1.What is an 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 amplitude values of F are finite, we call it a digital image.
Or
An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows.
In a (8-bit) greyscale image each picture element has an assigned intensity that ranges from 0 to 255. A grey scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey.

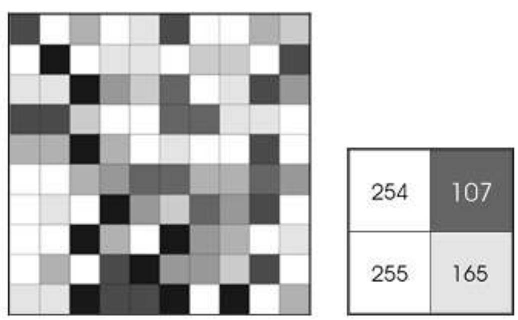
Types of an image

BINARY IMAGE– The binary image as its name suggests, contain only two pixel elements i.e 0 & 1,where 0 refers to black and 1 refers to white. This image is also known as Monochrome.

BLACK AND WHITE IMAGE– The image which consists of only black and white color is called BLACK AND WHITE IMAGE.

8 bit COLOR FORMAT– It is the most famous image format. It has 256 different shades of colors in it and commonly known as Grayscale Image. In this format, 0 stands for Black, and 255 stands for white, and 127 stands for gray.

16 bit COLOR FORMAT– It is a color image format. It has 65,536 different colors in it. It is also known as High Color Format. In this format the distribution of color is not as same as Grayscale image.



2. Sampling and Quantization

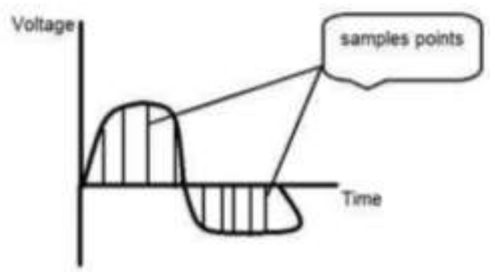
An image may be continuous with respect to the x- and y-coordinates, and also in amplitude. To convert it to digital form, we have to sample the function in both coordinates and in amplitude. Digitizing the coordinate values is called **sampling**. Digitizing the amplitude values is called **quantization.**

Sampling

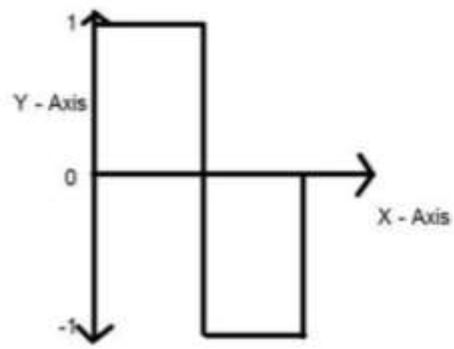
Sampling in image processing refers to the process of converting a continuous image into a discrete one by selecting a finite set of points or pixels from the continuous space.

Quantization

Quantization in image processing is a technique used to reduce the number of distinct levels of colors or intensities in an image. The process involves mapping a large set of input values to a smaller set of output values by dividing the input range into a limited number of discrete levels



Sampling



Quantization

Sampling	Quantization
Digitization of co-ordinate values.	Digitization of amplitude values.
x-axis(time) – discretized.	x-axis(time) – continuous.
y-axis(amplitude) – continuous.	y-axis(amplitude) – discretized.
Sampling is done prior to the quantization process.	Quantization is done after the sampling process.

Sampling	Quantization
It determines the spatial resolution of the digitized images.	It determines the number of grey levels in the digitized images.
It reduces c.c. to a series of tent poles over a time.	It reduces c.c. to a continuous series of stair steps.
A single amplitude value is selected from different values of the time interval to represent it.	Values representing the time intervals are rounded off to create a defined set of possible amplitude values.

3. Fundamental steps and components

Image acquisition
Acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling.

Image enhancement
Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image.

Image restoration
Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

Color image processing
Color image processing is an area that has been gaining in importance because of the significant increase in the use of digital images over the Internet.

Wavelets
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.

Image compression

Image compression is familiar (perhaps inadvertently) to most users of computers in the form of image file extensions, such as the jpg file extension used in the JPEG (Joint Photographic Experts Group) image compression standard.

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

Segmentation
Segmentation procedures partition an image into its constituent parts or objects.
In general, autonomous segmentation is one of the most difficult tasks in digital image processing

Representation and description
Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region (i.e., the set of pixels separating one image region from another) or all the points in the region itself.

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

Knowledge
Knowledge about a problem domain is coded into an image processing system in the form of a knowledge database.

4. Application of IP

Color Processing
Color processing includes processing of colored images and different color spaces that are used. For example RGB color model , YCbCr, HSV. It also involves studying transmission, storage, and encoding of these color images.

Pattern Recognition
Pattern recognition involves study from image processing and from various other fields that includes machine learning (a branch of artificial intelligence). In pattern recognition, image processing is used for identifying the objects in an images and then machine learning is used to train the system for the change in pattern

Video Processing
A video is nothing but just the very fast movement of pictures. The quality of the video depends on the number of frames/pictures per minute and the quality of each frame being used. Video processing involves noise reduction, detail enhancement, motion detection, frame rate conversion, aspect ratio conversion, color space conversion etc.

Line Follower Robot

Most of the robots today work by following the line and thus are called line follower robots. This helps a robot to move on its path and perform some tasks. This has also been achieved through image processing.

Hurdle Detection
Hurdle detection is one of the common task that has been done through image processing, by identifying different type of objects in the image and then calculating the distance between robot and hurdles.

X-ray Imaging
X-rays are among the oldest sources of radiation used for imaging.
The best known use of X-rays is medical diagnostics, but they also are used extensively in industry and other areas, like astronomy. X-ray for medical.

5. Brightness Adaption, Simultaneous Contrast, Map brand

Brightness adaptation
Brightness adaptation refers to the human visual system's ability to adjust its sensitivity to different levels of brightness in the environment.

Simultaneous contrast
Simultaneous contrast is a perceptual phenomenon in which the appearance of one color is influenced by the presence of surrounding colors. This effect occurs when colors are seen adjacent to each other, and the contrast between them is heightened due to the interaction of their respective hues, intensities, or values.

6. Adj , neighbors, pixels,

Two pixels are adjacent if they are neighbors and their intensity level 'V' satisfy some specific criteria of similarity. In binary images, 2 pixels are adjacent if they are neighbors & have some intensity values either 0 or 1. In gray scale, image contains more gray level values in range 0 to 255.

(a) 4-adjacency. Two pixels p and q with values from V are 4-adjacent if q is in the set N4(p).
(b) 8-adjacency. Two pixels p and q with values from V are 8-adjacent if q is in the set N8(p).
(c) m-adjacency (mixed adjacency).Two pixels p and q with values from V are m-adjacent if
(i) q is in N4(p), or
(ii) q is in ND(p) and the set has no pixels whose values are from V.

7. Spatial filtering

Spatial filtering is a process by which we can alter properties of an optical image by selectively removing certain spatial frequencies that make up an object, for example, filtering video data received from satellite and space probes, or removal of raster from a television picture or scanned image.

Types of Spatial filtering

Linear spatial filter
Linear spatial filter is simply the average of the pixels contained in the neighborhood of the filter mask. The idea is replacing the value of every pixel in an image by the average of the grey levels in the neighborhood define by the filter mask.

Non Linear Spatial filtering

A nonlinear filter replaces each pixel value with a nonlinear function of its surrounding pixels. Like the linear filters, the nonlinear filters operate on a neighborhood.

8.Transforming function

Transformation is a function. A function that maps one set to another set after performing some operations.

We will develop a system that whose input would be an image and output would be an image too. And the system would perform some processing on the input image and gives its output as an processed image.

Now function applied inside this digital system that process an image and convert it into output can be called as transformation function.

9. Shearing Diff between Horizontal & Vertical

Horizontal Shearing	Vertical Shearing
Each vertical line in the image is displaced horizontally by a certain amount	Each horizontal line in the image is displaced vertically by a certain amount
The points along each horizontal line remain unchanged.	The points along each vertical line remain unchanged.
The shear factor determines the amount of horizontal displacement	The shear factor determines the amount of vertical displacement.
The shearing matrix for a horizontal shear transformation typically looks like this: [1 shear_factor] [0 1]	The shearing matrix for a vertical shear transformation typically looks like this: [1 0] [shear_factor 1]

10. High Pass and Low Pass

High-Pass Filter:

A high-pass filter allows high-frequency components to pass through while attenuating or blocking low-frequency components. It is designed to emphasize the details and edges in an image, enhancing the fine features.
In image processing, high-pass filters are commonly used for tasks such as edge detection and sharpening. They highlight rapid changes in intensity, which often correspond to edges in an image.
Example: The Sobel and Laplacian filters are examples of high-pass filters commonly used for edge detection in images.

Low-Pass Filter:

A low-pass filter allows low-frequency components to pass through while attenuating or blocking high-frequency components. It is used to smooth or blur an image by reducing the impact of rapid intensity variations.
In image processing, low-pass filters are applied for tasks such as noise reduction and image smoothing. They are effective in reducing high-frequency noise or details that may not be significant for a particular analysis.
Example: The Gaussian filter is a popular low-pass filter used for smoothing and blurring in images

Both high-pass and low-pass filters are part of a broader category of filters known as band-pass filters, which selectively allow a certain range of frequencies to pass through while attenuating others. The choice between a high-pass or low-pass filter depends on the specific goals of the image processing task. Often, a combination of these filters is used to achieve the desired result, such as in image enhancement or feature extraction..

UNIT 2

1. Probability density function for noise

The Probability Density Function (PDF) defines the probability function representing the density of a continuous random variable lying between a specific range of values.

Gaussian Noise:
Gaussian noise arises in an image due to factors such as electronic circuit noise and sensor noise due to poor illumination or high temperature.

Rayleigh noise:
Rayleigh noise is usually used to characterize noise phenomena in range imaging.
Rayleigh noise is characterized by a probability density function (PDF) that follows the Rayleigh distribution. The probability density function for Rayleigh-distributed noise, denoted as $f(x;\sigma)$, is given by:

$$f(x;\sigma) = \frac{x}{\sigma^2} e^{-\frac{x^2}{2\sigma^2}}$$

Erlang (or gamma) Noise:
Gamma noise density finds application in laser imaging.

Gamma noise is named after the gamma correction function, which is a nonlinear operation applied to the pixel values in an image to compensate for the nonlinear relationship between pixel intensity and the physical brightness of a display device

Exponential Noise
Exponential noise is also commonly present in cases of laser imaging.

Uniform Noise
Uniform noise is commonly found in the case of poor lighting where the sensitivity of the sensor is such that is becomes harder to correctly measure the amount of light with great accuracy
Uniform noise is not practically present but is often used in numerical simulations to analyze systems.

Impulse Noise:
Impulse noise is a category of (acoustic) noise that includes unwanted, almost instantaneous (thus impulse-like) sharp sounds (like clicks and pops)—typically caused by electromagnetic interference, scratches on disks, gunfire, explosions, and synchronization issues in digital audio.

2. DFD & IDED

The Discrete Fourier Transform (DFT) is a fundamental tool in image processing used to analyze the frequency content of images. It is an extension of the Fourier Transform to discrete signals and is particularly valuable for representing images in the frequency domain. The DFT transforms a signal or image from its spatial domain (pixel values) to its frequency domain (amplitudes and phases of different frequencies).

Applications of the Discrete Fourier Transform in image processing include:

> **Frequency Analysis**: DFT helps in analyzing the frequency components present in an image. This is useful for tasks like detecting patterns, edges, or periodic structures.
>
> **Filtering**: Filtering in the frequency domain allows the removal or enhancement of specific frequencies. For example, high-pass filters can be used to enhance edges, while low-pass filters can be used for blurring.
>
> **Compression**: Transforming an image into the frequency domain can be part of compression techniques like JPEG. The less important high-frequency components can be quantized more aggressively or even discarded, leading to compression.
>
> **Image Reconstruction:** The inverse DFT can be applied to transform an image back from the frequency domain to the spatial domain, allowing for the reconstruction of the original image.

Inverse Discrete Fourier Transform (IDFT)

The Inverse Discrete Fourier Transform (IDFT) is the process of converting a signal or an image from the frequency domain back to the spatial domain. It is essentially the reverse operation of the Discrete Fourier Transform (DFT). The IDFT allows you to reconstruct the original signal or image from its frequency components.

Applications of the IDFT in image processing include image reconstruction after frequency domain manipulations, filtering, and compression. It's a crucial tool in transforming images between the spatial and frequency domains, allowing for analysis and processing in either domain as needed for specific applications.

3. Filtering and Image Frequency in Frequency domain

Filtering in frequency domain
Filtering techniques in the frequency domain are based on modifying the Fourier transform to achieve a specific objective, and then computing the inverse DFT to get us back to the spatial domain.

Basic Steps for Filtering in the Frequency Domain:
1. Multiply the input image by $(-1)^{x+y}$ to center the transform.
2. Compute F (u, v), the DFT of the image from (1).
3. Multiply F (u, v) by a filter function H (u, v).
4. Compute the inverse DFT of the result in (3).
5. Obtain the real part of the result in (4)
6. Multiply the result in (5) by (-1) x+y
Given the filter H (u, v) (filter transfer function) in the frequency domain, the
Fourier transform of the output image (filtered image) is given by:
G (u, v) = H (u, v) F (u, v)

Image Frequency
The term "image frequency" typically refers to the spatial frequencies present in an image. Spatial frequency refers to the rate of change of intensity or color in an image across space.

Low Spatial Frequencies:
Represent variations in intensity or color that change slowly across the image.
Associated with large-scale features, such as smooth transitions, broad gradients, or uniform regions.
Low-frequency components contribute to the overall structure and content of the image.

High Spatial Frequencies:
Represent variations in intensity or color that change rapidly across the image.
Associated with fine details, edges, or abrupt changes in intensity.
High-frequency components contribute to the finer details and sharpness of the image.

4. Smoothing and Sharpening in Frequency Domain

Smoothing

Smoothing is a low pass operation in the frequency domain. Smoothing is achieved in the frequency domain by high frequency attenuation of a specified range of high frequency components in the transform of a given image.
There are three types of lowpass filters: Ideal, Butterworth, and Gaussian Low pass filters

1. Ideal Low Pass filter
A low pass filter is a filter that “cuts off” all high frequency components of the Fourier transform that are at a distance greater than a specified distance D0 from the origin of the transform

2. A Butterworth low-pass filter
It is designed to allow low-frequency components to pass through while attenuating higher-frequency components. The Butterworth filter is characterized by its smooth frequency response and is commonly employed for applications where a gradual transition between the passband and stopband is desired

3. Gaussian Low pass filter
A Gaussian low-pass filter is a type of frequency domain filter used in signal processing and image processing. It is designed to attenuate higher-frequency components while allowing lower-frequency components to pass through. Gaussian filters are popular because they exhibit a smooth and isotropic (rotationally symmetric) response.

Sharpening

Image sharpening can be achieved by a high pass filtering process, which attenuates the low-frequency components without disturbing high-frequency information.
These are radially symmetric and completely specified by a cross section.

Ideal High Pass filter

It is designed to attenuate or remove low-frequency components from a signal or an image while allowing higher-frequency components to pass through

Butterworth High pass filter

It is designed to attenuate or remove low-frequency components from a signal or an image while allowing higher-frequency components to pass through

Gaussian High Pass filter

it is designed to attenuate or remove low-frequency components from a signal or an image while allowing higher-frequency components to pass through.

5. Image Restoration Degradation model with diagram

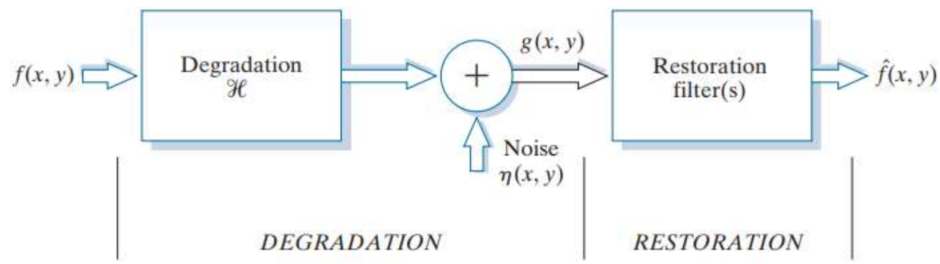


Image restoration is the process of recovering an image that has been degraded by some knowledge of degradation function ***H*** and the additive noise term $\eta(x, y)$. Thus in restoration, degradation is modelled and its inverse process is applied to recover the original image.

Terminology:

- $g(x, y)$ = degraded image
- $f(x, y)$ = input or original image
- $\hat{f}(x, y)$ = recovered or restored image
- $\eta(x, y)$ = additive noise term

6. Order Statistical Filter

These are nonlinear spatial filter whose response is based on ordering of the pixels contained in the image area compressed by the filter and the replacing the value of the center pixel with value determined by the ranking result.
The best example of this category is median filter. In this filter the values of the center pixel are replaced by median of gray levels in the neighborhood of that pixel.
Median filters are popular because, for certain types of random noise, they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters.

The different types of order statistics filters

Median Filtering :
Replaces the value of a pixel by the median of the pixel values in the neighborhood of that pixel

Max & Min Filtering :

The max filtering is achieved using the following equation
f(x,y) = max g(s,t)

The min filtering is achieved using the following equation
f(x,y) = min g(s,t)

Mid-point filtering :
Replaces the value of a pixel by the midpoint between the maximum and minimum pixels in a neighborhood

7. Periodic Noise

Periodic noise in image processing refers to unwanted patterns or variations in pixel intensity that repeat regularly across an image. Imagine your image has a repeating pattern or a regular oscillation in brightness, like a series of stripes or grids.

This kind of noise can be caused by various factors, such as electrical interference, uneven lighting, or sensor issues. When these factors introduce a consistent and repeating disturbance in the image, it creates periodic noise.

For example, if you've ever taken a photo in low light conditions and noticed some regular stripes or grids, especially in smartphone pictures, that could be a manifestation of periodic noise. It's as if the interference or variations in light occur at regular intervals, causing a repetitive pattern in the image.

7. Histogram Processing and Histogram Equalization

Histogram Processing

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

where rk is the kth gray level and nk is the number of pixels in the image having the level rk.
A normalized histogram is given by the equation $P(rk)=nk/n$ for $k=0,1, 2, . . ., L-1$

P(rk) gives the estimate of the probability of occurrence of gray level rk. The sum of all components of a normalized histogram is equal to 1.

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

Histogram equalization

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

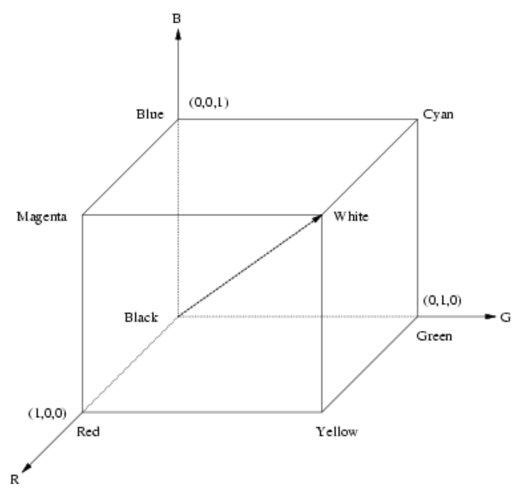
Let there be a continuous function with r being gray levels of the image to be enhanced.

The range of r is [0, 1] with r=0 repressing black and r=1 representing white.
The transformation function is of the form.
$S=T(r)$ where $0<r<1$

UNIT 3

1. Color Models

The RGB Model
In the RGB model, an image is composed of 3 independent image levels: red, green and blue. One is in each of the primary colors. (As seen in figure 5.10, the regular wavelengths are for the three primaries). The sum of each primary component present is specified in a particular color. The geometry for color defined with a Cartesian coordination system for RGB color model is shown in Figure 5.13. In the line between the black and white vertices is the grey scale spectrum, i.e. these colors made of equal quantities of each primary.



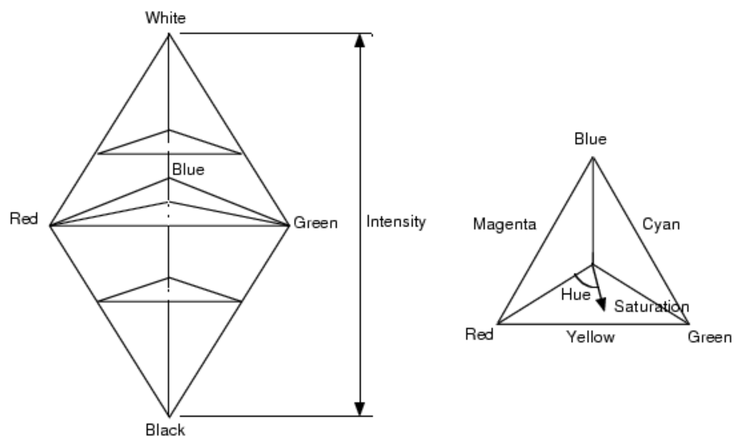
The CMY and CMYK Color Models
A subtractive model for absorption of the color, for example because of colored pigments in paints, is the CMY (cyan-magenta-yellow) model. While the **RGB model determines what's added to black** to obtain a particular color, the **CMY model determines what is subtracted from white**. The primaries are cyan, magenta and yellow in this case, the secondary color being red, green and blue.

When the surface is illuminated with a cyan pigment with white light, no red light, including magenta, yellow and blue, is reflected.
The RGB and CMY model relationship is defined by:

$$\begin{pmatrix} C \\ Y \\ M \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} - \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad \text{eq-1}$$

The HIS Color model

The HSI model would improve the RGB model. The color model of the hue saturation intensity is closely similar to the color sensing properties of human vision. The method, which transforms from RGB to HSI or back, is harder than other color models. I denote the intensity of light, H refers to the hue indicating the measure of the purity of colors, S refers to the saturation. If the saturation value of a color is high, it indicates that the color is the low white color. Three quantities of hue, saturation and intensity may be defined for color



2. Image compression

Image compression works by reducing the amount of data needed to represent an image while attempting to preserve its visual quality. There are two main approaches to image compression: lossless compression and lossy compression.

Lossless Compression:

Run-Length Encoding (RLE):

How it Works: Identical consecutive pixels are replaced with a count of the number of occurrences and the pixel value.
Example: Instead of storing "AAAAABBBBBBBBBCC," RLE would represent it as "5A9B2C."

Huffman Coding:

How it Works: Assign shorter codes to more frequently occurring pixel values and longer codes to less frequent ones.
Example: If 'A' occurs more frequently, it might be represented by a shorter binary code.

Lossy Compression:

Transform Coding:

How it Works: Transform the image data from its spatial domain to a frequency domain using mathematical transforms like Discrete Cosine Transform (DCT) or Discrete Wavelet Transform (DWT).
Example: JPEG compression uses DCT to transform an image into its frequency components.

Quantization:

How it Works: Reduce the precision of the transformed coefficients. In lossy compression, this step discards some information that may not be critical for human perception.
Example: If a coefficient is originally represented as 8 bits, quantization may reduce it to 4 bits.

Entropy Coding:

How it Works: Use variable-length coding schemes to represent the quantized data more efficiently.
Example: Shorter codes are assigned to more probable pixel values.

3. Huffman Coding

Huffman is the most popular way to remove coding redundancy. Huffman coding is a widely used algorithm for lossless data compression. It's particularly efficient for compressing data where some symbols occur more frequently than others.
Here's a simple explanation of how Huffman coding works:

Let's say you have the message "abracadabra."

Frequency Check: 'a' appears 5 times, 'b' twice, 'r' twice, 'c' once, 'd' once.
Priority List: 'a' (5), 'b' (2), 'r' (2), 'c' (1), 'd' (1).
Build a Tree: Combine 'c' and 'd' into 'cd' (2), then combine 'r' and 'b' into 'rb' (4), then combine 'rb' with 'cd' into 'rbcd' (6), finally combine 'a' with 'rbcd' into 'arbcd' (11).
Assign Binary Codes: 'a' gets '0', 'r' gets '10', 'b' gets '110', 'c' gets '1110', and 'd' gets '1111'.

Run-Length Coding

Run-Length Coding (RLE) is a simple yet effective method of lossless data compression. It works by representing sequences of identical elements (runs) with a single value and its count

Original String: "AAAABBBCCDAA"
Identify Runs: "AAA," "BBB," "CC," "D," "AA"
Encode Runs: "A3B3C2D1A2"
Encoded String: "A3B3C2D1A2"
Decoding: "AAA" + "BBB" + "CC" + "D" + "AA" = "AAAABBBCCDAA"

4. Wavelet transform

Wavelet transform is a mathematical tool used in signal processing and image compression. It allows you to analyze signals and images at different scales and resolutions, making it well-suited for tasks like compression, denoising, and feature extraction.

Continuous Wavelet Transform (CWT):

CWT is a continuous and infinitely flexible wavelet transform.
It involves transforming a signal into a continuous range of scales and positions.

Select a wavelet function that suits the characteristics of your data. Different wavelets have different shapes and properties.
The chosen wavelet is scaled and shifted across the signal at all possible scales and positions.
The transformation is computed by integrating the product of the signal and the scaled and shifted wavelet
The output of the CWT is a 2D representation, where one axis represents time, the other represents scale, and the color or intensity represents the strength of the wavelet response.

Discrete Wavelet Transform (DWT):

DWT is a discrete version of the wavelet transform.
It involves transforming a signal into a discrete set of scales and positions.

The signal is decomposed into approximate (low-frequency) and detail (high-frequency) components using a pair of wavelet and scaling functions.
This is often done through a process called multi-resolution analysis.
After decomposition, the resulting coefficients are sub-sampled, reducing the data size.
This process is repeated iteratively on the approximate components to achieve multilevel decomposition.
The output of the DWT is a set of coefficients representing the signal at different scales and resolutions

5. HAAR Transform

The HAAR wavelet transform, often referred to as the HAAR transform, is a type of wavelet transform that decomposes a signal or an image into approximation and detail coefficients. It is a simple yet effective transform with applications in signal processing and image compression.

The Haar wavelet basis consists of two functions:

- The Haar scaling function
- The Haar wavelet function

The Haar transform is applied by successively averaging and differencing adjacent values in the signal.

For a one-dimensional signal, the Haar transform involves dividing the signal into pairs of adjacent values, computing the average and the difference for each pair, and arranging the results.

For a two-dimensional image, the Haar transform is applied separately to rows and columns.

Applications of HAAR transform

Image Compression:
HAAR transform coefficients can be used to represent an image with reduced data, leading to compression.

Signal Processing:
Used in areas like audio and speech processing for feature extraction and de-noising.

6. Digital watermarking

Digital watermarking is a technique used to embed imperceptible information, known as a watermark, into digital media such as images, audio, or video. The primary purpose of digital watermarking is to provide a form of copyright protection, authentication, or tamper detection

Types of watermarking

1. Spatial Domain Watermarking:
2. Frequency Domain Watermarking:
3. Transform Domain Watermarking:

They defend the rights of their owners in a variety of ways

1. Copyright identification
2. Identification or fingerprinting of the user.
3. Authenticity determination
4. Automated monitoring
5. Copy protection

7.

A) Closing
A morphological operation that involves the dilation followed by erosion of an image to fill in gaps, smooth contours, and connect or close small breaks in object boundaries.

B) Opening
It is a morphological operation that consists of an erosion followed by a dilation, effectively removing small objects and smoothing the boundaries of larger objects in a binary or grayscale image.

C) Erosion
It is a morphological operation that removes fine details or boundaries from regions in a binary or grayscale image by applying a structuring element

D) Dilution
A morphological operation that expands the boundaries of regions in an image, often used for accentuating or enlarging features.

E) Hit or Miss
A morphological operation in image processing that identifies patterns in an image by combining the results of both erosion and complemented erosion with structuring elements.

F) Skeletonization
A process that reduces the representation of shapes in an image to their medial axes or skeletons, providing a simplified and thin representation of the structures.

G) Thickening
It is a morphological operation that enhances the boundaries and connectivity of regions in a binary image by adding pixels to the regions.

H) Thinning
Is the iterative removal of pixels along the object boundaries to reduce the width of the features, producing a skeletonized representation of the objects.

I) Pruning
The removal or reduction of certain components or features, often with the goal of simplifying or optimizing the representation of an image.

J) Convex Hull

It is the smallest convex polygon that encloses all foreground pixels in a binary image.

2. Segmentation

Image segmentation is a process in image processing that involves partitioning an image into meaningful, distinct regions or segments. The goal is to simplify the representation of an image into more manageable and semantically meaningful parts. Each segment typically corresponds to objects or regions with similar characteristics, such as color, intensity, or texture. Image segmentation is a fundamental step in various computer vision applications.

Few Types of Segmentation:

Thresholding
Thresholding is used to create binary images from a grayscale image
Divides an image into regions based on intensity levels or color values using a threshold

Region Growing:
Starts with seed points and grows regions by adding neighboring pixels that have similar properties.

Edge Detection-Based:
Identifies boundaries or edges in an image and segments based on changes in intensity or color gradients.

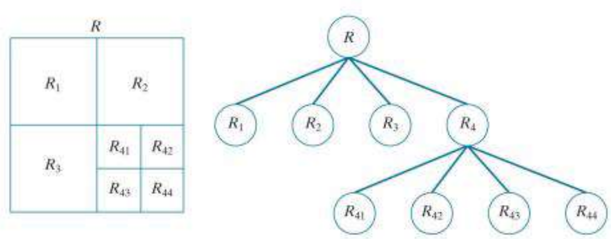
Watershed Segmentation:
Treats pixel intensities as topography and simulates the flooding of basins to separate regions.

Clustering-Based:
Groups pixels into clusters based on similarities in color, intensity, or feature space

Contour-Based:
Identifies and follows contours or outlines of objects in an image.

3. Region splitting

Region splitting is a type of image segmentation technique that divides an image into regions based on variations in pixel intensities. The method is a recursive approach where large regions are successively subdivided into smaller ones until certain criteria are met



4. Types of Edge detection

Edge detection is a fundamental step in image processing that involves identifying boundaries within an image, where a significant change in intensity or color occurs. Different edge detection methods emphasize different aspects of the edges or contours in an image.
Here are some common types of edge detection techniques:

First Order Derivatives

Sobel Operator
Utilizes convolution with Sobel kernels (one for horizontal changes and one for vertical changes) to highlight edges in both directions.

Prewitt Operator:
Similar to the Sobel operator, it employs convolution with Prewitt kernels for horizontal and vertical edge detection.

There is a gradient in the horizontal direction, and a gradient in the vertical direction, which is found by a mask. The mask also computes the gradient in the horizontal direction, which is found by another mask. $GGxx$ and $GGyy$ components can be found at different locations in an image by using these two masks. In this way, we can determine the strength and direction of the edge at a given location (x, y).

Second Order Derivatives

Laplacian of Gaussian (LoG):
Applies a Gaussian smoothing filter followed by Laplacian edge detection to highlight region with rapid intensity changes.

Marr-Hildreth (LoG with Zero Crossing):
Combines the Laplacian of Gaussian (LoG) operator with zero-crossing detection for edge localization.

Canny Edge Detector:
Employs a multi-stage algorithm involving smoothing, gradient calculation, non-maximum suppression, and edge tracking by hysteresis.

Zero Crossing Edge Detector:
Utilizes the concept of zero crossings in the second derivative of an image to identify edges.

Marr-Hildreth (LoG with Zero Crossing):
Combines the Laplacian of Gaussian (LoG) operator with zero-crossing detection for edge localization

Types of Thresholding

Global Thresholding:

A single threshold value is applied to the entire image to separate pixels into foreground and background.

Local Thresholding:

Applies different threshold values to different regions of the image based on local characteristics.

Adaptive Thresholding:

Divides the image into smaller regions and applies different threshold values to each region based on local characteristics.

Using Otsu's Method:

Automatically calculates an optimal global threshold by minimizing the intra-class variance of pixel intensities.

Hysteresis Thresholding (Double Thresholding):

Uses two threshold values, a lower threshold and an upper threshold, to classify pixels as potential edges

5. Watershed Algorithm

The Watershed algorithm is a segmentation technique in image processing that is particularly useful for separating touching or overlapping objects in an image

Basic Steps:

Gradient Computation:
Compute the gradient magnitude of the image to highlight regions of interest and potential boundaries.

Marker Generation:
Identify markers or seeds that indicate starting points for the flooding process. This can be done manually or automatically, for example, by thresholding or other methods.

Flood-Fill:
Simulate the flooding process by considering each pixel as a point in the landscape. The algorithm starts flooding from the markers, raising the water level until basins merge.

Segmentation:
The result is a partitioning of the image into catchment basins, where each basin corresponds to a segmented region. Boundaries between basins are considered as the final segmented contours.

Applications and Considerations:

Object Separation:
Watershed is particularly useful for separating objects or regions with complex shapes and touching boundaries.

Over segmentation:
Without proper preprocessing or marker control, Watershed can lead to oversegmentation, where small or undesired regions may be created.

Merging Basins:
Strategies are often employed to control the merging of basins to avoid unnecessary segmentation. This can involve using markers strategically.