UNIT-III

IMAGE ENHANCEMENT

IMAGE ENHANCEMENT IN SPATIAL DOMAIN:

3.1. Introduction

The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. Image enhancement approaches fall into two board categories.

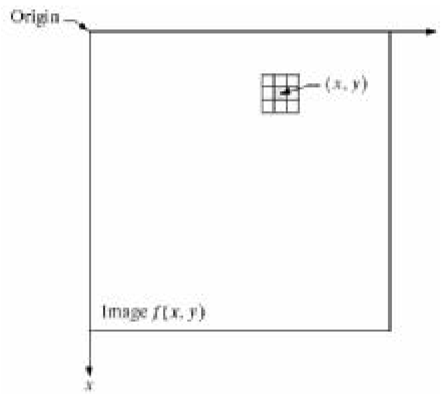
1. Spatial domain methods
2. Frequency domain methods

The term spatial domain refers to the image plane itself and approaches in this categories are based on direct manipulation of pixel in an image. Spatial domain process are denoted by the expression

$$g(x,y)=T[f(x,y)]$$

Where f(x,y)- input image, T- operator on f, defined over some neighborhood of f(x,y) and g(x,y)-processed image

The neighborhood of a point (x,y) can be explain by using as square or rectangular sub image area centered at (x,y).



The center of sub image is moved from pixel to pixel starting at the top left corner. The operator T is applied to each location (x,y) to find the output g at that location . The process utilizes only the pixel in the area of the image spanned by the neighborhood.

3.2 Basic Gray Level Transformation Functions

It is the simplest form of the transformations when the neighborhood is of size IXI. In this case g depends only on the value of f at (x,y) and T becomes a gray level transformation function of the forms

$$S=T(r)$$

r- Denotes the gray level of f(x,y)

s- Denotes the gray level of g(x,y) at any point (x,y)

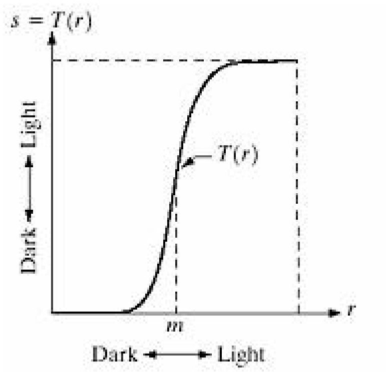
Because enhancement at any point in an image deepens only on the gray level at that point, technique in this category are referred to as point processing.

There are basically three kinds of functions in gray level transformation –

3.2.1 Point Processing:

(i) Contract stretching:

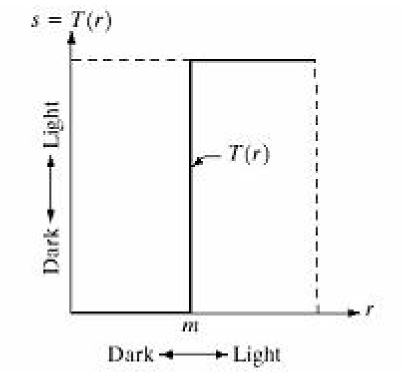
It produces an image of higher contrast than the original one. The operation is performed by darkening the levels below m and brightening the levels above m in the original image.



In this technique the value of r below m are compressed by the transformation function into a narrow range of s towards black .The opposite effect takes place for the values of r above m.

(ii) Thresholding function:

It is a limiting case where T(r) produces a two levels binary image. The values below m are transformed as black and above m are transformed as white.



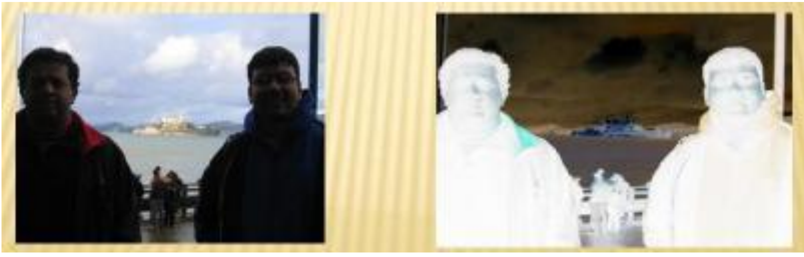
3.2.2 Basic Gray Level Transformation:

These are the simplest image enhancement techniques.

(i) Image Negative:

The negative of in image with gray level in the range [0, l, -1] is obtained by using the negative transformation. The expression of the transformation is

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



Reverting the intensity levels of an image in this manner produces the equivalent of a photographic negative. This type of processing is practically suited for enhancing white or gray details embedded in dark regions of an image especially when the black areas are dominant in size.

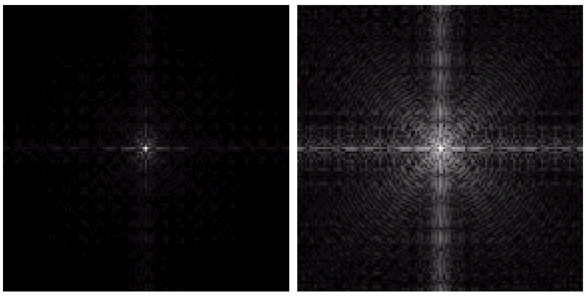
(ii) Log transformations:

The general form of the log transformation is **s= c log(1+r)**

Where c- constant and r ≥ o

This transformation maps a narrow range of gray level values in the input image into a wider range of output gray levels. The opposite is true for higher values of input levels. We would use this transformations to expand the values of dark pixels in an image while compressing the higher level values. The opposite is true for inverse log transformation. The log transformation function has an important characteristic that it compresses the dynamic range of images with large variations in pixel values.

Eg- Fourier spectrum



(iii) Power Law Transformation:

Power law transformations has the basic form

$$S=cr^y$$

Where c and y are positive constants.

Power law curves with fractional values of y map a narrow range of dark input values into a wider range of output values, with the opposite being true for higher values of input gray levels. We may get various curves by varying values of y.

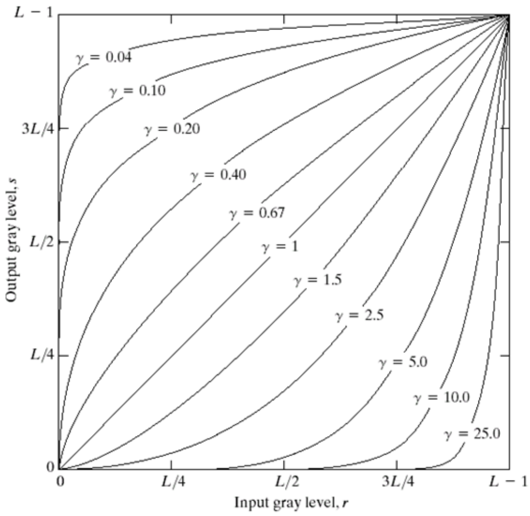


FIGURE 3.6 Plots of the equation $s = cr^{\gamma}$ for various values of γ ($c = 1$ in all cases).

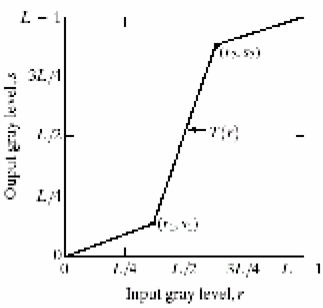
A variety of devices used for image capture, printing and display respond according to a power law. The process used to correct this power law response phenomenon is called gamma correction. For eg-CRT devices have intensity to voltage response that is a power function. Gamma correction is important if displaying an image accurately on a computer screen is of concern. Images that are not corrected properly can look either bleached out or too dark. Color phenomenon also uses this concept of gamma correction. It is becoming more popular due to use of images over the internet. It is important in general purpose contract manipulation. To make an image black we use y>1 and y<1 for white image.

3.2.3 Piece wise linear transformation functions:

The principal advantage of piecewise linear functions is that these functions can be arbitrarily Complex. But their specification requires considerably more user input.

(i) Contrast Stretching:

It is the simplest piecewise linear transformation function. We may have various low contrast images and that might result due to various reasons such as lack of illumination, problem in imaging sensor or wrong setting of lens aperture during image acquisition. The idea behind contrast stretching is to increase the dynamic range of gray levels in the image Being processed.



The location of points (r1,s1) and (r2,s2) control the shape of the curve

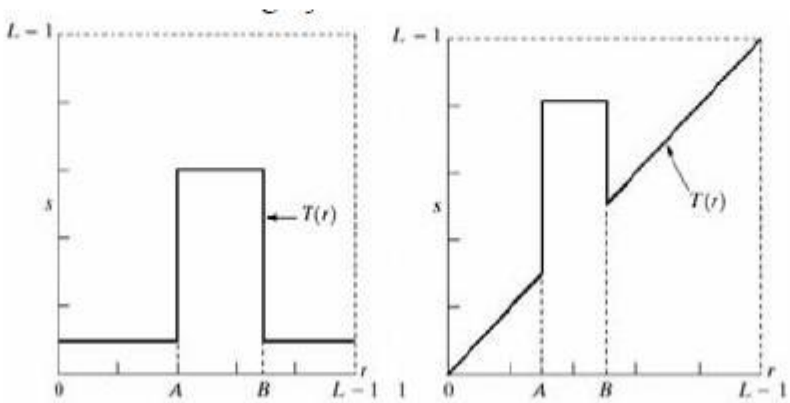
a) If r1=r2 and s1=s2, the transformation is a linear function that deduces no change in gray levels.

b) If r1=s1, s1=0 , and s2=L-1, then the transformation become a thresholding function that creates a binary image

c) Intermediate values of (r1, s1) and (r2, s2) produce various degrees of spread in the gray value of the output image thus effecting its contract.

Generally r1≤ r2 and s1≤ s2 so that the function is single valued and monotonically increasing.

(ii) Gray Level Slicing:



Highlighting a specific range of gray levels in an image is often desirable. For example when enhancing features such as masses of water in satellite image and enhancing flaws in x- ray images.

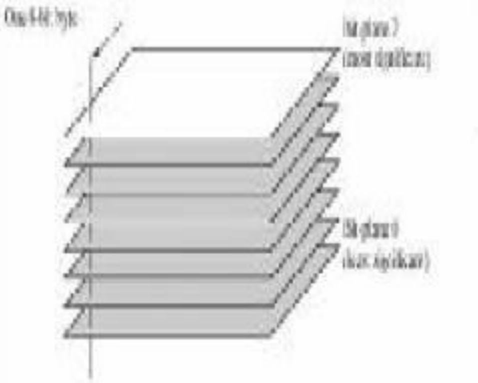
There are two ways of doing this-

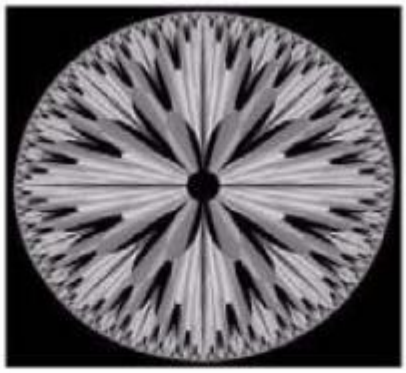
(1) One method is to display a high value for all gray level in the range. Of interest and a low value for all other gray level.

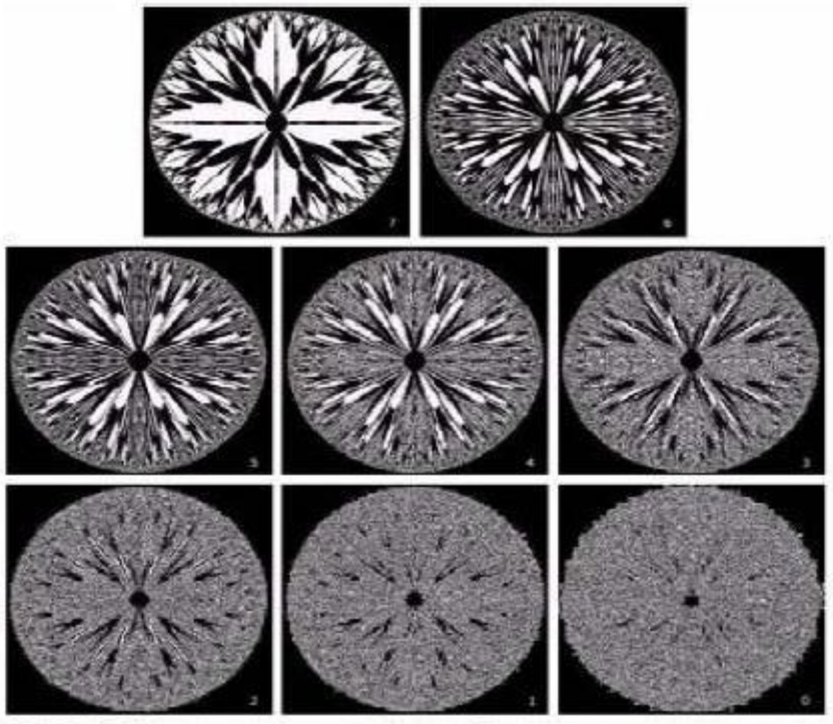
(2) Second method is to brighten the desired ranges of gray levels but preserve the background and gray level tonalities in the image.

(iii) Bit Plane Slicing:

Sometimes it is important to highlight the contribution made to the total image appearance by specific bits. Suppose that each pixel is represented by 8 bits. Imagine that an image is composed of eight 1-bit planes ranging from bit plane 0 for the least significant bit to bit plane 7 for the most significant bit. In terms of 8-bit bytes, plane 0 contains all the lowest order bits in the image and plane 7 contains all the high order bits.







High order bits contain the majority of visually significant data and contribute to more subtle details in the image. Separating a digital image into its bits planes is useful for analyzing the relative importance played by each bit of the image. It helps in determining the adequacy of the number of bits used to quantize each pixel. It is also useful for image compression.

3.3 Histogram Processing:

The histogram of a digital image with gray levels in the range [0, L-1] is a discrete function of the form

$$\mathbf{H(r_k)=n_k}$$

where r_k is the kth gray level and n_k is the number of pixels in the image having the level r_k..

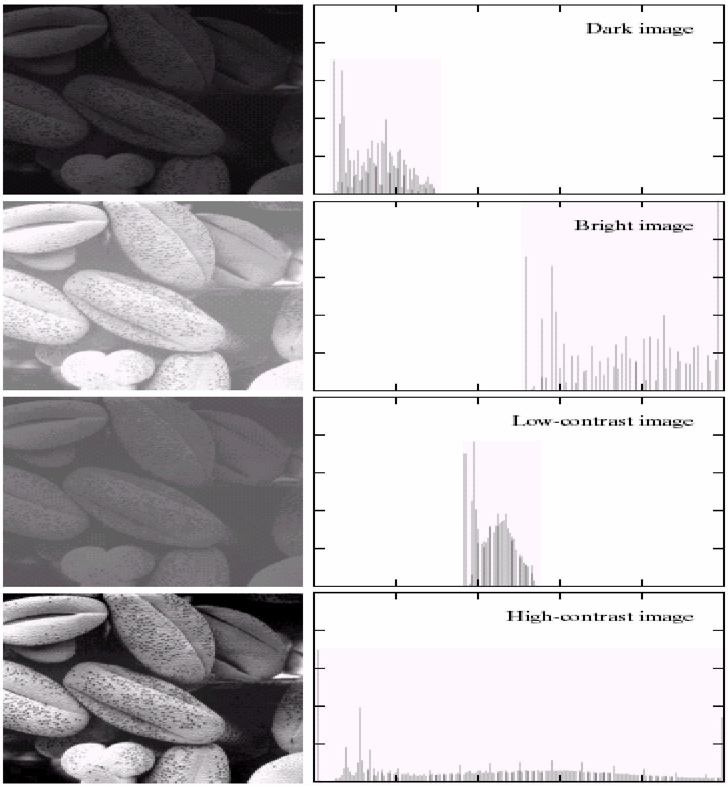
A normalized histogram is given by the equation

$$p(r_k)=n_k/n \text{ for } k=0,1,2,\ldots..,L-1$$

$P(r_k)$ gives the estimate of the probability of occurrence of gray level r_k.

The sum of all components of a normalized histogram is equal to 1.

The histogram plots are simple plots of H(rk)=nk versus rk.



In the dark image the components of the histogram are concentrated on the low (dark) side of the gray scale. In case of bright image the histogram components are baised towards the high side of the gray scale. The histogram of a low contrast image will be narrow and will be centered towards the middle of the gray scale.

The components of the histogram in the high contrast image cover a broad range of the gray scale. The net effect of this will be an image that shows a great deal of gray levels details and has high dynamic range.

3.3.1 Histogram Equalization:

Histogram equalization is a common technique for enhancing the appearance of images. Suppose we have an image which is predominantly dark. Then its histogram would be skewed towards the lower end of the grey scale and all the image detail are compressed into the dark end of the histogram. If we could ‘stretch out’ the grey levels at the dark end to produce a more uniformly distributed histogram then the image would become much clearer.

Let there be a continuous function with r being gray levels of the image to be enhanced. The range of r is [0, 1] with r=0 repressing black and r=1 representing white. The transformation function is of the form

$$S=T(r) \text{ where } 0<r<1$$

It produces a level s for every pixel value r in the original image. The transformation function is assumed to fulfill two condition T(r) is single valued and monotonically increasing in the internal 0<T(r)<1 for 0<r<1.The transformation function should be single valued so that the inverse transformations should exist. Monotonically increasing condition preserves the increasing order from black to white in the output image. The second conditions guarantee that the output gray levels will be in the same range as the input levels. The gray levels of the image may be viewed as random variables in the interval [0.1]. The most fundamental descriptor of a random variable is its probability density function (PDF) Pr(r) and Ps(s) denote the probability density functions of random variables r and s respectively. Basic results from an elementary probability theory states that if Pr(r) and Tr are known and T-1(s) satisfies conditions (a), then the probability density function Ps(s) of the transformed variable is given by the formula

$$P_s(s) = P_r(r)\frac{dr}{ds},$$

Thus the PDF of the transformed variable s is the determined by the gray levels PDF of the input image and by the chosen transformations function.

A transformation function of a particular importance in image processing

$$s = T(r) = \int_0^r P_r(w)dw$$

This is the cumulative distribution function of r.

Using this definition of T we see that the derivative of s with respect to r is

$$\frac{ds}{dr} = P_r(r).$$

Substituting it back in the expression for Ps we may get

$$P_s(s) = P_r(r)\frac{1}{P_r(r)} = 1$$

An important point here is that Tr depends on Pr(r) but the resulting Ps(s) always is uniform, and independent of the form of P(r). For discrete values we deal with probability and summations instead of probability density functions and integrals. The probability of occurrence of gray levels rk in an image as approximated

$$Pr(r) = nk/N$$

N is the total number of the pixels in an image.

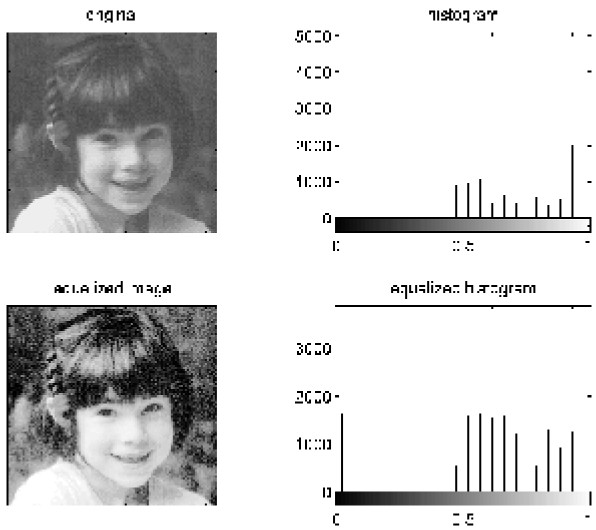
nk is the number of the pixels that have gray level rk.

L is the total number of possible gray levels in the image.

The discrete transformation function is given by

$$s_k = T(r_k) = \sum_{i=0}^{k} \frac{n_i}{N} = \sum_{i=0}^{k} P_r(r_i).$$

Thus a processed image is obtained by mapping each pixel with levels rk in the input image into a corresponding pixel with level sk in the output image. A plot of Pr (rk) versus rk is called a histogram. The transformation function given by the above equation is the called histogram equalization or linearization. Given an image the process of histogram equalization consists simple of implementing the transformation function which is based information that can be extracted directly from the given image, without the need for further parameter specification.



Equalization automatically determines a transformation function that seeks to produce an output image that has a uniform histogram. It is a good approach when automatic enhancement is needed.

3.3.2 Histogram Matching (Specification):

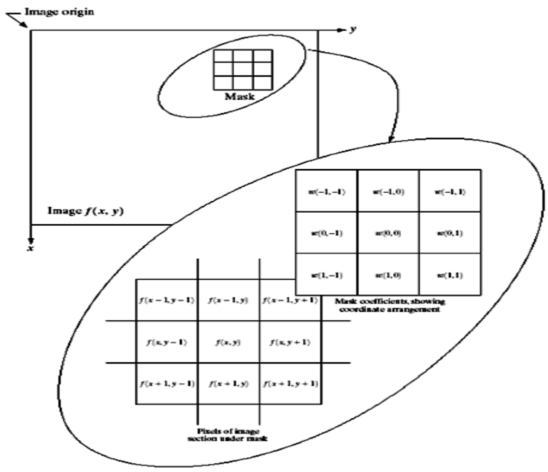
In some cases it may be desirable to specify the shape of the histogram that we wish the processed image to have. Histogram equalization does not allow interactive image enhancement and generates only one result: an approximation to a uniform histogram. Sometimes we need to be able to specify particular histogram shapes capable of highlighting certain gray-level ranges. The method use to generate a processed image that has a specified histogram is called histogram matching or histogram specification.

Algorithm:

1. Compute sk=Pf (k), k = 0, …, L-1, the cumulative normalized histogram of f .
2. Compute G(k), k = 0, …, L-1, the transformation function, from the given histogram hz 3. Compute G-1(sk) for each k = 0, …, L-1 using an iterative method (iterate on z), or in effect, directly compute G-1(Pf (k))
4. Transform f using G-1(Pf (k)) .

3.4 Basic filtering through the enhancement:

Spatial filtering is an example of neighborhood operations, in this the operations are done on the values of the image pixels in the neighborhood and the corresponding value of a sub image that has the same dimensions as of the neighborhood This sub image is called a filter, mask, kernel, template or window; the values in the filter sub image are referred to as coefficients rather than pixel. Spatial filtering operations are performed directly on the pixel values (amplitude/gray scale) of the image The process consists of moving the filter mask from point to point in the image. At each point (x,y) the response is calculated using a predefined relationship.



For linaer spatial filtering the response is given by a sum of products of the filter coefficient and the corresponding image pixels in the area spanned by the filter mask. The results R of liner filtering with the filter mask at point (x,y) in the image is

$$R = w(-1,-1)f(x-1, y-1) + w(-1,0)f(x-1, y) + \cdots + w(0,0)f(x, y) + \cdots + w(1,0)f(x+1, y) + w(1,1)f(x+1, y+1)$$

The sum of products of the mask coefficient with the corresponding pixel directly under the mask. The coefficient w (0,0) coincides with image value f(x,y) indicating that mask it centered at (x,y) when the computation of sum of products takes place. For a mask of size MxN we assume m=2a+1 and n=2b+1, where a and b are nonnegative integers. It shows that all the masks are of add size. In the general liner filtering of an image of size f of size M*N with a filter mask of size m*m is given by the expression

$$g(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x + s, y + t)$$

Where a= (m-1)/2 and b = (n-1)/2

To generate a complete filtered image this equation must be applied for x=0, 1, 2, -----M-1 and y=0,1,2---,N-1. Thus the mask processes all the pixels in the image. The process of linear filtering is similar to frequency domain concept called convolution. For this reason, linear spatial filtering often is referred to as convolving a mask with an image. Filter mask are sometimes called convolution mask.

R= W,Z,+W2, Z2 +….+ Wmn Zmn

Where w's are mask coefficients and z's are the values of the image gray levels corresponding to those coefficients, mn is the total number of coefficients in the mask.

An important point in implementing neighborhood operations for spatial filtering is the issue of what happens when the center of the filter approaches the border of the image. There are several ways to handle this situation.

i) To limit the excursion of the center of the mask to be at distance of less than (n-1) /2 pixels form the border. The resulting filtered image will be smaller than the original but all the pixels will be processed with the full mask.

ii) Filter all pixels only with the section of the mask that is fully contained in the image. It will create bands of pixels near the border that will be processed with a partial mask.

iii) Padding the image by adding rows and columns of o's & or padding by replicating rows and columns. The padding is removed at the end of the process.

IMAGE ENHANCEMENT IN FREQUENCY DOMAIN:

3.5 Basics of filtering in frequency domain:

Basic steps of filtering in frequency Domain

i) Multiply the input image by (-1) X+Y to centre the transform

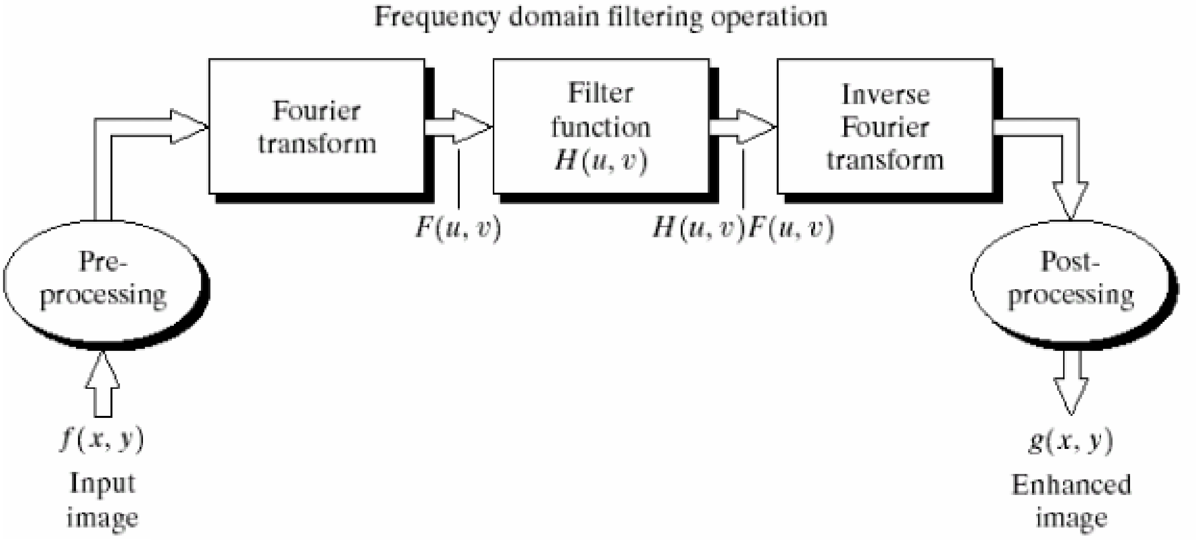
ii) Compute F(u,v), Fourier Transform of the image

iii) Multiply f(u,v) by a filter function H(u,v)

iv) Compute the inverse DFT of Result of (iii)

v) Obtain the real part of result of (iv)

vi) Multiply the result in (v) by $(-1)^{x=y}$



H(u,v) called a filter because it suppresses certain frequencies from the image while leaving others unchanged.

3.6 Image smoothing:

Edges and other sharp transition of the gray levels of an image contribute significantly to the high frequency contents of its Fourier transformation. Hence smoothing is achieved in the frequency domain by attenuation a specified range of high frequency components in the transform of a given image. Basic model of filtering in the frequency domain is

$$G(u,v) = H(u,v)F(u,v)$$

F(u,v) - Fourier transform of the image to be smoothed objective is to find out a filter function H (u,v) that yields G (u,v) by attenuating the high frequency component of F (u,v)

There are three types of low pass filters

1. Ideal
2. Butterworth
3. Gaussian

(i) Ideal Low pass filter:

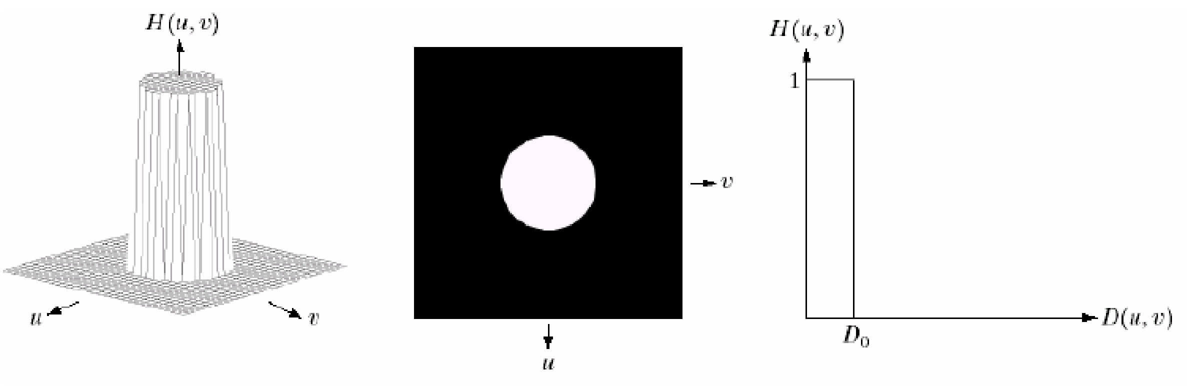
It is the simplest of all the three filters. It cuts of all high frequency component of the Fourier transform that are at a distance greater that a specified distance D0 form the origin of the transform. it is called a two – dimensional ideal low pass filter (ILPF) and has the transfer function

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

Where D0 is a specified nonnegative quantity and D(u,v) is the distance from point (u,v) to the center of frequency rectangle. If the size of image is M*N , filter will also be of the same size so center of the frequency rectangle (u,v) = (M/2, N/2) because of center transform

$$D(u,v) = (u^2 + v^2)^{1/2}$$

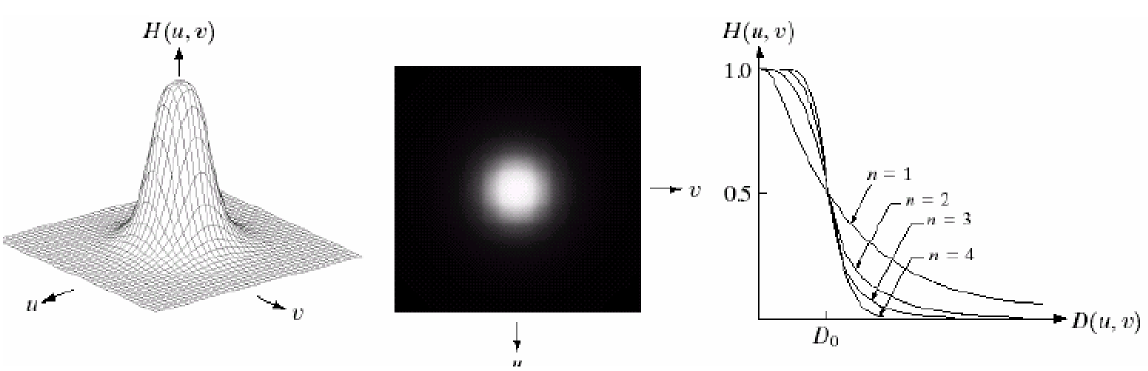
Because it is ideal case. So all frequency inside the circle are passed without any attenuation where as all frequency outside the circle are completely attenuated. For an ideal low pass filter cross section, the point of transition between H (u,v) =1 and H(u,v)=0 is called of the " cut of frequency".



(ii) Butterworth Low pass filter:

It has a parameter called the filter order. For high values of filter order it approaches the form of the ideal filter whereas for low filter order values it reach Gaussian filter. It may be viewed as a transition between two extremes. The transfer function of a Butterworth low pass filter (BLPF) of order n with cut off frequency at distance Do from the origin is defined as

$$H(u,v) = \frac{1}{1 + [D(u,v)/D_0]^{2n}}$$



Most appropriate value of n is 2.It does not have sharp discontinuity unlike ILPF that establishes a clear cutoff between passed and filtered frequencies. Defining a cutoff frequency is a main concern in these filters. This filter gives a smooth transition in blurring as a function of increasing cutoff frequency. A Butterworth filter of order 1 has no ringing. Ringing increases as a function of filter order. (Higher order leads to negative values).

(iii) Gaussian Low pass filter:

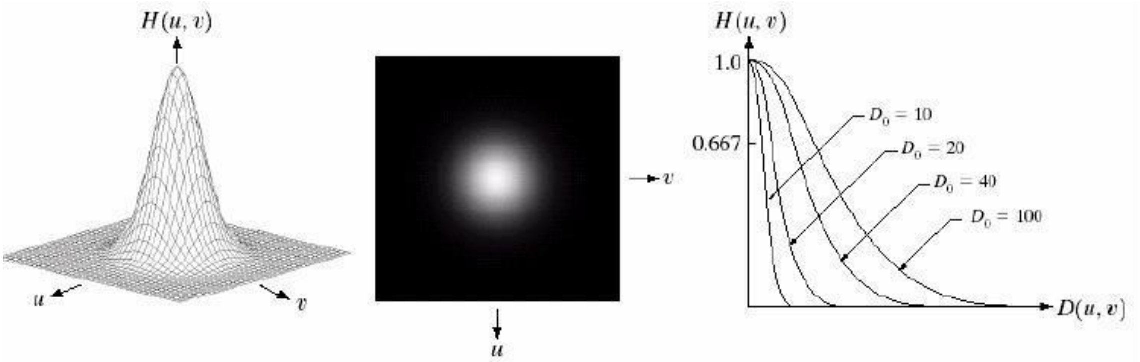
The transfer function of a Gaussian low pass filter is

$$H(u,v) = e^{-D^2(u,v)/2\sigma^2}$$

Where D(u,v)- the distance of point (u,v) from the center of the transform

σ = D0- specified cut off frequency

The filter has an important characteristic that the inverse of it is also Gaussain.



3.7 Image Sharpening:

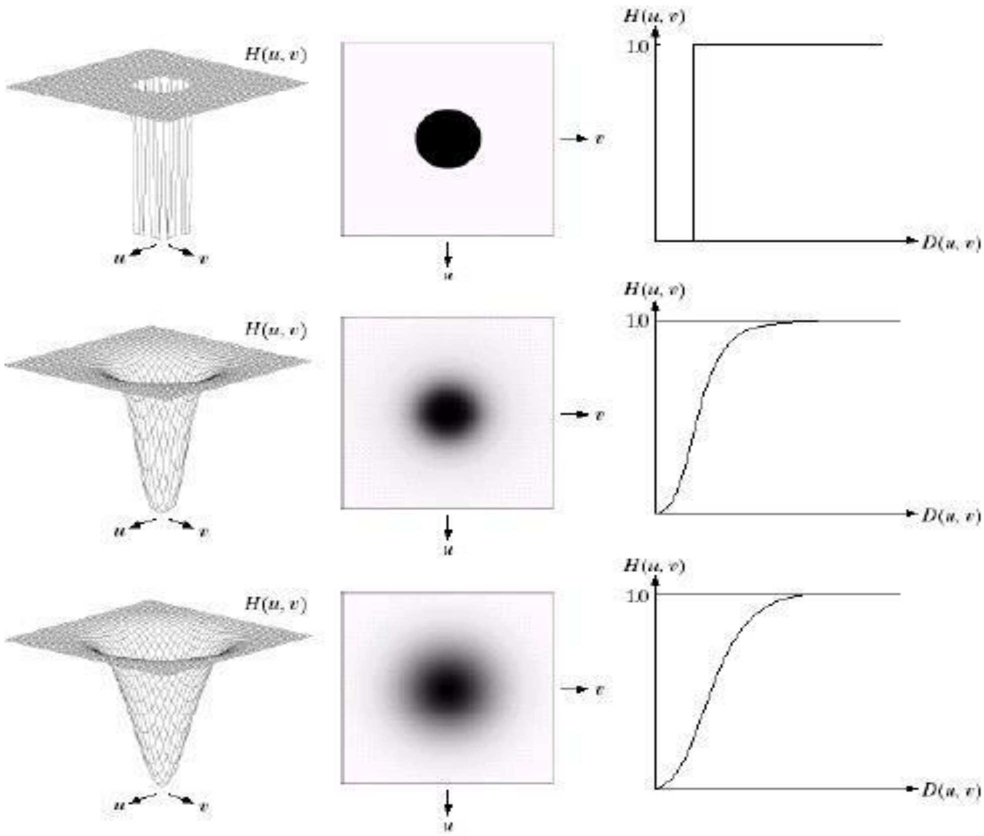


Image sharpening can be achieved by a high pass filtering process, which attenuates the low frequency components without disturbing high-frequency information. These are radially symmetric and completely specified by a cross section. If we have the transfer function of a low pass filter the corresponding high pass filter can be obtained using the equation

$$Hhp\ (u, v) = 1 - Hlp\ (u, v)$$

(i) Ideal High pass filter:

This filter is opposite of the Ideal Low Pass filter and has the transfer function of the form

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

(ii) Butterworth High pass filter:

The transfer function of Butterworth High Pass filter of order n is given by the equation

$$H(u,v) = \frac{1}{1 + [D_0 / D(u,v)]^{2n}}$$

(iii) Guassian High pass filter:

The transfer function of a Gaussain High Pass Filter is given by the equation

$$H(u,v) = 1 - e^{-D^2(u,v)/2\sigma^2}$$

3.8 Homomorphic filtering:

Homomorphic filters are widely used in image processing for compensating the effect of no uniform illumination in an image. Pixel intensities in an image represent the light reflected from the corresponding points in the objects. As per as image model, image f(z,y) may be characterized by two components: (1) the amount of source light incident on the scene being viewed, and (2) the amount of light reflected by the objects in the scene. These portions of light are called the illumination and reflectance components, and are denoted i (x , y) and r (x , y) respectively. The functions i (x , y) and r (x , y) combine multiplicatively to give the image function f (x , y):

f (x , y) = i (x , y).r(x, y) ----------(1)

where $0 < i(x, y) < a$ and $0 < r(x, y) < 1$. Homomorphic filters are used in such situations where the image is subjected to the multiplicative interference or noise as depicted in equation 1. We cannot easily use the above product to operate separately on the frequency components of illumination and reflection because the Fourier transform of f (x , y) is not separable; that is

F[f(x,y)) not equal to F[i(x, y)].F[r(x, y)].

We can separate the two components by taking the logarithm of the two sides

ln f(x,y) = ln i(x, y) + ln r(x, y).

Taking Fourier transforms on both sides we get,

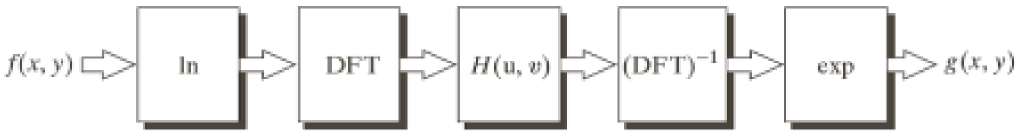
F[ln f(x,y)} = F[ln i(x, y)} + F[ln r(x, y)].

that is, **F(x,y) = I(x,y) + R(x,y),**

where F, I and R are the Fourier transforms ln f(x,y),ln i(x, y) ,

and ln r(x, y). respectively. The function F represents the Fourier transform of the sum of two images: a low-frequency illumination image and a high-frequency reflectance image. If we now apply a filter with a transfer function that suppresses low- frequency components and enhances high-frequency components, then we can suppress the illumination component and enhance the reflectance component. Taking the inverse transform of F (x , y) and then anti-logarithm, we get

f' (x , y) = i' (x , y) + r'(x, y)



3.9 Color Image enhancement:

Color of an object is determined by the nature of the light reflected from it. When a beam of sunlight passes through a glass prism, the emerging beam of light is not white but consists instead of a continuous spectrum of colors ranging from violet at one end to red at the other. As shown in figure, the color spectrum may be divided into six broad regions: violet, blue, green,yellow, orange, and red. When viewed in full color no color in the spectrum ends abruptly, but rather each color blends smoothly into the next.

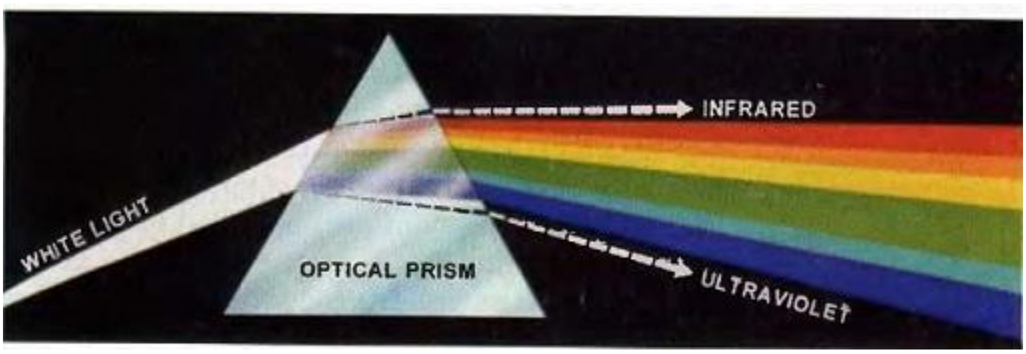


Fig: Color spectrum seen by passing white light through a prism.

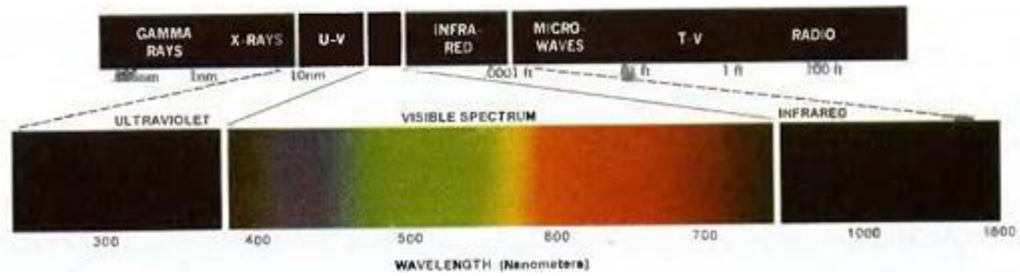


Fig: Wavelength comprising the visible range of electromagnetic spectrum

As illustrated in Figure, visible light is composed of a relatively narrow band of frequencies in the electromagnetic spectrum. A body that reflects light that is 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. Characterization of light is central to the science of color. If the light is achromatic (void of color), its only attribute is its intensity, or amount. Achromatic light is what viewers see on a black and white television set. Three basic quantities are used to describe the quality of a chromatic light source: radiance, luminance, andbrightness.

Radiance:

Radiance is the total amount of energy that flows from the light source, and it is usually measuredinwatts(W).

Luminance:

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:

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

Cones are the sensors in the eye responsible for color vision. Detailed experimental evidence has established that the 6 to 7 million cones in the human eye can be divided into three principal sensing categories, corresponding roughly to red, green, and blue. Approximately65% of all cones are sensitive to red light, 33% are sensitive to green light, and only about 2% are sensitive to blue (but the blue cones are the most sensitive).

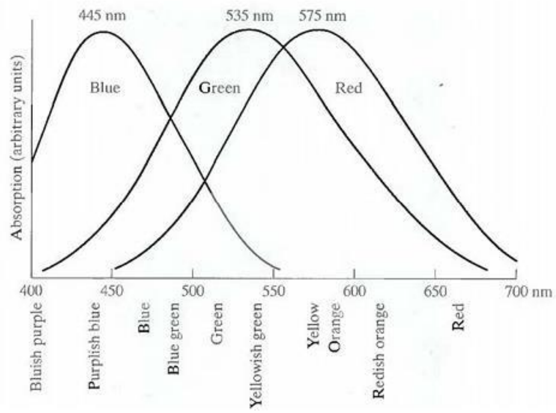


Fig: Absorption of light by RGB cones in human eye

Figure shows average experimental curves detailing the absorption of light by the red, green, and blue cones in the eye. Due to these absorption characteristics of the human eye, colors arc seen as variable combinations of the so- called primary colors red (R), green (G), and blue (B).The primary colors can be added to produce the secondary colors of light --magenta (red plus blue), cyan (green plus blue), and yellow (red plus green). Mixing the three primaries, or a secondary with its opposite primary color, in the right intensities produces white light. The characteristics generally used to distinguish one color from another are brightness, hue, and saturation. Brightness embodies the chromatic notion of intensity. Hue is an attribute associated with the dominant wavelength in a mixture of light waves. Hue represents dominant color as perceived by an observer. Saturation refers to the relative purity or the amount of white light mixed with a hue. The pure spectrum colors are fully saturated. Colors such as pink(red and white) and lavender (violet and white) are less saturated, with the degree of saturation being inversely proportional to the amount of white light-added. Hue and saturation taken together are called chromaticity, and. therefore, a color may be characterized by its brightness and chromaticity.