IMAGE PROCESSING

<u>Presented By:</u>
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<u>Lecture Details:</u>

Topic Name: Introduction to Image Processing

IP/ CSE III B.Tech I Sem

Outline

- Scope of the Course
- Course Pre-requisites
- Course Objectives
- Course Outcomes
- Course Contents
- Introduction to Image Processing

Course Scope

- **Aim:**

  -- To learn various techniques to process the image.

- **Main Reference:**

  -- Digital Image Processing Second Edition by Rafael C. Gonzalez Richard E. Woods Prentice Hall

- **Supplementary References:**

  -- Digital Image Processing by Bhabatosh Chanda and Dwijesh Majumder, PHI

  -- Fundamentals of Digital Image Processing by Anil K Jain, PHI4.

Course Pre-requisites

- Linear Algebra
- Differential Equations
- Probability and Statistics
- Fourier Series

Course Objectives

- Understand the fundamentals of an image and the basic principles of image processing.
- Design and Implement the algorithms that perform basic image processing (Image Enhancement and Image Restoration)
- Learn Image Segmentation and Image Compression techniques.
- Learn to work with color images using Color Image Processing.

Course Outcomes

- Able to apply basic transformations on images.
- Ability to perform spatial and frequency domain analysis and enhance the images.
- Noise removal of the images using various Image Restoration techniques
- Segment the images for processing based on Region of Interest.
- Able to Compress the images for processing using Lossless or Lossy compression techniques

Course Contents

- Digital Image Fundamentals
- Image Enhancement
  - In Spatial Domain
  - In Frequency Domain
- Image Restoration
- Color Image Processing
- Image Compression
- Image Segmentation

Topics

- Introduction to Image Processing
- Representation of Digital Images
- Types of Images
- Application areas of Digital Image Processing

What is Image Processing?

The eye records the scene and send signals to the brain. These signals are processed in the brain and some meaningful information is obtained.

Two things happened in the above scenario:

i) The scene has been recorded by the eye.

ii) The brain processed the scene and gave out a signal.

This process is called **Image Processing.**

What is Digital Image Processing?

- With the advent of computers and technology, images captured from the camera are fed into a computer where algorithms are written to process the image. Here camera replaces human eye.
- The way of processing the images captured by the camera through a digital computer is called **Digital Image Processing.**

What is a Digital Image ?

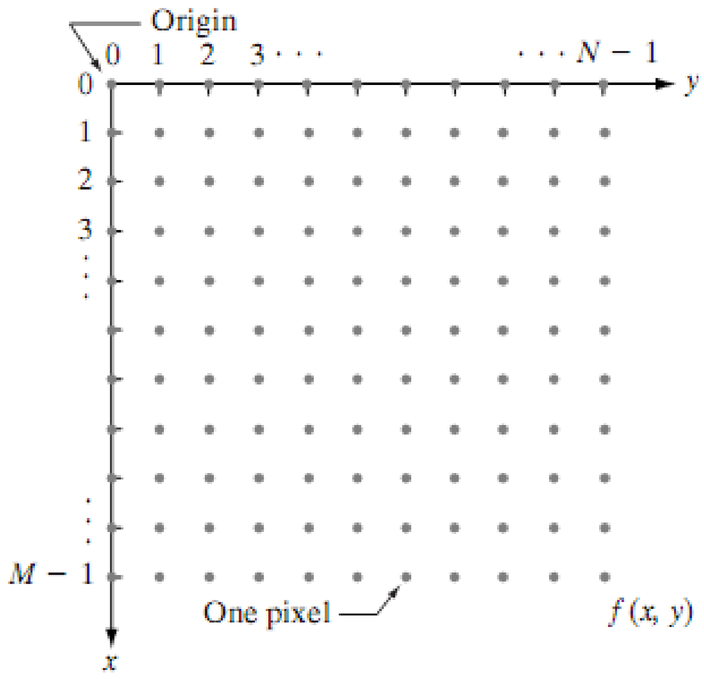
- An image may be defined as a two-dimensional function, $f(x, y)$, where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the **intensity or gray level** of the image at that point.
- When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a **digital image.**
- A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels, and **pixels**.

Representation of Digital Images

- Assume that an image f(x, y) is sampled so that the resulting digital image has M rows and N columns. The values of the coordinates (x, y) now become discrete quantities.
- The coordinates at the origin are (x, y) = (0, 0). The next coordinate values along the first row of the image are represented as (x, y) = (0, 1) and so on.
- The image can be represented in the below matrix form:

$$f(x, y) = \begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0,N-1) \\ f(1,0) & f(1,1) & \cdots & f(1,N-1) \\ \vdots & \vdots & & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & f(M-1,N-1) \end{bmatrix}.$$

Representation of Digital Images (Cont)



Types of Images

- **Black and White or Binary Images:** It contains only two pixel values 0 and 1. Here '0' refers to black whereas '1' refers to white.
- **Gray scale Images:** It has pixel values ranging from 0 to 255 for an 8 bit image. Here '0' refers to black, '255' refers to white, '127' is gray.
- **Color Images:** It has also pixel values ranging from 0 to 255 for an 8 bit image. But it has three color components Red, Green, Blue (RGB). Each color component ranges from 0 to 255. A color image contains three matrices, each for color component.

Types of Images (Cont)

Sl. No.	Type of Images	Range
1	Color Image	RGB Components 0 to255
2	Black & White	0 and 1
3	Gray Scale Image	0 to 255

Application areas of Digital Image Processing

- Office Automation
- Medical Field
- Criminology
- Remote Sensing
- Meteorology
- Astronomy and Space applications
- Information Technology
- Military and Scientific applications

Video Links

1. Introduction to Digital Image Processing
2. Applications of Image Processing

Questions

1. What is a Digital Image? How it is represented?

2. Mention the applications of Digital Image Processing

3. List the various types of Images.

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COMPONENTS OF IMAGE PROCESSING SYSTEM

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Lecture Details:

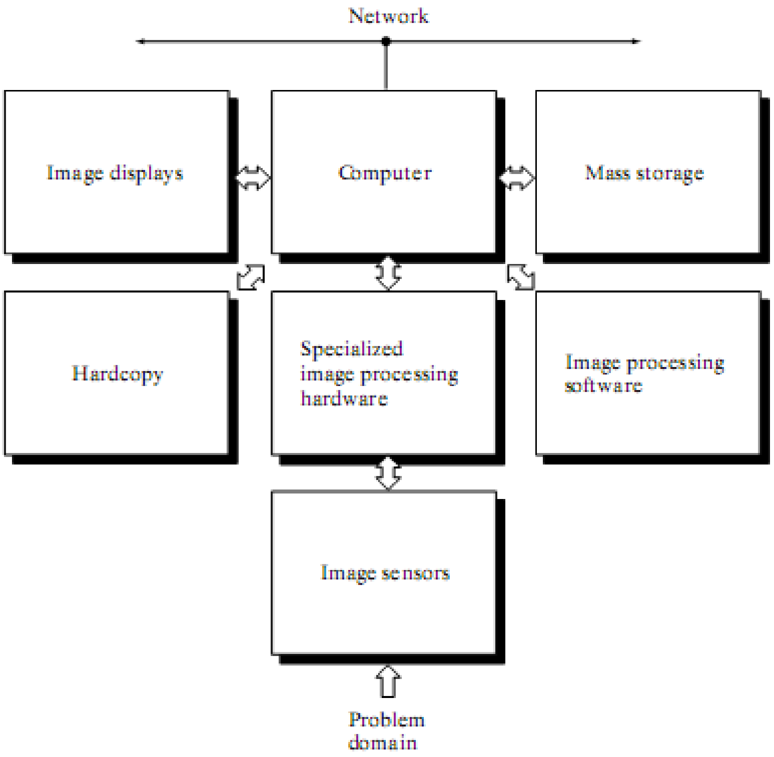
Topic Name: Components & Steps of Image Processing

IP/ CSE III B.Tech I Sem

Outline

- Components of Image Processing
- Functionality of each component
- Steps involved in Image Processing
- Significance of each step of Image Processing

Components of Image Processing System



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Components of Image Processing System (Cont)

The figure shows the basic components of a typical Image Processing system. The function of each component is discussed in the following paragraphs.

Image Sensing:

With reference to sensing, two elements are required to acquire digital images. The first is a physical device that is sensitive to the energy radiated by the object we wish to image. The second, called a digitizer, is a device for converting the output of the physical sensing device into digital form.

Specialized image processing Hardware:

Specialized image processing hardware usually consists of the digitizer just mentioned, plus hardware that performs other primitive operations, such as an arithmetic logic unit (ALU), which performs arithmetic and logical operations in parallel on entire images. This is also called as Front end subsystem.

Components of Image Processing System (Cont)

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Computer:

The computer in an image processing system is a general-purpose computer and can range from a PC to a super computer.

Image Processing Software:

Software for image processing consists of specialized modules that perform specific tasks. A well-designed package also includes the capability for the user to write code that, as a minimum, utilizes the specialized modules.

Mass storage:

Mass storage capability is a must in image processing applications since we are dealing with thousands, or even millions, of images.

Components of Image Processing System (Cont)

Image Displays:

Image displays in use today are mainly color TV monitors (Preferably flat screen).

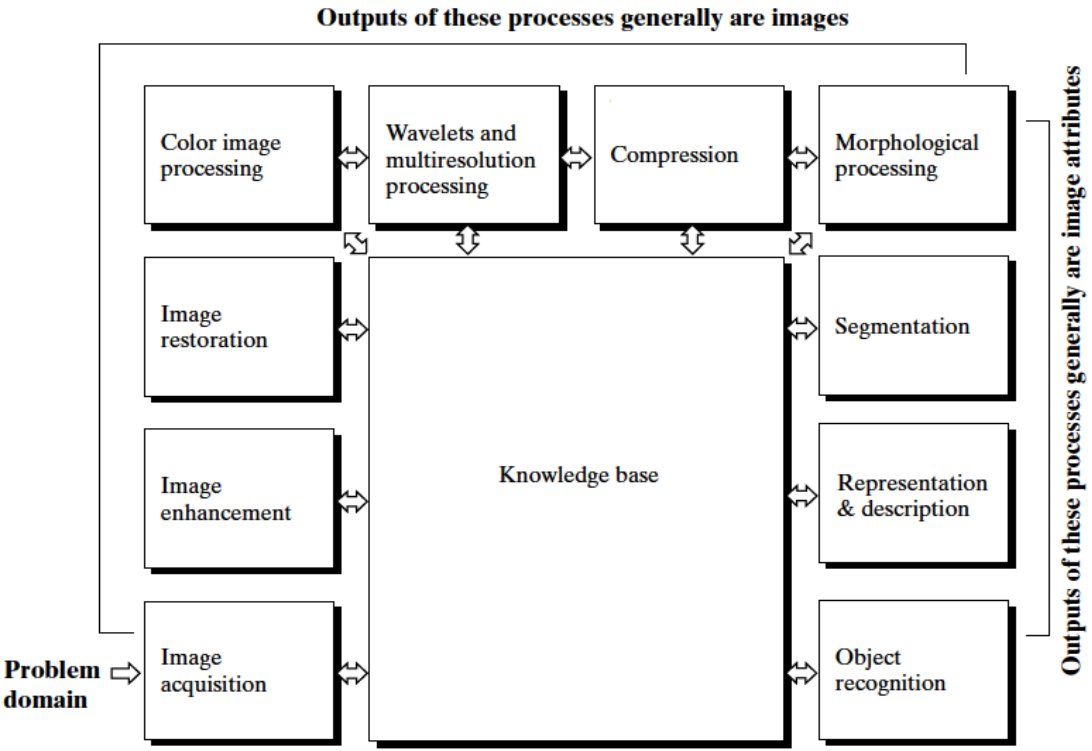
Hardcopy:

Hardcopy devices for recording images include laser printers, digital units, such as optical and CD-ROM disks, Pen drives etc.

Networking:

Networking is almost a default function in any computer system in use today. Higher Bandwidth internet is required when working with image transmission. Fortunately, this situation is improving quickly as a result of optical fiber and other broadband technologies.

Steps in Image Processing



Steps in Image Processing (Cont)

Image Acquisition:

In this first step, image is sensed by illumination from source and reflection from sensors. It also involves preprocess such a scaling.

Image Enhancement

Image Enhancement is simply to highlight the certain features of an image such as increasing the brightness or contrast of the image so that it may look better. It is based on human subjective preferences.

Image Restoration:

Image Restoration deals with improving the appearance of the image. It is objective since it is based on mathematical and probabilistic models of image degradation.

Steps in Image Processing (Cont)

Color Image Processing:

Unlike the previous steps, it deals with modeling and processing of color images.

Wavelets & multi resolution processing:

Wavelets are the foundation for representing images in various degrees of resolution.

Compression:

Compression, as the name implies, deals with techniques for reducing the storage required to save an image, or the bandwidth required to transmit it.

Morphological Processing:

Morphological processing deals with tools for extracting image components that are useful in the representation and description of shape.

Steps in Image Processing (Cont)

Segmentation:

It is the process in which the image is partitioned into small segments. So, we can extract more accurate image attributes.

Representation and description:

Boundary representation deals with shaping of corner or inflections. It also separate from one image from another. Regional representation mainly focused on internal properties of an image such as contrast, texture etc.

Recognition:

Recognition is the process that assigns a label (e.g., “vehicle”) to an object based on its Descriptors.

Video Links

1. Steps and Components of Image Processing

Questions

1.Explain the steps involved in Image Processing.

2.Explain the components of an Image Processing system.

THANK YOU

IMAGE FORMATION & DIGITIZATION CONCEPTS

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<u>Lecture Details:</u>
Topic Name: Image Formation & Digitization
IP/ CSE III B.Tech I Sem

Outline

- Image Formation in the Eye
- Digital Image Formation
- A Simple Image Formation Model
- Image Sampling & Quantization

Image Formation in the Eye

Graphical representation of the eye looking at a palm tree. Point *C* is the optical center of the lens.

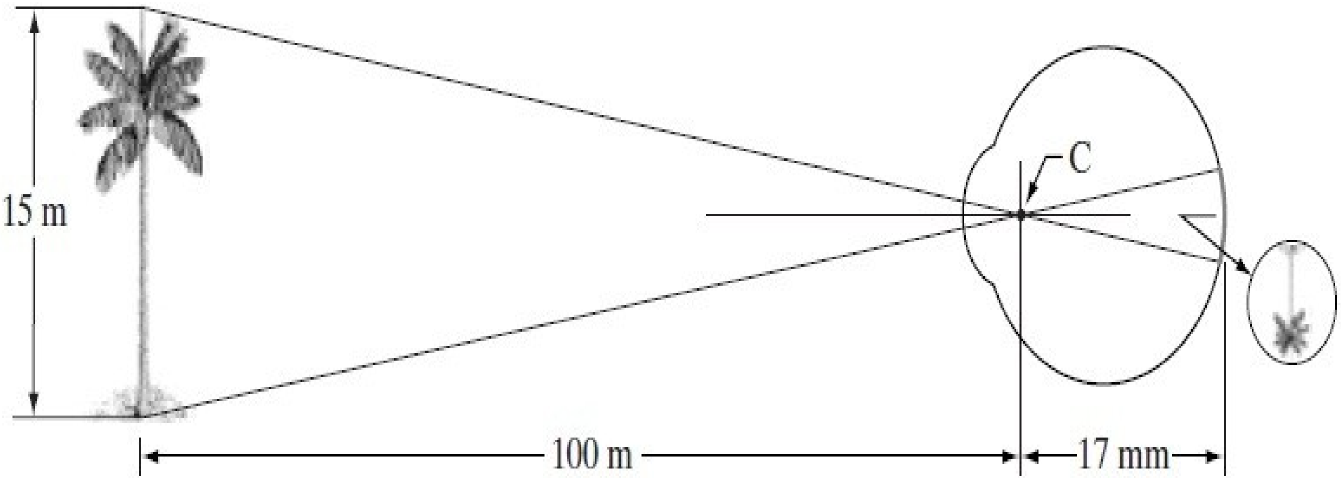
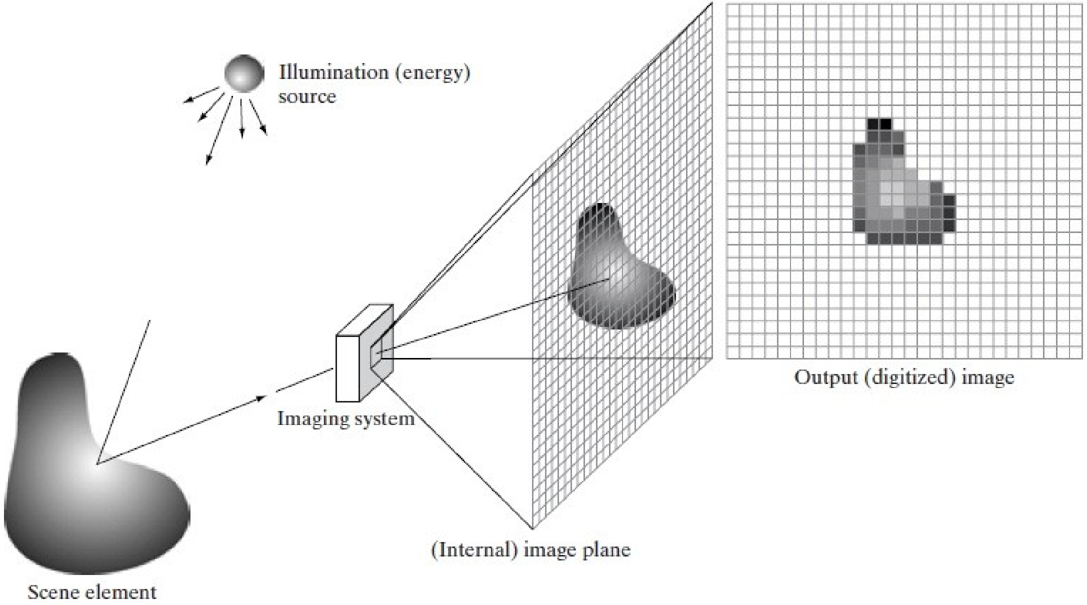


Image Formation in the Eye (Cont)

The figure is a graphical representation of a human eye looking at a Palm tree.

- First consider the object palm tree, when the light ray (Sun light) is incident on the object palm tree, the light leaves the surface of the object traveling in a wide range of directions.
- Although the object is scattering light in all directions, only a small proportion of the light scattered from it reaches the eye.
- When light rays arrives at the eye, the first surface it reaches is the cornea. The rays changes the direction when they pass through the cornea due to refraction. The parts of the eye responsible for most of the refraction of light passing through the eye are the cornea and the lens.
- The light rays reaches to the retina which is the innermost part of the eye and image is formed on the retina causing rods and cones to become excited which ultimately send signals to the brain and then image is flipped right side up. Initially the object is inverted, that is because the human eye forms an inverted image on the retina as shown in the figure.

Digital Image Formation



a b c d e

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.

Digital Image Formation (Cont)

The figure is a digital image acquisition process using sensor arrays.

- Firstly the energy from an illumination source being reflected from a scene element.
- The first function performed by the imaging system is to collect the incoming energy and focus it onto an image plane.
- If the illumination is light, the front end of the imaging system is a lens, which projects the viewed scene onto the lens focal plane.
- The scene or image projected on to the focal plane is a continuous image, it is converted to digital using the digitizer which is the another section of Imaging system.
- Digitization is to be done for an image as it can be used in wide range of applications.

A Simple Image Formation Model

- When an image is generated from a physical process, its values are proportional to energy radiated by a physical source (e.g., electromagnetic waves).

$$0 < f(x,y) < \infty$$

- Here f(x,y) depends on two important components:

i. Amount of source illumination incident on the scene being viewed denoted as i(x,y)

ii. Amount of illumination reflected by the objects in the scene denoted as r(x,y)

- The product of these forms:

$$f(x,y) = i(x,y)\, r(x,y)$$

$$\text{where } 0 < i(x,y) < \infty \text{ and } 0 < r(x,y) < 1$$

- We call the intensity of a monochrome image at any coordinates (x0, y0) the gray level (L) of the image at that point. That is, L=f(x0,y0)
- It is evident that L lies in the range Lmin≤L ≤Lmax (0 to L-1)

Image Sampling and Quantization

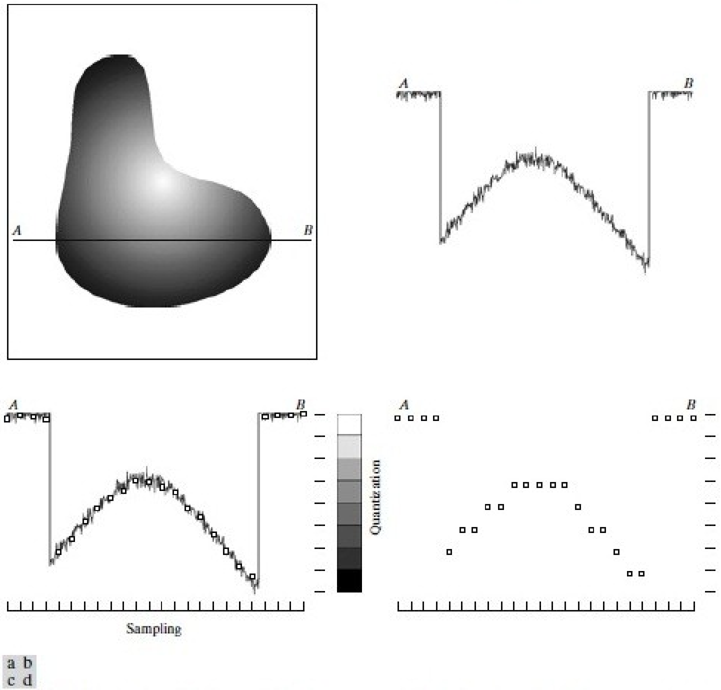


FIGURE 2.16 Generating a digital image. (a) Continuous image. (b) A scan line from A to B in the continuous image, used to illustrate the concepts of sampling and quantization. (c) Sampling and quantization. (d) Digital scan line.

Image Sampling and Quantization (Cont)

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The figure is the process of Image sampling and quantization.

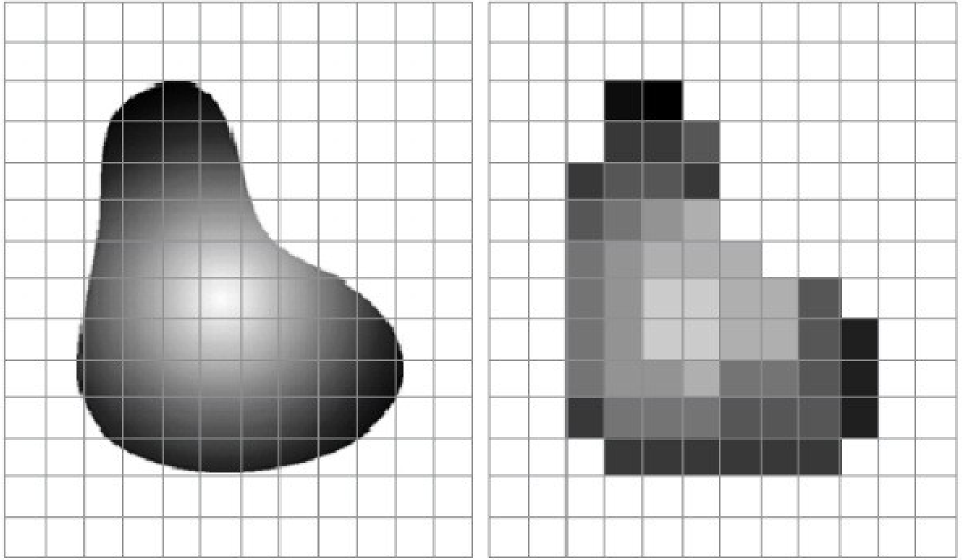
- Fig.(a) shows continuous image, f(x, y), that we want to convert to digital form
- To convert it to digital form, we have to sample the function in both coordinates and in amplitude. Digitizing the coordinate values is called **sampling.** Digitizing the amplitude values is called **quantization**.
- The one-dimensional function shown in fig.(b) is a plot of amplitude (gray level) values of the continuous image along the line segment AB in fig.(a). The random variations are due to image noise.
- To sample this function, we take equally spaced samples along line AB, as shown in fig.(c). The location of each sample is given by a vertical tick mark in the bottom part of the fig (c).
- The samples are shown as small white squares superimposed on the function. The set of these discrete locations gives the sampled function.

Image Sampling and Quantization (Cont)

However, the values of the samples still span (vertically) a continuous range of gray-level values. In order to form a digital function, the gray-level values also must be converted (quantized) into discrete quantities

- The right side of fig.(c) shows the gray-level scale divided into eight discrete levels, ranging from black to white.
- The vertical tick marks indicate the specific value assigned to each of the eight gray levels. The continuous gray levels are quantized simply by assigning one of the eight discrete gray levels to each sample.

Image Sampling and Quantization (Cont)



Result after Image Sampling and Quantization
a) Continuous Image b) After Sampling & Quantization

Questions

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1. Explain Image Sampling and Quantization.

2. Explain the process of Image Acquisition using Sensor arrays.

3. Explain simple image formation model.

THANK YOU

NEIGHBORS OF PIXEL, ADJACENCY, CONNECTIVITY

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Lecture Details:
Topic Name: Neighbors of Pixel and its concepts
IP/ CSE III B.Tech I Sem

Outline

- Neighbors of Pixel
- Connectivity
- Adjacency
- Regions and Boundaries
- Distance Measures

Neighbors of Pixel

- A pixel p at coordinates (x, y) has four horizontal and vertical neighbors whose coordinates are given by (x+1, y), (x-1, y), (x, y+1), (x, y-1). This set of pixels, called the 4-neighbors of p, is denoted by N4 (p). Each pixel is a unit distance from (x, y), and some of the neighbors of p lie outside the digital image if (x, y) is on the border of the image.
- The four diagonal neighbors of p have coordinates (x+1, y+1), (x+1, y-1), (x-1, y+1), (x-1, y-1) and are denoted by ND (p). These points, together with the 4-neighbors, are called the 8-neighbors of p, denoted by N8 (p).

(x-1,y-1)	(x-1,y)	(x-1,y+1)
(x,y-1)	p(x, y)	(x,y+1)
(x+1,y-1)	(x+1,y)	(x+1,y+1)

Connectivity

Connectivity:

Two pixels are said to be connected if they are adjacent in some sense.

(i) They should be neighbors (N4 (p), ND (p) or N8 (p))

(ii)Their intensity values (gray values) should be similar.

Example:

For a Binary image B, two pixels p & q are said to be connected if

1) q is in N(p) and
2) B(p) = B(q)

Adjacency

Adjacency:

Let V be set of gray levels used to define adjacency of two pixels p, q $\in$ V, three types of adjacency are defined:

i) 4-adjacency:

Two pixels p and q with values from V are 4-adjacent if q is in the set N4 (p).

ii) 8-adjacency:

Two pixels p and q with values from V are 8-adjacent if q is in the set N8 (p).

iii) m-adjacency (mixed adjacency):

Two pixels p and q with values from V are m-adjacent if

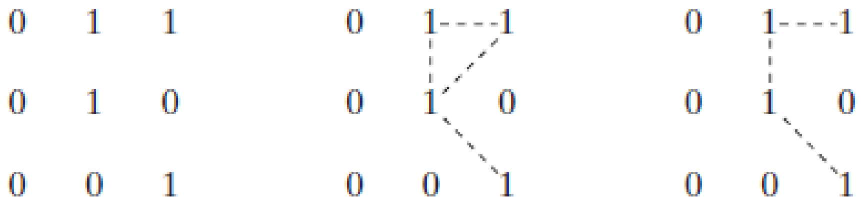
q is in N4 (p), or

q is in ND (p) and the set $N4(p) \cap N4(q)$ has no pixels whose values are from V.

Adjacency (Cont)

Adjacency:

Let V be set of gray levels V={1} used to define adjacency of two pixels p, q ∈ V, three types of adjacency are defined:



(a) Arrangement of pixels; (b) pixels that are 8-adjacent (shown dashed) to the center pixel; (c) *m*-adjacency.

Regions and Boundaries

- Let S represent a subset of pixels in an image. Two pixels p and q are said to be connected in S if there exists a path between them consisting entirely of pixels in S. For any pixel p in S, the set of pixels that are connected to it in S is called a connected component of S. If it only has one connected component, then set S is called a connected set.

- Let R be a subset of pixels in an image. We call R a region of the image if R is a connected set. The boundary (also called border or contour) of a region R is the set of pixels in the region that have one or more neighbors that are not in R. If R happens to be an entire image (which we recall is a rectangular set of pixels), then its boundary is defined as the set of pixels in the first and last rows and columns of the image

Distance Measures

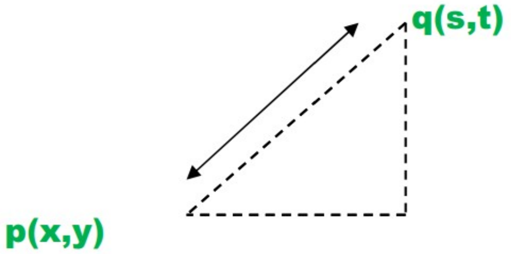
Distance measures are used to find the distance between the pixels.

For pixels p, q, and z, with coordinates (x, y), (s, t), and (v, w), respectively, D is a distance function or metric if

(a) D(p, q) >= 0 (D(p, q)=0 iff p=q),

(b) D(p, q) = D(q, p), and

(c) D(p, z) <= D(p, q) + D(q, z)



The following are the distance measures we have:

1)Euclidean distance

2)City Block distance

3)Chess Board distance

Distance Measures (Cont)

Euclidean Distance:

The Euclidean distance between p and q is defined as:

$$D_e(p,q) = \left[(x-s)^2 + (y-t)^2\right]^{\frac{1}{2}}.$$

1.41	1.0	1.41
1.0	0.0	1.0
1.41	1.0	1.41

The Euclidean distance is the straight-line distance between two pixels.

City Block Distance:

It is also called as D4 distance and the distance between p and q is defined as:

$$D_4(p,q) = |x-s| + |y-t|.$$

$$\begin{array}{ccccc} & & 2 & & \\ & 2 & 1 & 2 & \\ 2 & 1 & 0 & 1 & 2 \\ & 2 & 1 & 2 & \\ & & 2 & & \end{array}$$

The city block distance metric measures the path between the pixels based on a 4-connected neighborhood. Pixels whose edges touch are 1 unit apart and pixels diagonally touching are 2 units apart.

Distance Measures (Cont)

Chess Board Distance:

It is also called as D8 distance and the distance between p and q is defined as:

$$D_8(p, q) = \max(|x - s|, |y - t|).$$

The chessboard distance metric measures the path between the pixels based on an 8-connected neighborhood. Pixels whose edges or corners touch are 1 unit apart.

$$\begin{matrix} 2 & 2 & 2 & 2 & 2 \\ 2 & 1 & 1 & 1 & 2 \\ 2 & 1 & 0 & 1 & 2 \\ 2 & 1 & 1 & 1 & 2 \\ 2 & 2 & 2 & 2 & 2 \end{matrix}$$

Questions

1.Explain the relationship between pixels.

2.List and Explain the types of adjacency.

3.Explain briefly about distance measures.

THANK YOU

IMAGE ENHANCEMENT IN SPATIAL DOMAIN

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Lecture Details:
Topic Name: Image Enhancement in Spatial Domain
IP/ CSE III B.Tech I Sem

Outline

- Introduction to Image Enhancement
- Introduction to Image Enhancement in Spatial Domain
- Thresholding
- Basic Gray level transformations

Image Enhancement

- **Definition:** Image Enhancement is simply to highlight the certain features of an image.

  Ex: Increasing the brightness or contrast of an image so that it may look better than the original.
- It is a subjective process. It is based on human perception.

  Ex: One image which is good for one person may not be good for another person.
- It can be performed in two domains:

  Image Enhancement in Spatial Domain:

  The term spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image

  Image Enhancement in Frequency Domain:

  Frequency domain processing techniques are based on modifying the Fourier transform of an image.

Image Enhancement in Spatial Domain

- In Spatial Domain, we will take an input image, processing will be done on that input image and generates the output.
- Here **Processing** means some operations or some changes will be done to the pixels of the input image.
- Let the input image function be f(x,y) and output image function be g(x,y) and 'T' may be any operation performed on the pixels of the input image in spatial domain.

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

Here f(x,y) is an input image

T is Transformation operator defined on some neighborhood of (x,y)

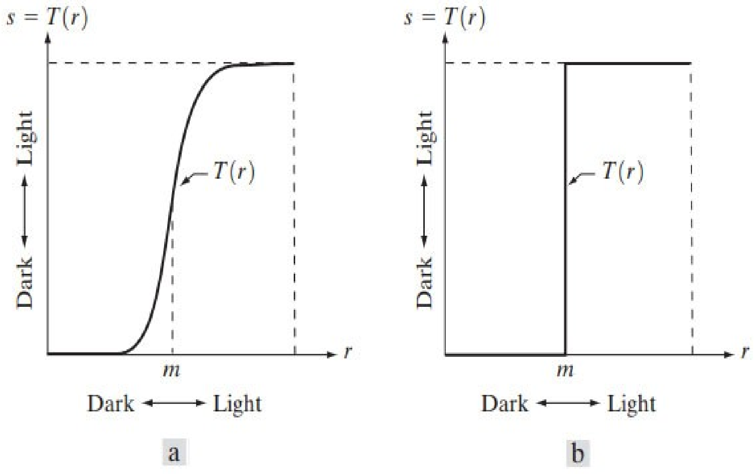
g(x,y) is an output image

- For simple notation, it can be represented as s=T(r)

where s is g(x,y) and r is f(x,y) and T is transformation operator

Thresholding

- For example, if T(r) has the form shown in Fig. (a), the effect of this transformation would be to produce an image of higher contrast than the original by darkening the levels below m and brightening the levels above m in the original image. In this technique, known as contrast stretching, the values of r below m are compressed by the transformation function into a narrow range of s, toward black.
- The opposite effect takes place for values of r above m. In the limiting case shown in Fig.(b), T(r) produces a two-level (binary) image. A mapping of this form is called a Thresholding function.



Gray- level transformation functions

Basic Gray level Transformations

The following are the basic gray level transformations:

1) Point transformation

2) Linear transformations (Negative and Identity)

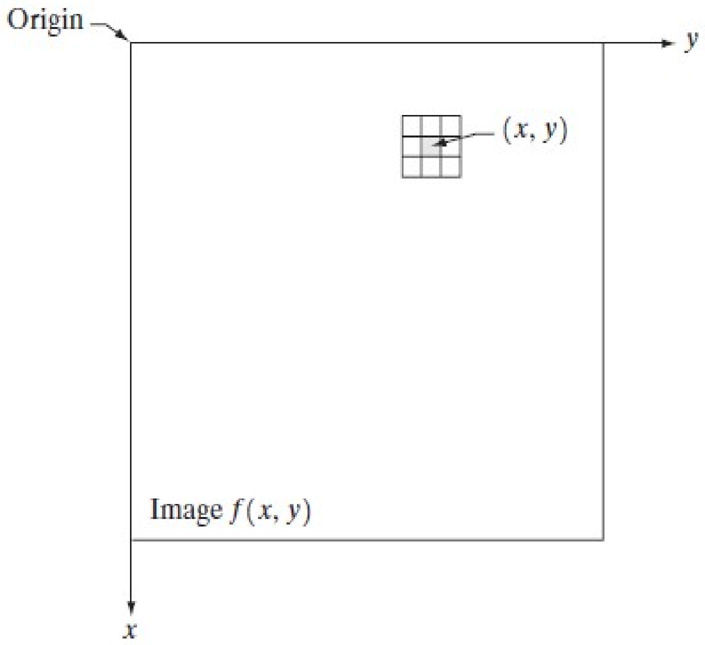
3) Logarithmic transformations (log and inverse-log transformations)

4) Power-law transformations (nth power and nth root transformations)

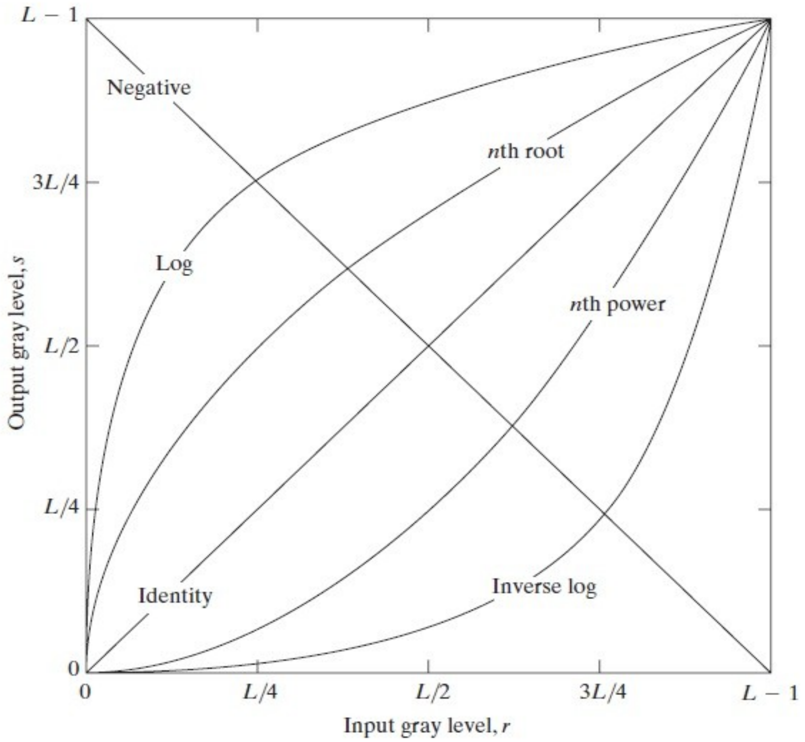
5) Piece wise Linear transformations

Point Transformation

- The principal approach in defining a neighborhood about a point (x, y) is to use a square or rectangular sub image area centered at (x, y), as shown in the figure.
- The center of the sub image is moved from pixel to pixel starting, say, at the top left corner. The operator T is applied at each location (x, y) to yield the output, g, at that location.
- The process utilizes only the pixels in the area of the image spanned by the neighborhood.
- The simplest form of T is when the neighborhood is of size 1*1 (that is, a single pixel).
- This process is called point to point processing



Basic Gray-level transformation functions used for Image Enhancement



Linear Transformations

Image Negative:

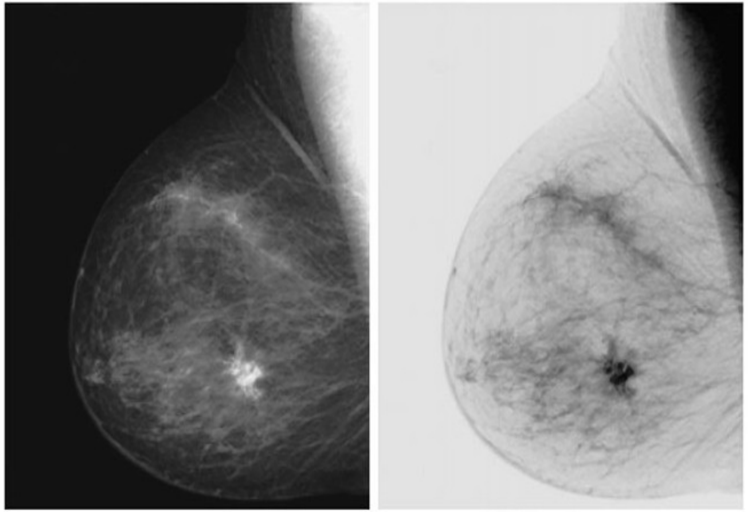
- The negative of an image with gray levels in the range [0, L-1] is obtained by using the negative transformation shown in Figure, which is given by the expression

$$s = L - 1 - r$$

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

Image Identity:

- Identity transformation is shown by a straight line. Each value of the input image is directly mapped to each other value of output image. That results in the identical output image hence is called identity transformation.



(a) Original digital mammogram.

(b) Negative image obtained using the negative transformation

Logarithmic Transformations

- The general form of the log transformation is

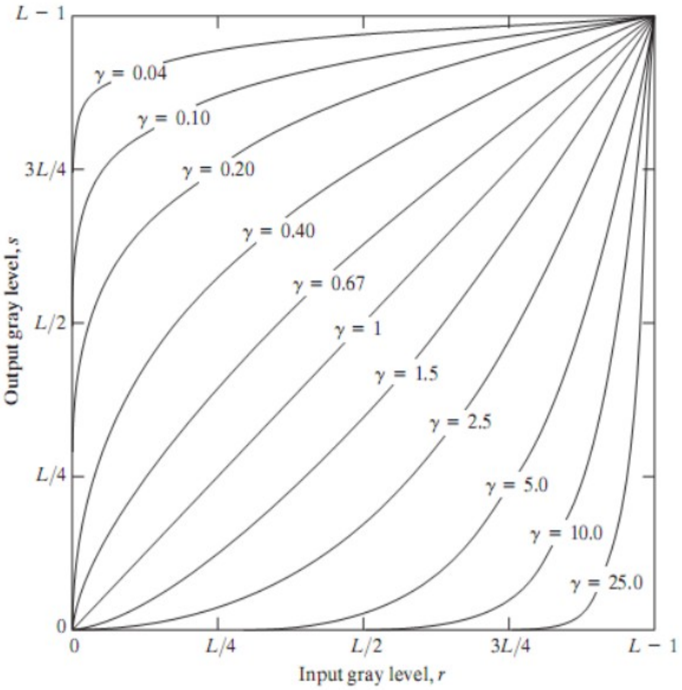
$$s = c \log (1 + r)$$

  is where c is a constant, and it is assumed that $r \geq 0$.
- The shape of the log curve in Figure shows that this transformation maps a narrow range of low gray-level values in the input image into a wider range of output levels. We would use a transformation of this type to expand the values of dark pixels in an image while compressing the higher-level values. This is called Log Transformation
- The shape of the inverse log curve in the figure shows that this transformation maps a narrow range of high gray level values in the input image into a wider range of output pixels. We use this type of transformation to expand the values of bright pixels in an image while compressing the lower level values. This is called Inverse Log Transformation.

Power law Transformations

- There are further two transformation in power law transformations, that include nth power and nth root transformation. These transformations can be given by the expression: $s = cr^{\gamma}$

  where c and r are positive constants
- If γ<1, it maps a narrow range of dark pixel values in an input image into a wider range of output values and with the opposite being true for higher values of input image.
- 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. This type of transformation is used for enhancing images for different type of display devices. The gamma of different display devices is different.



Piece wise Linear Transformations

The following are the Piece wise Linear transformations:

1) Contrast Stretching

2) Gray level or Intensity level slicing

3) Bit plane slicing

Contrast Stretching

- One of the simplest piecewise linear functions is a contrast-stretching transformation.
- Low contrast images can result from

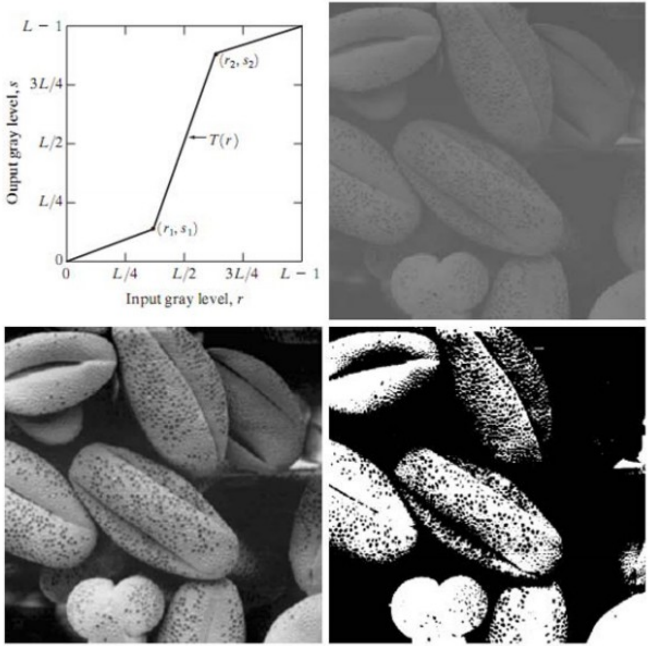
  i. Poor illumination

  ii. Lack of dynamic range in the imaging sensor

  iii. Wrong setting of a lens aperture during image acquisition.
- The idea behind contrast stretching is to increase the dynamic range of the gray levels in the image being processed.

Contrast Stretching (cont)

- Figure (a) shows a typical transformation used for contrast stretching. The locations of points (r1 , s1) and (r2 , s2) control the shape of the transformation function.
- If r1=s1 and r2=s2, the transformation is a linear function that produces no changes in gray levels.
- Figure (b) shows an 8-bit image with low contrast.
- In general, r1 ≤ r2 and s1 ≤ s2 is assumed so that the function is single valued and monotonically increasing. Figure (c) shows the result of contrast stretching, obtained by setting (r1, s1)=(rmin,0) and (r2, s2)=(rmax,L-1) where rmin and rmax denote the minimum and maximum gray levels in the image, respectively. Thus, the transformation function stretched the levels linearly from their original range to the full range [0, L-1].
- If r1=r2, s1=0 and s2=L-1, the transformation becomes a thresholding function that creates a binary image. It can be seen in figure (d)

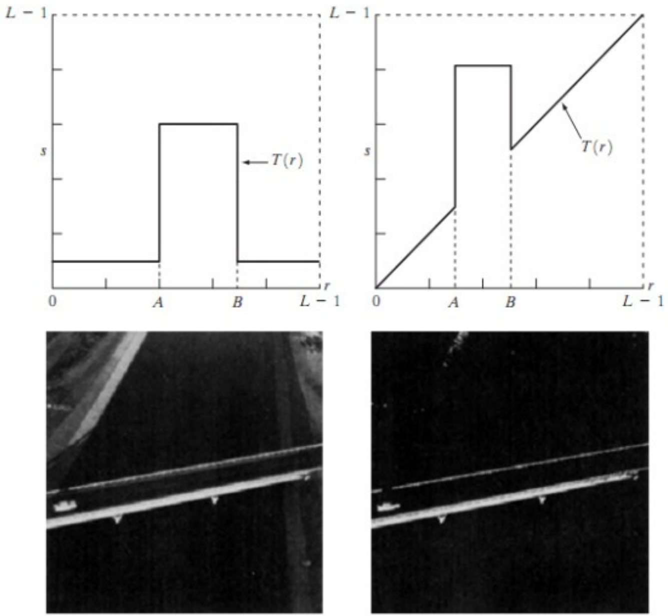


Contrast Stretching (a) Form of Transformation function (b) A low-contrast image (c) Result of contrast stretching (d) Result of thresholding.

Gray level Slicing

- It is also known as Intensity level slicing.
- It is used to enhance the intensity values in the image.
- There are two approaches:

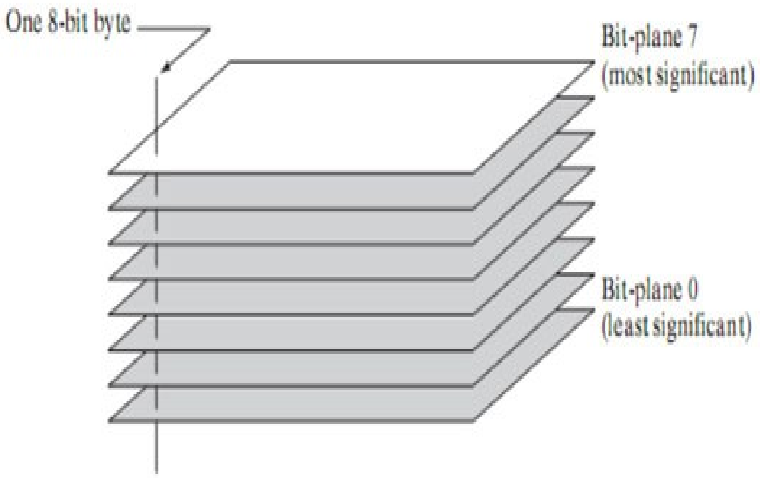
1. One approach is that we enhance the desired range of gray levels and other gray levels are suppressed.
2. Another approach is we enhance the desired range of gray levels but also preserve the remaining part of gray levels.



(a) This transformation highlights range [A, B] of gray levels and reduce all others to a constant level (b) This transformation highlights range [A, B] but preserves all other levels (c) An image (d) Result of using the transformation in (a).

Bit Plane Slicing

- Sometimes it is desired to know the contribution of each bit in image. Let us assume an 8 bit image, where every pixel is represented by 8 bits.
- Imagine that the 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 as shown in the figure.
- Plane 0 contains all the lowest order bits in the bytes comprising the pixels in the image and plane 7 contains all the high-order bits.
- Note that the higher-order bits (especially the top four) contain the majority of the visually significant data.
- The other bit planes contribute to more subtle details in the image.



Bit-plane representation of an 8-bit image.

Questions

1. What Image Enhancement?

2. Explain Basic gray level transformations.

3. What is the need for gamma corrections?

4. What is Bit plane slicing and Intensity level slicing?

THANK YOU

HISTOGRAM PROCESSING

Presented By:
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Lecture Details:
Topic Name: Histogram Equalization
IP/ CSE III B.Tech I Sem

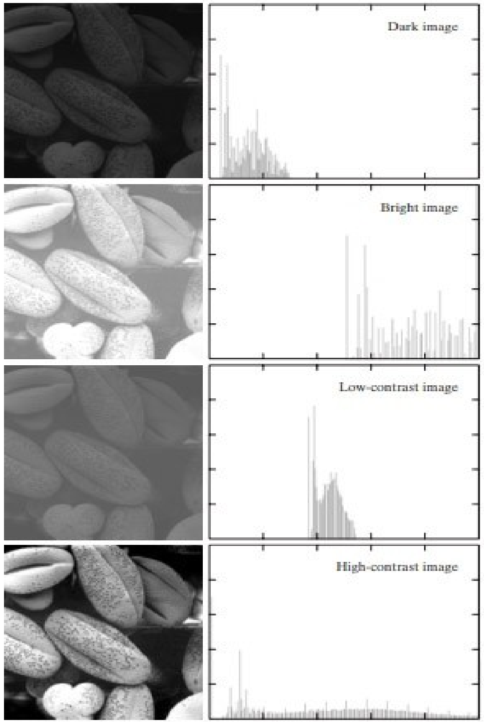
Outline

- Introduction to Histogram
- Histogram Processing
- Histogram Equalization
- Enhancement using Arithmetic/Logical Operations

Histogram

- **Definition:** Histogram is a graph indicating the number of times each gray level occurs in the image.
- It is a popular tool in real time image processing.
- The following indicates the appearance of a image from its histogram

1) In a dark image, the gray levels would be clustered at the lower end i.e., very near to origin.
2) In a bright image, the gray levels would be clustered at the upper end i.e., very far from origin near the maximum levels.
3) In a low contrast image, the gray levels would be clustered at middle, will have a narrow histogram at middle.
4) In a well or high contrast image, the gray levels would be well spread out over much of the range i.e., Histogram will be uniformly distributed through scale.



Histogram Processing

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

  $h(r_k)=n_k$,

  where r_k is kth gray level

  n_k is number of pixels having gray level r_k

  Ex: $h(20) = 50$

  It means gray level 20 is appearing 50 times in image.
- It is common practice to normalize a histogram by dividing each of its values by the total number of pixels in the image, denoted by n.
- Thus, a normalized histogram is given by $p(r_k) = n_k/n$, for $k=0, 1,\ldots, L-1$. Loosely speaking, $p(r_k)$ gives an estimate of the probability of occurrence of gray level r_k. Note that the sum of all components of a normalized histogram is equal to 1

  Ex: $h(0) = 10$, $h(1) = 20$, $h(2) = 30$, $h(3) = 10$

  Total = $10+20+30+10 = 70$. $p(r_2) = 30/70 = 3/7$

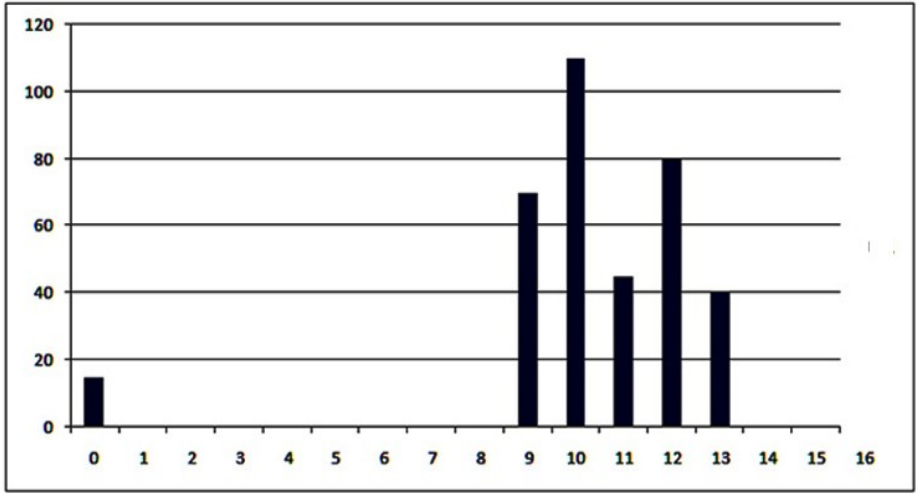
Histogram Equalization

- Histogram equalization is used to enhance contrast of an image
- We must know two important concepts which are used in equalizing histograms i.e PMF and CDF
- **PMF** stands for probability mass function. It gives the probability of occurrence of gray level or you can say that it basically gives the count or frequency of each gray level. p(rk) =nk/n
- **CDF** stands for cumulative distributive function. It calculates the cumulative sum of all the values that are calculated by PMF. It basically sums the previous one.
- After calculating CDF, you have to multiply the CDF value with (L-1).
- Round the CDF*L-1 value to make it discrete level.

Example for Histogram Equalization

- Let us look at an example to equalize a Histogram:
- Take a 4 bit image. The number of gray levels would be 2n-1. That means 2^4-1 = 15 gray levels. So, we have taken 15 gray levels named with 'k' (0 to 15). And the occurrences of each gray level named with nk. And the corresponding Histogram is shown. It produces low contrast image. Let us equalize it.

k	nk
0	15
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	70
10	110
11	45
12	80
13	40
14	0
15	0



Example for Histogram Equalization (Cont)

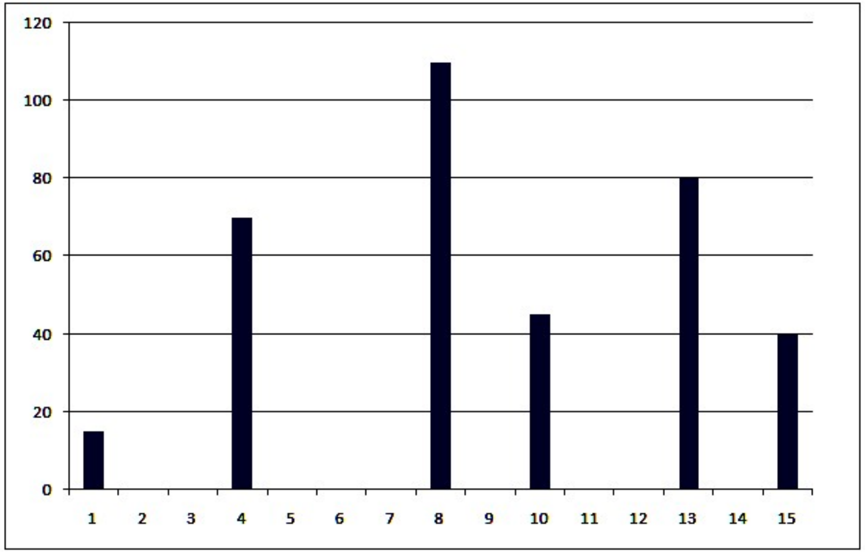
- Now we have to equalize the Histogram by following all the rules.
- In the figure we calculated PMF, CDF and CDF * L-1 and then finally K^1.
- Now we have to draw the histogram taking the values of k^1 and nk to get the equalized Histogram.

k	nk	p=nk/n	CDF	CDF*L-1	K^1
0	15	0.042	0.042	0.63	1
1	0	0.000	0.042	0.63	1
2	0	0.000	0.042	0.63	1
3	0	0.000	0.042	0.63	1
4	0	0.000	0.042	0.63	1
5	0	0.000	0.042	0.63	1
6	0	0.000	0.042	0.63	1
7	0	0.000	0.042	0.63	1
8	0	0.000	0.042	0.63	1
9	70	0.194	0.236	3.55	4
10	110	0.306	0.542	8.13	8
11	45	0.125	0.667	10.01	10
12	80	0.222	0.889	13.34	13
13	40	0.111	1.000	15.01	15
14	0	0.000	1.000	15.01	15
15	0	0.000	1.000	15.01	15

Example for Histogram Equalization (Cont)

- Now we have constructed Histogram for the values of k^1 and nk.
- We have got an Equalized Histogram. It will generate a well or high contrast image.
- In this way, Histogram Equalization is used for Image Enhancement

k^1	nk
1	15
1	0
1	0
1	0
1	0
1	0
1	0
1	0
1	0
4	70
8	110
10	45
13	80
15	40
15	0
15	0



Enhancement using Arithmetic/Logic Operations

- The Arithmetic and logical operations in image enhancement are applied on two or more images.
- The operations are applied in a pixel by pixel way i.e., the value of each pixel on the output image depends on the value of the corresponding pixels in the input images, hence the input images must be of same size.
- There are very wide range of applications using these arithmetical and logical operations. The main advantage is very simple and fast.

Enhancement using Arithmetic/Logic Operations (Cont)

Arithmetic Operators:

- Arithmetic addition is used in image averaging to reduce errors and noise. It is represented as z=imadd(x,y) where x and y are input images and z is the resultant output image after addition.
- Arithmetic subtraction is used in medical imaging where we have to remove static background information. It is represented as z = imsubtract(x,y).
- Arithmetic multiplication and division is used for gray level modification. They are represented as z=immultiply(x,y) and z=imdivide(x,y)

Enhancement using Arithmetic/Logic Operations (Cont)

Logical Operators:

- Logical Operators are often used to combine two images (Mostly binary images)
- In the case of integer images the logical operator is normally applied in a bitwise way.

Example:

Suppose A hold the value 60 and B holds the value 13. Let us perform AND OR NOT operations on these two values.

AND	OR
A – 60 – 1 1 1 1 0 0	A – 60 – 1 1 1 1 0 0
B – 13 – 0 0 1 1 0 1	B – 13 – 0 0 1 1 0 1
------------------------	------------------------
0 0 1 1 0 0	1 1 1 1 0 1

Questions

1. What is a Histogram? Explain Histogram Equalization with an example.

2. Explain Enhancement using Arithmetic/Logical operators

THANK YOU

SPATIAL FILTERING

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Lecture Details:
Topic Name: Filtering in Spatial Domain
IP/ CSE III B.Tech I Sem

Outline

- Introduction to Spatial Filtering
- Smoothing Spatial Filters
- Sharpening Spatial Filters

Spatial Filtering

- Some neighborhood operations work with the values of the image pixels in the neighborhood and the corresponding values of a sub image that has the same dimensions as the neighborhood.
- The sub image is called as filter, mask or kernel.
- The values in a filter sub image are referred to as coefficients, rather than pixels.
- The process consists simply of moving the filter mask from point to point in an image. At each point (x, y), the response of the filter at that point is calculated using a predefined relationship.
- The response is given by a sum of products of the filter coefficients and the corresponding image pixels in the area spanned by the filter mask.

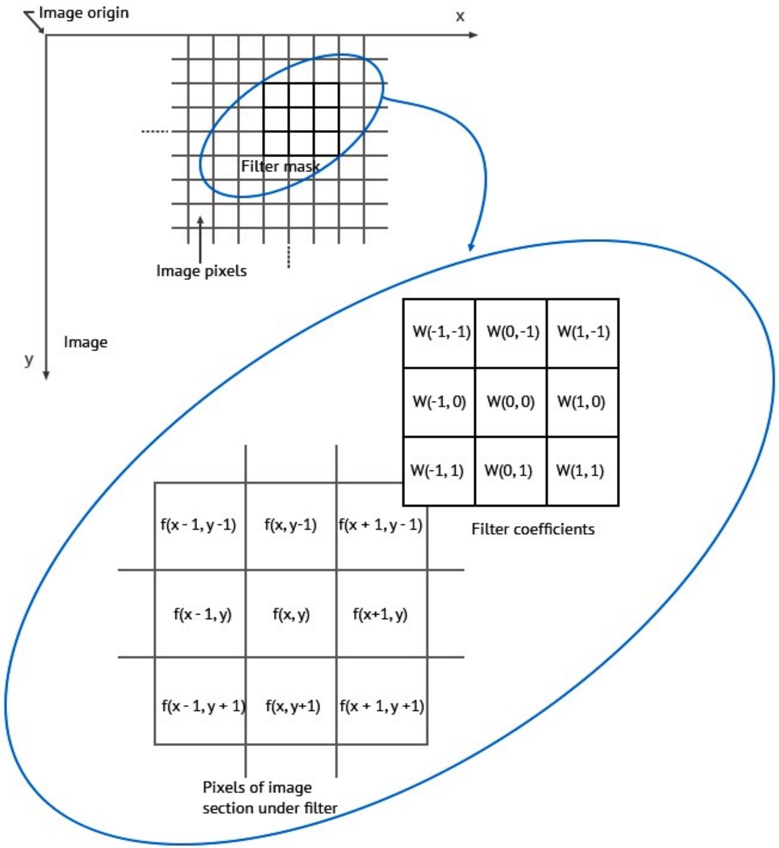
Spatial Filtering (Cont)

- The mechanics of spatial filtering are illustrated in Figure.
- For the 3 x 3 mask shown in Figure, the result (or response), R, of linear filtering with the filter mask at a point (x, y) in the image is:

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

In general, linear filtering of an image f of size $M \times N$ with a filter mask of size $m \times n$ is given by the expression:

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



Smoothing Spatial Filters

- The basic use of Smoothing filter method is for blurring and noise reduction.
- Blurring is the process of filling gaps in lines or curves
- It is also used as preprocessing for removal of small object before extracting large object information from an image.
- It is divided into two types

  1.Mean Smoothing or Linear Smoothing

  2.Order statistics filters or Non Linear Smoothing

Smoothing Spatial Filters (Cont)

Mean Smoothing or Linear Smoothing:

In mean smoothing, we replace the value of every pixel in image by the average/arithmetic mean of the gray levels in the neighborhood defined by the filter mask.

There are two categories:

1)Averaging Filter

2)Weighted Averaging Filter

Smoothing Spatial Filters (Cont)

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Averaging Filter:

- Use of the averaging filter yields the standard average of the pixels under the mask.
- A spatial averaging filter in which all coefficients are equal is sometimes called a box filter.
- This can best be seen by substituting the coefficients of the mask in which is the average of the gray levels of the pixels in the 3 x 3 neighborhood defined by the mask. Note that, instead of being 1/9, the coefficients of the filter are all 1's.The idea here is that it is computationally more efficient to have coefficients valued 1. At the end of the filtering process the entire image is divided by 9.

$$\frac{1}{9} \times \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

$$R = \frac{1}{9} \sum_{i=1}^{9} z_i,$$

Smoothing Spatial Filters (Cont)

Weighted Averaging Filter:

- This mask yields a so-called weighted average, terminology used to indicate that pixels are multiplied by different coefficients, thus giving more importance (weight) to some pixels at the expense of others.
- In the mask shown in Figure the pixel at the center of the mask is multiplied by a higher value than any other, thus giving this pixel more importance in the calculation of the average. The other pixels are inversely weighted as a function of their distance from the center of the mask.

$$\frac{1}{16} \times \begin{array}{|c|c|c|}\hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array}$$

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

Smoothing Spatial Filters (Cont)

Order Statistics Filters or Non Linear Smoothing:

- Order-statistics filters are nonlinear spatial filters whose response is based on ordering (ranking) the pixels contained in the image area encompassed by the filter, and then replacing the value of the center pixel with the value determined by the ranking result.
- It is used remove impulse noise, also called salt-and-pepper noise.

There are two categories:

1)Median: We first sort the values of the pixel in question and its neighbors, determine their median, and assign the value to that pixel. For example, in a 3*3 neighborhood the median is the 5th largest value, in a 5*5 neighborhood the 13th largest value, and so on.

$$R = \text{median } \{g(s,t)\}$$

2) Minimum and Maximum: Min. filter is used to find the darkest point & Max. filter is used to find the brightest point of an image. $R = \min \{g(s,t)\}$ and $R = \max \{g(s,t)\}$

Sharpening Spatial Filters

- The principal objective of sharpening is to highlight fine detail in an image or to enhance detail that has been blurred, either in error or as a natural effect of a particular method of image acquisition.
- The term sharpening is referred to the techniques suited for enhancing the intensity transitions.
- In images, the borders between objects are perceived because of the intensity change: more crisp the intensity transitions, more sharp the image.
- In Smoothing, We took the averaging of pixels which is equal to the integration of pixels whereas here in Sharpening, it is opposite, we will do the differentiation of pixels.
- It is divided into two types

    1. Use of First order derivatives – The Gradients
    2. Use of Second order derivatives – The Laplacian

Sharpening Spatial Filters (Cont)

First Order derivative:

- Since the image is a discrete function, the traditional definition of derivative cannot be applied.
- Hence, a suitable operator have to be defined such that it satisfies the main properties of the first derivative:
  1. It is equal to zero in the regions where the intensity is constant;
  2. It is different from zero for an intensity transition;
  3. It is constant on ramps where the intensity transition is constant.
- The natural derivative operator is the difference between the intensity of neighboring pixels (spatial differentiation).
- For simplicity, the mono-dimensional case can be considered:

$$\partial f / \partial x = f(x+1) - f(x)$$

- Since it is defined using the next pixel it cannot be computed for the last pixel of the row.

Sharpening Spatial Filters (Cont)

Second Order derivative:

- Similarly, the second derivative operator can be defined as:

$$\partial^2 f / \partial x^2 = f(x+1) + f(x-1) - 2f(x)$$

- This operator satisfies the following properties:
  1. It is equal to zero where the intensity is constant;
  2. It is different from zero at the begin of a step (or a ramp) of the intensity;
  3. It is equal to zero on the constant slope ramps.
- Since it is defined using the previous and next pixels it cannot be computed with respect to the first and the last pixels of each row

Sharpening Spatial Filters (Cont)

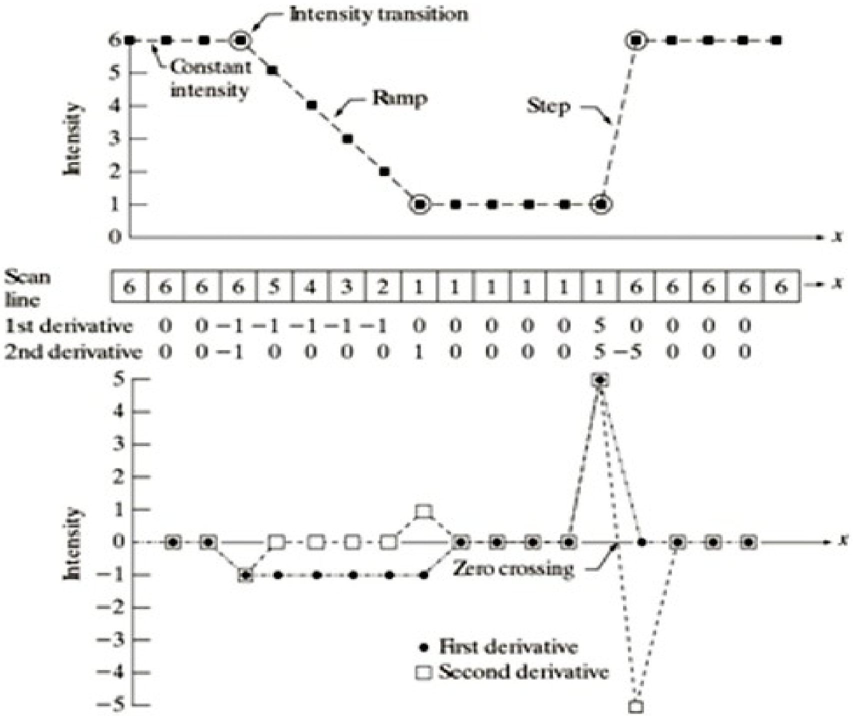
Derivatives of an Image : Example

0	0	0
0	-1	1
0	0	0

1st order derivative mask

0	0	0
1	-2	1
0	0	0

2nd order derivative mask



Sharpening Spatial Filters (Cont)

Using First Order Derivative: The Gradient of an Image:

- First order derivatives in image processing are implemented using the magnitude of the gradient.
- For a bi-dimensional function, f (x, y):

$$\nabla f \equiv \text{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

- The magnitude of the vector is given by:

$$M(x, y) = \text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2}$$

- It is often approximated as $M(x, y) \approx |gx| + |gy|$

Sharpening Spatial Filters (Cont)

- The masks shown in the figure are used to compute the gradient.
- A 3 x 3 region of an image (the z's are gray-level values) and masks used to compute the gradient at point labeled z5 .

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Robert:

-1	0
0	1

0	-1
1	0

Prewitt:

-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

Gx = (z7+z8+z9) - (z1+z2+z3)

Gy = (z3+z6+z9) – (z1+z4+z7)

Sobel:

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

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

Gx = (z7+2z8+z9) - (z1+2z2+z3)

Gy = (z3+2z6+z9) – (z1+2z4+z7)

Sharpening Spatial Filters (Cont)

Using Second Order Derivative: The Laplacian:

- Usually the sharpening filters make use of the second order operators.
- A second order operator is more sensitive to intensity variations than a first order operator.
- The Laplacian is represented by: $$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$
- The partial second order derivative on x and y direction is:

$$\frac{\partial^2 f}{\partial^2 x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$

$$\frac{\partial^2 f}{\partial^2 y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

- The digital implementation of the two-dimensional Laplacian is obtained by summing these two components:

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

Sharpening Spatial Filters (Cont)

- The masks shown in the figure are used to compute the Laplacian

0	1	0
1	–4	1
0	1	0

1	1	1
1	–8	1
1	1	1

0	–1	0
–1	4	–1
0	–1	0

–1	–1	–1
–1	8	–1
–1	–1	–1

$$g(x, y) = \begin{cases} f(x, y) - \nabla^2 f(x, y) & \text{if the center coefficient of the Laplacian mask is negative} \\ f(x, y) + \nabla^2 f(x, y) & \text{if the center coefficient of the Laplacian mask is positive.} \end{cases}$$

Questions

1.Explain Smoothing Spatial Filters?

2.Explain Sharpening Spatial Filters?

THANK YOU

IMAGE ENHANCEMENT IN FREQUENCY DOMAIN

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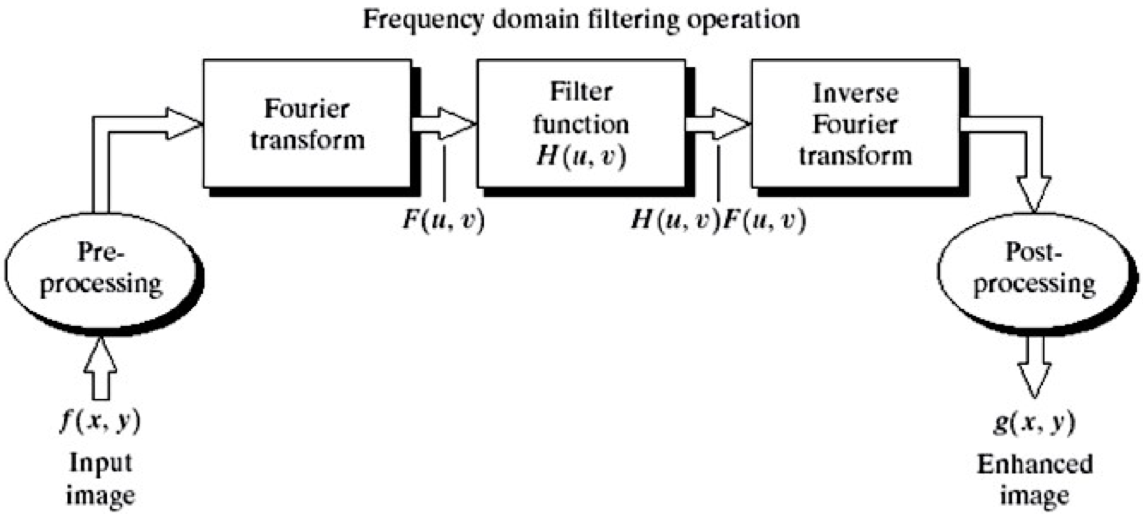
Lecture Details:
Topic Name: Image Enhancement in Frequency Domain
IP/ CSE III B.Tech I Sem

Outline

- Introduction to Frequency Domain
- Fourier Transform
- Smoothing Frequency Domain Filters
- Sharpening Frequency Domain Filters

Frequency Domain



Basic steps for filtering in the frequency domain

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

Frequency Domain (Cont)

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- The frequency domain methods of image enhancement are based on convolution theorem.
- This is represented as $g(x, y) = h(x, y)*f(x, y)$

  where $g(x, y)$ = Resultant or Output image

  $h(x, y)$ = Position invariant operator

  $f(x, y)$= Input image
- The Fourier transform representation of equation above is,

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

  The function H (u, v) in equation is called transfer function.

Frequency Domain (Cont)

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Definition:

- **Frequency domain**:- Deal with the rate at which the pixel values are changing in spatial domain.
- In the frequency or Fourier domain, the value and location are represented by sinusoidal relationships that depend upon the frequency of a pixel occurring within an image.
- In this domain, pixel location is represented by its x- and y-frequencies and its value is represented by an amplitude.
- Images can be transformed into the frequency domain to determine which pixels contain more important information and whether repeating patterns occur.
- Frequency components are divided into two major components.
    1. **High frequency components** correspond to edges in an image.
    2. **Low frequency components** in an image correspond to smooth regions.

Fourier Transform

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- A signal can be converted from spatial domain into frequency domain using mathematical operators called transformation.
- The following are the kinds of transforms:

  1.Fourier Series

  2.Fourier transformation

  3. Laplace transform

  4.Z transform
- Here we will use Fourier transformation

Fourier Transform (Cont)

- The general idea is that the image (f(x,y) of size M x N) will be represented in the frequency domain (F(u,v)).

For an image of size MxN pixels

2-D DFT

$$F(u,v)=\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)e^{-j2\pi(ux/M+vy/N)}$$

u = frequency in x direction, $u = 0 ,\ldots, M\text{-}1$
v = frequency in y direction, $v = 0 ,\ldots, N\text{-}1$

2-D IDFT

$$f(x,y)=\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}F(u,v)e^{j2\pi(ux/M+vy/N)}$$

$x = 0 ,\ldots, M\text{-}1$
$y = 0 ,\ldots, N\text{-}1$

Frequency Domain Filtering

Like Spatial Domain Filtering, Frequency Domain Filtering also done in two types:

1)Smoothing Frequency Domain Filters

2)Sharpening Frequency Domain Filters

1) Smoothing Frequency Domain Filters:

Smoothing is achieved in the frequency domain by dropping out high frequency components and allowing only low frequency components. It is of three types:

i. Ideal Low pass filter
ii. Butterworth Low pass filter
iii. Gaussian Low pass filter

2) Sharpening Frequency Domain Filters:

Sharpening is achieved in the frequency domain by dropping out low frequency components and allowing only high frequency components. It is of three types:

iv. Ideal High pass filter
v. Butterworth High pass filter
vi. Gaussian High pass filter

Smoothing Frequency Domain Filters

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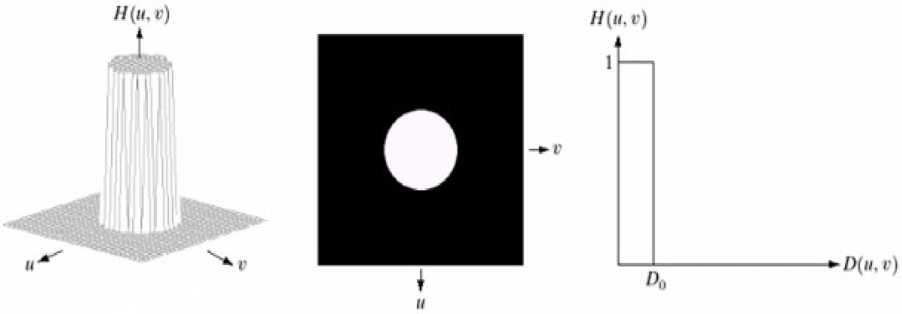
Ideal Low pass Filter (ILPF):

- ILPF is the simplest low pass filter that "cuts off" all high frequency components of the DFT that are at a distance greater than a specified distance D0 from the origin of the (centered) transform.
- The ILPF indicates that all frequencies inside a circle of radius D0 are passed with no attenuation, whereas all frequencies outside this circle are completely attenuated.

The transfer function of this filter is:

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

where D_0 is the cutoff frequency, and $D(u,v) = \sqrt{(u - M/2)^2 + (v - N/2)^2}$



(a) (b) (c)

Figure 7.1 (a) Ideal lowpass filter. (b) ILPF as an image. (c) ILPF radial cross section

Smoothing Frequency Domain Filters (Cont)

Butterworth Low pass Filter (GLPF):

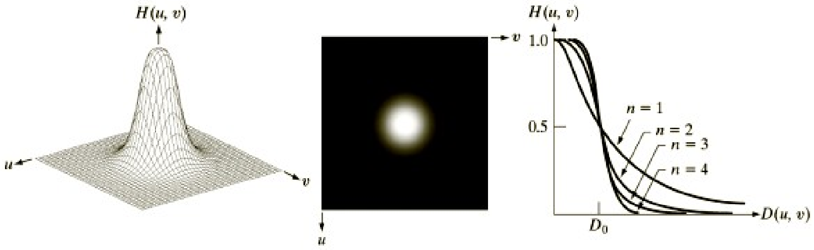
- The transfer function of a Butterworth low pass filter (BLPF) of order n , and with cutoff frequency at a distance D0 from the origin, is defined as: (fig)
- Unlike ILPF, the BLPF transfer function does not have a sharp discontinuity.

$$H(u,v) = \frac{1}{1+[D(u,v)/D_0]^{2n}}, \qquad (4.8\text{-}5)$$

where $D(u,v)$ is given by

$$D(u,v) = \sqrt{(u-P/2)^2 + (v-Q/2)^2}. \qquad (4.8\text{-}2)$$

Figure shows a perspective plot, image display, and radial cross sections of the BLPF function.



(a) Perspective plot of a Butterworth lowpass-filter transfer function. (b) Filter displayed as an image. (c) Filter radial cross sections of orders 1 through 4.

Smoothing Frequency Domain Filters (Cont)

Gaussian Low pass Filter (GLPF):

The GLPF with cutoff frequency D_0 is defined as:

$$H(u,v) = e^{-D^2(u,v)/2D_0{}^2}$$

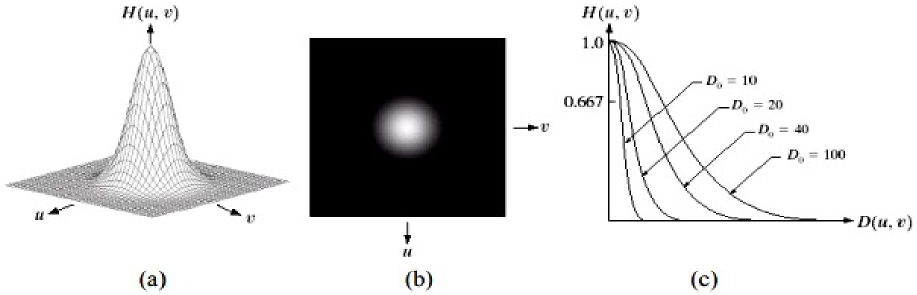


Figure 7.4 (a) Gaussian lowpass filter. (b) GLPF as an image. (c) GLPF radial cross section

- Unlike ILPF, the GLPF transfer function does not have a sharp transition that establishes a clear cutoff between passed and filtered frequencies. Instead, GLPF has a smooth transition between low and high frequencies.

Sharpening Frequency Domain Filters

- Edges and sudden changes in gray levels are associated with high frequencies. Thus to enhance and sharpen significant details we need to use high pass filters in the frequency domain.
- For any low pass filter, there is high pass filter.

$$H_{hp}(u,v) = 1 - H_{lp}(u,v)$$

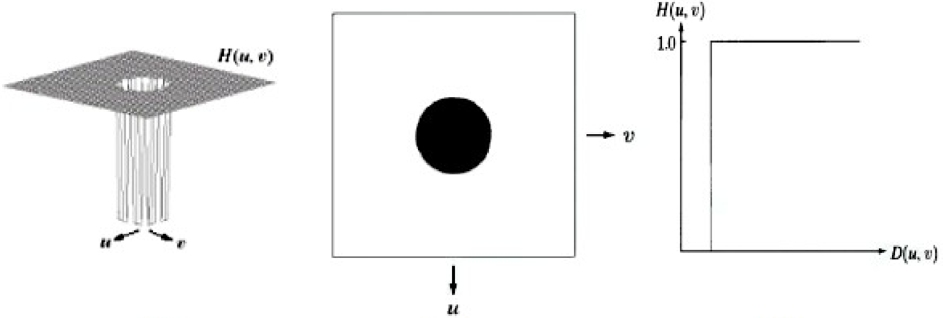
Sharpening Frequency Domain Filters (Cont)

Ideal High pass Filter (IHPF):

- The IHPF cuts off all low frequencies of the DFT but maintain the high ones that are within a certain distance from the center of the DFT.
- The IHPF sets to zero all frequencies inside a circle of radius D0 while passing, without attenuation, all frequencies outside the circle.

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

where D_0 is the cutoff frequency, and $D(u,v) = \sqrt{(u-M/2)^2 + (v-N/2)^2}$



(a) (b) (c)

Figure 7.8 (a) Ideal highpass filter. (b) IHPF as an image. (c) IHPF radial cross section

Smoothing Frequency Domain Filters (Cont)

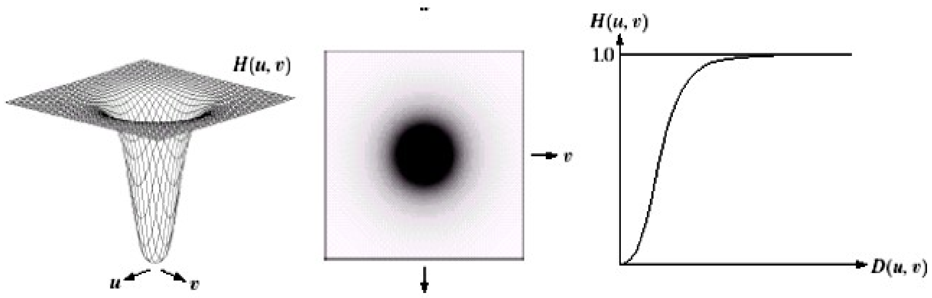
Butterworth High pass Filter (BHPF):

- This Butterworth high pass filter is the reverse operation of the Butterworth low pass filter.
- The transfer function of a Butterworth High pass filter (BHPF) is shown in (fig).

The Butterworth high pass filter is given as:

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

where n is the order and D0 is the cut off distance as before



Smoothing Frequency Domain Filters (Cont)

Gaussian High pass Filter (GHPF):

The Gaussian Highpass Filter (GHPF) with cutoff frequency at distance D_0 is defined as:

$$H(u,v) = 1 - e^{-D^2(u,v)/2{D_0}^2}$$

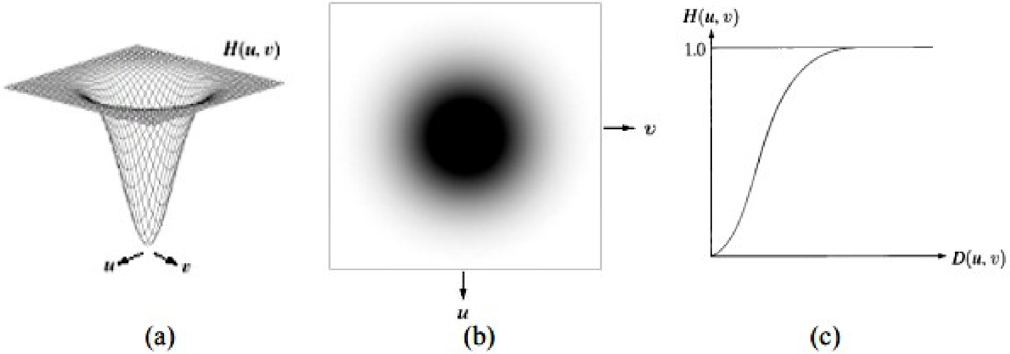


Figure 7.10 (a) Gaussian highpass filter. (b) GHPF as an image. (c) GHPF radial cross section

Questions

1.Explain Smoothing Filters in Frequency Domain?

2.Explain Sharpening Filters in Frequency Domain?

References

1.Digital Image Processing Second Edition Rafael C. Gonzalez Richard E. Woods Prentice Hall

2.https://www.uotechnology.edu.iq/ce/Lectures/Image_Processing_4th/DIP_Lecture7.pdf

3.http://portal.unimap.edu.my/portal/page/portal30/Lecture%20Notes/KEJURUTERAAN_KOMPUTER/Semester%201%20Sidang%20Akademik%2020172018/EKT460%20Image%20Processing/EKT460-Lecture3-ver1.pdf

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THANK YOU

UNIT III

IMAGE RESTORATION

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Lecture Details:

Topic Name: Introduction to Image Restoration

IP/ CSE III B.Tech I Sem

Outline

- Introduction to Image Restoration
- Image Enhancement vs. Image Restoration
- Image Degradation/Restoration Model
- Introduction to Noise
- Types of Noises

What is Image Restoration?

Definition:

Image restoration is the process of recovering or restoring an image from a degraded version of the image.

Image degradation can be occurred at:

- Image Sensor noise
- Blur due to misfocus
- Blur due to motion
- Noise from transmission channel
- Noise due to blur

What is Image Restoration? (cont)

- Restoration tries to reconstruct the image by using a clear knowledge of degradation phenomenon
- We will try to identify the degradation process and attempt to reverse it.

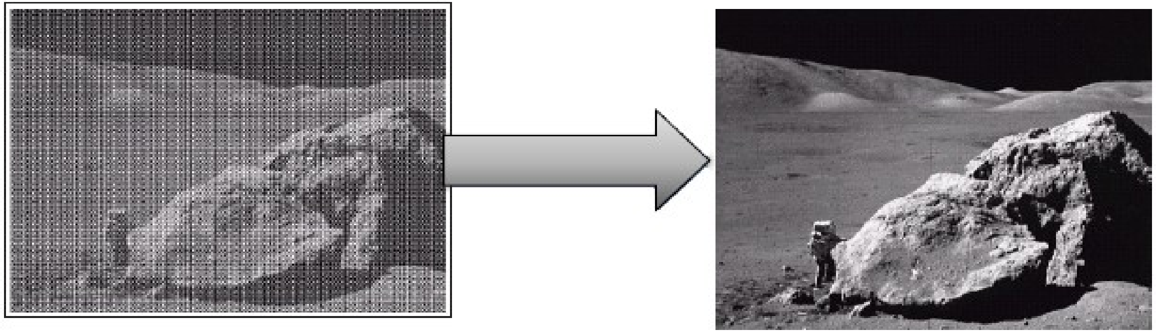

Fig: Degraded image

Fig: Restored Image

Image Enhancement vs. Image Restoration

- Image Enhancement is a subjective process whereas Image Restoration is an objective process.
- The result of Enhancement varies from one person to another person. Image which is good for one person may not be good for another person
- The result of Restoration depends on probabilistic methods involved which is accepted by all.

Image Degradation/Restoration Model

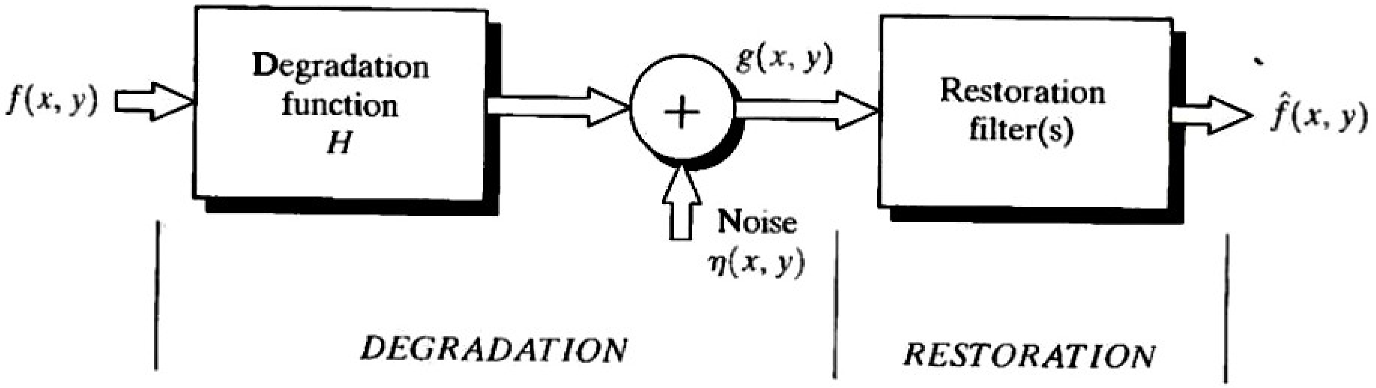

Fig. model of the image degradation/restoration process.

$g(x,y)=f(x,y)*h(x,y)+\eta(x,y)$ — **Spatial Domain**

$G(u,v)=F(u,v)H(u,v)+N(u,v)$ — **Frequency Domain**

Image Restoration/Degradation Model (Cont)

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- Take an input image f(x,y)
- Apply degradation function 'H' (h(x,y)) on to the input image f(x,y)
- Add noise to it also which is denoted by η(x, y).
- Then we get the output image which is degraded image i.e;

$$g(x, y) = h(x, y) * f(x, y) + \eta(x, y) \quad \text{(Spatial domain)}$$

$$G(u, v) = H(u, v)\, F(u, v) + N(u, v) \quad \text{(Frequency domain)}$$

- The objective of restoration is to obtain an estimate of f(x, y), input image. The estimate should be as close as possible to the original input image which is denoted as $\hat{f}(x, y)$

Noise

Noise is defined as any degradation in image signal caused by external disturbance. If an image is being sent electronically from one place to another through wire or wireless transmission, we expect some errors to occur in image signals. Thus errors will appear on image output in different ways depending upon the type of disturbance in signal.

Some sources of Noise are:

- When the image is scanned from a photograph made on film, here noise can be produced from the damaged film or from the scanner used to take the image.
- If the image is taken directly in a digital format the mechanism for gathering the data can introduce noise.
- Insufficient light is also a cause of noise due to which sensor temperature may introduce the noise.
- Scratches and dust particles present in the scanner screen is also a cause of creating noise.
- Interference in transmission channel during electronic transmission can create noise in the original image.

Types of Noises

Types of noises:

1. Salt & Pepper noise (Impulse noise)
2. Gaussian noise (Additive noise, Amplifier noise)
3. Speckle noise (Multiplicative Noise)
4. Periodic noise

Some other types of noises are:

5. Uniform Noise
6. Exponential Noise
7. Rayleigh Noise
8. Gamma Noise

Salt & Pepper noise

- Salt & Pepper noise is also called data drop noise because statistically its drop the original data values.
- The salt and pepper noise is generally caused by malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process. This noise is seen in data transmission.
- An image containing Salt and Pepper noise will have dark pixels in bright regions and bright pixels in the dark regions.
- The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a “salt and pepper” like appearance. It is found that an 8- bit image, the typical value for pepper noise is 0 and for salt noise it is 255.
- Salt and Pepper noise is sometimes known as Impulse noise or Spike noise or Random noise or Independent noise.

Salt & Pepper noise (Cont)

Let us consider 3x3 image matrices which are shown in the Fig. 3. Suppose the central value of matrices is corrupted by Pepper noise. Therefore, this central value i.e., 212 is given in Fig. 3 is replaced by value zero.

In this connection, we can say that, this noise is inserted dead pixels either dark or bright. So in a salt and pepper noise, progressively dark pixel values are present in bright region and vice versa

254	207	210
97	212	32
62	106	20

254	207	210
97	0	32
62	106	20

Figure 3 The central pixel value is corrupted by Pepper noise

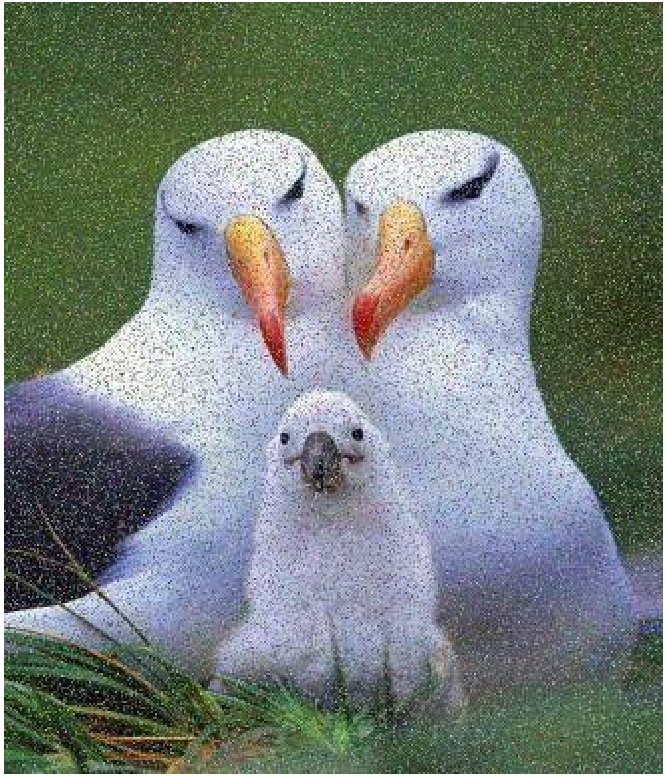


Fig: Salt & Pepper Noise image

Gaussian Noise

Gaussian Noise:

- It is also called as electronic noise or amplifier noise because it arises in amplifiers or detectors. It is caused by natural sources such as thermal vibration of atoms and discrete nature of radiation of warm objects .
- Gaussian noise is evenly distributed over the signal.
- Each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. That's the reason why it is also known as additive noise
- Gaussian noise generally disturbs the gray values in digital images.

Fig: Gaussian Noise image

Speckle noise

Speckle Noise:

- Speckle noise can be modelled by random values multiplied by pixel values so it is known as multiplicative noise.
- Their appearance is seen in coherent imaging system such as laser, radar and acoustics etc.
- Medical images are usually corrupted by noise in its acquisition and Transmission. The existence of Speckle Noise affects the tasks of individual interpretation and diagnosis
- Speckle noise is mainly present in Ultrasound image, Satellite images.

Fig: Speckle Noise image

Periodic Noise

Periodic Noise:

- This noise is generated from electronics interferences, especially in power signal during image acquisition.
- This noise has special characteristics like spatially dependent and sinusoidal in nature at multiples of specific frequency.
- It’s appears in form of conjugate spots in frequency domain.
- It can be conveniently removed by using a narrow band reject filter or notch filter in frequency domain

(a) Original image

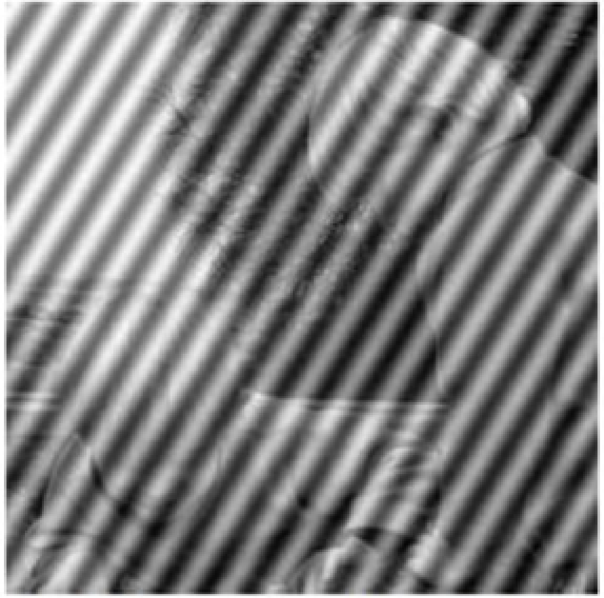
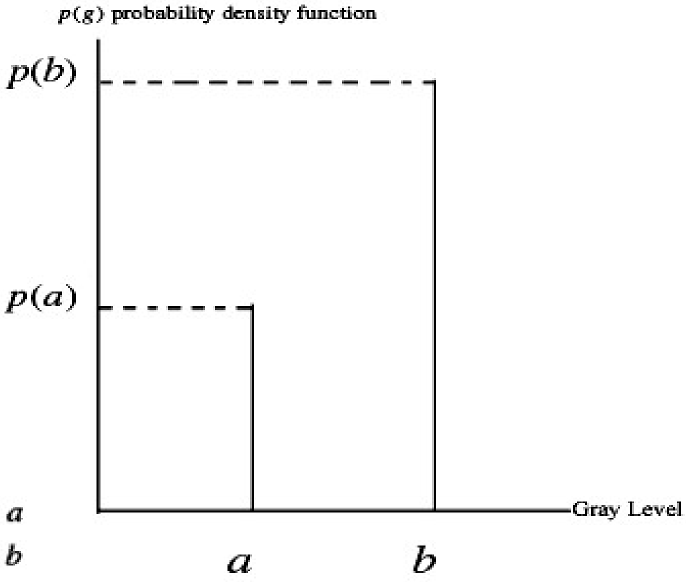


Fig 5.3 Twin image corrupted by periodic noise

Some Noise Probability Functions



$$P(g)=\begin{cases} Pa & \text{for } g=a \\ Pb & \text{for } g=b \\ 0 & \text{otherwise} \end{cases}$$

Figure The PDF of Salt and Pepper noise

Fig. shows the PDF of Salt and Pepper noise, if mean is zero and variance is 0.05. Here we will meet two spike one is for bright region (where gray level is less) called 'region a' and another one is dark region (where gray level is large) called 'region b', we have clearly seen here the PDF values are minimum and maximum in 'region a' and 'region b', respectively

Gaussian noise generally disturbs the gray values in digital images. That is why Gaussian noise model essentially designed and characteristics by its PDF or normalizes histogram with respect to gray value. This is given as

$$P(g) = \sqrt{\frac{1}{2\pi\sigma^2}}e^{-\frac{(g-\mu)^2}{2\sigma^2}} \qquad (1)$$

Where g = gray value, $\sigma =$ standard deviation and $\mu =$ mean. Generally Gaussian noise mathematical model represents the correct approximation of real world scenarios. In this noise model, the mean value is zero, variance is 0.1 and 256 gray levels in terms of its PDF, which is shown in Fig. 1.

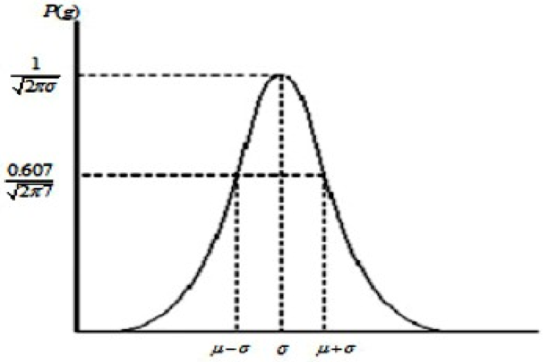
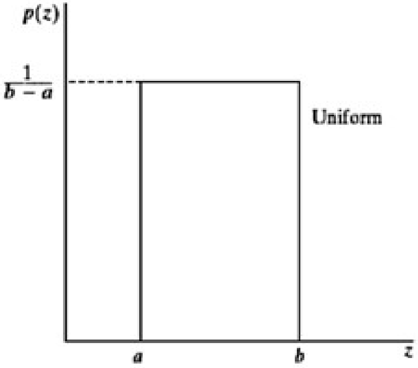


Figure 1 PDF of Gaussian noise

Uniform Noise

The uniform noise cause by quantizing the pixels of image to a number of distinct levels is known as quantization noise. It has approximately uniform distribution. In the uniform noise the level of the gray values of the noise are uniformly distributed across a specified range. Uniform noise can be used to generate any different type of noise distribution. This noise is often used to degrade images for the evaluation of image restoration algorithms. This noise provides the most neutral or unbiased noise .[4] $p(z)=\begin{cases}\dfrac{1}{b-a} & \text{if } a\le z\le b\\ 0 & \text{otherwise}\end{cases}$

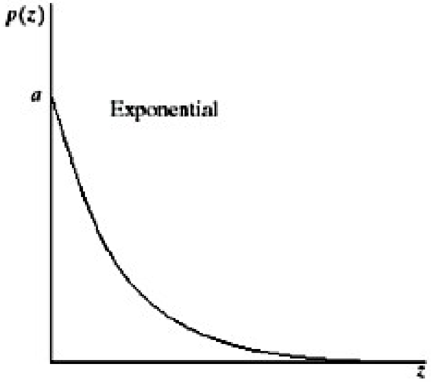
The mean and variance of this density are given by $\mu=(a+b)/2$ and $\sigma^2=\dfrac{(b-a)^2}{12}$



Exponential Noise

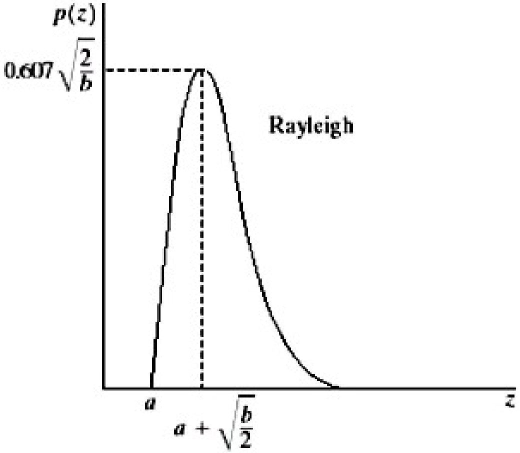
$$p(z) = \begin{cases} ae^{-az} & \text{for } z \geq 0 \\ 0 & \text{for } z < 0 \end{cases}$$

The mean and variance of this density are given by $\mu = 1/a$ and $\sigma^2 = \dfrac{1}{a^2}$



Rayleigh Noise

Radar range and velocity images typically contain noise that can be modeled by the Rayleigh distribution.



The mean and variance of this density are given by

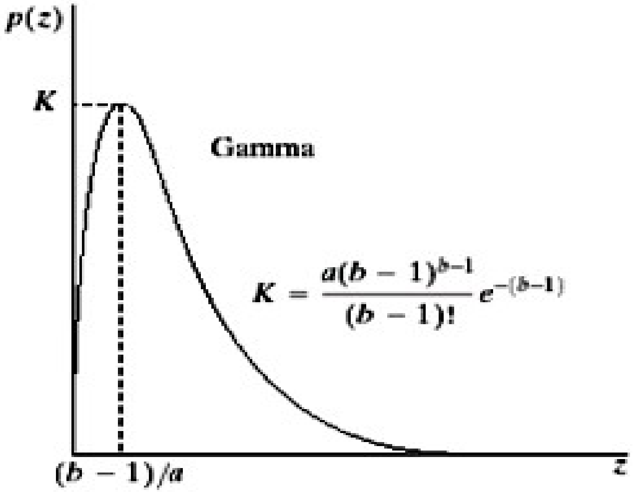
$\mu = a + \sqrt{\pi b/4}$ and $\sigma^2 = \dfrac{b(4-\pi)}{4}$ a and b can be obtained through mean and variance.

Erlang (Gamma) Noise

$$p(z)=\begin{cases}\dfrac{a^b z^{b-1}}{(b-1)!}e^{-az} & \text{for } z\ge 0\\ 0 & \text{for } z<0\end{cases}$$

The mean and variance of this density are given by

$\mu=b/a$ and $\sigma^2=\dfrac{b}{a^2}$ a and b can be obtained through mean and variance



Questions

1.What is Image Restoration ?

2.Differentiate between Image Enhancement and Image Restoration.

3.Explain Image Degradation/Restoration Model.

4.Generalize the various noise models implemented in Image Restoration

THANK YOU

Image Restoration using Spatial Domain Filtering

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Lecture Details:
Topic Name: Spatial Filtering in Image Restoration
IP/ CSE III B.Tech I Sem

Outline

- Mean Filters
- Order Statistics filters
- Adaptive filters

Spatial Filters used for Image Restoration

1) Mean Filters:

- Arithmetic mean filter
- Geometric mean filter
- Harmonic mean filter
- Contra-harmonic mean filter

2) Order statistics filters:

- Median filter
- Max and min filters
- Mid-point filter
- alpha-trimmed filters

3) Adaptive filters:

- Adaptive local noise reduction filter.
- Adaptive median filter

Arithmetic Mean Filter (AMF)

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This is the simplest of the mean filters. Let Sxy represent the set of coordinates in a rectangular sub image window of size m X n, centred at point (x, y). The arithmetic mean filtering process computes the average value of the corrupted image g(x, y) in the area defined by Sxy. The value of the restored image f at any point (x, y) is simply the arithmetic mean computed using the pixels in the region defined by Sxy.

In other words:

$$\hat{f}(x, y) = \frac{1}{mn} \sum_{(s,t)\in S_{xy}} g(s, t).$$

This operation can be implemented using a convolution mask in which all coefficients have value 1/mn.

It is used to remove uniform noise and Gaussian noise.

Geometric Mean Filter (GMF)

An image restored using a geometric mean filter is given by the expression:

$$\hat{f}(x,y) = \left[\prod_{(s,t)\in S_{xy}} g(s,t) \right]^{\frac{1}{mn}}.$$

Here, each restored pixel is given by the product of the pixels in the sub image window, raised to the power 1/mn. A geometric mean filter achieves smoothing comparable to the arithmetic mean filter, but it tends to lose less image detail in the process.

Harmonic Mean Filter (HMF)

The harmonic mean filtering operation is given by the expression:

$$\hat{f}(x, y) = \frac{mn}{\sum_{(s,t)\in S_{xy}} \frac{1}{g(s, t)}}.$$

The harmonic mean filter works well for salt noise, but fails for pepper noise. It does well also with other types of noise like Gaussian noise.

Contra Harmonic Mean Filter (CHMF)

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The contra harmonic mean filtering operation yields a restored image based on the expression:

$$\hat{f}(x, y) = \frac{\sum_{(s,t)\in S_{xy}} g(s, t)^{Q+1}}{\sum_{(s,t)\in S_{xy}} g(s, t)^{Q}}$$

where Q is called the order of the filter. This filter is well suited for reducing or virtually eliminating the effects of salt-and-pepper noise. For positive values of Q, the filter eliminates pepper noise. For negative values of Q it eliminates salt noise. It cannot do both simultaneously.

MEDIAN FILTER

The best-known order-statistics filter is the median filter, which, as its name implies, replaces the value of a pixel by the median of the gray levels in the neighbourhood of that pixel:

$$\hat{f}(x, y) = \underset{(s,t)\in S_{xy}}{\text{median}}\{g(s, t)\}.$$

The original value of the pixel is included in the computation of the median. Median filters are quite popular because, for certain types of random noise, they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters of similar size. It is used for removing salt & pepper noise.

MAX and MIN Filters

Although the median filter is by far the order-statistics filler most used in image processing, it is by no means the only one. The median represents the 50th percentile of a ranked set of numbers, but the reader will recall from basic statistics that ranking lends itself to many other possibilities. For example, using the 100th percentile results in the so-called max filter, The 0th percentile filter is the min filter and they are given by

$$\hat{f}(x, y) = \max_{(s,t)\in S_{xy}} \{g(s, t)\}. \qquad \hat{f}(x, y) = \min_{(s,t)\in S_{xy}} \{g(s, t)\}.$$

Max filter is useful for finding the brightest points in an image. It reduces pepper noise.

Min filter is useful for finding the darkest points in an image. It reduces salt noise

MID POINT FILTER

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The midpoint filter simply computes the midpoint between the maximum and minimum values in the area encompassed by the filter and is represented as:

$$\hat{f}(x, y) = \frac{1}{2}\left[\max_{(s,t)\in S_{xy}}\{g(s, t)\} + \min_{(s,t)\in S_{xy}}\{g(s, t)\}\right].$$

Note that this filter combines order statistics and averaging. This filter works best for randomly distributed noise, like Gaussian or uniform noise.

Alpha – trimmed mean filter

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It is a filter formed by deleting the d/2 lowest and the d/2 highest gray-level values of g(s,t) in the neighbourhood Sxy. where the value of d can range from 0 to mn – 1.

Let gr (s, t) represent the remaining mn - d pixels. A filter formed by averaging these remaining pixels is called an alpha-trimmed mean filter

$$\hat{f}(x, y) = \frac{1}{mn - d} \sum_{(s,t) \in S_{xy}} g_r(s, t)$$

When d = 0, the alpha- trimmed filter reduces to the arithmetic mean filter. For other values of d, the alpha-trimmed filter is useful in situations involving multiple types of noise, such as combination of salt-and-pepper and Gaussian noise.

Adaptive local noise reduction filter

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The simplest statistical measures of a random variable are its mean and variance. These are reasonable parameters on which to base an adaptive filler because they are quantities closely related to the appearance of an image. The mean gives a measure of average gray level in the region over which the mean is computed, and the variance gives a measure of average contrast in that region. It is given by:

$$\hat{f}(x, y) = g(x, y) - \frac{\sigma_\eta^2}{\sigma_L^2}\left[g(x, y) - m_L\right].$$

(a) $g(x, y)$, the value of the noisy image at (x, y);

(b) σ_η^2, the variance of the noise corrupting $f(x, y)$ to form $g(x, y)$;

(c) m_L, the local mean of the pixels in S_{xy};

(d) σ_L^2, the local variance of the pixels in S_{xy}.

Adaptive local noise reduction filter (Cont)

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The behavior of the filter to be as follows:

1. If σ^2_η is zero, the filler should return simply the value of g (x, y). This is the trivial, zero-noise case in which g (x, y) is equal to f (x, y).

2. If the local variance is high relative to σ^2_η the filter should return a value close to g (x, y). A high local variance typically is associated with edges, and these should be preserved.

3. If the two variances are equal, we want the filter to return the arithmetic mean value of the pixels in S_{xy}. This condition occurs when the local area has the same properties as the overall image, and local noise is to be reduced simply by averaging.

Adaptive median filter

The adaptive median filter also works in a rectangular window area Sxy. Unlike those filters, however, the adaptive median filter changes (increases) the size of Sxy during filter operation, depending on certain conditions. The output of the filter is a single value used to replace the value of the pixel at (x, y), the particular point on which the window Sxy is centred at a given time.

Consider the following notations:

z_{min} = minimum gray level value in Sxy

z_{max} = maximum gray level value in Sxy

z_{med} = median of gray levels in Sxy

z_{xy} = gray level at coordinates (x, y)

S_{max} = maximum allowed size of Sxy.

Adaptive median filter (cont)

The adaptive median filtering algorithm works in two levels, denoted level A and level B, as follows:

Level A: $A1 = Z_{med} - Z_{min}$

$A2 = Z_{med} - Z_{max}$

If $A1 > 0$ AND $A2 < 0$, Go to level B

Else increase the window size

If window size $\leq S_{max}$ repeat level A

Else output z_{xy}

Level B: $B1 = Z_{xy} - Z_{min}$

$B2 = Z_{xy} - Z_{max}$

If $B1 > 0$ AND $B2 < 0$, output zxy

Else output z_{med}

Questions

1. Explain Restoration filters in the presence of Image Noise. (Or)

   Explain Image restoration using spatial domain filtering.

2. Explain Mean filters used in Image restoration.

3. Explain Order Statistic filters used in Image restoration.

4. Explain Mean filters used in Image restoration.

THANK YOU

Periodic Noise removal using Frequency Domain Filtering in Image Restoration

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Lecture Details:
Topic Name: Frequency domain filtering in Image Restoration
IP/ CSE III B.Tech I Sem

Outline

- Introduction to Periodic Noise
- Band Reject Filters
- Band Pass Filters

Periodic Noise

- Periodic noise is generated from electronics interferences, especially in power signal during image acquisition.
- It is sinusoidal at multiples of a specific frequency and periodic in nature.
- The occurrence of uniform bars over an image is a manifestation of periodic noise
- It can be conveniently removed by using a narrow **band reject filters** and **band pass filters** in frequency domain

(a) Original image

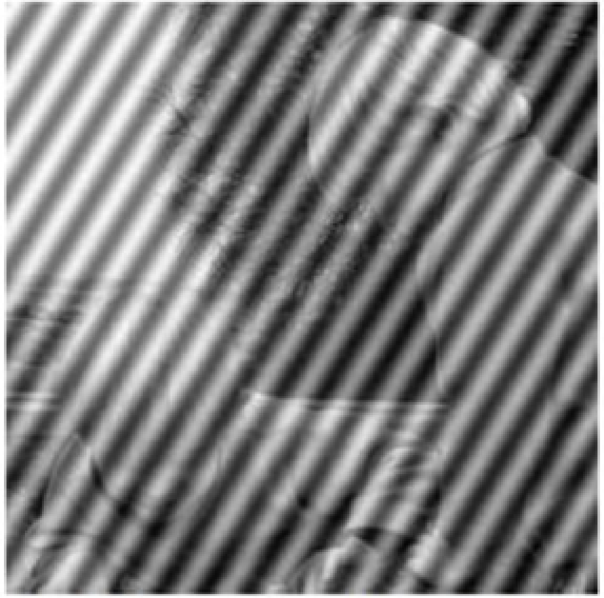


Fig 5.3 Twin image corrupted by periodic noise

Band Reject Filters

- Band reject filters remove or attenuate a certain band of frequencies.
- A band reject filter is useful when the general location of the noise in the frequency domain is known.
- A band reject filter blocks frequencies within the chosen range and lets frequencies outside of the range pass through.

Three types:

1. Ideal Band Reject filter
2. Butterworth Band Reject filter
3. Gaussian Band Reject filter

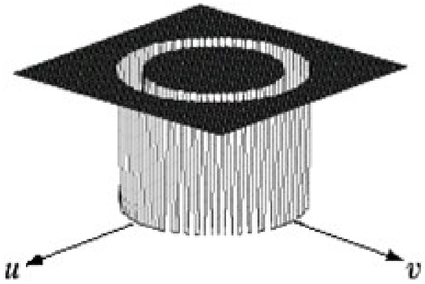
Ideal Band Reject Filter

$$H(u,v)=\begin{cases}1 & \text{if } D(u,v)<D_0-W/2\\ 0 & \text{if } D_0-W/2\le D(u,v)\le D_0+W/2\\ 1 & \text{if } D(u,v)>D_0+W/2\end{cases}$$

D_0 is its radial centre

$D(u, v)$ is the distance from the origin, and

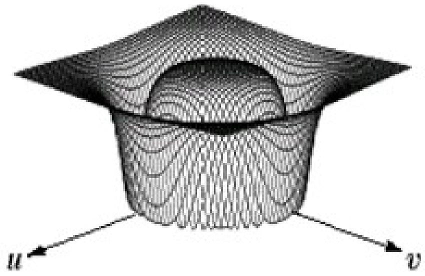
W is the width of the frequency band.



Butterworth and Gaussian Band Reject Filters

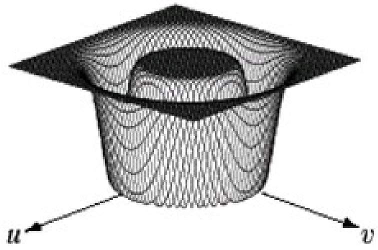
Butterworth band reject filter (order *n*)

$$H(u,v) = \frac{1}{1+\left[\dfrac{D(u,v)W}{D^2(u,v)-D_0^2}\right]^{2n}}$$



Gaussian band reject filter

$$H(u,v) = 1 - e^{-\frac{1}{2}\left[\frac{D^2(u,v)-D_0^2}{D(u,v)W}\right]^2}$$



Band Pass filters

- It is obtained from Band Reject Filter.
- It performs the opposite operation of a band reject filter.

$$H_{bp}(u,v)=1-H_{br}(u,v)$$

- Performing straight Band pass filtering on an image is not a common procedure because it generally removes too much image detail.
- It is quite useful in isolating the effect on an image of selected frequency bands.

Estimating the Degradation Function

- Weather the spatial or frequency domain, knowledge of degradation function is important.
- Estimation of degradation function H is important in image restoration.

There are mainly three ways to estimate the degradation function **H** :

1. Estimation by Observation
2. Estimation by Experimentation.
3. Estimation by Mathematical Modelling

Questions

1.Explain Periodic noise removal using frequency domain filtering.

2.Explain Band Reject filters.

3.Explain the ways of estimating the degradation function.

THANK YOU

Estimating the Degradation Function and Inverse Filtering

Presented By:
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Lecture Details:
Topic Name: Frequency domain filtering in Image Restoration
IP/ CSE III B.Tech I Sem

Outline

- Estimating the Degradation Function
- Inverse Filtering

Estimating the Degradation Function

- Since the degradation is modeled as convolution, image restoration is commonly called ***image deconvolution***.
- There are three ways to estimate the degradation function:
  - Mathematical modeling
  - Experimentation
  - Image observation
- The process of image restoration by an estimated degradation function is commonly called ***blind deconvolution***.
- To see how these approaches work, let's focus on a degradation only case, without any noise component first.

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

Estimation by Mathematical Modeling

- For estimation by mathematical modeling, we take into account the physical properties of the degradation operation.
- For example, using the physical characteristics of the air turbulence, we can model the degradation in aerial photos as:

$$H(u,v) = e^{-2k(u^2+v^2)^{5/6}}$$

- Here **k** is a constant dependent on the nature of turbulence.
- By changing **k**, we can simulate blurring of aerial images.

Estimation by Mathematical Modeling (Cont)

Fig: Negligible Turbulence

Fig: Severe Turbulence, k=0.0025

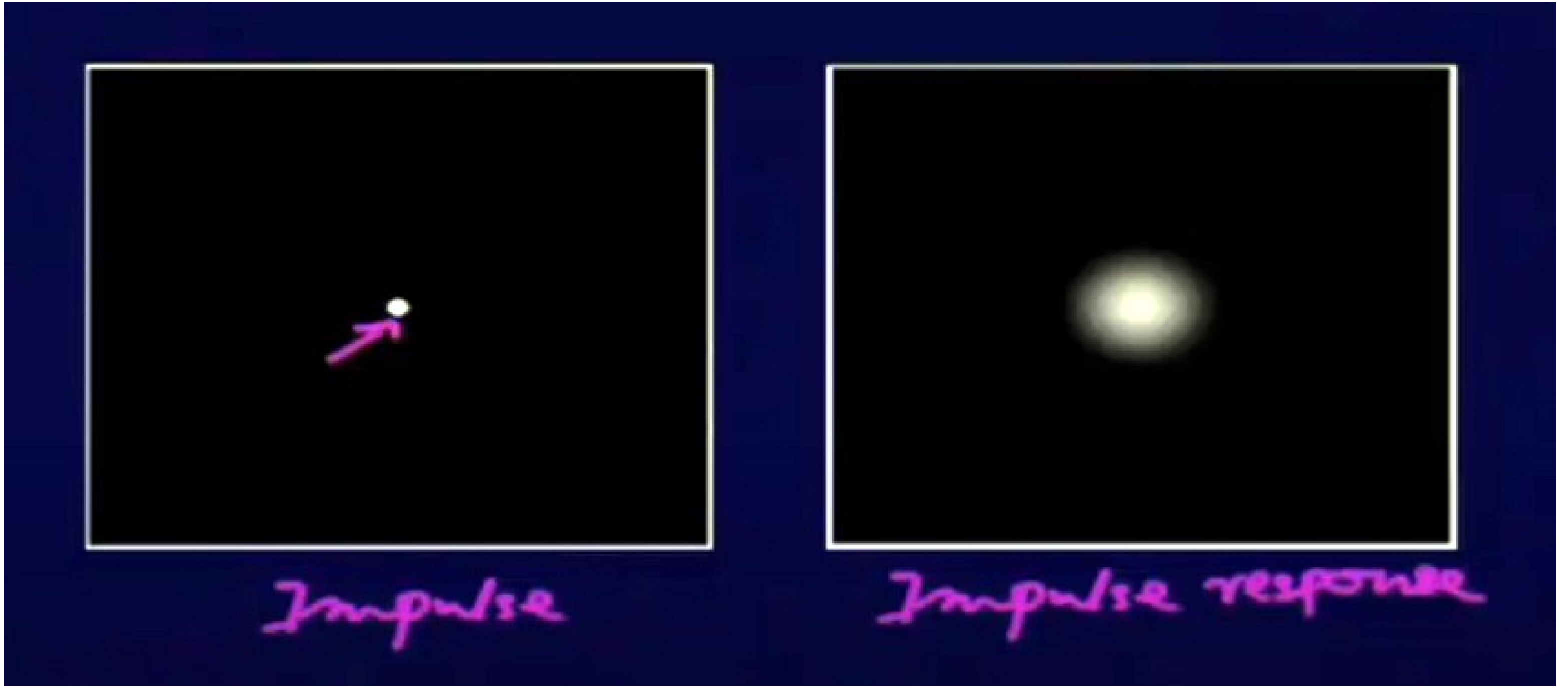
Fig: Mid Turbulence, k=0.001

Fig: Low Turbulence, k=0.00025

Estimation by Experimentation

- If equipment similar to the equipment used to acquire the degraded image is available, it is possible in principle to obtain an accurate estimate of the degradation.
- So, here we try to setup imaging system which is similar to original to obtain the impulse response.
- In this process, we have to simulate the impulse by a bright spot of light falling on the camera lens.
- It should be very small with higher intensity (laser) which will be equivalent to impulse so that the captured image is called as impulse response to the bright spot of light.

Estimation by Experimentation (Cont)



Estimation by Experimentation (Cont)

- f(x,y) is the impulse image and converting it by applying Fourier transform to F(u,v).
- Fourier transform of an impulse is always constant. Let it be ‘A’. Therefore F(u,v)=A

We know that G(u,v) = H(u,v) F(u,v)

From the above equation

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

$$H(u,v)=\frac{G(u,v)}{A}$$

Estimation by Observation

- Without any knowledge of the degradation function, we can gather information from image itself.
- For example if the image is blurred, we can inspect a small section containing both image features and background to estimate how edges are blurred.

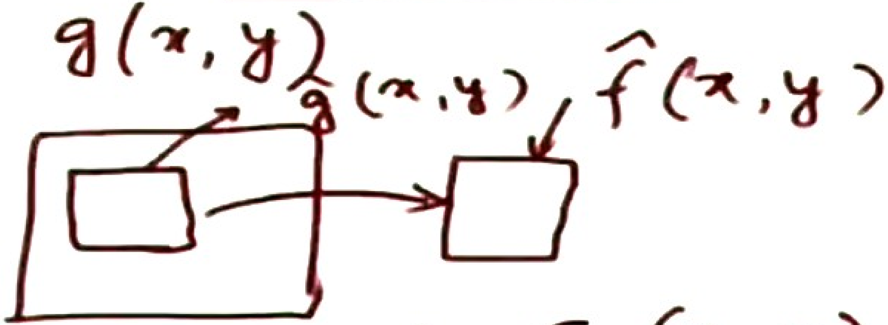
$g_s(x, y)$: observed section

$\hat{f}_s(x, y)$: expected restored section

$$H_s(u,v) = \frac{G_s(u,v)}{\hat{F}_s(u,v)}$$

Estimation by Observation (Cont)

Observation



$$g_s(x,y) \Longleftrightarrow G_s(u,v)$$

$$f_s(x,y) \Longleftrightarrow F_s(u,v)$$

$$H_s(u,v) = \frac{G_s(u,v)}{F_s(u,v)}$$

Inverse Filtering

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- Now the question is how the restoration procedure should be done?
- The simplest approach is inverse filtering, which means to obtain the restored image, the degraded image is element-wise divided by the estimated degradation transfer function in the frequency domain:

$$\begin{aligned}\hat{F}(u,v) &= \frac{G(u,v)}{H(u,v)} \\ &= \frac{H(u,v)F(u,v)+N(u,v)}{H(u,v)} \\ &= F(u,v)+\frac{N(u,v)}{H(u,v)}\end{aligned}$$

- This seems simple enough, especially if there is no noise component.
- But what if there is noise? Then even if we know the degradation function, we cannot recover the original image since we don't know **N(u,v)**.

Wiener Filtering

- The inverse filtering approach makes no explicit provision for handling noise
- This Wiener Filtering approach incorporates both the degradation function and statistical characteristics of noise into the restoration process.
- The method is founded on considering images and noise as random processes.

- wiener filter finds an estimate $f(x,y)$ of the original image $f(x,y)$ such that the mean square error is minimized.
- The minimized error is given as

$$e^2 = E\{(f(x,y) - \hat{f}(x,y))\}^2$$

- Where $E(.)$ is the expected value.

Wiener Filtering (Cont)

- The estimation in frequency domain is given as

$$F(u,v)=\left[\frac{1}{H(u,v)}\cdot\frac{|H(u,v)|^2}{|H(u,v)|^2+\gamma\left|\frac{S_n(u,v)}{S_f(u,v)}\right|}\right]\cdot G(u,v)$$

- $S_n(u,v)$ is the Power spectra of the noise
- $S_f(u,v)$ is the Power spectra of the image

Wiener Filtering (Cont)

- The value of ‘Y’ is very crucial
- if ‘Y’ is zero , the expression simply reduces to a simple inverse filter
- If ‘Y’ is one , this is called wiener filter and when ‘Y’ becomes a variable and assumes different values , this is called parametric wiener filter

Questions

1.Explain the ways of estimating the degradation function.

2.Explain Inverse Filtering.

THANK YOU

COLOR IMAGE PROCESSING

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Lecture Details:
Topic Name: Introduction to color image processing & color fundamentals
IP/ CSE III B.Tech I Sem

Outline

- Introduction to Color Image Processing
- Color Fundamentals

Color Image Processing

Color Image Processing

Color Image Processing is divided into two major areas:

1) Full Color Processing:

- Images are acquired with a full color sensor such as color TV camera or color scanner.
- Used in publishing, visualization, and the Internet.

2) Pseudo Color Processing:

- Assigning a color to a particular monochrome intensity or range of intensities.
- It is mostly used for human interpretation.

Color Image Fundamentals

- Color of an object is determined by the nature of the light reflected from it.
- In 1666, Sir Isaac Newton discovered that when a beam of sunlight passes through a glass prism, the emerging beam of light is split into a spectrum of colors ranging from violet at one end to red at the other.

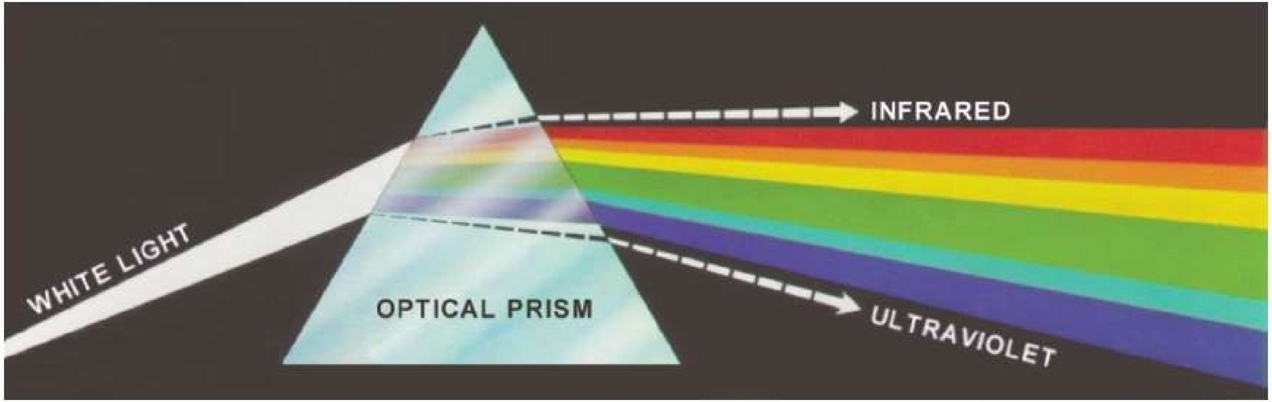
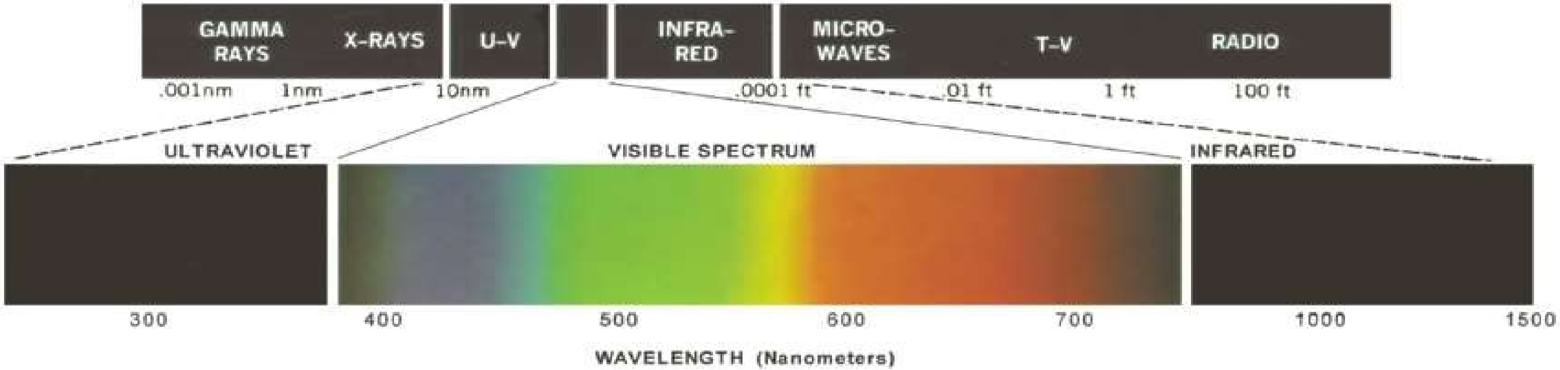


FIGURE 6.1 Color spectrum seen by passing white light through a prism. (Courtesy of the General Electric Co., Lamp Business Division.)

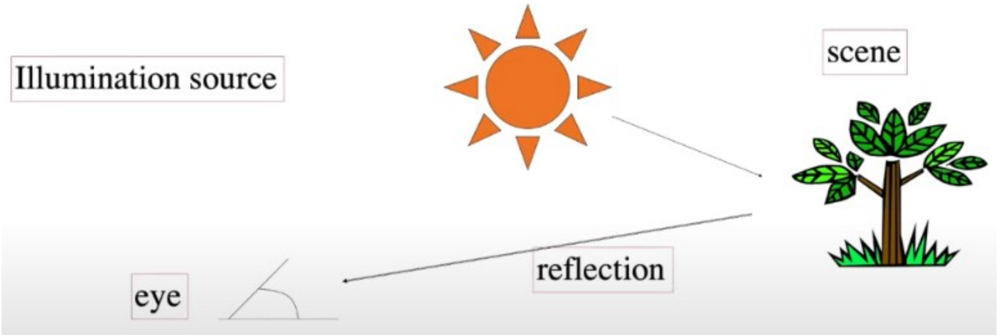
Color Image Fundamentals (Cont)

- As shown in below fig., 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 favours reflectance in a limited range of the visible spectrum exhibits some shades of color.



Color Image Fundamentals (Cont)

- When viewed in full color, no color in the spectrum ends abruptly, but rather each color blends smoothly into the next.
- Green objects reflect wavelength in the 500 nm to 570 nm range while absorbing most of the energy at other wavelengths.
- If the light is achromatic (void of color), its only attribute is its intensity, or amount.
- Chromatic light spans EM from 380 to 780 nm.



Color Image Fundamentals (Cont)

There are three basic quantities that describe the quality of the light:

1) Radiance is the total amount of energy that flows from the light source, and it is usually measured in watts (W).
2) 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.
3) 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

Color Image Fundamentals (Cont)

- Cones are the sensors in the eye responsible for color vision. About 6 to 7 million cones in the human eye can be divided into three principal sensing categories, corresponding roughly to red, green, and blue
- Approximately 65% of all cones are sensitive to red light, 33% are sensitive to green light, and only about 2% are sensitive to blue.
- 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).
- According to CIE (International Commission on Illumination) wavelengths of blue = 435.8 nm, green =546.1 nm, and red = 700 nm

Color Image Fundamentals (Cont)

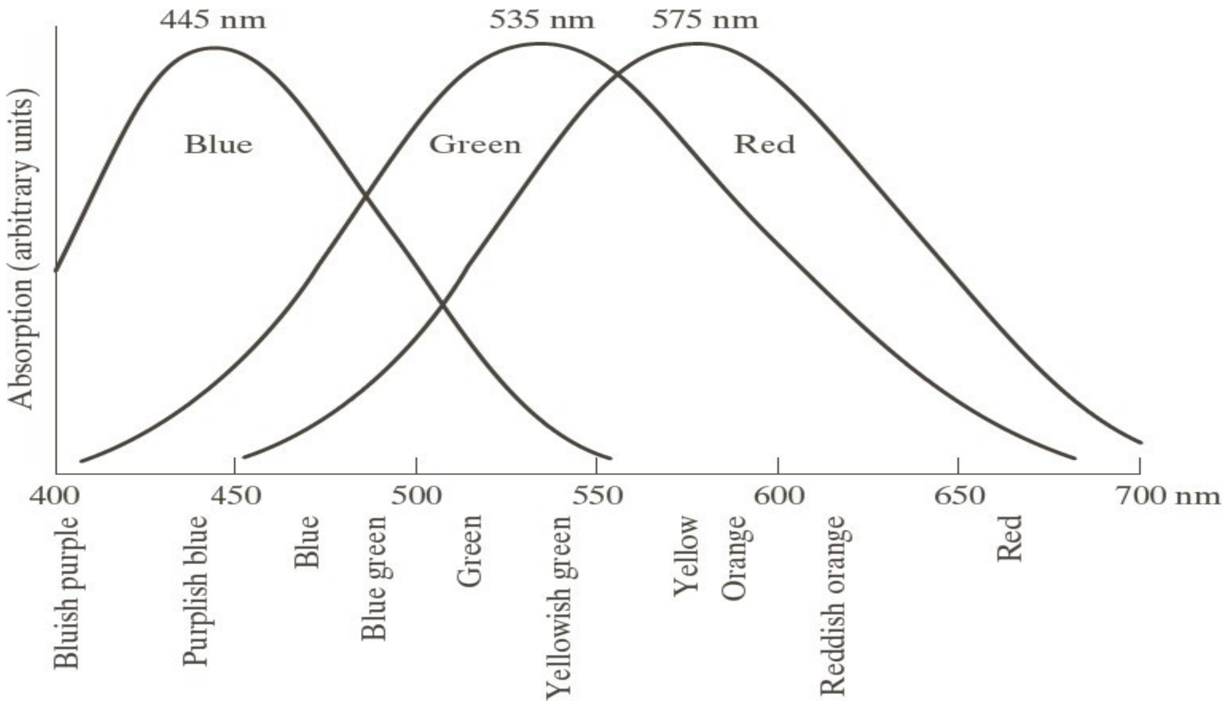
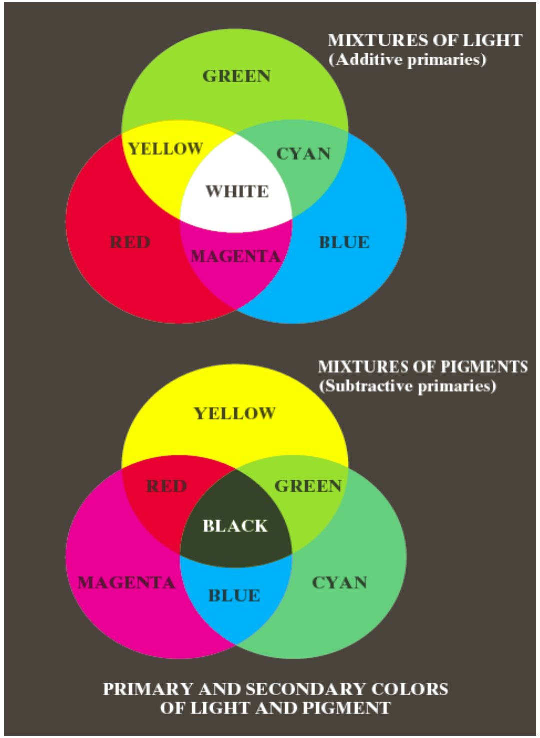


FIGURE 6.3 Absorption of light by the red, green, and blue cones in the human eye as a function of wavelength.

Color Image Fundamentals (Cont)

- 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).
- The primary colors of the light should be the opposite of the primary color of a pigment.
- If we mix Red, Green and Blue in appropriate proportion, we generate white light and similarly for the pigments, we will generate black color



Color Image Fundamentals (Cont)

- 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 which are not a spectrum color
- Hue and saturation taken together are called chromaticity, and therefore, a color may be characterized by its brightness and chromaticity

Color Image Fundamentals (Cont)

- The amounts of red, green, and blue lights needed to form any particular color are called the **Tristimulus** values and are denoted X, Y, and Z, respectively.

Tri-chromatic coefficients:

- Let X, Y, Z: tri-stimulus values representing the amounts of red, green, and blue needed to form any particular color.

$$x = \frac{X}{X+Y+Z}, y = \frac{Y}{X+Y+Z},$$
$$z = \frac{Z}{X+Y+Z}$$

- The sum of the chromatic coefficients x+y+z=1.

THANK YOU

COLOR MODELS

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Lecture Details:
Topic Name: Color Models
IP/ CSE III B.Tech I Sem

Outline

- Introduction to Color Models
- Types of Color Models

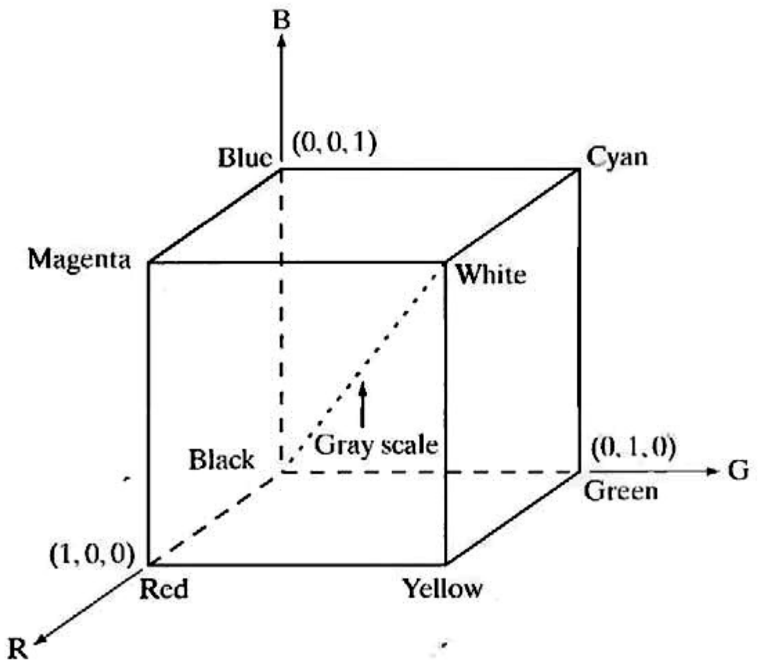
Color Models

- The purpose of a color model (also called color space or color system) is to facilitate the specification of colors in some standard, generally accepted way.
- In essence, a color model is a specification of a coordinate system and a subspace within that system where each color is represented by a single point.
- There are two types of color models: **Additive** models and **Subtractive** models
- Additive color models use light to display color while subtractive models are used for printing inks.
- Colors perceived in additive models are the result of transmitted light where as colors perceived in subtractive models are the result of reflected light
- There are three types of color models:

1)RGB Color Model - Additive Model
2)CMY Color Model - Subtractive Model
3)HSI Color Model

RGB Color Model

- In the RGB model, each color appears in its primary spectral components of red, green, and blue.
- This model is based on a Cartesian coordinate system.
- The color subspace of interest is the cube shown in Fig., in which RGB values are at three corners; cyan, magenta, and yellow are at three other corners; black is at the origin; and white is at the corner farthest from the origin.



RGB Color Model (Cont)

- In this model, the gray scale (points of equal RGB values) extends from black to white along the line joining these two points.
- The different colors in this model arc points on or inside the cube, and are defined by vectors extending from the origin.
- For convenience, the assumption is that all color values have been normalized so that the cube shown in Fig. is the unit cube. That is, all values of R, G. and B are assumed to be in the range [0, 1].
- Images represented in the RGB color model consist of three component images, one for each primary color. When fed into an RGB monitor, these three images combine on the phosphor screen to produce a composite color image.
- The number of bits used to represent each pixel in RGB space is called the pixel depth.

RGB Color Model (Cont)

- Consider an RGB image in which each of the red, green, and blue images is an 8-bit image.
- Under these conditions each RGB color pixel [that is, a triplet of values (R, G, B)] is said to have a depth of 24 bits Color image planes times the number of bits per plane).
- The term full-color image is used often to denote a 24-bit RGB color image. The total number of colors in a 24-bit RGB image is (28)3 = 16,777,216.
- RGB is ideal for image color generation (as in image capture by a color camera or image display in a monitor screen), but its use for color description is much more limited.

CMY Color Model

- Cyan, magenta, and yellow are the secondary colors of light or, alternatively, the primary colors of pigments.
- For example, when a surface coated with cyan pigment is illuminated with white light, no red light is reflected from the surface. That is, cyan subtracts red light from reflected white light, which itself is composed of equal amounts of red, green, and blue light.
- Most devices that deposit colored pigments on paper, such as color printers and copiers, require CMY data input or perform an RGB to CMY conversion internally. This conversion is performed using the simple operation by the equation below where, again, the assumption is that all color values have been normalized to the range [0, 1].

$$\begin{bmatrix} C \\ M \\ Y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

CMY Color Model (Cont)

- Equation demonstrates that light reflected from a surface coated with pure cyan does not contain red (that is, C = 1 - R in the equation).
- Similarly, pure magenta does not reflect green, and pure yellow does not reflect blue.
- Equation also reveals that RGB values can be obtained easily from a set of CMY values by subtracting the individual CMY values from 1.
- As indicated earlier, in image processing this color model is used in connection with generating hardcopy output, so the inverse operation from CMY to RGB generally is of little practical interest.
- Equal amounts of the pigment primaries, cyan, magenta, and yellow should produce black. In practice, combining these colors for printing produces a muddy-looking black, not actual black
- To solve this problem, CMYK color model is introduced which is having 4 components Cyan, Magenta, Yellow and Black. ’K’ stands for Black.

HSI Color Model

- When we see a color object, we describe it by its hue, saturation, and brightness.

- We know that:
  - Hue is a color attribute that describes a pure color (pure yellow, orange, or red),
  - Saturation gives a measure of the degree to which a pure color is diluted by white light.
  - 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.

HSI Color Model (Cont)

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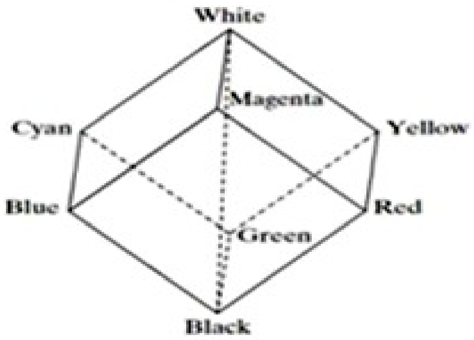
- The *HSI (Hue, Saturation, Intensity) color model, decouples the intensity component* from the color-carrying information (hue and saturation) in a color image.
- As a result, the HSI model is an ideal tool for developing image processing algorithms based on color descriptions
- RGB is ideal for image color generation (as in image capture by a color camera or image display in a monitor screen), but its use for color *description is much more limited.*

HSI Color Model (Cont)

- An RGB color image can be viewed as three monochrome intensity images (representing red, green, and blue), so we could extract intensity from an RGB image.
- In the arrangement shown in figure, the line (intensity axis) joining the black and white vertices is vertical.
- To determine the intensity component of any color point in figure, simply pass a plane *perpendicular to the intensity axis and* containing the color point.
- The intersection of the plane with the intensity axis would give us a point with intensity value in the range [0, 1].
- The saturation (purity) of a color increases as a function of distance from the intensity axis.

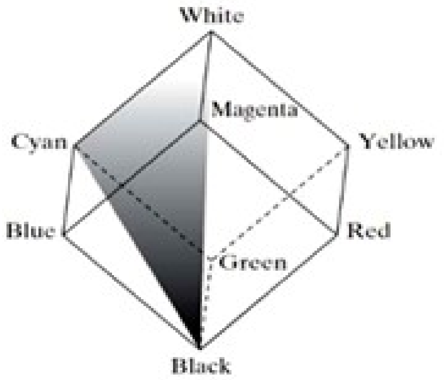
Conceptual relationships between the RGB and HSI color models.



HSI Color Model (Cont)

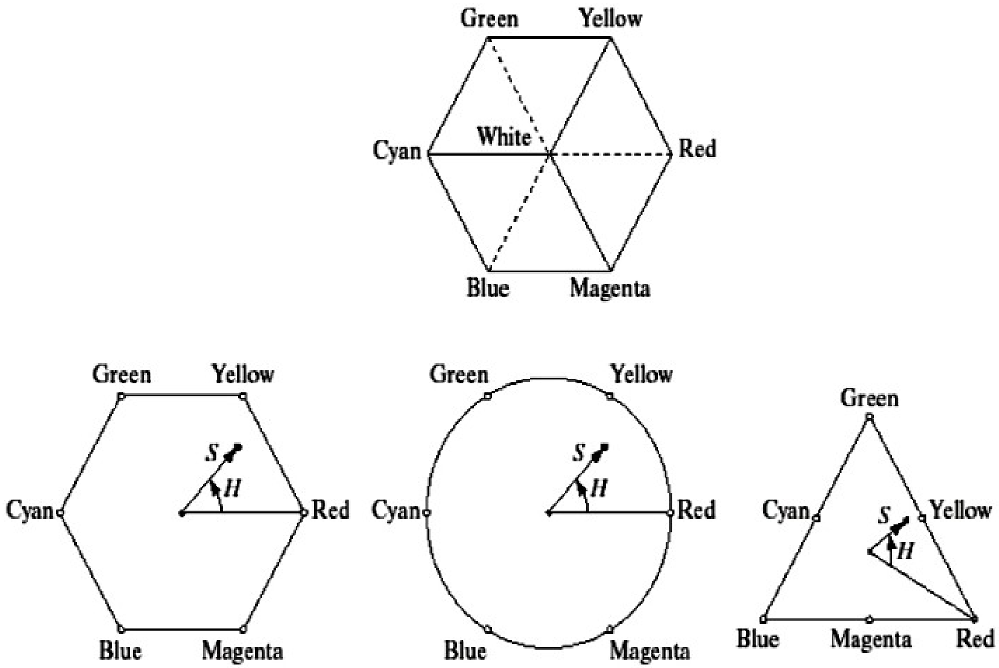
- *All points contained in the plane segment defined by the intensity* axis and the boundaries of the cube have the *same hue (cyan in this* case).
- All colors generated by three colors lie in the triangle defined by those colors.
- If two of those points are black and white and the third is a color point, all points on the triangle would have the same hue because the black and white components cannot change the hue.

By rotating the shaded plane about the vertical intensity axis, we would obtain different hues.



HSI Color Model (Cont)

- In Fig 1 the primary colors are separated by 120°. The secondary colors are 60° from the primaries, which means that the angle between secondaries is also 120°.
- Fig 2 shows the same hexagonal shape and an arbitrary color point (shown as a dot).The hue of the point is determined by an angle from some reference point.
- Usually an angle of 0° from the red axis designates 0 hue, and the hue increases counter clockwise from there.



Questions

1. What is a Color Model? Explain the types of color models in detail. **14M**
2. What is the purpose of Color Model? Explain RGB model in detail. **7M**

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Color Model Conversions and Color Image Smoothing & Sharpening

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Lecture Details:
Topic Name: Color model conversions, Smoothing & Sharpening
IP/ CSE III B.Tech I Sem

Outline

- Conversion of Color Models
  - RGB to HSI Color Model
  - HSI to RGB Color Model
- Color Image Smoothing
- Color Image Sharpening

Conversion from RGB to HSI Color Model

Given an image in RGB color format, the H component of each RGB pixel is obtained using the equation

$$H = \begin{cases} \theta & \text{if } B \leq G \\ 360 - \theta & \text{if } B > G \end{cases} \qquad (1)$$

With

$$\theta = \cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}}\right\}. \qquad (2)$$

The saturation component is given by

$$S = 1 - \frac{3}{(R+G+B)}[\min(R, G, B)]. \qquad (3)$$

Finally, the intensity component is given by

$$I = \frac{1}{3}(R+G+B). \qquad (4)$$

It is assumed that the RGB values have been normalized to the range [0, 1] and that angle θ is measured with respect to the red axis of the HST space. Hue can be normalized to the range [0, 1] by dividing by 360° all values resulting from Eq. (1). The other two HSI components already are in this range if the given RGB values are in the interval [0, 1].

Conversion from HSI to RGB Color Model

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Given values of HSI in the interval [0,1], one can find the corresponding RGB values in the same range. The applicable equations depend on the values of H. There are three sectors of interest, corresponding to the 120° intervals in the separation of primaries.

RG sector ($0^\circ \leq H < 120^\circ$):

When H is in this sector, the RGB components are given by the equations

$$B = I\,(1 - S)$$
$$G = 3\,I - (R + B)$$
$$R = I\,[1 + (S * \cos H / \cos(60^\circ - H)]$$

GB sector ($120^\circ \leq H < 240^\circ$):

If the given value of H is in this sector, first subtract 120° from it.

$$H = H - 120^0$$

Then the RGB components are

$$R = I\,(1 - S)$$
$$B = 3\,I - (R + G)$$
$$G = I\,[1 + (S * \cos H / \cos(60^\circ - H)]$$

Conversion from HSI to RGB Color Model (Cont)

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BR sector ($240^o \le H \le 360^o$):

If H is in this range, subtract 240^o from it

$$H = H - 240^0$$

Then the RGB components are

$$G = I\,(1 - S)$$

$$R = 3\,I - (B + G)$$

$$B = I\,[1 + (S * \cos H / \cos(60^o - H)]$$

Color Image Smoothing

- In this color smoothing, the color component Ċ(x, y) will be given by 1/K summation of c (x, y) where this c (x, y), this is actually a vector having 3 components in RGB space, this will be red, green and blue components and this averaging has to be done for ∀(x, y), for all locations (x, y) which is in the neighbourhood of point (x, y).
- We can simply do this operation in a plane vice manner 1/ k into summation R (x, y) ∀(x, y) within the neighbourhood of $N_{x,y}$, 1/k summation of G (x, y) and 1/k summation of B (x, y), the average of these vectors gives us the smooth image.

Smoothing

Vector

$$\bar{c}(x,y) = \frac{1}{k}\sum_{\forall (x,y)\in N_{x,y}} c(x,y)$$

$$\bar{c}(x,y) = \begin{bmatrix} \frac{1}{k}\sum_{\forall (x,y)\in N_{x,y}} R(x,y) \\ \frac{1}{k}\sum G(x,y) \\ \frac{1}{k}\sum B(x,y) \end{bmatrix}$$

Color Image Sharpening

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- Like sharpening in intensity or gray level images, color images can also be sharpened by using second order derivative operators like Laplacian operator.
- If we apply the Laplacian operator on all 3 planes - the red plane, green plane and blue plane separately and then combine those results, we will get the sharpened image.
- In the RGB color system, the Laplacian of the vector c is given by:

$$\nabla^2[\mathbf{c}(x, y)] = \begin{bmatrix} \nabla^2 R(x, y) \\ \nabla^2 G(x, y) \\ \nabla^2 B(x, y) \end{bmatrix}$$

0	1	0
1	–4	1
0	1	0

1	1	1
1	–8	1
1	1	1

0	–1	0
–1	4	–1
0	–1	0

–1	–1	–1
–1	8	–1
–1	–1	–1

Questions

1. Explain the process of converting RGB to HSI model? **7M**
2. Explain the process of converting HSI to RGB Model? **7M**
3. Explain Color Image Smoothing and Sharpening? **7M**

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THANK YOU

Color Transformations and Color Image Segmentation

Presented By:
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Lecture Details:
Topic Name: Color Transformations and Segmentation
IP/ CSE III B.Tech I Sem

Outline

- Color Transformations
    - Intensity Modification
    - Color Complements
    - Tone correction
- Color Segmentation

Color Transformations

Use to transform colors to colors.

Formulation:

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

$f(x,y)$ = input color image, $g(x,y)$ = output color image

T = operation on f over a spatial neighborhood of (x,y)

When only data at one pixel is used in the transformation, we can express the transformation as:

$$s_i = T_i(r_1, r_2, \quad , r_n)$$

$i = 1, 2, \ldots, n$

Where r_i = color component of $f(x,y)$

s_i = color component of $g(x,y)$

For RGB images, $n = 3$

Color Transformations (Cont)

- We have used many basic gray level transformations on intensity images. In the same way, there are some transformation functions to be applied on Color images also.
- Some of the basic color transformations are:

  1. Intensity Modification
  2. Color Complements
  3. Tonal Correction

Intensity Modification

RGB

$$s_i = k r_i \quad i = 1, 2, 3$$

(R → 1, G → 2, B → 3)

HSI

$$s_3 = k r_3$$
$$s_1 = r_1$$
$$s_2 = r_2$$

CMY

$$s_i = k r_i + (1 - k)$$

Formula for RGB:

$$s_R(x, y) = k r_R(x, y)$$
$$s_G(x, y) = k r_G(x, y)$$
$$s_B(x, y) = k r_B(x, y)$$

Formula for HSI:

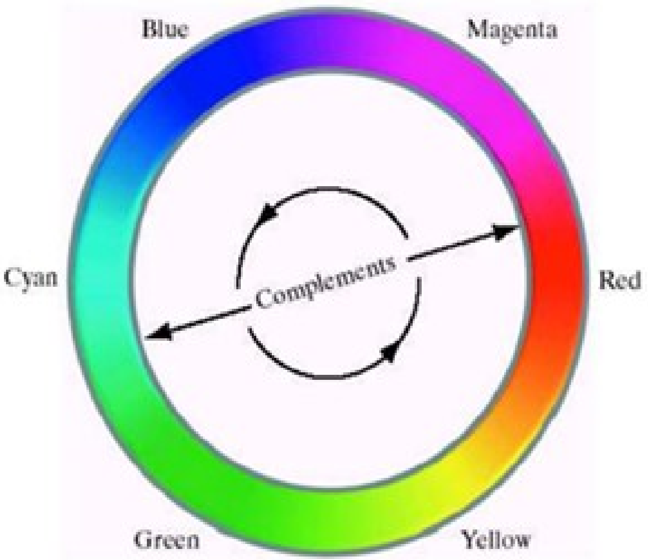
$$s_I(x, y) = k r_I(x, y)$$

Formula for CMY:

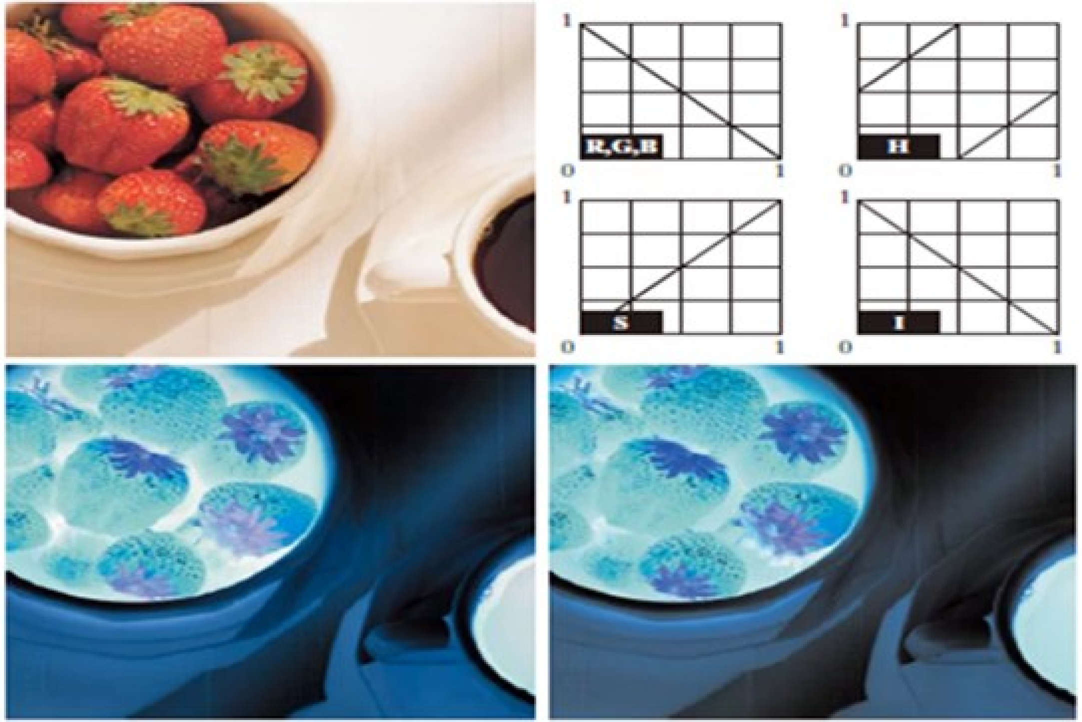
$$s_C(x, y) = k r_C(x, y) + (1 - k)$$
$$s_M(x, y) = k r_M(x, y) + (1 - k)$$
$$s_Y(x, y) = k r_Y(x, y) + (1 - k)$$

Color Complements

- Color component replaces each color with its opposite color in the color circle of the Hue component shown in figure.
- If we take the color at any point on the circle, the color which is located at the diagonally opposite location in this circle is the complement of the other colour.
- This simply says that hues which are directly opposite to one another in the colour circles, they are complements of each other.
- This operation is analogous to image negative in a gray scale image.

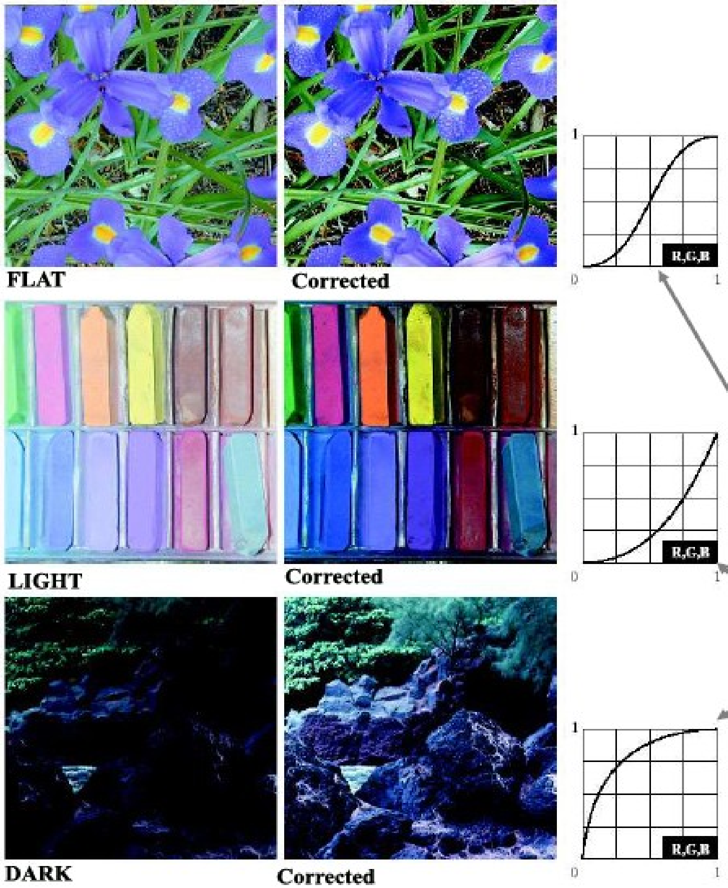


Color complement transformations.(a) Original image. (b)Complement transformation functions. (c) Complement of (a) based on the RGB mapping functions.(d) An approximation of the RGB complement using HIS transformations



Tone Correction

- The other kind of application of this color image processing is say, correction of tones or tone correction.
- In the gray scale images, we have seen an image can be of low contrast, very high contrast depending upon the distribution of the intensity values.
- In the same manner, for colour images, we define the tone. So, a colour image may have a flat, light and dark tones. These tones are determined by the distribution of the intensity values of different RGB components within the image.
- We can apply the similar type of transformations here in Tone correction as we have done in the case of intensity images for contrast enhancement.



In these examples, only brightness and contrast are adjusted while keeping color unchanged.

This can be done by using the same transformations for all RGB Compnents

Contrast enhancement

Power law transformations

Color Segmentation

- Segmentation is a process that partitions an image into regions and partitioning an image into regions based on color is known as color segmentation.
- It is done in two ways:
    - Segmentation in HSI color space
    - Segmentation in RGB color space

Segmentation in HSI color space

- If anybody want to segment an image based on color, and in addition, to carry out the process on individual planes, it is natural to think first of the HSI space because color is conveniently represented in the hue image.
- Typically, saturation is used as a masking image in order to isolate further regions of interest in the hue image.
- The intensity image is used less frequently for segmentation of color images because it carries no color information.
- Segmentation is one area in which better results generally are obtained by using RGB color vectors.

Segmentation in RGB color space

- Segmentation in RGB color space is a straight forward approach.
- Suppose that the objective is to segment objects of a specified color range in an RGB image.
- Given a set of sample color points representative of the colors of interest, we obtain an estimate of the "average" color that we wish to segment. Let this average color be denoted by the RGB vector **a**.
- The objective of segmentation is to classify each RGB pixel in a given image as having a color in the specified range or not. In order to perform this comparison, it is necessary to have a measure of similarity.
- One of the simplest measures is the Euclidean distance.

Segmentation in RGB color space (Cont)

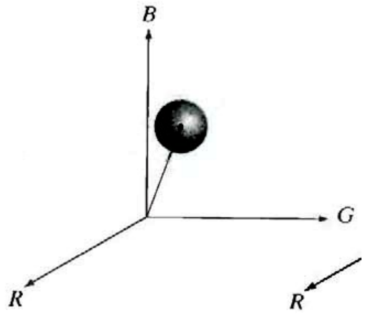
- Let **z** denote an arbitrary point in RGB space. **z** is similar to **a** if the distance between them is less than a specified threshold, Do.
- The Euclidean distance between **z** and **a** is given by:

$$
\begin{aligned}
D(\mathbf{z}, \mathbf{a}) &= \|\mathbf{z} - \mathbf{a}\| \\
&= \left[(\mathbf{z} - \mathbf{a})^T(\mathbf{z} - \mathbf{a})\right]^{\frac{1}{2}} \\
&= \left[(z_R - a_R)^2 + (z_G - a_G)^2 + (z_B - a_B)^2\right]^{\frac{1}{2}}
\end{aligned}
$$

- where the subscripts R, G, and B, denote the RGB components of vectors **a** and **z**.

Segmentation in RGB color space (Cont)

- The locus of points such that $D(z, a) \leq D_o$ is a solid sphere of radius D_o as shown in figure:
- Points contained within or on the surface of the sphere satisfy the specified color criterion; points outside the sphere do not.



Questions

1. Explain color transformations in color image processing? **7M**
2. Explain the process of color segmentation in detail ? **7M**

THANK YOU

IMAGE SEGMENTATION

Presented By:
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Lecture Details:
Topic Name: Introduction to Image Segmentation
IP/ CSE III B.Tech I Sem

Topics

- Detection of Discontinuities
- Edge linking and Boundary Detection
- Thresholding

Outline

- Introduction to Image Segmentation
- Detection of discontinuities
  - Point detection
  - Line detection
  - Edge detection

Image Segmentation

- Image Segmentation is another major step in Digital Image Processing
- Segmentation subdivides an image into constituent regions or objects known as segments.
- Each of these segments can be analyzed to extract some information so that those information's are useful for high level machine vision applications.
- The level to which the subdivision is carried depends on the problem being solved i.e; Segmentation of an image should be stopped when the objects of interest in an application have been isolated.

Image Segmentation (Cont)

- Segmentation algorithms generally are based on one of two basic properties of intensity values.
    1. Discontinuity
    2. Similarity
- **Discontinuity**: It is to partition an image based on abrupt changes in intensity (such as edges)
- **Similarity:** It is to partition an image into regions that are similar according to a set of predefined criteria.

Image Segmentation (Cont)

Two approaches

Discontinuity based
- Isolated Points
- Lines
- Edges

Similarity based
- Thresholding
- Region Growing
- Region Splitting & Merging

Detection of Discontinuities

- In discontinuity based approach, the partition or subdivision of an image is carried out based on some abrupt changes in intensity levels of an image.
- We are mainly interested in identification of isolated points or identification of lines or identification of edges present in the image.
- There are three basic types of gray level discontinuities:

  1.Point detection

  2.Line detection

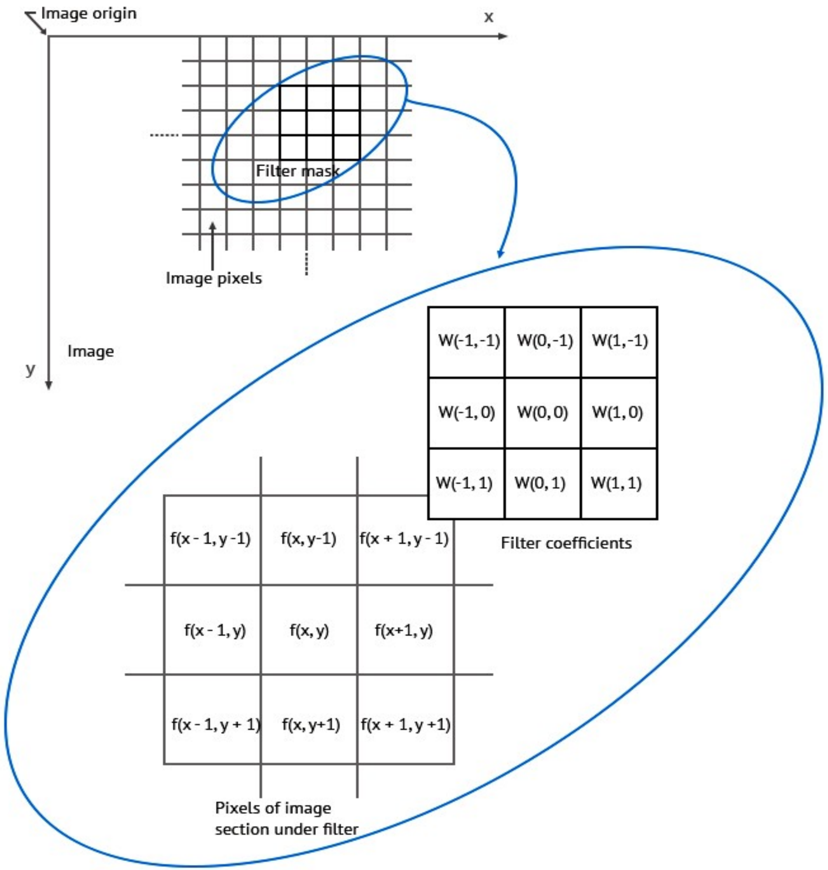
  3.Edge detection

- The most common way to look for discontinuities is to run a mask through the image

- For the 3 x 3 mask shown in Figure, the result (or response), R, of linear filtering with the filter mask at a 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 response 'R' is given by a sum of products of the filter coefficients and the corresponding image pixels in the area spanned by the filter mask.



Point Detection

- The detection of isolated points in an image is straight forward in principle.
- Mask for point detection is shown in the figure.
- We say that a point will be detected at location on which mask is centred. This formulation measures the weighted differences between the centre point and its neighbours.
- A point has been detected at the location as which the mask is centred if $|R| > T$

  where T = Non negative predefined Threshold value
- The mask used is Laplacian mask. The sum of the mask coefficients is zero indicating that the mask response is zero in areas of constant gray level.

mask

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

Line Detection

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The masks used for Line detection are shown below:

–1	–1	–1
2	2	2
–1	–1	–1

Horizontal

–1	–1	2
–1	2	–1
2	–1	–1

+ 45°

–1	2	–1
–1	2	–1
–1	2	–1

Vertical

2	–1	–1
–1	2	–1
–1	–1	2

–45°

- If the horizontal mask is moved around the image, it would respond more strongly to lines oriented horizontally.
- The similar idea is used with other masks also.

Line Detection (Cont)

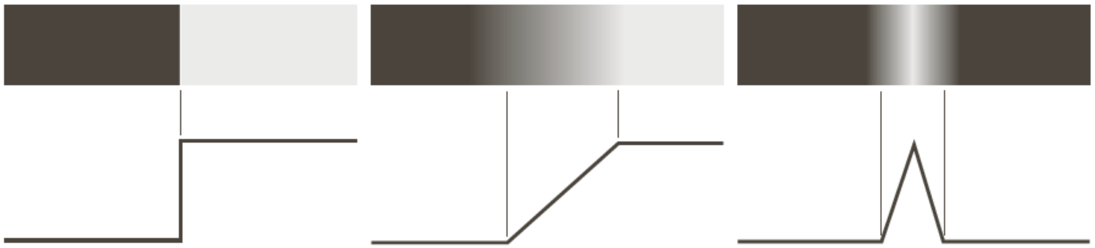
- Suppose we run all the masks on the image, let R1, R2, R3, R4 denotes the response of the horizontal, +45 degree, vertical and -45 degree masks respectively.
- If, at a certain point in the image

$$|R_i| > |R_j|, \text{ for all } j \neq i$$

- That point is said to be more likely associated with a line in the direction of mask 'i'.
- **Ex:** Let Ri=R1 then if it is greater than Rj = R2, R3 and R4, We can say that the point is associated with a horizontal line.

Edge Detection

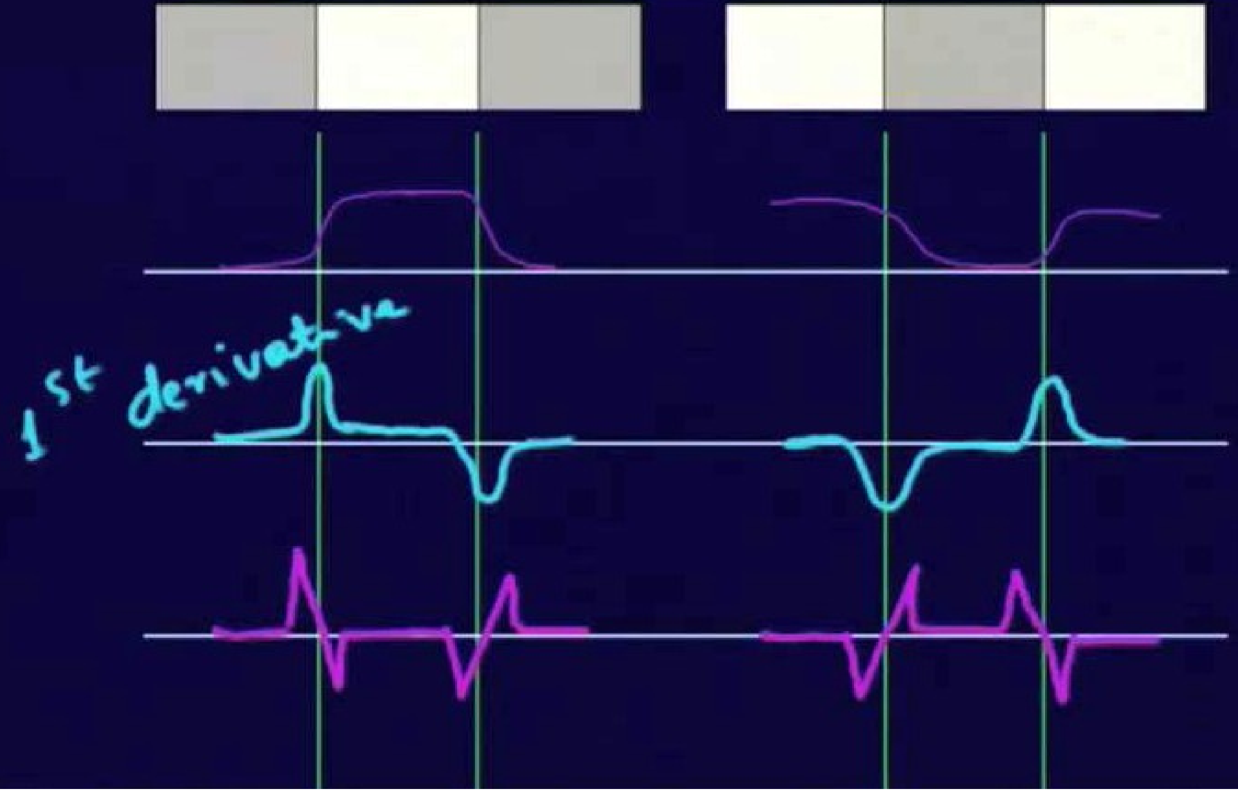
- Edge Detection is one of the most important phenomena in Image Processing.
- Edge Detection is the most common approach for detecting meaningful discontinuities in the gray levels.
- Edge can be defined as a set of connected pixels that lies in the boundary between two regions.
- For detecting edges in an image, we use the approaches of first and second order derivatives.



a b c

FIGURE 10.8 From left to right, models (ideal representations) of a step, a ramp, and a roof edge, and their corresponding intensity profiles.

Edge Detection



Edge Detection (Cont)

- We have taken 2 typical cases. In the first case, we have shown a typical image region where we have a transition from a dark region to a brighter region and then again to a dark region as we move from left to right in the horizontal direction. In the next one, vice versa.
- First, We have drawn intensity profile along a horizontal line. So here, you find that we have modelled this transition as a gradual transition, not as an abrupt transition. The reason is because of quantization sampling; all almost all the abrupt transitions in the intensity levels are converted to such gradual transitions.

Edge Detection (Cont)

- In first order derivative whenever there is a transition from a brighter intensity to a darker intensity or vice versa, there is a discontinuity in intensity levels. It is positive at the leading edge whereas it is negative at the tailing edge.
- In the second order derivative, it is positive on the darker side of the edge and it is negative on the brighter side of the edge and that can be verified in both the situations.
- Second order derivative is very sensitive to the noise present in the image and that is the reason why they are not usually used for edge detection operation.
- However we can find some zero crossings in the second derivative and this zero crossing information can be used to exactly identify the location of an edge whenever there is a gradual transition of the intensity from dark to bright or from bright to dark.

Using First order derivatives – The Gradient

- First order derivatives in image processing are implemented using the magnitude of the gradient.
- For a bi-dimensional function, f (x, y):

$$\nabla f \equiv \text{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

- The magnitude of the vector is given by:

$$M(x, y) = \text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2}$$

- It is often approximated as M(x, y) ≈ |gx | + |gy |
- Let a(x,y) represent the angle of vector, then the angle is given by:

$$\alpha(x, y) = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$

- The masks shown in the figure are used to compute the gradient.
- A 3 x 3 region of an image (the z's are gray-level values) and masks used to compute the gradient at point labeled z5 .

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Robert:

-1	0
0	1

0	-1
1	0

Prewitt:

-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

Gx = (z7+z8+z9) - (z1+z2+z3)

Gy = (z3+z6+z9) – (z1+z4+z7)

Sobel:

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

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

Gx = (z7+2z8+z9) - (z1+2z2+z3)

Gy = (z3+2z6+z9) – (z1+2z4+z7)

Using Second order derivatives – The Laplacian

- The Laplacian is represented by:

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

- The partial second order derivative on x and y direction is:

$$\frac{\partial^2 f}{\partial^2 x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y)$$

$$\frac{\partial^2 f}{\partial^2 y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y)$$

- The digital implementation of the two-dimensional Laplacian is obtained by summing these two components:

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

- The masks shown in the figure are used to compute the Laplacian

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1

$$g(x, y) = \begin{cases} f(x, y) - \nabla^2 f(x, y) & \text{if the center coefficient of the Laplacian mask is negative} \\ f(x, y) + \nabla^2 f(x, y) & \text{if the center coefficient of the Laplacian mask is positive.} \end{cases}$$

Laplacian of a Gaussian (LoG)

- We said that the Laplacian operator is very sensitive to noise; to reduce the effect of noise, We have to first smooth the image using a Gaussian operator and then apply Laplacian operator and these 2 operations together called a Laplacian of Gaussian or LOG operator.

LoG.

$$h(x,y) = \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

$$x^2+y^2 = r^2$$

$$\nabla^2 h = \left(\frac{r^2-\sigma^2}{\sigma^4}\right)\exp\left(-\frac{r^2}{2\sigma^2}\right)$$

0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

THANK YOU

EDGE LINKING AND BOUNDARY DETECTION

Lecture Details:
Topic Name: Edge Linking
IP/ CSE III B.Tech I Sem

Presented By:
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Outline

- Edge Linking and Boundary Detection
  - Local Edge Linker
  - Global Edge Linker

Edge Linking and Boundary Detection

- Edge detectors yield pixels in an image that lie on edges. Next step is to collect these pixels together into set of edges.
- Edge linking process takes an unordered set of edge pixels produced by an edge detector as an input to form an ordered list of edges.
- Edge linking is needed due to the following reasons:
  - Due to non uniform illumination - If the scene is not uniformly illuminated that leads to detection of edge points where the boundary points will not be continuous .
  - Presence of noise – If the image is noisy, there may be some spurious edge points which are not actually edge points of the boundary points of any of the regions.

Edge Linking and Boundary Detection (Cont)

- Edge linking procedures assemble edge points into meaningful boundaries.
- There are mainly two approaches for Edge linking operations:
    - Local Processing
    - Global Processing

Local Processing

- It is one of the simplest approach of Edge linking.
- In this local processing approach, we take an edge detected image as input using either of the edge detection operators. (Prewitt, Sobel or LoG operators)
- Analyse the characteristics of pixels in a small neighbourhood (3x3, or 5x5) about every point that has undergone edge detection. All points that are similar are linked, forming a boundary of pixels that share some common properties.
- There are 2 principal properties for establishing similarity of edge pixels:-
  - Strength of the response of the gradient operator used to produce the edge pixel
  - Direction of the gradient

Local Processing (Cont)

- A point in the predefined neighbourhood of (x,y) is linked to the point (x^1,y^1) if both magnitude and direction criteria of both the points are satisfied.
- The difference in the magnitudes of the points $\nabla(x,y)$ and $\nabla(x^1,y^1)$ should be less than or equal to Non-negative threshold denoted by 'T'.
- The difference in the angles of the points $\alpha(x,y)$ and $\alpha(x^1,y^1)$ should be less than or equal to some Non-negative angle threshold denoted by 'A'.
- This process is repeated for every location in the image

$$(x', y') \in N_{xy}$$

$$(x', y') \ \& \ (x, y)$$

$$|\nabla f(x,y) - \nabla f(x',y')| \leq T$$

$$|\alpha(x,y) - \alpha(x',y'| < A$$

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THRESHOLDING

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Lecture Details:

Topic Name: Thresholding

IP/ CSE III B.Tech I Sem

Outline

- Thresholding
  - Global Threshold
  - Local Threshold
  - Adaptive or Dynamic Threshold

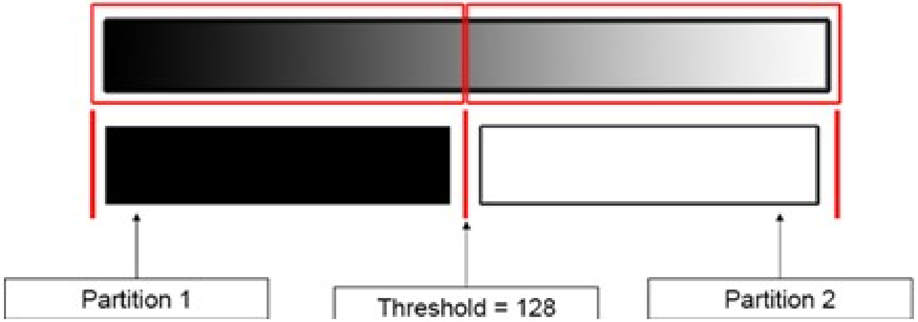
Thresholding

- Thresholding is usually the first step in any segmentation approach.
- In this section we discus technique for partitioning images directly into region based on intensity values/properties of these values.
- One way to extract the object from background is to select threshold T.

  Pick a threshold T.

  1.Pixels above threshold get new intensity A.

  2.Pixels above threshold get new intensity B.



Thresholding (Cont)

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- Suppose that an image f(x,y) is composed of light objects on a dark background, and the following figure is the histogram of the image.

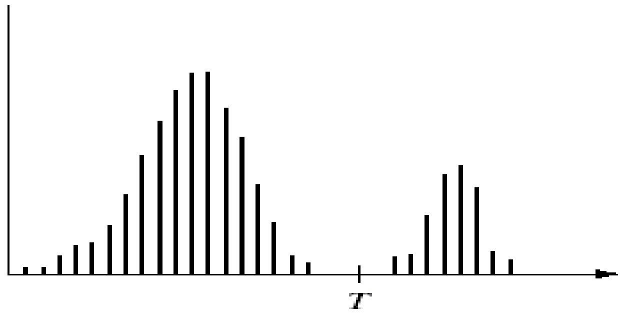

Image with dark background and a light object

- In such cases, the object and background pixels have gray levels in two dominant modes.

Thresholding (Cont)

- One way to extract the objects from the background is to select a threshold T that separates object from background.
- As in fig (a) Any point (x,y) for which f(x,y) > T is called an object point; otherwise the point is called a background point.

$$g(x, y) = \begin{cases} 1 & \textit{if } \; f(x,y) > T \\ 0 & \textit{f } \; f(x,y) \le T \end{cases}$$

Multilevel Thresholding

- It is also possible to extract objects that have a specific intensity range using multiple thresholds.

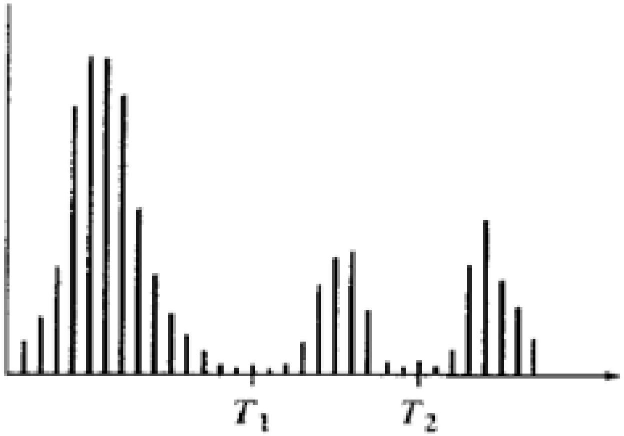

Image with dark background and two light objects

Multilevel Thresholding

A point (x,y) belongs

- to an object class if $T_1 < f(x,y) \leq T_2$
- to another object class if $f(x,y) > T_2$
- to background if $f(x,y) \leq T_1$

$$g(x, y) = \begin{cases} a & \text{if } f(x,y) > T_2 \\ b & \text{if } T_1 \leq f(x, y) \leq T_2 \\ c & \text{if } f(x, y) \leq T_1 \end{cases}$$

Thresholding

- Thresholding involves a test against a function T of the form:

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

where $f(x,y)$ is gray-level at (x,y) and $p(x,y)$ denotes some local property, for example average gray level in neighbourhood

- Now we will see global, local and adaptive thresholds based on the above said function

A thresholded image $g(x, y)$ is defined as

$$g(x,y) = \begin{cases} 1, & f(x,y) > T \\ 0, & f(x,y) \leq T \end{cases},$$

where 1 is object and 0 is background

When $T = T[\,f(x,y)\,]$, threshold is **global**

When $T = T[p(x,y),\ f(x,y)]$, threshold is **local**

When $T = T[x,\ y,\ p(x,y),\ f(x,y)]$, threshold is **dynamic** or **adaptive**

THANK YOU

IMAGE COMPRESSION

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Lecture Details:
Topic Name: Introduction to Image Compression
IP/ CSE III B.Tech I Sem

Topics

- Introduction to Image Compression
- Image Compression Model
- Lossless or Error-free Compression
- Lossy or Error Compression

Outline

- Introduction to Image Compression
- Compression Ratio
- Data Redundancy
    - Coding Redundancy
    - Inter Pixel Redundancy
    - Psycho visual Redundancy
- Image Compression Model

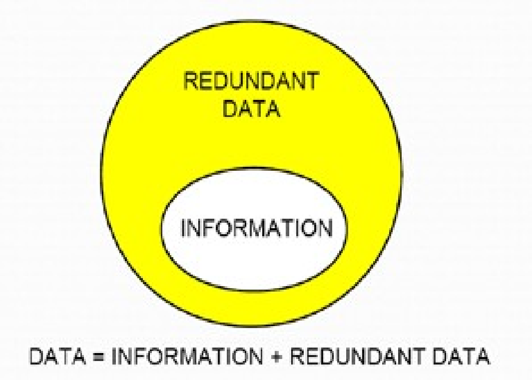
Image Compression

- The field of image compression continues to grow at a rapid pace because the cost of data transmission and storage is very expensive
- Image compression is used to compress the image data for easy transmission and easy storage.
- Applications that require image compression are many and varied such as:

1. Internet
2. Business
3. Multimedia applications
4. Digital and Satellite TV
5. Medical imaging
6. Video Conferencing

Image Compression (Cont)

- Data and information are not synonymous terms.
- Data is raw facts which are encountered in image processing.
- Information is an interpretation of data in meaningful way.
- **Data is the means by which information is conveyed.**
- A data that is not relevant to represent any information is called data redundancy.



Types of Data:
Text data
Binary Data
Image data
Sound data
Video data

Image Compression (Cont)

The term Data Compression refers to the process of reducing the amount of data required to represent a given quantity of information.

<u>Need for Data Compression:</u>

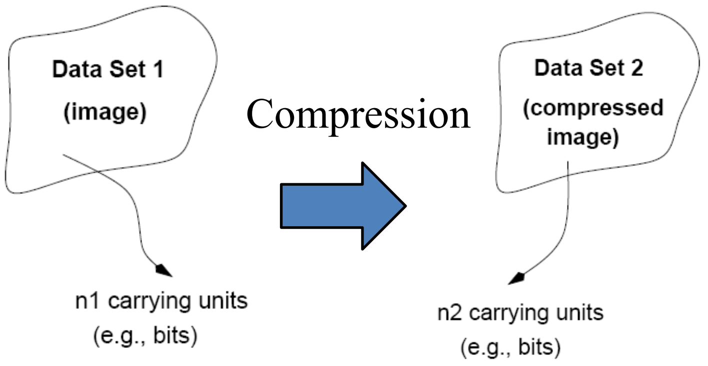
1)Storage: Reduce the size of the data to store more information in less storage space.

2)Transmission: Reduction of data size results in reduction of transmission time.

3)Faster Computation: Facilitate the faster execution of the program.

Compression Ratio

- If n1 and n2 denote the number of information carrying units in two data sets that represent the same information, then the compression ratio is given by $C_R = n1/n2$.



Compression ratio: $$C_R = \frac{n_1}{n_2}$$

Data Redundancy

- Data redundancy is the centre issue in digital image compression and it is given by:

$$R_D = 1 - \frac{1}{C_R}$$

(a) Now if $n_1 = n_2$; $C_R = 1$; $R_D = 0$
that represents that first data has no redundant information.

(b) If $n_2 << n_1$

So, $C_R = \frac{n_1}{n_2}$
$C_R \rightarrow \infty$
$R_D \rightarrow 1$

That represents highly redundant data and high compression can be done.

(c) If $n_2 >> n_1$

So, $C_R = \frac{n_1}{n_2}$
$C_R \rightarrow 0$
$R_D \rightarrow -\infty$

It means now second data is larger in comparison to original one.

Types of Data Redundancy

- There are three types of Data Redundancy as given below:

  1. Coding Redundancy

  2. Inter Pixel Redundancy

  3. Psycho visual Redundancy

- Data compression attempts to reduce one or more of these redundancy types.

Coding Redundancy

- Coding Redundancy:
- **If the gray levels of an image are coded in a way that uses more code symbols than absolutely necessary to represent each gray level, the resulting image is said to contain coding redundancy.**
- **Let** r_k is in range [0, 1] and represent image gray levels. Probability of occurrence is given by:

$$p_r(r_k) = \frac{n_k}{n} \qquad k = 0, 1, 2, \ldots, L - 1$$

If number of bits used to represent each r_k is given by $l(r_k)$, then average number of bits required to represent each pixel is:

$$L_{avg} = \sum_{k=0}^{L-1} l(r_k) p_r(r_k).$$

Thus, the total number of bits required to represent an M x N image is given by: MNL_{avg} .

Inter Pixel Redundancy

- ❑ This type of redundancy is related with the inter-pixel correlations within an image.
- ❑ Much of the visual contribution of a single pixel is redundant and can be guessed from the values of its neighbors.

Example: consider an image with a constant background

The visual nature of the image background is given by many pixels that are not actually necessary

This is known as **Spatial Redundancy** or **Geometrical Redundancy**

Psycho Visual Redundancy

- The eye and the brain do not respond to all visual information with same sensitivity.
- Some information is neglected during the processing by the brain. Elimination of this information does not affect the interpretation of the image by the brain.
- Edges and textural regions are interpreted as important features and the brain groups and correlates such grouping to produce its perception of an object.

- **Psycho visual redundancy** is distinctly vision related, and its elimination does result in loss of information.
- **Quantization** is an example. When 256 levels are reduced by grouping to 16 levels, objects are still recognizable. The compression is 2:1, but an objectionable graininess and contouring effect results.

Image Compression Model

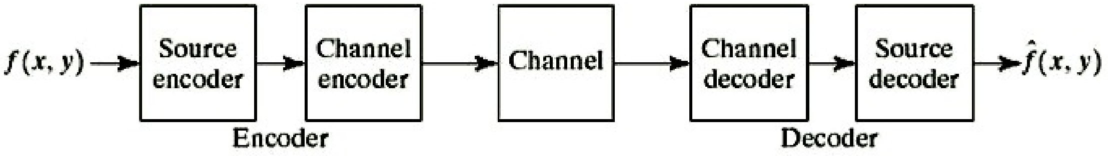


FIGURE 8.5 A general compression system model.

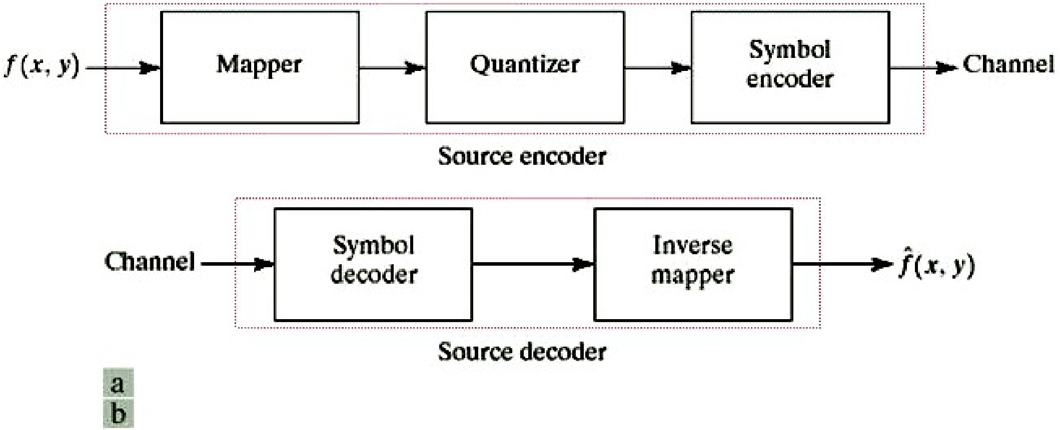


FIGURE 8.6 (a) Source encoder and (b) source decoder model.

Image Compression Model (Cont)

- Two Major components of Image Compression Model are:

  1. Encoder (Compression)
  2. Decoder (Decompression)

- The Encoder is made up of a source encoder which removes input redundancies such as coding, inter pixel and psycho visual redundancies, and a channel encoder, which increases the noise immunity of the source encoder's output.
- The decoder includes a channel decoder followed by a source decoder.
- If the channel between the encoder and decoder is noise free, the channel encoder and decoder are omitted.

Image Compression Model (Cont)

Stages of Encoding:

It consists of three stages as shown in the figure:

1. Mapper
2. Quantizer
3. Symbol Encoder

- In the first stage, the mapper transforms the input data into a format designed to reduce inter pixel redundancies in the input image. It is reversible process.
- In the second stage, the quantizer will reduce the accuracy of mapper's output. It is used to reduce psycho visual redundancies. This operation is irreversible.
- In the third stage, the symbol encoder generates a fixed or variable length code to represent the quantizer output. It assigns the shortest code to the most frequently occurring output values. It is reversible process.
- Upon its completion, the input image has been processed for the removal of all 3 redundancies.

Image Compression Model (Cont)

Stages of Decoding:

It consists of two stages as shown in the figure:

1. Symbol Decoder
2. Inverse Mapper

- Here in this decoding, the inverse operations of encoder are performed.
- Since the Quantization is the irreversible process, an inverse quantizer block is not included in the decoder block.
- We will perform symbol decoder and inverse mapper operations to get back the original image (approximate or estimate) before compression.

Questions

1.What is Image Compression? Explain the need of Image Compression.

2.Draw the sketch of Image Compression model and Explain?

THANK YOU

IMAGE COMPRESSION TECHNIQUES

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Lecture Details:
Topic Name: Image Compression Techniques
IP/ CSE III B.Tech I Sem

Outline

- Image Compression Techniques
  - Lossless Compression
  - Lossy Compression

Image Compression Techniques

- Image compression is used to compress the image data for easy transmission and easy storage.
- Image Compression refers to the process of reducing the amount of data required to represent a given quantity of information.
- The image compression techniques are broadly classified into two categories as below:

1. Lossless Compression
2. Lossy Compression

Lossless Compression

- After lossless compression, a file can be restored in its original form.
- No quality degradation happens in Lossless compression
- Lossless Compression is used in Text, images, sound.
- Lossless Compression is also termed as reversible compression.
- Lossless compression reduces the size but less as compared to lossy compression.
- It is also called as error free compression, we get very low compression ratio.

Techniques:

1. Huffman Coding (Variable length coding)
2. Run-Length Encoding
3. Arithmetic Coding
4. Lossless predictive coding

Lossy Compression

- After lossy compression, a file cannot be restored to its original form.
- In Lossy compression, Data's quality is compromised.
- Lossy compression is used in Images, audio, video.
- Lossy compression is also termed as irreversible compression.
- Lossy compression reduces the size of file to large extent.

Techniques:

1. Lossy Predictive coding
2. Transform coding
3. Wavelet coding

Huffman Coding

- Huffman Coding is a type of variable length coding.
- It is the most popular technique for removing coding redundancy named after D.A.Huffman, who developed the procedure in 1952.
- In this technique, Coding redundancy can be eliminated by choosing a better way of assigning the codes.
- Huffman Coding yields the smallest number of code symbols per source symbol.
- The resulting code is optimal

Huffman Coding (Cont)

The Huffman coding algorithm is given as:

1. Assign the symbols according to descending order of probability of occurrence.
2. Now add the lowest two probabilities and get the new probability.
3. New probability is placed at appropriate position according to descending order.
4. Repeat step2 until one node remain.
5. Assign 0 to the higher up symbol and 1 to the lower down symbol.
6. Now trace the code symbols going backwards.

Huffman Coding Example

Original source		Source reduction			
Symbol	Probability	1	2	3	4
a_2	0.4	0.4	0.4	0.4	0.6
a_6	0.3	0.3	0.3	0.3	0.4
a_1	0.1	0.1	0.2	0.3	
a_4	0.1	0.1	0.1		
a_3	0.06	0.1			
a_5	0.04				

Huffman Coding Example (Cont)

Original source			Source reduction							
Symbol	Probability	Code	1		2		3		4	
a_2	0.4	1	0.4	1	0.4	1	0.4	1	0.6	0
a_6	0.3	00	0.3	00	0.3	00	0.3	00	0.4	1
a_1	0.1	011	0.1	011	0.2	010	0.3	01		
a_4	0.1	0100	0.1	0100	0.1	011				
a_3	0.06	01010	0.1	0101						
a_5	0.04	01011								

$$L_{avg} = \sum_{k=0}^{L-1} l(r_k)p_r(r_k)$$

$$L_{avg} = 1(0.4)+2(0.3)+3(0.1)+4(0.1)+5(0.06)+5(0.04)$$
$$= 2.2\ bits$$

Run-length Coding

- Run-length Coding is the simplest lossless compression technique.
- It runs on sequences having same value occurring many consecutive times and it encode the sequence to store only a single value and its count.

Example 1:

Input: AAABBCDDDD
Encoded: 3A2B1C4D
Decoded: AAABBCDDDD

Example 2:

Input: 11111111111111100000000000000000001111 - 38bits
(15,1), (19,0), (4,1)
(01111,1) , (10011,0), (00100,1) - 18bits

Arithmetic Coding

Arithmetic Coding	Huffman Coding
Complex technique for coding short messages	Simple Technique
Gives optimum result	Does not give optimum result
There is no one to one correspondence between source symbol and code word	There is one to one correspondence between source symbol and code word
Compression Ratio is more	Compression Ratio is less
Execution time is more	Execution time is less

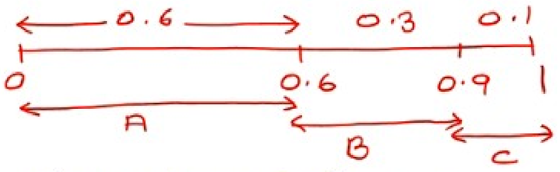
Arithmetic Coding (Cont)

Example: Code the string CAB using arithmetic coding.

Character	A	B	C
Probability	0.6	0.3	0.1

Solution:

① Divide the range into 0 – 1



* First character → C

Range → 0.9 — 1

$\boxed{0.1}$

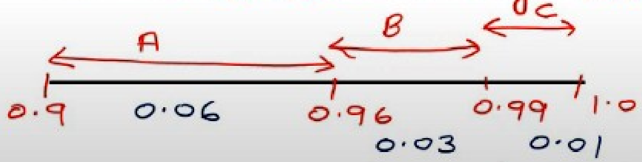
code would start in this range only.

Divided among symbols according to prob.

Cumulative Character Probability Table

Character	Cumulative Probability
A	0.9+0.6×0.1=0.96
B	0.96+0.3×0.1=0.99
C	0.99+0.1×0.1 =1.0

(2) Resultant new range is:-



Arithmetic Coding (Cont)

* Next character → A

0.9 — 0.96

code

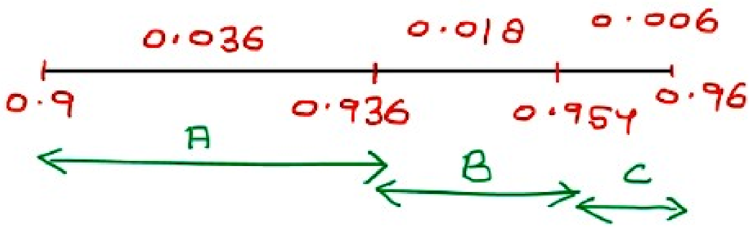
Range = 0.96 − 0.9 = 0.06

as per given prob

Cumulative Character Probability Table

Character	Cumulative Probability
A	$0.9 + 0.6 \times 0.06 = 0.936$
B	$0.936 + 0.3 \times 0.06 = 0.954$
C	$0.954 + 0.1 \times 0.06 = 0.96$

(3) Resultant Range is →



* Next character → B → END

Range : 0.936 − 0.954

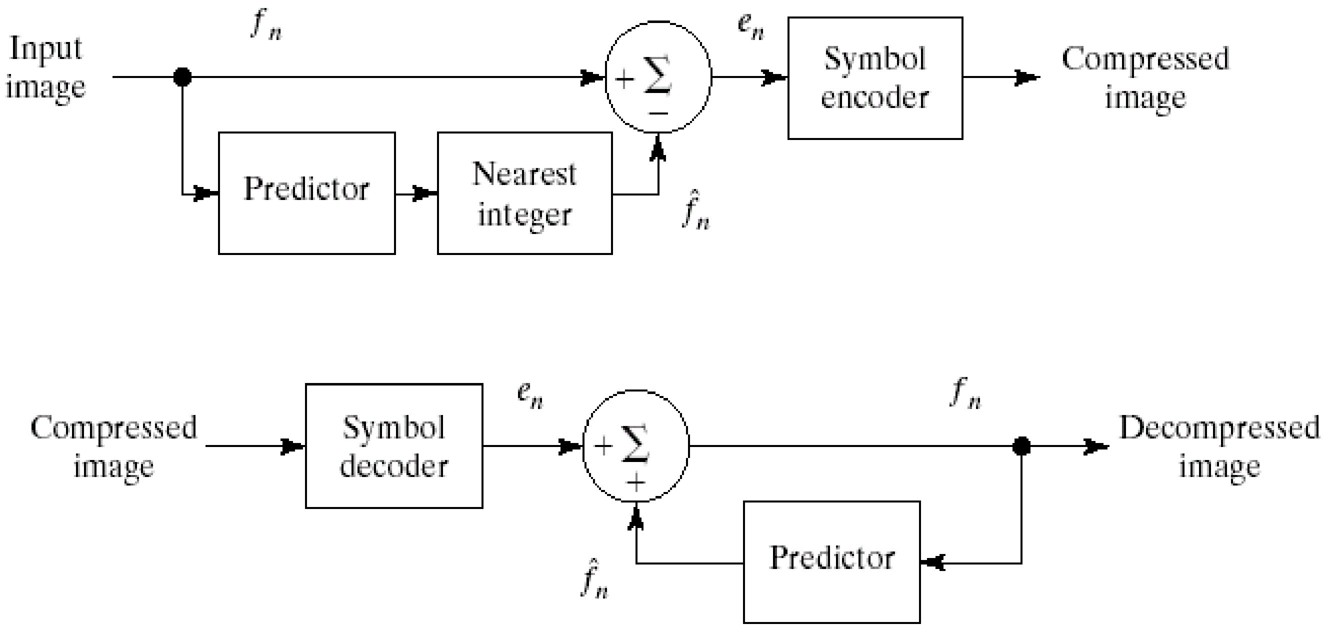
* Final code for string CAB

0.936 − 0.954

Lossless Predictive Coding

- The above three techniques (Huffman coding, run-length coding and Arithmetic coding) we have discussed till now are removing coding redundancies.
- Lossless predictive coding is based on eliminating the inter-pixel redundancies of closely spaced pixels by applying coding to the new information in each pixel.
- The new information of a pixel is defined as the difference between the actual and a predicted value of that pixel.
- The coding system consists of an encoder and a decoder, each contains an identical predictor as shown in the figure

Lossless Predictive Coding (Cont)



a
b

FIGURE 8.19 A lossless predictive coding model: (a) encoder; (b) decoder.

Lossless Predictive Coding (Cont)

- The predictor generates the anticipated value of that pixel based on some number of past inputs. The anticipated value is f˜(n) for the current pixel f(n).
- The predictor is coded using f(n) and f˜ (n)

$$e_n = f(n) - \hat{f}(n)$$

- We have applied a nearest integer in logic circuit that causes to round off the value generated by the predictor e_n, is also called as predictor error.
- If we have two successive pixels equal then e_n will be zero. After generation of e_n , we apply variable length coding that will remove the coding redundancy.

Lossless Predictive Coding (Cont)

- At the decoder side performs the inverse operation

$$f(n) = e_n + \hat{f}(n)$$

- Prediction is usually formed by a linear combination of 'm' previous pixels.

$$\hat{f}(n) = round\left[\sum_{i=1}^{m} \alpha_i f(n-i)\right]$$

m is the order of linear predictor,

round is function used to denote the rounding to nearest integer operation.

α_i for i = 1,2… m are prediction coefficients.

- 1 Dimensional predictive coding:

$$\hat{f}(x,y) = round\left[\alpha f(x, y-i)\right]$$

Lossless Predictive Coding Example

Example: Consider the pixel {23, 34, 39, 47, 55, 63}. Demonstrate the predictive coding.

Solution:

Value	Predictive Coding
23	23
34	34 − 23 = 11
39	39 − 34 = 5
47	47 − 39 = 8
55	55 − 47 = 8
63	63 − 55 = 8

Lossless Predictive Coding Example

Example: Consider the pixel {23, 34, 39, 47, 55, 63}. Demonstrate the predictive coding.

* max. value in original sequence
  = 63
  ↓
  requires 6 bits + 1 bit for sign
* No. of bits required to code original message = 6 X 7 = 42
* Predicted coded sequence
  → max. value is 23
  ↓
  (5 bits + 1 bit for sign)
  → Total no. of bits required =
  6 × 6 = 36

Lossless Predictive Coding Example

- If the difference crosses the threshold limit, it creates a problem known as Overloading.
- Solution to this is to ignore the differences and use the original message for coding.

Consider the pixel {23, **64**, 39, 47, 55, 63}

Value	Predictive Coding
23	23 ✓
64	64-23 = 41
39	39-64 = -25 ✓
47	47-39 = 8 ✓
55	55-47 = 8 ✓
63	63-55 = 8 ✓

* original sample $= 6 \times (6+1)$
$= 42$

* After ⇒
$= 5 \times (5+1) + 1\,(6+1)$
$= 5 \times 6 + 7$
$= 30 + 7 = 37$

Questions

1.Explain the differences between lossless compression and lossy compression?

2.Explain lossless compression ?

3.Explain Huffman coding technique in Image compression with example?

4.Explain lossless predictive coding with example?

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THANK YOU

LOSSY COMPRESSION TECHNIQUES

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Lecture Details:
Topic Name: Lossy Compression Techniques
IP/ CSE III B.Tech I Sem

Outline

- Lossy Compression Techniques
  - Lossy Predictive Coding
  - Transform Coding
  - Wavelet Coding

Lossy Compression

- After lossy compression, a file cannot be restored to its original form.
- In Lossy compression, Data's quality is compromised.
- Lossy compression is used in Images, audio, video.
- Lossy compression is also termed as irreversible compression.
- Lossy compression reduces the size of file to large extent.

Techniques:

1. Lossy Predictive coding
2. Transform coding
3. Wavelet coding

Lossy Predictive Coding

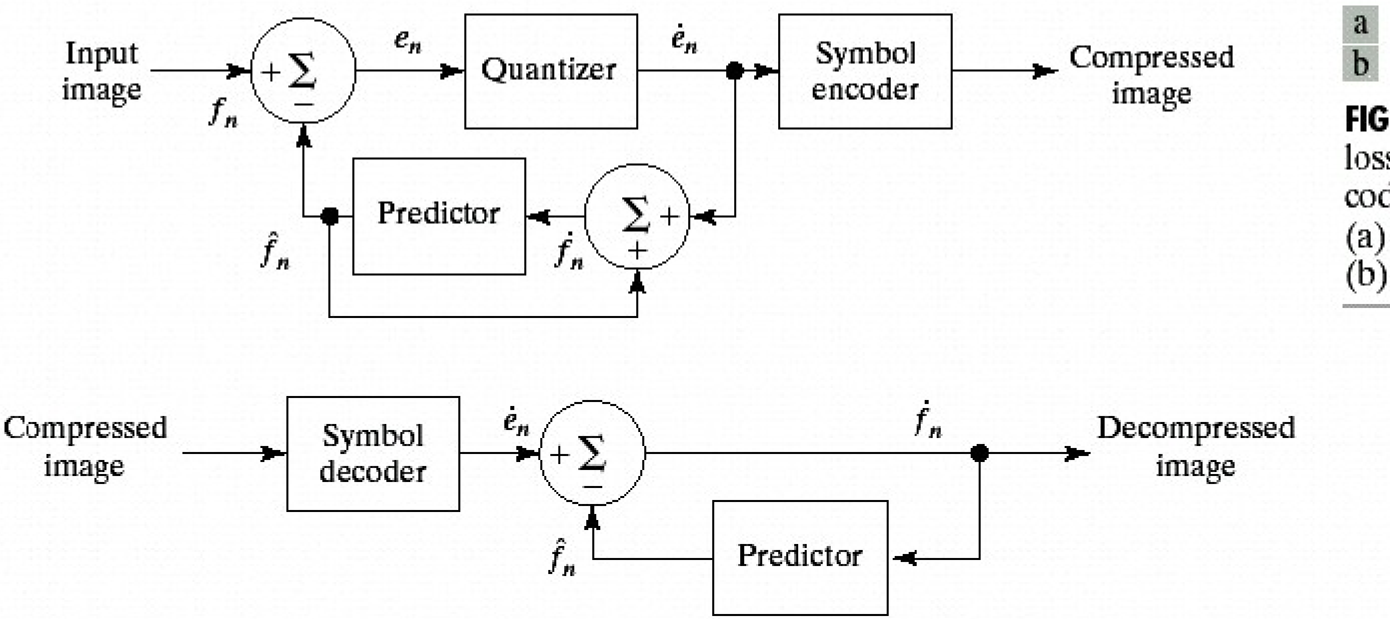


FIGURE 8.21 A lossy predictive coding model: (a) encoder and (b) decoder.

Lossy Predictive Coding (Cont)

- We have drawn the block diagram of lossy predictive system as shown in the above figure 8.21.
- It is an extension of the idea of lossless predictive coding.
- The practical difference between lossless predictive coding and lossy predictive coding is that we use quantizer in the case of lossy compression system.
- The predictor generates the anticipated value of that pixel based on some number of past inputs. The anticipated value is f^(n) for the current pixel f(n).
- The predictor is coded using f(n) and f^ (n)

$$e_n = f(n) - \hat{f}(n)$$

Lossy Predictive Coding (Cont)

- e_n is given as input to the quantizer to remove psycho visual redundancy.
- The quantizer output is denoted as $\ddot{e}_n$ and it is send as input to the symbol encoder to remove coding redundancy as well as to the predictor to add to the previous prediction with a feedback loop, where its input denoted $\dot{f}_n$ is generated as a function of past predictions and corresponding quantized errors.
- That is:

$$\dot{f}_n = \dot{e}_n + \hat{f}_n$$

Lossy Predictive Coding Example

Consider the pixel {23, **64**, 39, 47, 55, 63}

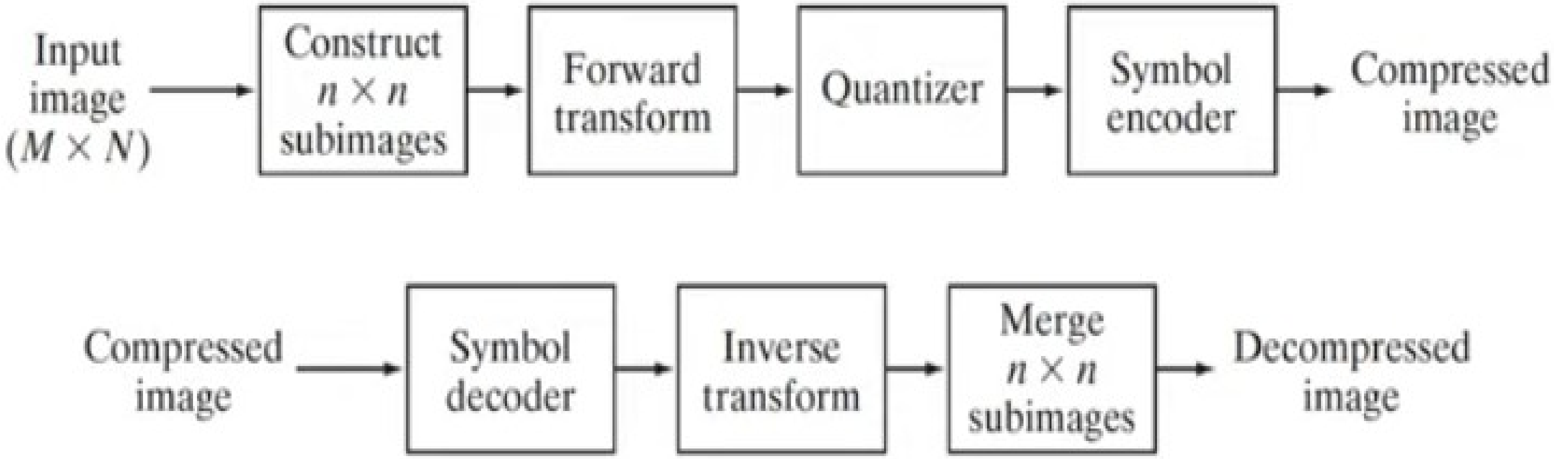
Value	Predictive Coding
23	23 ✓
64	64-23 = 41 → overloading = 31
39	39-64 = -25 ✓
47	47-39 = 8 ✓
55	55-47 = 8 ✓
63	63-55 = 8 ✓

6 × 6 = 36 bits

max. 5 bits are required + 1 sign bit = 6

5 bits
↳ 31 value
↳ drastically reduces no. of bits
↳ Loss of information increases

Transform Coding

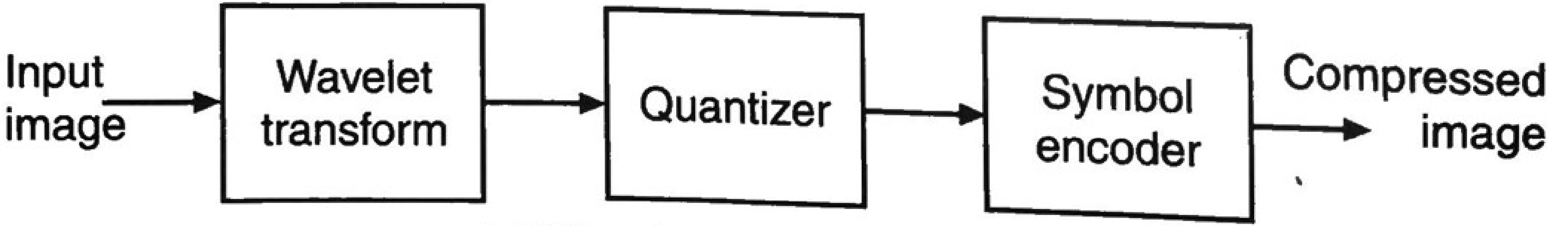


Transform Coding (Cont)

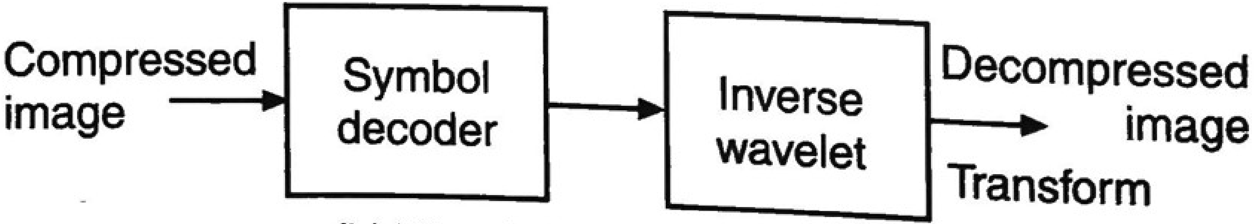
Let us discuss the basic steps of encoding using transform coding.

1. First of all an $N \times N$ input image is subdivided into subimages of size $n \times n$. During the subdivision of an image into subimages it should be cared that correlation (redundancy) between adjacent subimages is reduced to minimum level. Most popular subimage sizes are 8×8 and 16×16. Thus image has been converted into small pack of information that are easy to process.
2. Now by transformation (Fourier transform in case of digital signal is referred as discrete fourier transform, DFT) we generate transformation coefficient by the subimages.
3. By quantization process, generally we remove the redundant information.
4. Now apply variable length coding for reducing coding redundancy.

Wavelet Coding



(a) Wavelet coding: Encoder



(b) Wavelet coding: Decoder

Wavelet Coding (Cont)

- Wavelets are mathematical functions that splits up data into different frequency components, and then study each component with a resolution matched to its scale.
- Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called as “ wavelets ”.
- Wavelet transform is a reliable and better technique than that of Fourier transform technique.
- The main difference is that wavelets are well localized in both time and frequency domain whereas the standard Fourier transform is only localized in frequency domain.
- There is no need of sub image construction like in Transform coding technique

Wavelet Coding (Cont)

- At the encoder side, Transformation of spatial information into frequency domain is done using wavelet transform.
- The transformed image is quantized i.e. when some data samples usually those with insignificant energy levels are discarded.
- Quantized image is sent to symbol encoder for variable length coding to reduce the coding redundancy.
- At the decoding side, there is symbol decoder and Inverse wavelet to reconstruct the compressed image in the spatial domain.
- The Quantizer is not present at the decoder as it is an irreversible process.
- The advantage of wavelet compression is that, in contrast to Transform coding, wavelet algorithm does not divide image into blocks, but analyze the whole image.

Questions

1.Explain Lossy Compression techniques?

2.Explain Lossy Predictive Coding with example?

THANK YOU