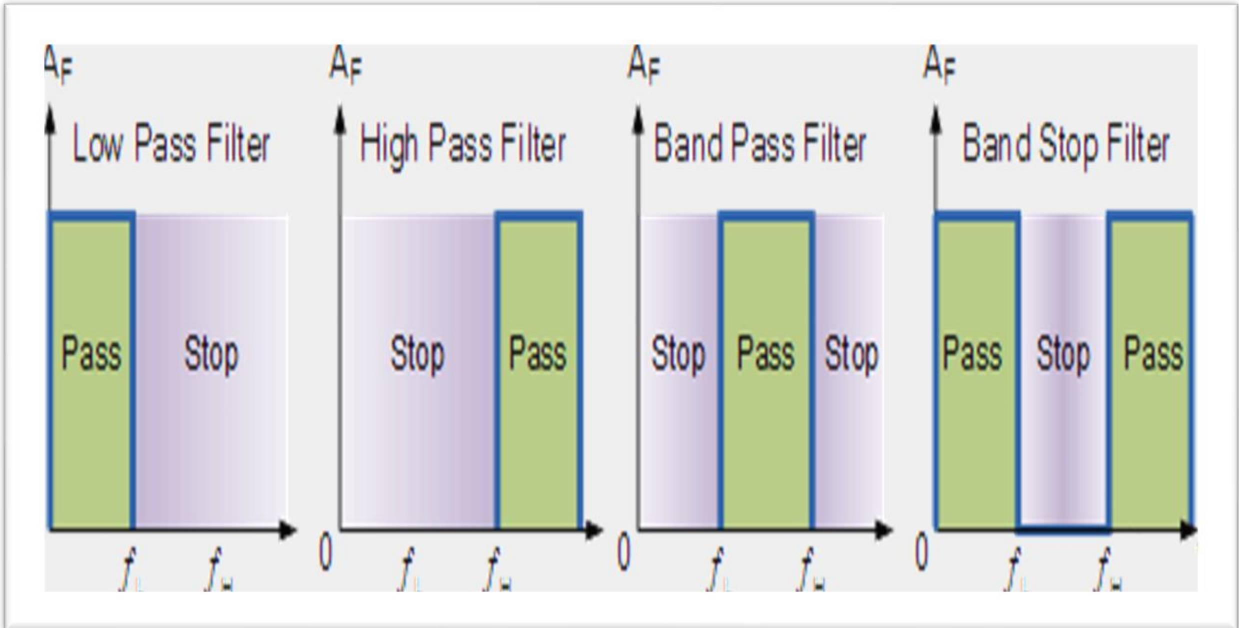
The classification is based on the frequency range that the filter allows to pass through

1-The low-pass filter allows low-frequency signals ranging from 0 Hz to the designed cut-off frequency point and attenuates higher frequencies

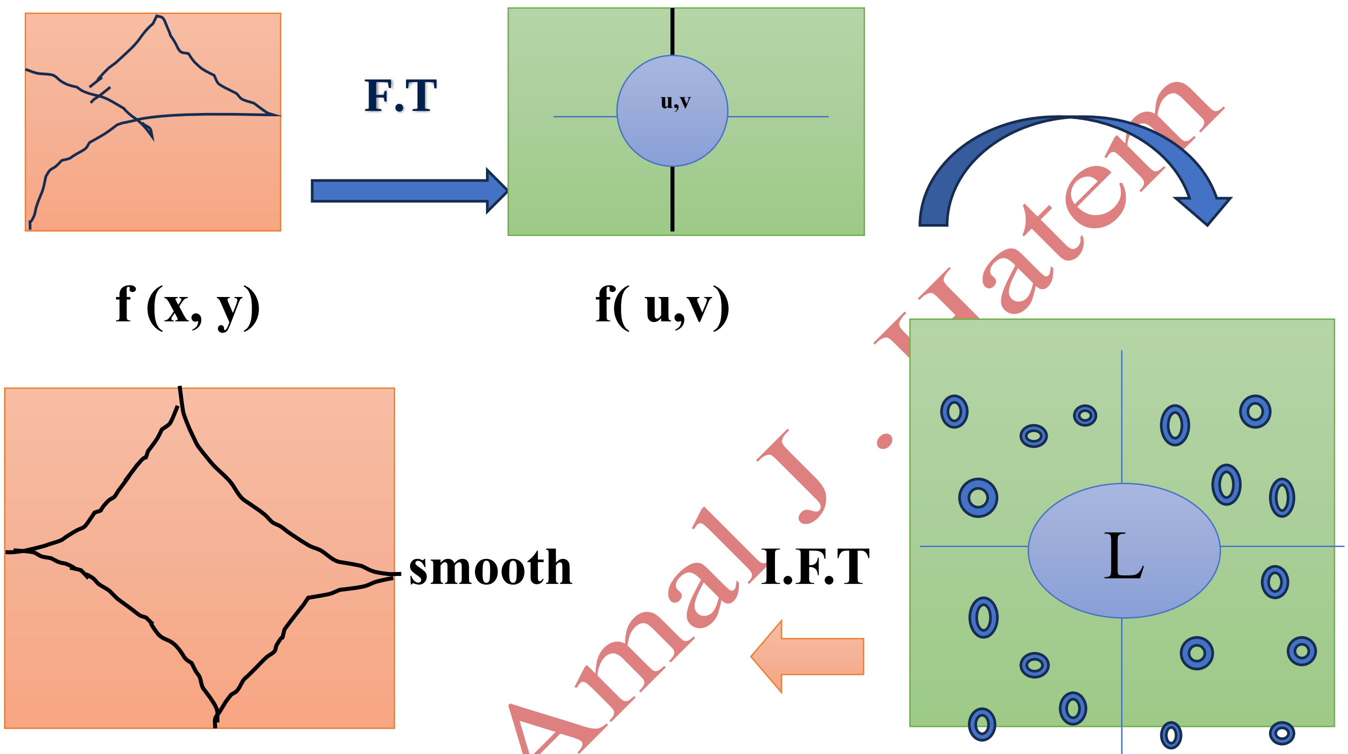
3-The high-pass filter allows those signals above the cut-off frequency and blocks all signals below.

4-A band-pass filter allows signals within a specified frequency range to pass while blocking higher and lower frequencies outside that range.

5- Band Stop attenuates signals within the specified band or band and allows higher and lower frequencies to pass outside the band.

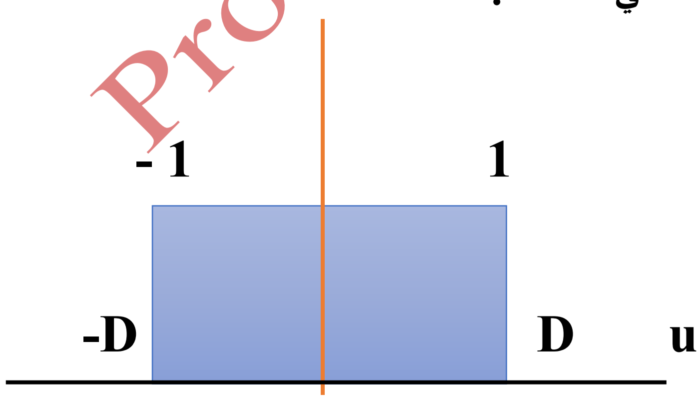

A_F
Low Pass Filter
Pass
Stop
A_F
High Pass Filter
0
Stop
Pass
A_F
Band Pass Filter
0
Stop
Pass
Stop
A_F
Band Stop Filter
0
Pass
Stop
Pass

(4-2-2-1) Low pass Filter



In the frequency range, a low-pass filter softens the image because high frequencies include image details such as edges, and low-pass filters process these edges to give us a smooth image.

✓ D يعمل على تنعيم عالي للصورة وتشوه عالي للحافات.

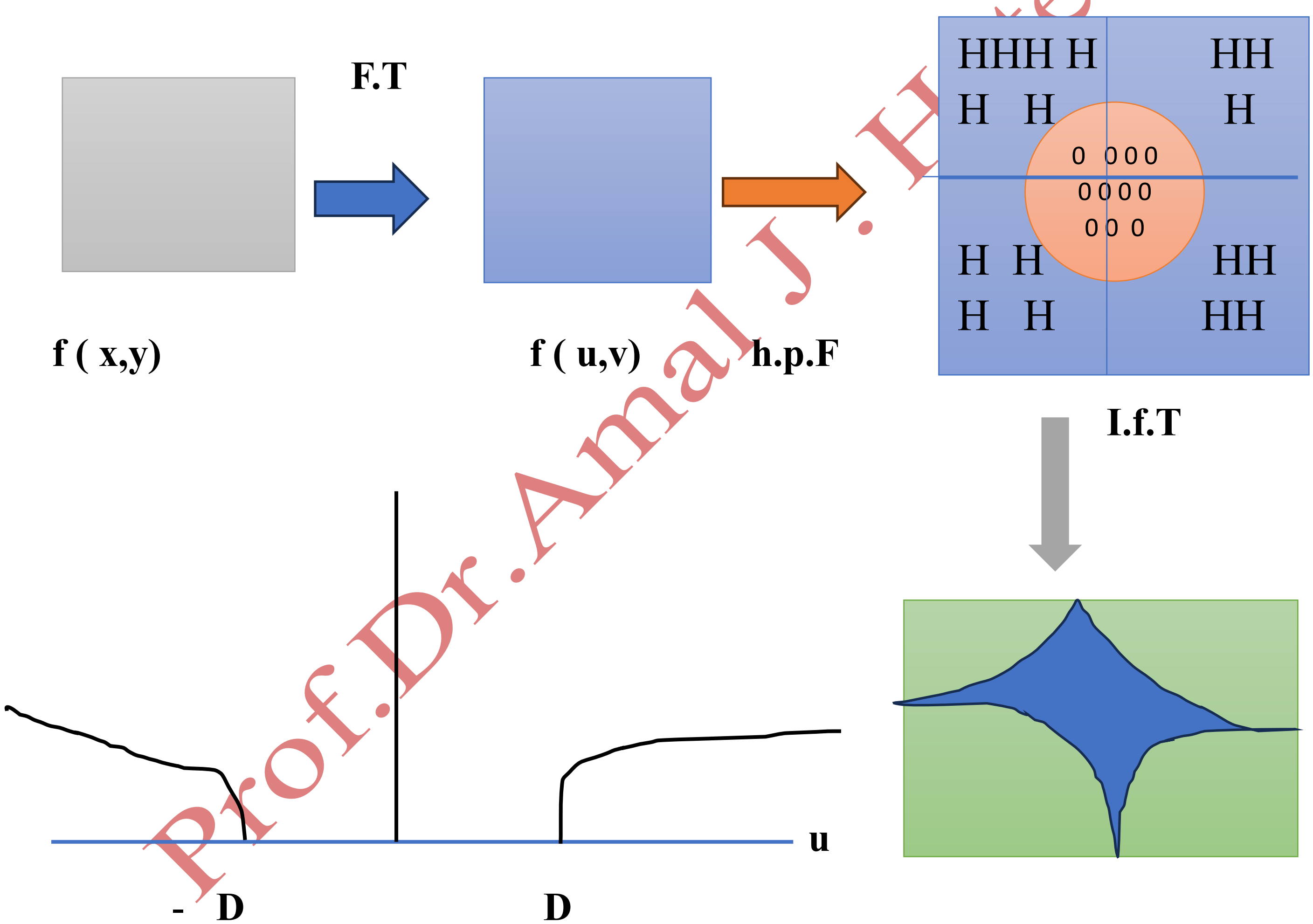


				f(x) u>1
?	?	0	0	f(u) = 0

(4-2-2-2) High pass Filter

A filter that converts the image from spatial coordinates to frequency coordinates using Fourier transforms.

This filter passes high frequencies and cuts low frequencies in the frequency cutoff region.



0	0	?	?

u≤ 1

D عندما يقل فان سمك الحافة يزداد

(4-3) Fourier transforms

Fourier transform is a mathematical process used to convert mathematical functions from the time domain to the frequency domain. It is useful for analyzing signals and knowing the frequencies they contain.

There are two formulas for Fourier transformations: one for the forward transformation from spatial coordinates to frequency coordinates and the other for the inverse transformation from frequency coordinates to spatial coordinates.

The first formula is called the forward Fourier formula in (1D)

$$F(u) = \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x)\, e^{\frac{-2\pi i u x}{N}} \qquad \ldots\ldots(4\text{-}12)$$

The Second formula is called the inverse Fourier formula

$$F(x) = \frac{1}{\sqrt{N}} \sum_{u=0}^{N-1} f(u)\, e^{\frac{+2\pi i u x}{N}} \qquad \ldots\ldots(4\text{-}13)$$

The Fourier transform allows for the decomposition of an image into a weighted sum of 2-D sinusoidal terms. Assuming an N×N image, the equation for the 2-D discrete Fourier Transform (2-D DFT).

$$f\,(u,v) = \frac{1}{\sqrt{MN}} \sum_{X=0}^{M-1} \sum_{y=0}^{N-1} f\,(x,y)\; e^{\frac{-2\pi i\,(ux+vy)}{MN}}$$

Where $e^{ix} = \cos x + i \sin x$

The inverse Fourier transform is given by:

$$f\,(x,y) = \frac{1}{\sqrt{MN}} \sum_{X=0}^{M-1} \sum_{y=0}^{N-1} f\,(u,v)\; e^{\frac{+2\pi i\,(ux+vy)}{MN}}$$

Example: - Find the forward Fourier transform of the following matrix

2	3	4	7

Solution: -

x	x	x	x
0	1	2	3
2	3	4	7

f (x) = ? , f (0) = 2 , f(1) = 3 , f (2) =4 ,f (3) =7

F.DFT

$$F(u) = \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x)\ e^{\frac{-2\pi iux}{N}}$$

$$F(u) = \frac{1}{\sqrt{4}} \sum_{x=0}^{3} f(x)\ e^{\frac{-2\pi iux}{4}}$$

$$F(u) = \frac{1}{2} \sum_{x=0}^{3} f(x)\ e^{\frac{-\pi iux}{2}}$$

F(0)=$\frac{1}{2}\sum_{x=0}^{3}$ $f(0)\ e^{\frac{-\pi i x 0}{2}} + f(1)\, e^{\frac{-\pi i x 0}{2}} + f(2)\, e^{\frac{-\pi i x 0}{2}} + f(3) e^{\frac{-\pi i x 0}{2}}$

$\because e^{0} = 1$

$$F(0) = \frac{1}{2}\, [\,2 + 3 + 4 + 7] = \frac{16}{2} = 8$$

F (0) = 8+ 0i .... (1)

$$e^{-i\theta} = \cos\theta - i \sin\theta$$

$$F(1) = \frac{1}{2}\sum_{x=0}^{3} \quad f(x)\ e^{\frac{-\pi i x 1}{2}}$$

$$F(1) = \frac{1}{2}\Big[\ \sum_{x=0}^{3} \quad f(x)\,\{\cos\left(\frac{\pi x}{2}\right) - i \sin\left(\frac{\pi x}{2}\right)\}\Big]$$

$$F(1) = \frac{1}{2}\ [\quad \{ f(0) * \cos(0) + f(1) * \cos\left(\frac{\pi}{2}\right) + f(2) * \cos(\pi) + f(3) * \cos\left(\frac{3\pi}{2}\right)\} - i\,\{f(0) * \sin(0) + f(1) * \sin\left(\frac{\pi}{2}\right) + f(2) * \sin(\pi) + f(3) * \sin\left(\frac{3\pi}{2}\right)\}]$$

$$F(1) = \frac{1}{2}\,[\{(2 * 1) + (3 * 0) + (4 * -1) + (7 * 0)\} - i\{(2 * 0) + (3 * 1) + (4 * 0) + (7 * -1)\}]$$

$$= \frac{1}{2}\ [\,(2 - 4) - i(3 - 7)]$$

$$= \frac{1}{2}\ [-2 + 4i] = -1 + 2i$$

F (1) = $-1 + 2i$ .... (2)

$$F(u) = \frac{1}{2}\sum_{x=0}^{3} f(x)\; e^{\frac{-\pi i u x}{2}}$$

$$F(2) = \frac{1}{2}\sum_{x=0}^{3} f(x)\; e^{\frac{-\pi i 2 x}{2}}$$

$$F(2) = \frac{1}{2}\sum_{x=0}^{3} f(x)\; e^{-i\pi x}$$

$$\because\; e^{-i\pi x} = \boldsymbol{cos}(\pi x) - i\sin(\pi x)$$

F (2) $= \frac{1}{2}$ [$\{ f(0) * \cos(0) + f(\mathbf{1}) * \cos(\pi) + f(\mathbf{2}) * \cos(\mathbf{2}\pi) + f(\mathbf{3}) * \cos(\mathbf{3}\pi)\} - i\{f(0) * \sin(0) + f(1) * \sin(\pi) + f(\mathbf{2}) * \sin(2\pi) + f(\mathbf{3}) * \sin(3\pi)\}$]

F (2) = $\frac{1}{2}$ $[\{(2 * 1) + (3 * -1) + (4 * 1) + (7 * -1)\}$
- $i\,\{(2 * 0) + (3 * 0) + (4 * 0) + (7 * 0)\}]$

F (2) = $\frac{1}{2}$ [{2-3+4-7}- 0 i] $= \frac{1}{2}[6 - 10 - 0i] = -2 - 0i$

F (2) = $-2 - 0i$ ………………………... (3)

$$F(u) = \frac{1}{2}\sum_{x=0}^{3} f(x)\ e^{\frac{-i\pi ux}{2}}$$

$$F(3) = \frac{1}{2}\sum_{x=0}^{3} f(x)\ e^{\frac{-i\pi 3x}{2}}$$

$$F(3) = \frac{1}{2}\sum_{x=0}^{3} f(x)\ e^{\frac{-i3\pi x}{2}}$$

$$e^{\frac{-i3\pi x}{2}} = \cos(\frac{3\pi x}{2}) - i\sin(\frac{3\pi x}{2})$$

$F(3) = \frac{1}{2}[\ \{f(0) * \cos(0) + f(1) * \cos\left(\frac{3\pi}{2}\right) + f(2) * \cos(3\pi) + f(3) * \cos\left(\frac{9\pi}{2}\right)\} - i\{f(0) * \sin(0) + f(1) * \sin\left(\frac{3\pi}{2}\right) + f(2) * \sin(3\pi) + f(3) * \sin\left(\frac{9\pi}{2}\right)\}]$

$F(3) = \frac{1}{2}[\{(2 * 1) + (3 * 0) + (4 * -1) + (7 * 0)\} - i\{(2 * 0) + (3 * -1) + (4 * 0) + (7 * 1)\}$

$F(3) = \frac{1}{2}[\{2 - 4\} - i\{-3 + 7\}] = \frac{1}{2}[-2 - 4i] = -1 - 2i$

$\therefore F(3) = -1 - 2i \ldots\ldots\ldots(4)$

F(u) = F(0) = 8 +0i , F (1) = -1+2i

F(2) = -2 -0i , F(3) = $-1 - 2i$

$\therefore F(u) =$

8+0i	**-1+2i**	**-2-0i**	**-1 -2i**

1) $\therefore F(u) =$

8	**-1+2i**	**-2**	**-1 -2i**

2) The low pass Filter is

u≥ 1

8	**-1+2i**	**0**	**0**

3) The high pass Filter is

u ≤ 1

0	**0**	**-2**	**-1 -2i**