2021

5 (a)

Smoothing Filter		Sharpening Filter
Gives a blur effect by smoothing out the noise.	1.	~~Sharpen~~ Enhances the edges of objects in image
Uses low pass filters	2	Uses high pass filters.
Removes the high frequency contents	3	Removes the low freq. contents.
Can be done in spatial domain by pixel averaging in neighbors	4	Can be done to find difference by the neighbours.
examples - linear - Averaging filter - Weighted average	5	High-boost filtering & unsharp masking
Sum of mask co-efficients = 1	6.	Sum of mask coefficients is 0
Smoothing non-linear - Order statistics filter	7.	Derivative filters - 1st - 2nd (laplacian)

Sharpening filters are sometimes applied after smoothing filters to enhance the edges & details in image without introducing too much noise.

SMOOTHING filter can help to reduce noise in the image. while sharpening filter can help to enhance the edges and details.

(b) The given ~~equation~~ -

$$g(x,y) = f(x,y) - \cancel{2}\nabla^2 f$$

In the given equation the center is negative.

In the given equation ~~use~~ It's used in image enhancement in sharping image.

$g(x,y)$: The resulting enhance image, obtained by substracting the laplacian of the original image from original image. The operator enhances the edges and fine details in image.

$f(x,y)$: Represents original image in 2D func of pixels

$\nabla^2 f$: The laplatian operator ∇^2 computes the 2nd Order derivative of image function f w.r.t both x & y. It measures the rate of change of intensity at each pixel in image.

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

The general equation for 1D in 1st order

$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

& For 2nd order

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

For 2D ~~image~~ image –

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

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

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

The ~~laplacian~~ Co-efficient matrix for the ~~laplatio~~ Laplacian mask –

0	x-1,y	0
x,y-1	f(x,y)	x,y+1
0	x+1,y	0

0	1	0
1	-4	1
0	1	0

Now for the given equation the entire enhancement can be combined to

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

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

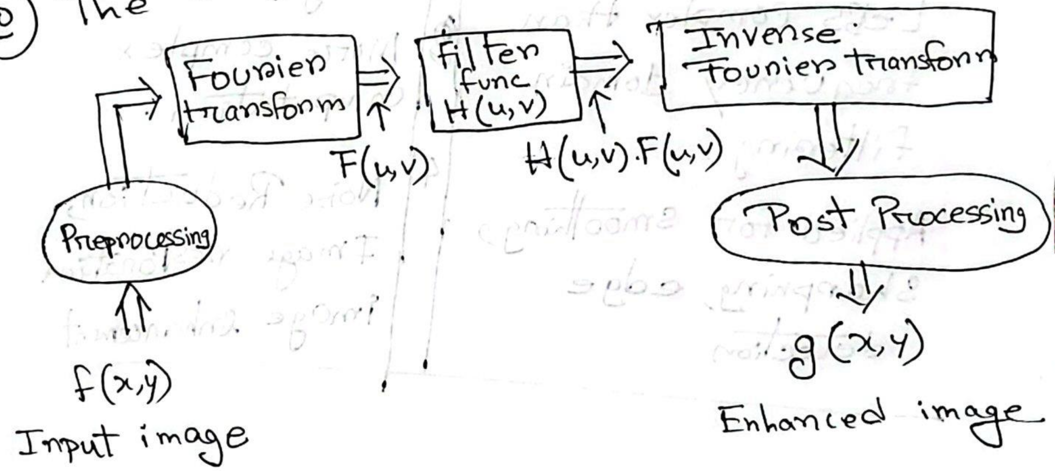
$$= 5f(x,y) - f(x+1,y) - f(x-1,y) - f(x,y+1) - f(x,y-1).$$

Then the new filter mask -

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

So the whole construction of new image ~~can be~~ co-ordinate can be done with a single step.

(c) The steps of frequency domain image filtering-

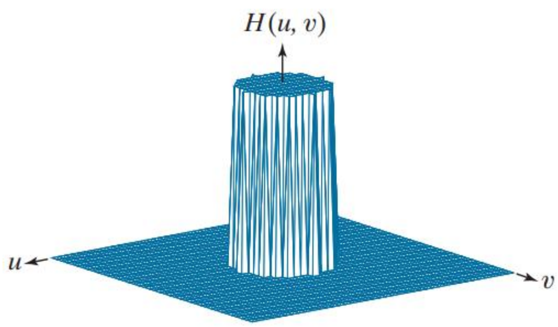
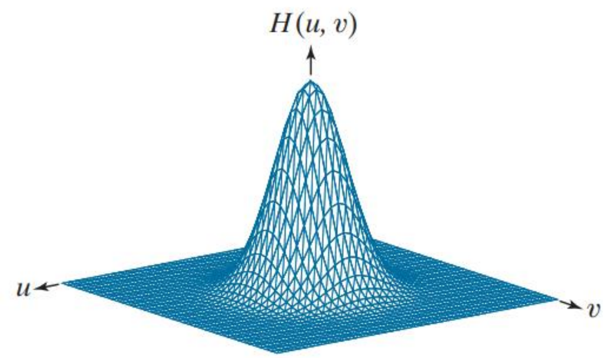
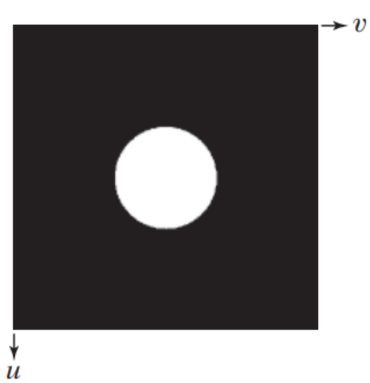
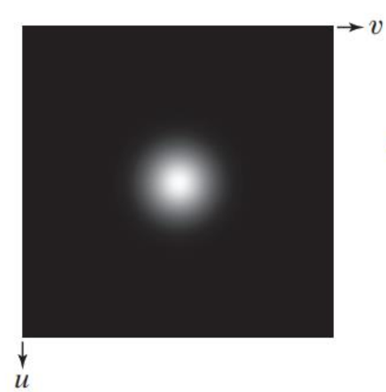


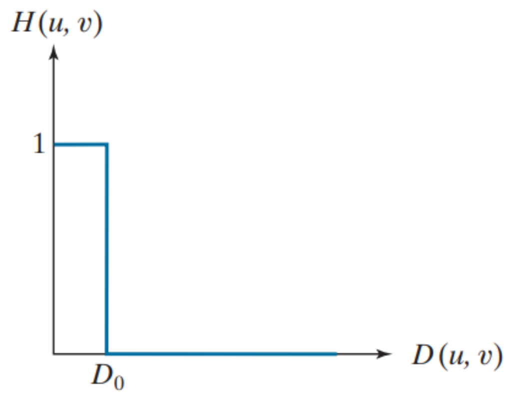
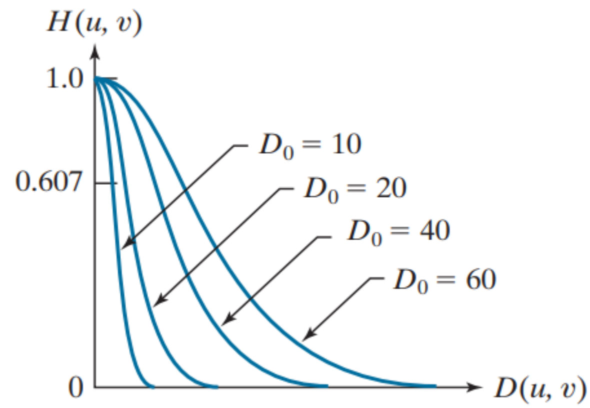
To filter an image in frequency domain.

1. Compute F(u,v) the DFT of Image
2. Multiply F(u,v) by a filter func H(u,v)
3. Compute the inverse DFT of Result

Spatial Domain Filtering		Frequency domain fi
Applied directly to the image pixel	1	Applied to the Fourier tranform of the image
Can directly manipulate the image pixels	2	Can selectively enhance or suppress certain frequencies in the image
Less complex than frequency domain filtering	3	More complex computation.
Applied for smoothing, sharpning, edge detection	4	Noise Reduction, Image restoration image enhancement

6.(a) Compare Ideal and Gaussian low pass filter with their characteristics curves and mathematical expressions. [3.00]

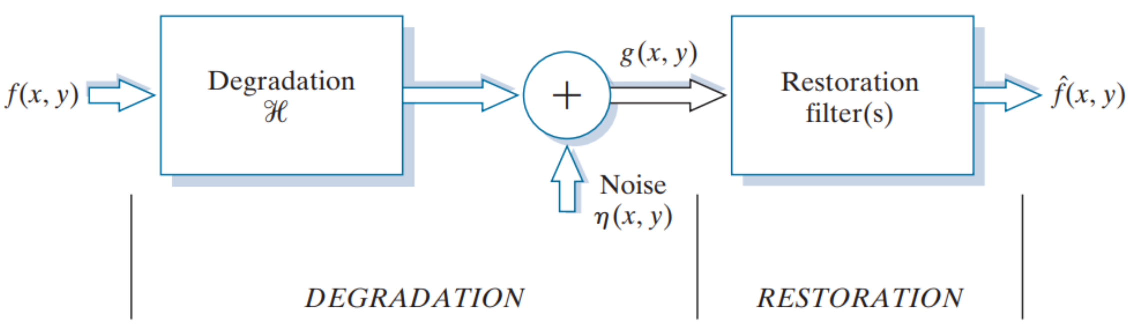
Ideal low pass filter	Gaussian low pass filter
A sharp cutoff at the cutoff frequency, with all frequencies above the cutoff frequency completely attenuated.	A smooth bell-shaped curve, with frequencies above the cutoff frequency attenuated but not completely eliminated.
The transfer function for the ideal low pass filter can be given as: $H(u,v)=\begin{cases}1 & \text{if } D(u,v)\le D_0\\ 0 & \text{if } D(u,v)>D_0\end{cases}$ where $D(u,v)$ is given as: $D(u,v)=[(u-M/2)^2+(v-N/2)^2]^{1/2}$	The transfer function of a Gaussian lowpass filter is defined as: $H(u,v)=e^{-D^2(u,v)/2D_0^2}$
Perspective plot 	Perspective plot 
Radial cross section 	Radial cross section 

Function displayed as an image 	Function displayed as an image 
Used in theoretical or educational contexts to demonstrate the concept of ideal filtering with sharp cutoffs	Gaussian low-pass filters are widely used in practical image and signal processing applications where a gradual and smooth transition from pass band to stop band is desired

(b) Define image restoration process. Suppose you have an image with gray levels. Illustrate its histograms after adding Gaussian and exponential noises. [3.00]

Answer:

Image restoration is the process of improving the quality of a degraded image. This may involve removing noise, blurring, or other artifacts that have been introduced into the image



The image restoration process typically involves the following steps:

1. **Identifying the type of degradation**: The first step is to identify the type of degradation that has affected the image. This can be done by examining the histogram of the image and other visual features.

2. **Choosing a restoration technique**: Once the type of degradation has been identified, a suitable restoration technique can be chosen. There are many different image restoration techniques available, each with its own advantages and disadvantages.

3. **Applying the restoration technique**: Once a restoration technique has been chosen, it is applied to the image. This may involve filtering the image, deconvolution the image, or using other techniques to improve the image quality.

4. **Evaluating the restored image:** Once the restoration technique has been applied, the restored image should be evaluated to ensure that it is of acceptable quality. This may involve examining the histogram of the restored image and other visual features.

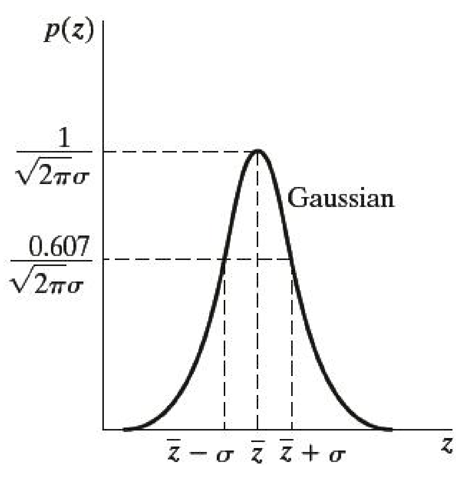
Gaussian Noise

Because of its mathematical tractability in both the spatial and frequency domains, Gaussian noise models are used frequently in practice. In fact, this tractability is so convenient that it often results in Gaussian models being used in situations in which they are marginally applicable at best.

The PDF of a *Gaussian* random variable, z, is defined by the following familiar expression:

$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(z-\bar{z})^2}{2\sigma^2}} \qquad -\infty < z < \infty \tag{5-3}$$

where z represents intensity, $\bar{z}$ is the mean (average) value of z, and σ is its standard deviation. Figure 5.2(a) shows a plot of this function. We know that for a Gaussian random variable, the probability that values of z are in the range $\bar{z} \pm \sigma$ is approximately 0.68; the probability is about 0.95 that the values of z are in the range $\bar{z} \pm 2\sigma$.



Exponential Noise

The PDF of *exponential* noise is given by

$$p(z) = \begin{cases} ae^{-az} & z \geq 0 \\ 0 & z < 0 \end{cases} \tag{5-10}$$

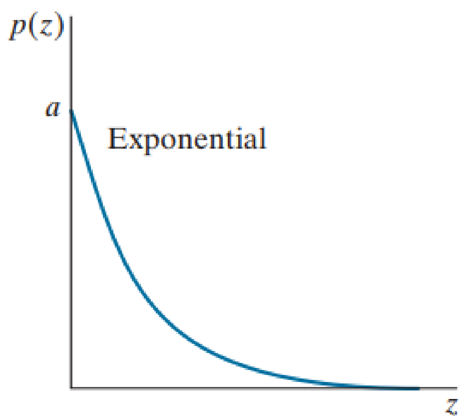
where $a > 0$. The mean and variance of z are

$$\bar{z} = \frac{1}{a} \tag{5-11}$$

and

$$\sigma^2 = \frac{1}{a^2} \tag{5-12}$$

Note that this PDF is a special case of the Erlang PDF with $b = 1$. Figure 5.2(d) shows a plot of the exponential density function.



Illustrate its histograms after adding Gaussian and exponential noises.

(c) How the proper detection of noise model enhances the image restoration? Explain Alpha-Trimmed mean filter. [2.75

Answer:

(part-1)

Histogram analysis

(part-2)

Alpha-Trimmed Mean Filter

Suppose that we delete the $d/2$ lowest and the $d/2$ highest intensity values of $g(r,c)$ in the neighborhood S_{xy}. Let $g_R(r,c)$ represent the remaining $mn-d$ pixels in S_{xy}. A filter formed by averaging these remaining pixels is called an *alpha-trimmed mean filter*. The form of this filter is

$$\hat{f}(x,y) = \frac{1}{mn-d} \sum_{(r,c)\in S_{xy}} g_R(r,c) \qquad (5\text{-}31)$$

where the value of d can range from 0 to $mn-1$. When $d=0$ the alpha-trimmed filter reduces to the arithmetic mean filter discussed earlier. If we choose $d = mn-1$, the filter becomes a median filter. For other values of d, the alpha-trimmed filter is useful in situations involving multiple types of noise, such as a combination of salt-and-pepper and Gaussian noise.

7. (a) Explain the terms Hue and saturation of a color image. 2

Answer:

- **Hue** determines the specific colors present in the image. It describes whether a pixel is predominantly red, green, blue, or any other color on the color wheel.
- **Saturation** determines how intense or vivid those colors are. Highly saturated regions in an image will have strong, pure colors, while de-saturated regions will appear more muted or washed out.

(b) Describe the procedures to convert colors from RGB to HSI and HSI to RGB. 5

Converting Colors from RGB to HSI

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

$$H = \begin{cases} \theta & \text{if } B \le G \\ 360 - \theta & \text{if } B > G \end{cases} \tag{6-16}$$

with†

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}} \right\} \tag{6-17}$$

The saturation component is given by

$$S = 1 - \frac{3}{(R+G+B)}\left[\min(R,G,B)\right] \tag{6-18}$$

† It is good practice to add a small number in the denominator of this expression to avoid dividing by 0 when $R = G = B$, in which case θ will be 90°. Note that when all RGB components are equal, Eq. (6-18) gives $S = 0$. In addition, the conversion from HSI back to RGB in Eqs. (6-20) through (6-30) will give $R = G = B = I$, as expected, because, when $R = G = B$, we are dealing with a grayscale image.

Finally, the intensity component is obtained from the equation

$$I = \frac{1}{3}(R + G + B) \tag{6-19}$$

Converting Colors from HSI to RGB

Given values of HSI in the interval $[0, 1]$, we now want to 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 (see Fig. 6.11). We begin by multiplying H by $360°$, which returns the hue to its original range of $[0°, 360°]$.

RG sector $(0° \leq H < 120°)$: When H is in this sector, the RGB components are given by the equations

$$B = I(1 - S) \tag{6-20}$$

$$R = I\left[1 + \frac{S\cos H}{\cos(60° - H)}\right] \tag{6-21}$$

and

$$G = 3I - (R + B) \tag{6-22}$$

GB sector $(120° \leq H < 240°)$: If the given value of H is in this sector, we first subtract $120°$ from it:

$$H = H - 120° \tag{6-23}$$

Then, the RGB components are

$$R = I(1 - S) \tag{6-24}$$

$$G = I\left[1 + \frac{S\cos H}{\cos(60° - H)}\right] \tag{6-25}$$

and

$$B = 3I - (R + G) \quad (6\text{-}26)$$

BR sector $(240° \leq H \leq 360°)$: Finally, if H is in this range, we subtract 240° from it:

$$H = H - 240° \quad (6\text{-}27)$$

Then, the RGB components are

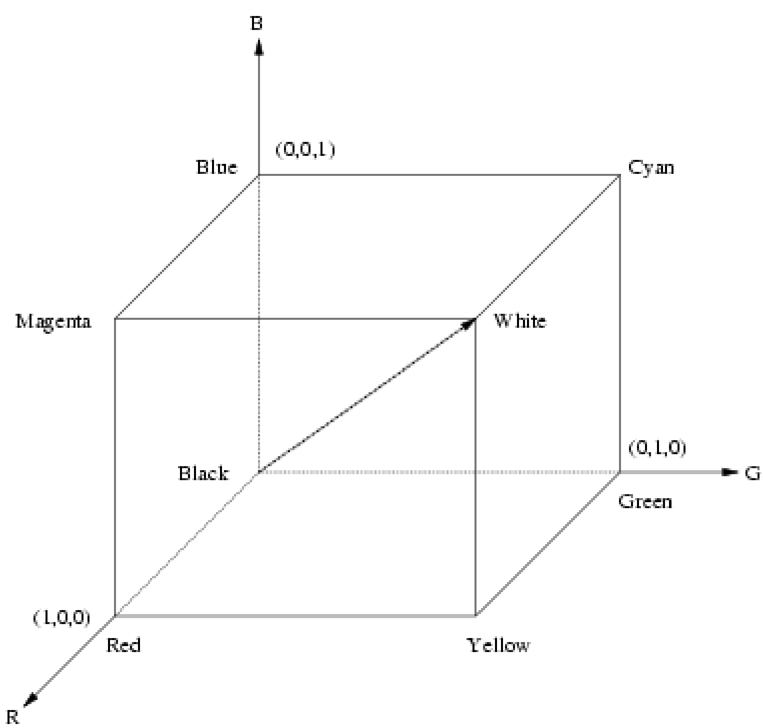
$$G = I(1 - S) \quad (6\text{-}28)$$

$$B = I\left[1 + \frac{S\cos H}{\cos(60° - H)}\right] \quad (6\text{-}29)$$

and

$$R = 3I - (G + B) \quad (6\text{-}30)$$

(c) Explain the color components of a color image with figure. 1.75

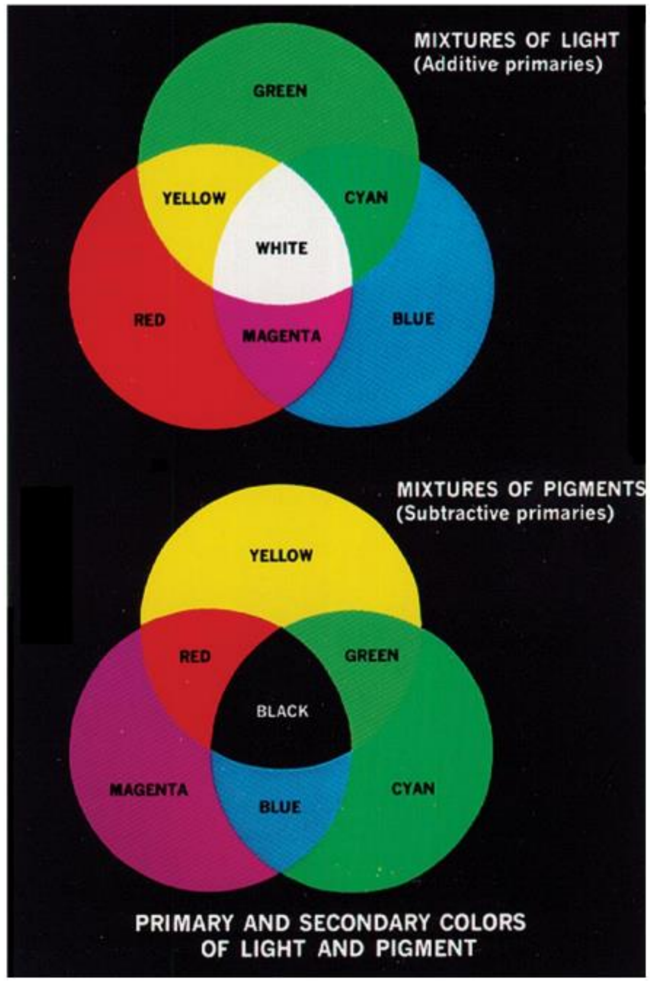


Mixing light

Light

Primary and secondary colors are swapped

Pigment



8. (a) Define structuring element, erosion and dilation with examples. [3.00]

Structuring element: A structuring element is **a small matrix of pixel**s that is used to **probe an image** in morphological image processing. It is used to define the neighborhood of each pixel in the image and to determine the value of the output pixel based on the values of the pixels in the neighborhood.

Erosion: Erosion is a morphological operation that removes pixels from the edges of objects in an image. It is performed by sliding the structuring element over the image and replacing each pixel with the minimum value of the pixels in the neighborhood.

Erosion of image f by structuring element s is given by $f \ominus s$

The structuring element s is positioned with its origin at (x, y) and the new pixel value is determined using the rule:

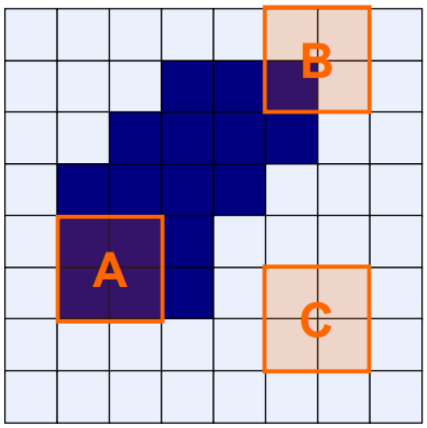
$$g(x, y) = \begin{cases} 1 \text{ if } \ s \text{ fits } \ f \\ 0 \text{ otherwise} \end{cases}$$

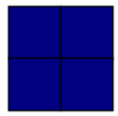
Dilation: Dilation is a morphological operation that adds pixels to the edges of objects in an image. It is performed by sliding the structuring element over the image and replacing each pixel with the maximum value of the pixels in the neighborhood.

Dilation of image f by structuring element s is given by $f \oplus s$

The structuring element s is positioned with its origin at (x, y) and the new pixel value is determined using the rule:

$$g(x, y) = \begin{cases} 1 \text{ if } \ s \text{ hits } \ f \\ 0 \text{ otherwise} \end{cases}$$





Structuring Element

Fit: All *on pixels* in the structuring element cover *on pixels* in the image

Hit: Any *on pixel* in the structuring element covers an *on pixel* in the image

All morphological processing operations are based on these simple ideas

Structuring elements can be any size and make any shape

However, for simplicity we will use rectangular structuring elements with their origin at the middle pixel

1	1	1
1	1	1
1	1	1

0	1	0
1	1	1
0	1	0

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Application of dilation
Repair breaks (bridging the gaps)
Repair intrusions
Enlarges the object

Dilation is denoted by $A \oplus B$.

* Erosion

→ It is the set of all points in the image where the structuring element "fits into".

→ Consider each foreground pixel in the input image. If the structuring element matches completely with the pixel values, write a "1" at the origin of the structuring element.

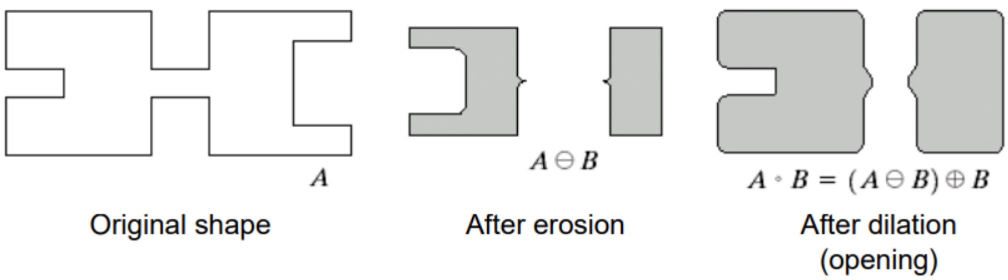
Application of erosion
- Split apart joined objects
- Strip away extrusions
- Shrink the objects

https://youtu.be/bRa770kRapc?si=lYfVtWx-GjPsMYu2

(b) Define opening operation and explain boundary detection method using morphological image processing. [2.75]

The opening of image f by structuring element s, denoted $f \circ s$ is simply an erosion followed by a dilation

$$f \circ s = (f \ominus s) \oplus s$$



(c) Explain the method to calculate entropy of an image. Compare lossy and lossless compression. [3.00]

Answer:

Entropy is a measure of the **uncertainty or randomness in a system**. In the context of image processing, entropy can be used to measure the amount of information contained in an image. A **higher entropy image contains more information than** a lower entropy image.

To calculate the entropy of an image, we first need to calculate the probability of each pixel value. This can be done using a histogram. Once we have the probability of each pixel value, we can use the following equation to calculate the entropy:

$$entropy = -\Sigma\ p(i) * \log_2(p(i))$$

where $p(i)$ is the probability of pixel value i.

Lossy compression reduces the file size of an image by permanently removing some of the original data. This can be done by quantizing the pixel values or by removing high-frequency components of the image. Lossy compression can introduce artifacts into the image, but it can achieve much higher compression ratios than lossless compression.

Lossless compression reduces the file size of an image without removing any of the original data. This is done by finding redundancies in the image data and exploiting them to reduce the file size. Lossless compression cannot achieve as high compression ratios as lossy compression, but it does not introduce any artifacts into the image.

Comparison of lossy and lossless compression:

Characteristic	Lossy compression	Lossless compression
Compression ratio	High	Low
Image quality	Reduced	Preserved
Typical applications	Digital photography, video encoding, web streaming	Archiving, medical imaging, document imaging

2020

5. (a) Mention the general model of spatial filtering for image enhancement. Discuss the effects of mask size in spatial filtering. 3

https://www.geeksforgeeks.org/spatial-filtering-and-its-types/

The **spatial domain enhancement** is based on pixels in a small range (neighbor). This means the transformed intensity is determined by the gray values of those points within the neighborhood, and thus the spatial domain enhancement is also called **neighborhood operation** or **neighborhood processing**.

A digital image can be viewed as a two-dimensional function f (x, y), and the x-y plane indicates spatial position information, called the **spatial domain**. The filtering operation based on the x-y space neighborhood is called **spatial domain filtering**.

Spatial filtering with a template

The filtering process is to move the filter point-by-point in the image function f (x, y) so that the center of the filter coincides with the point (x, y). At each point (x, y), the filter's response is calculated based on the specific content of the filter and through a predefined relationship called 'template'.

If the pixel in the neighborhood is calculated as a linear operation, it is also called 'linear spatial domain filtering', otherwise, it's called 'nonlinear spatial domain filtering'. Figure 2.3.1 shows the process of spatial filtering with a 3 × 3 template (also known as a filter, kernel, or window).

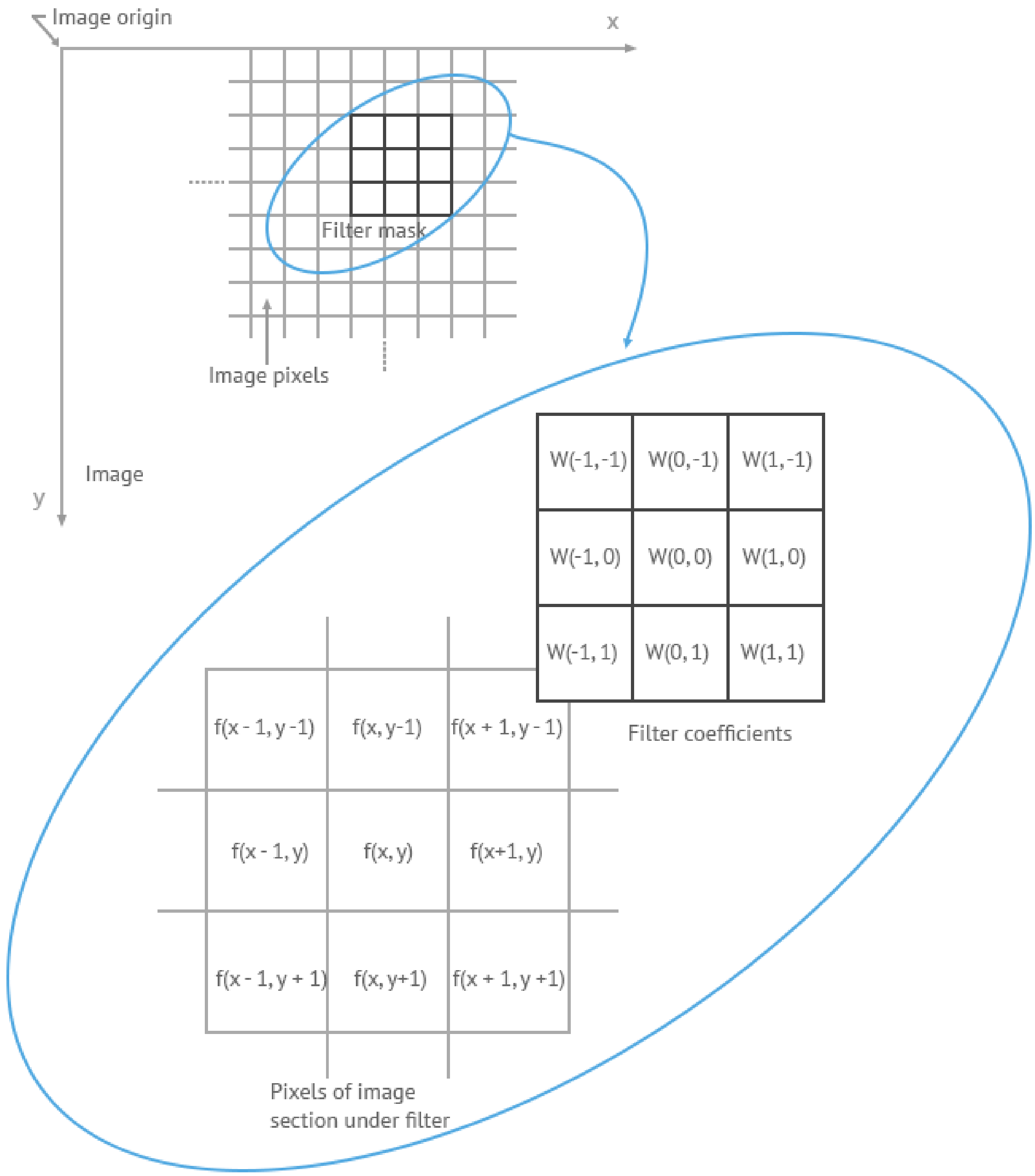


Figure 3.28 illustrates the mechanics of linear spatial filtering using a 3×3 kernel. At any point (x, y) in the image, the response, $g(x, y)$, of the filter is the sum of products of the kernel coefficients and the image pixels encompassed by the kernel:

$$g(x,y) = w(-1,-1)f(x-1,y-1) + w(-1,0)f(x-1,y) + \dots \\ + w(0,0)f(x,y) + \dots + w(1,1)f(x+1,y+1) \tag{3-30}$$

As coordinates x and y are varied, the center of the kernel moves from pixel to pixel, generating the filtered image, g, in the process.†

Observe that the center coefficient of the kernel, $w(0,0)$, aligns with the pixel at location (x, y). For a kernel of size $m \times n$, we assume that $m = 2a+1$ and $n = 2b+1$, where a and b are nonnegative integers. This means that our focus is on kernels of odd size in both coordinate directions. In general, linear spatial filtering of an image of size $M \times N$ with a kernel of size $m \times n$ is given by the expression

$$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t)f(x+s,y+t) \tag{3-31}$$

where x and y are varied so that the center (origin) of the kernel visits every pixel in f once. For a fixed value of (x, y), Eq. (3-31) implements the *sum of products* of the form shown in Eq. (3-30), but for a kernel of arbitrary odd size. As you will learn in the following section, this equation is a central tool in linear filtering.

(b) Define cross-convolution and autocorrelation with example. Mention the applications of autocorrelation. 2.75

Correlation consists of moving the center of a kernel over an image, and computing the sum of products at each location. The mechanics of spatial convolution are the same, except that the correlation kernel is rotated by 180°. Thus, when the values of a kernel are symmetric about its center, correlation and convolution yield the same result.

Cross-convolution, also known as cross-correlation, is a mathematical operation used in signal processing and image processing to measure the similarity between two signals or images. It involves comparing one signal with another by sliding one signal (or kernel) over the other and computing a measure of similarity at each relative position. Cross-convolution is often used in tasks like image matching, pattern recognition, and feature detection

Autocorrelation in digital image processing refers to the computation of the autocorrelation function for an image. Autocorrelation is a mathematical technique that measures **the similarity between an image and a shifted** (or displaced) **version of itself**. It helps in identifying **repetitive patterns, periodic structures, and symmetries within an image**. Autocorrelation is commonly used in various image processing applications, including **pattern recognition, texture analysis, and feature detection.**

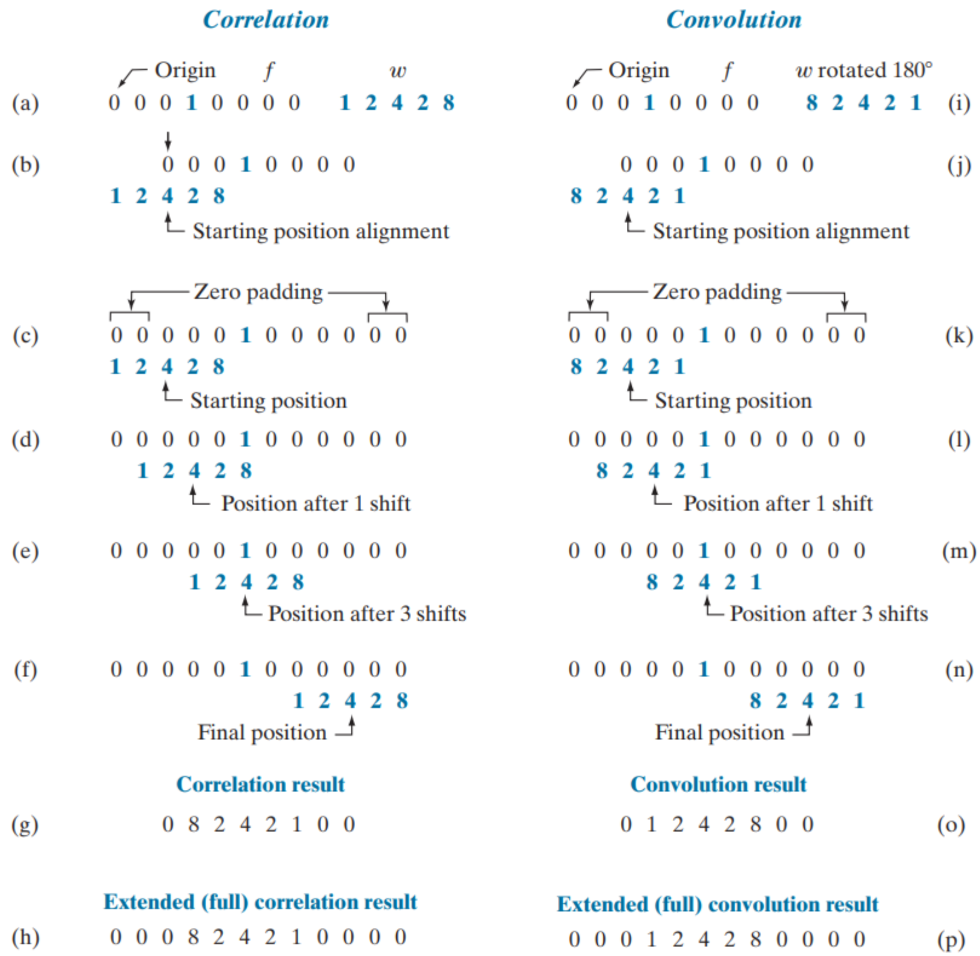


FIGURE 3.29 Illustration of 1-D correlation and convolution of a kernel, w, with a function f consisting of a discrete unit impulse. Note that correlation and convolution are functions of the variable x, which acts to *displace* one function with respect to the other. For the extended correlation and convolution results, the starting configuration places the right-most element of the kernel to be coincident with the origin of f. Additional padding must be used.

(c) Why edge detection is necessary? Explain thresholding based image enhancement. 3

Answer:

Edge detection is massively important as it is in many cases the first step to object recognition. An edge is a set of connected pixels that lie on the boundary between two regions.

It is used to identify the boundaries of objects in images. Edge detection is necessary for a variety of reasons, including:

- **Object recognition**: Edge detection is often used as the first step in object recognition algorithms. By detecting the edges of objects in an image, these algorithms can more easily identify and classify the objects.
- **Image segmentation:** Edge detection can also be used for image segmentation, which is the process of dividing an image into different regions. This can be useful for tasks such as identifying different objects in an image or extracting specific features from an image.
- **Feature extraction**: Edge detection can also be used for feature extraction, which is the process of identifying and extracting important features from an image. This can be useful for tasks such as object recognition, image retrieval, and medical imaging.

Thresholding is usually the first step in any segmentation approach

We have talked about simple single value thresholding already

Single value thresholding can be given mathematically as follows:

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

(need more explanation)

6. (a) Illustrate the application of sharpening filter in image enhancement. Formulate Laplacian mask using derivative filter. 3

Answer:

Sharpening spatial filters seek to highlight fine details

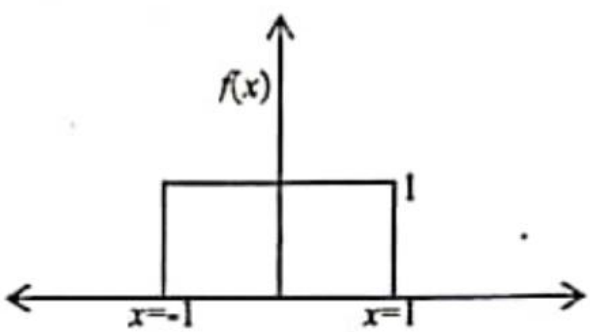
- – Remove blurring from images
- – Highlight edges

Sharpening filters are based on spatial differentiation.

Sharpening filters can also help to restore some of the information that was lost or distorted during the acquisition, processing, or storage of the images, such as due to camera shake, lens blur, noise, or compression.

using derivative filter.

(b) Compare frequency domain filtering with spatial domain. Illustrate the Fourier transform of the following function: 3

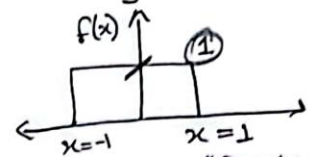


2021 5-b 1st part

1st question- (2021- 5c 2nd Part)

2020 − 6 (b)

Illustrate Fourier transform of following function:



Ans:

$$F(\mu) = \int_{-1}^{1} f(x)\, e^{-j2\pi\mu x}\, dx$$

$$z = -j2\pi\mu x$$

$$= \int_{-1}^{1} 1 \cdot e^{-j2\pi\mu x}\, dx$$

$$\int e^{zx}\, dx = \frac{e^{zx}}{z} + c$$

$$= \left[\frac{e^{-j2\pi\mu x}}{-j2\pi\mu}\right]_{-1}^{1}$$

$$= \frac{1}{-j2\pi\mu}\left[e^{-j2\pi\mu x}\right]_{-1}^{1}$$

$$= \frac{-1}{j2\pi\mu}\left[e^{-j2\pi\mu} - e^{-j2\pi\mu(-1)}\right]$$

$$= \frac{-1}{j2\pi\mu}\left[e^{-j2\pi\mu} - e^{j2\pi\mu}\right]$$

$$= \frac{-1}{j2\pi\mu}\left[\cancel{\cos(2\pi\mu)} - j\sin(2\pi\mu) - \cancel{\cos(2\pi\mu)} - j\sin(2\pi\mu)\right]$$

$$= \frac{-1}{\cancel{j2}\pi\mu}\cdot\left[-\cancel{2j}\sin(2\pi\mu)\right]$$

$$= \frac{\sin(2\pi\mu)}{\pi\mu}$$

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

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

(c) Explain the limitations of ideal sharpening filter. How it can be resolved? 2.75

Sharpening filters are a powerful tool for enhancing images, but they have some limitations.

Noise amplification: One of the main limitations of sharpening filters is that they can amplify noise in the image. This is because noise is typically high-frequency information, and sharpening filters are designed to amplify high-frequency information. As a result, sharpening filters can make noise more visible in an image.

Artifact introduction: Another limitation of sharpening filters is that they can introduce artifacts into the image. Artifacts are unwanted visual features that can be created by image processing algorithms. For example, sharpening filters can create ringing artifacts, which are halos around the edges of objects in an image.

Other limitations

Sharpening filters can also have other limitations, such as:

- Edge overshoot: Sharpening filters can overshoot edges, making them appear brighter or darker than they should be.
- Reduced image contrast: Sharpening filters can reduce the overall contrast of the image.
- Increased computational cost: Sharpening filters can be computationally expensive to implement.

Here are some additional tips for using sharpening filters:

- Use a sharpening filter that is designed for the type of image that you are sharpening. For example, there are different sharpening filters for photographs, medical images, and satellite images.
- Start with a low sharpening amount and increase it gradually until you are satisfied with the results.
- Be careful not to oversharpen the image, as this can make it look unnatural and artificial.
- If you are unsure how to use a sharpening filter, consult a professional photographer or image processing expert.

By understanding the limitations of sharpening filters and the tips above, you can use sharpening filters to enhance your images without introducing noise or artifacts

7. (a) Why image segmentation is necessary? Illustrate the process of detecting horizontal and vertical lines in an image with appropriate mask. 3.

Answer:

Image Segmentation

It is a stage of transition methods whose inputs methods in which the outputs images are from image processing and outputs are the inputs are images attributes extracted images, to but from those

Segmentation refers to an image into the process of partitioning multiple regions. Image segmentation is typically objects and boundaries used to locate in images.

710 **Chapter 10** Image Segmentation

Horizontal

−1	−1	−1
2	2	2
−1	−1	−1

+45°

2	−1	−1
−1	2	−1
−1	−1	2

Vertical

−1	2	−1
−1	2	−1
−1	2	−1

−45°

−1	−1	2
−1	2	−1
2	−1	−1

a b c d

FIGURE 10.6 Line detection kernels. Detection angles are with respect to the axis system in Fig. 2.19, with positive angles measured counterclockwise with respect to the (vertical) *x*-axis.

(b) Explain the basic global thresholding method for image segmentation. 3

Thresholding

1) Thresholding

→ It is carried out with the assumption that the range of intensity levels covered by objects of interest is different from the background.

Thresholding is an important technique for image segmentation

- ❖ It produces uniform regions based on the threshold criteria, T
- ❖ Key parameter of thresholding process is the choice of threshold value

- ❖ If thresholding operation depends upon only grey scale value, it is known as **Global Thresholding**
- ❖ In case neighborhood properties (or some local properties) is also taken into account, method is known as **Local Thresholding**
- ❖ If case T depends on pixel coordinates also, it is known as **Dynamic (or Adaptive) Thresholding**

BASIC GLOBAL THRESHOLDING

When the intensity distributions of objects and background pixels are sufficiently distinct, it is possible to use a single (*global*) threshold applicable over the entire image. In most applications, there is usually enough variability between images that, even if global thresholding is a suitable approach, an algorithm capable of estimating the threshold value for each image is required. The following iterative algorithm can be used for this purpose:

1. Select an initial estimate for the global threshold, T.
2. Segment the image using T in Eq. (10-46). This will produce two groups of pixels: G_1, consisting of pixels with intensity values $> T$; and G_2, consisting of pixels with values $\leq T$.
3. Compute the average (mean) intensity values m_1 and m_2 for the pixels in G_1 and G_2, respectively.
4. Compute a new threshold value midway between m_1 and m_2:

$$T = \frac{1}{2}(m_1 + m_2)$$

5. Repeat Steps 2 through 4 until the difference between values of T in successive iterations is smaller than a predefined value, ΔT.

Book- 748

(c) Explain the model of noisy image. 2

We can consider a noisy image to be modelled as follows:

$$g(x, y) = f(x, y) + \eta(x, y)$$

where $f(x, y)$ is the original image pixel, $\eta(x, y)$ is the noise term and $g(x, y)$ is the resulting noisy pixel

If we can estimate the model the noise in an image is based on this will help us to figure out how to restore the image

8. (a) Explain derivative based edge detection. It does work properly for noisy image - why? 3.75

Answer:

Derivative-based edge detection is a method for detecting edges in images by calculating **the derivatives** of the image intensity. The derivatives of the image intensity represent the rate of change of the intensity in different directions. Edges in an **image are typically characterized by sharp changes** in intensity, so by finding the locations where the derivatives of the image intensity are high, we can identify the edges in the image.

Derivative-based edge detection method, calculate the derivatives of the image intensity, which are less sensitive to noise. This is because the derivatives represent the rate of change of the intensity, which is less affected by noise than the overall change in intensity.

One common derivative-based edge detection method is the Laplacian operator. The **Laplacian operator is a second-order derivative operator**, which means that it calculates the second derivative of the image intensity. The second derivative of the image intensity is a measure of the curvature of the intensity surface. **Edges in an image typically correspond to high curvature of the intensity surface**, so by finding the locations where the Laplacian of the image intensity is high, we can identify the edges in the image.

Here are some examples of how derivative-based edge detection can be used to improve the accuracy of edge detection in noisy images:

- Medical imaging: Derivative-based edge detection can be used to detect the edges of tumors and other lesions in medical images, even in the presence of noise.
- Satellite imagery: Derivative-based edge detection can be used to detect the boundaries of different land cover types in satellite imagery, even in the presence of noise.
- Industrial inspection: Derivative-based edge detection can be used to detect defects in industrial products, such as cracks and scratches, even in the presence of noise.

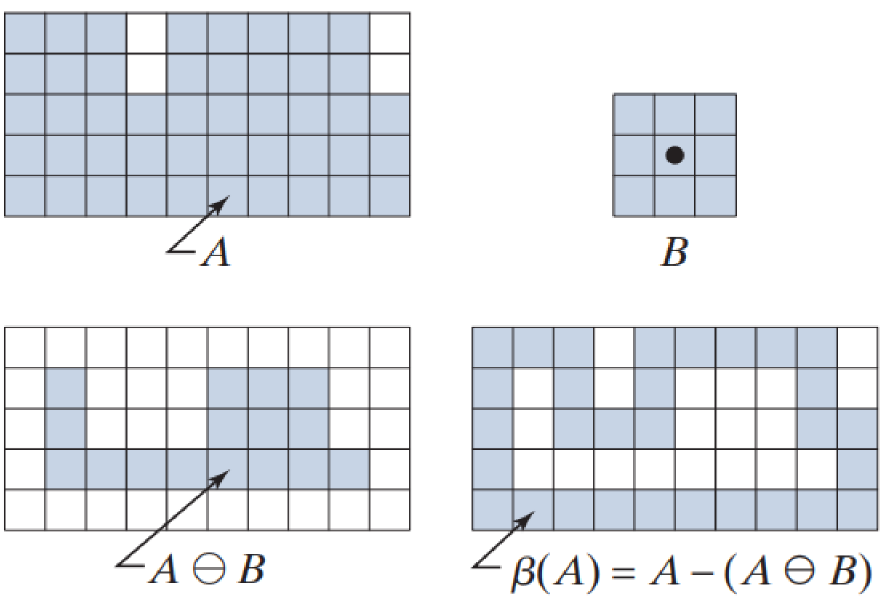
(b) Illustrate boundary extraction method in morphological image processing. 2

BOUNDARY EXTRACTION

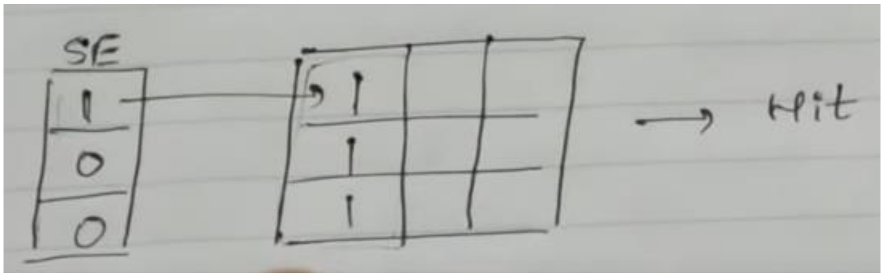
The boundary of a set A of foreground pixels, denoted by $\beta(A)$, can be obtained by first eroding A by a suitable structuring element B, and then performing the set difference between A and its erosion. That is,

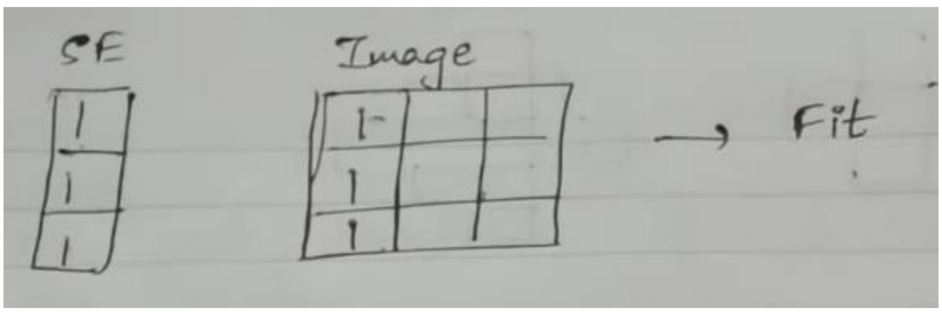
$$\beta(A) = A - (A \ominus B) \tag{9-18}$$

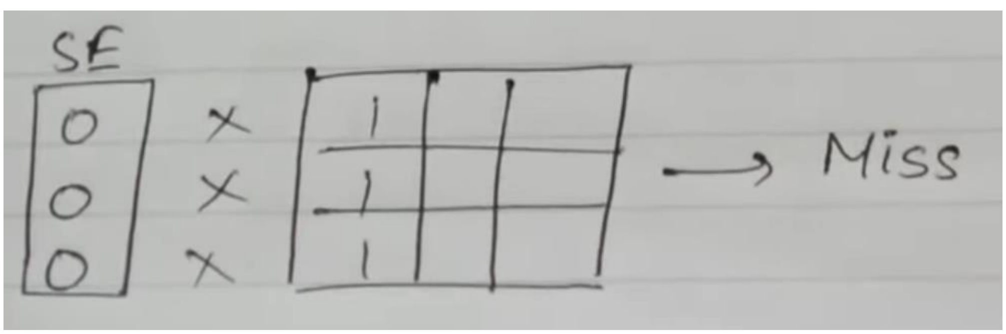
Figure 9.15 illustrates the mechanics of boundary extraction. It shows a simple binary object, a structuring element B, and the result of using Eq. (9-18). The structuring element in Fig. 9.15(b) is among the most frequently used, but it is not unique. For example, using a 5×5 structuring element of 1's would result in a boundary between 2 and 3 pixels thick. It is understood that the image in Fig. 9.15(a) was padded with a border of background elements, and that the results were cropped back to the original size after the morphological operations were completed.



(c) Define hit, fit and structuring element with examples 3







2019

5 a) Differentiate between convolution and correlation. The single value threshold usually converts the image into binary image. Suppose you have an 8-bit gray level image of size 256x256. How much memory is required to store it after single value thresholding? 2.75

Characteristic	Convolution	Correlation
Definition	Convolution is a mathematical operation that takes two functions and produces a third function.	Correlation is a mathematical operation that takes two functions and produces a measure of similarity between the two functions.
Direction of filtering	Convolution is a linear operation that filters in one direction.	Correlation is a linear operation that filters in both directions.
Use of mask	Convolution uses a mask to filter the input image.	Correlation uses a mask to compare the input image to a reference image.
Output image	*The output image of a convolution operation is a filtered version of the input image.*	*The output of a correlation operation is a measu re of similarity between the input image and the reference image.*
Applications	Convolution is used for a variety of image processing tasks, such as edge detection, noise reduction, and image sharpening.	Correlations used for a variety of image processing tasks, such as template matching and image registration.

If you have an 8-bit gray scale image of size 256x256 and you perform single-value thresholding to convert it into a binary image, the memory required to store the binary image is significantly reduced.

In an 8-bit gray scale image, each pixel can take on one of 256 (2^8) different values, representing various shades of gray from 0 (black) to 255 (white). However, after thresholding, you reduce each pixel to one bit, representing either 0 (black) or 1 (white).

So, for a 256x256 image, the memory required to store the binary image is calculated as follows:

- Original image: 8 bits per pixel (8-bit grayscale) x 256 (width) x 256 (height) = 8 bits x 256 x 256 = 524,288 bits
- Binary image: 1 bit per pixel (after thresholding) x 256 (width) x 256 (height) = 1 bit x 256 x 256 = 65,536 bits

After single-value thresholding, the binary image only requires 65,536 bits (or 8,192 bytes) of memory to store. This is a significant reduction in memory compared to the original 8-bit grayscale image.

b) Explain the effects of mask size for spatial filtering. **3**

Answer:

- The mask size determines the extent of the neighborhood considered for processing each pixel in an image.
-
- The size of the mask in spatial filtering has a significant impact on the output image. Larger masks typically produce more blurring, while smaller masks produce less blurring. This is because larger masks average over more pixels, which reduces the contrast between adjacent pixels.
- Effects of mask size for different types of spatial filtering:
- Smoothing filters: Smoothing filters are used to reduce noise and blur images. Larger masks produce more blurring, while smaller masks produce less blurring.
- Edge detection filters: Edge detection filters are used to identify edges in images. Larger masks can suppress noise and produce smoother edges, while smaller masks can produce sharper edges but also more noise.
- Sharpening filters: Sharpening filters are used to enhance the edges in an image. Larger masks can produce more blurring, while smaller masks can produce sharper edges but also more noise.
- Here are some examples of how mask size affects the output image for different types of spatial filtering:

Smoothing filters:

- A 3x3 averaging mask will produce a slightly blurred image.
- A 5x5 averaging mask will produce a more blurred image than a 3x3 averaging mask.
- A 9x9 averaging mask will produce an even more blurred image than a 5x5 averaging mask.

Edge detection filters:

- A 3x3 Sobel filter will produce noisy edges.
- A 5x5 Sobel filter will produce smoother edges than a 3x3 Sobel filter.
- A 9x9 Sobel filter will produce even smoother edges than a 5x5 Sobel filter, but it will also suppress some of the finer details in the image.

- Sharpening filters:
  - A 3x3 Laplacian filter will produce sharp edges, but it will also amplify noise in the image.
  - A 5x5 Laplacian filter will produce less sharp edges than a 3x3 Laplacian filter, but it will also reduce noise in the image.
  - A 9x9 Laplacian filter will produce even less sharp edges than a 5x5 Laplacian filter, but it will also reduce even more noise in the image.

When to use different mask sizes:

The choice of mask size depends on the desired outcome. For example, if the goal is to remove noise from an image, then a larger mask can be used to produce a smoother image. However, if the goal is to preserve fine details in an image, then a smaller mask should be used.

Here are some general guidelines for choosing a mask size:

- Smoothing filters: Use a larger mask to produce a more blurred image. Use a smaller mask to produce a less blurred image.
- Edge detection filters: Use a larger mask to produce smoother edges. Use a smaller mask to produce sharper edges.
- Sharpening filters: Use a larger mask to produce less sharp edges and reduce noise. Use a smaller mask to produce sharper edges and amplify noise.

It is important to note that these are just general guidelines. The best mask size to use will depend on the specific image and the desired outcome.

c) Define sharpening filter and mention its application in image processing. 3

Answer:

A sharpening filter is a type of image processing filter that is used to enhance the edges and fine details in an image. Sharpening filters work by amplifying the high-frequency components of the image. High-frequency components are the components of an image that correspond to sharp edges and fine details.

Sharpening filters are commonly used in image processing for a variety of tasks, including:

- Improving the quality of blurry images: Sharpening filters can be used to improve the quality of blurry images by enhancing the edges and fine details in the image. This can be useful for images that have been blurred due to camera shake, motion blur, or atmospheric haze.
- Enhancing the visibility of features in an image: Sharpening filters can be used to enhance the visibility of features in an image by making the edges and fine details more pronounced. This can be useful for tasks such as object recognition, feature extraction, and image segmentation.
- Creating artistic effects: Sharpening filters can also be used to create artistic effects in images. For example, a sharpening filter can be used to create a cartoon-like effect in an image.

Here are some specific examples of how sharpening filters can be used in image processing:

- Medical imaging: Sharpening filters can be used to enhance the visibility of medical images, such as X-rays and MRI scans. This can help doctors to better diagnose diseases and injuries.
- Satellite imagery: Sharpening filters can be used to enhance the visibility of satellite images. This can help to improve the accuracy of land cover classification and other tasks.
- Photography: Sharpening filters are commonly used in photography to improve the quality of images and to enhance the visibility of features such as facial features and landscape details.

6.

a) What do you mean by full-color and pseudo-color image processing? Derive trichromatic coefficient from tri-stimulus. 3

Answer:

Full-color image referred to **as true-color or color image processing**, deals with images where each pixel is represented by **multiple color channels**, typically **the three** primary colors - red, green, and blue (RGB). In a full-color image, each pixel's color is defined by the intensity values of these three channels.

This representation allows for a wide range of colors and is commonly used in digital photography and displays. Full-color image processing involves operations like color correction, image enhancement, and various image analysis techniques in the RGB color space.

Pseudo-color image processing is the processing of images that have been acquired with a single-channel sensor. Single-channel sensors typically measure the intensity of light at a specific wavelength. Pseudo-color images are created by assigning a color to each pixel value in the image. This is often done using a color lookup table (LUT).

Pseudo-color images are often used in scientific and engineering applications to visualize data that is not visible to the human eye. For example, pseudo-color images can be used to visualize infrared images, satellite images, and medical images.

Trichromatic coefficients are used to convert tri-stimulus values to RGB values. Tri-stimulus values are the responses of the three types of cone cells in the human eye to red, green, and blue light. RGB values are the color values that are used to display images on computer monitors and televisions.

https://www.electrical4u.com/tristimulus-values-and-chromaticity-coordinates/

Hue and saturation taken together are called *chromaticity* and, therefore, a color may be characterized by its brightness and chromaticity. The amounts of red, green, and blue needed to form any particular color are called the *tristimulus* values, and are denoted, X, Y, and Z, respectively. A color is then specified by its *trichromatic coefficients*, defined as

$$x = \frac{X}{X + Y + Z} \tag{6-1}$$

$$y = \frac{Y}{X + Y + Z} \tag{6-2}$$

and

$$z = \frac{Z}{X + Y + Z} \tag{6-3}$$

We see from these equations that

$$x + y + z = 1 \tag{6-4}$$

For any wavelength of light in the visible spectrum, the tristimulus values needed to produce the color corresponding to that wavelength can be obtained directly from curves or tables that have been compiled from extensive experimental results (Poynton [1996, 2012]).

b) Discus the model of the image degradation and restoration process. 3.75

Spatial and Frequency Domain Representation

- If H is a linear, position-invariant process, then the degraded image is given in the spatial domain by

g(x, y)=h(x, y) * f(x, y)+ η(x, y)

Where,

$h(x, y)$–spatial representation of the degradation function

* - indicates spatial convolution

$\eta(x, y)$- Additive noise term

$f(x, y)$- Input Image

- The degraded image is given in the frequency domain by

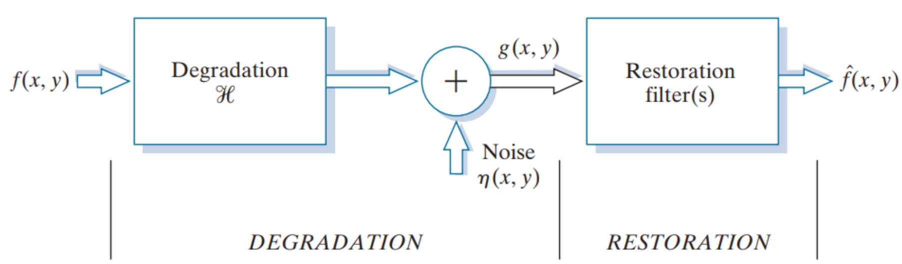
$G(u, v)= H(u, v)F(u, v)+N(u, v)$

Where,

The terms in capital letters are the Fourier transforms of the terms in the above equation.

- The degradation process for an image uses a degradation function together with an additive noise term.
- This operates on an input image $f(x, y)$ to produce a degraded image $g(x, y)$
- Given $g(x, y)$, some knowledge of the degradation function H, some knowledge about the additive noise term $\eta(x, y)$ the objective of restoration is to obtain an estimate $\hat{f}(x, y)$ will be to $f(x, y)$.

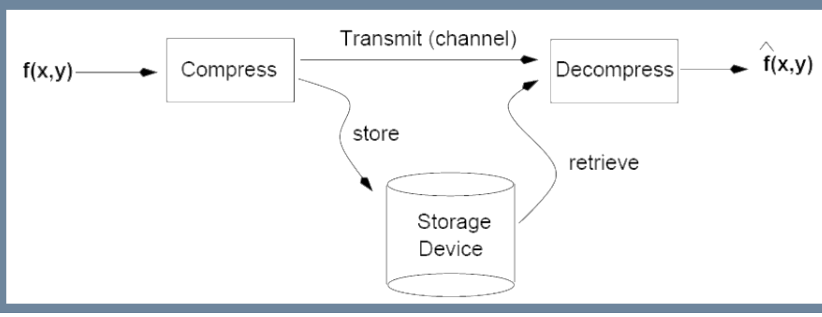
FIGURE 5.1 A model of the image degradation/restoration process.



c) Define compression ratio. How are shift codes generated? 2

Data compression is the process of encoding data so that it takes less storage space or less transmission time than it would if it were not compressed

The goal of image compression is to reduce the amount of data required to represent a digital image.



The term *data compression* refers to the process of reducing the amount of data required to represent a given quantity of information. In this definition, *data* and *information* are not the same; data are the means by which information is conveyed. Because various amounts of data can be used to represent the same amount of information, representations that contain irrelevant or repeated information are said to contain *redundant data*. If we let b and b' denote the number of bits (or information-carrying units) in two representations of the same information, the *relative data redundancy*, R, of the representation with b bits is

$$R = 1 - \frac{1}{C} \tag{8-1}$$

where C, commonly called the *compression ratio*, is defined as

$$C = \frac{b}{b'} \tag{8-2}$$

If $C = 10$ (sometimes written 10:1), for instance, the larger representation has 10 bits of data for every 1 bit of data in the smaller representation. The corresponding relative data redundancy of the larger representation is 0.9 ($R = 0.9$), indicating that 90% of its data is redundant.

7.

a) Discuss geometric and harmonic mean filter with their application. 3

Geometric Mean Filter

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

$$\hat{f}(x,y) = \left[\prod_{(r,c)\in S_{xy}} g(r,c) \right]^{\frac{1}{mn}} \tag{5-24}$$

where Π indicates multiplication. Here, *each* restored pixel is given by the product of *all* the pixels in the subimage area, raised to the power $1/mn$. As Example 5.2 below illustrates, a geometric mean filter achieves smoothing comparable to an arithmetic mean filter, but it tends to lose less image detail in the process.

Applications of the geometric mean filter

The geometric mean filter is commonly used in the following applications:

- Image smoothing: The geometric mean filter can be used to smooth images without introducing excessive blurring. This is useful for reducing noise in images and for improving the visibility of edges and other features.
- Medical imaging: The geometric mean filter can be used to improve the quality of medical images, such as X-rays and MRI scans. This can help doctors and other medical professionals to better diagnose diseases and injuries.
- Satellite imaging: The geometric mean filter can be used to improve the quality of satellite images. This can help scientists to better study the Earth and its environment.

Harmonic Mean Filter

The *harmonic mean* filtering operation is given by the expression

$$\hat{f}(x,y) = \frac{mn}{\displaystyle\sum_{(r,c)\in S_{xy}} \frac{1}{g(r,c)}} \tag{5-25}$$

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.

Applications of the harmonic mean filter

The harmonic mean filter is commonly used in the following applications:

- Edge detection: The harmonic mean filter can be used to detect edges in images. This is useful for a variety of applications, such as object recognition and image segmentation.
- Medical imaging: The harmonic mean filter can be used to improve the quality of medical images, such as X-rays and MRI scans. This can help doctors and other medical professionals to better diagnose diseases and injuries.
- Satellite imaging: The harmonic mean filter can be used to improve the quality of satellite images. This can help scientists to better study the Earth and its environment.

The geometric mean filter **is more effective at smoothing images without introducing excessive blurring.** It is also less sensitive to outliers than the harmonic mean filter. However, the geometric mean filter can sometimes preserve too much noise, especially in low-contrast images.

The harmonic mean filter is more **effective at preserving edges and other features**. It is also more sensitive to outliers than the geometric mean filter. However, the harmonic mean filter can sometimes over smooth images, especially in high-contrast images.

b) Explain band reject filter to eliminate periodic noise. 3

Answer:

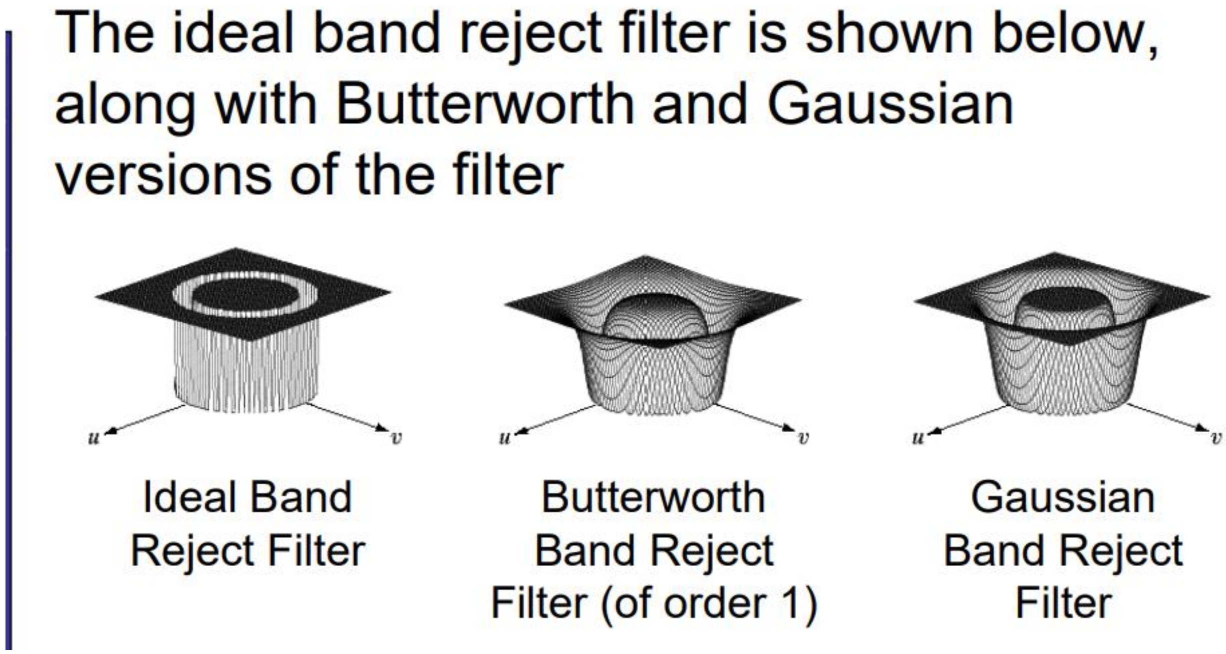
If frequencies in the band are filtered out, the band filter is called a bandreject filter.

Removing periodic noise form an image involves removing a particular range of frequencies from that image

Band reject filters can be used for this purpose

An ideal band reject filter is given as follows:

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



c) Explain the effects of noise in derivative based edge detection. 2.75

Noise is a major challenge in derivative-based edge detection. Derivative-based edge detectors work **by detecting changes in the intensity of the image pixels**. Noise can cause spurious changes in the intensity of the image pixels, which can lead to false positives and false negatives in the edge detection results.

Here are some of the specific effects of noise in derivative-based edge detection:

- False positives: Noise can cause derivative-based edge detectors to detect edges where there are none. This is because noise can cause spurious changes in the intensity of the image pixels, which can be misinterpreted as edges.
- False negatives: Noise can also cause derivative-based edge detectors to miss edges. This is because noise can obscure real edges in the image.

- Edge blurring: Noise can also blur the edges detected by derivative-based edge detectors. This is because noise can cause the edges to be spread out over a larger area in the image.

There are a number of ways to reduce the effects of noise in derivative-based edge detection. One way is to use a noise reduction filter before applying the edge detector. This can help to reduce the amount of noise in the image and improve the accuracy of the edge detection results.

Another way to reduce the effects of noise in derivative-based edge detection is to use a non-linear edge detector. Non-linear edge detectors are more robust to noise than linear edge detectors.

8.

a) Define morphological image processing. Explain opening method with example. 4

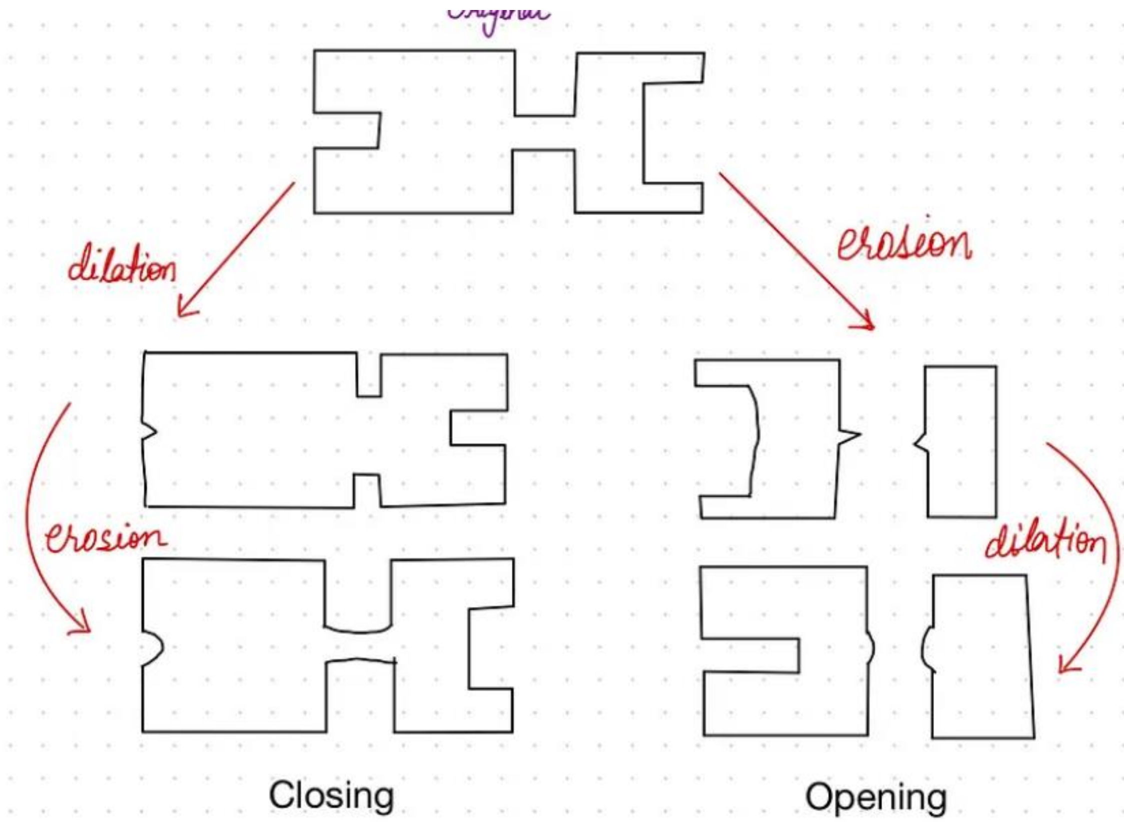
Morphological image processing is **a set of image processing operations that are based on the shape or morphology of features in an image**. Morphological operations are typically applied to binary images, but they can also be applied to grayscale images.

Morphological operations are based on the following two basic operations:

- Erosion: Erosion removes pixels from the boundaries of objects in an image.
- Dilation: Dilation adds pixels to the boundaries of objects in an image.

Other morphological operations can be constructed by combining erosion and dilation.

Opening is a morphological operation that is used to remove small objects and thin lines from an image. It is performed by first **eroding the image and then dilating it.** The erosion removes small objects and thin lines, while the dilation restores the size and shape of the remaining objects.



https://towardsdatascience.com/understanding-morphological-image-processing-and-its-operations-7bcf1ed11756

b) Discuss about basic global thresholding algorithm for image segmentation. 3

Answer: 2020 7b

c) Define data redundancy. Illustrate the image compression model. 1.75

Data Redundancy

- Data that provide no relevant information=*redundant data* or *redundancy*.
- Image compression techniques can be designed by reducing or eliminating the Data Redundancy
- Image coding or compression has a goal to reduce the amount of data by reducing the amount of redundancy.

Let n_1 and n_2 refer to amounts of data in two data sets that carry the same information

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

Relative data redundancy: $R_D = 1 - \frac{1}{C_R} = 1 - \frac{n_2}{n_1}$
(of the first data set, n_1)

- if $n_1 = n_2$, $C_R = 1$ and $R_D = 0$, relative to the second data set, the first set contains no redundant data
- if $n_1 >> n_2$, $C_R \rightarrow \infty$, and $R_D \rightarrow 1$, relative to the second data set, the first set contains highly redundant data
- if $n_1 << n_2$, $C_R \rightarrow 0$, and $R_D \rightarrow -\infty$, relative to the second data set, the first set is highly compressed

  $C_R = 10$ means 90% of the data in the first data set is redundant

Data Redundancy

- If $n_1 = n_2$, $C_R=1$ and $R_D=0$ → *no redundancy*
- If $n_1 >> n_2$, $C_R \rightarrow \infty$ and $R_D \rightarrow 1$ → *high redundancy*
- If $n_1 << n_2$, $C_R \rightarrow 0$ and $R_D \rightarrow -\infty$ → *undesirable*

- *A* compression ration of 10 (10:1) means that the first data set has 10 information carrying units (say, bits) for every 1 unit in the second (compressed) data set.

- In Image compression , 3 basic redundancy can be identified
  - » *Coding Redundancy*
  - » *Interpixel Redundancy*
  - » *Psychovisual Redundancy*

Image Compression Models

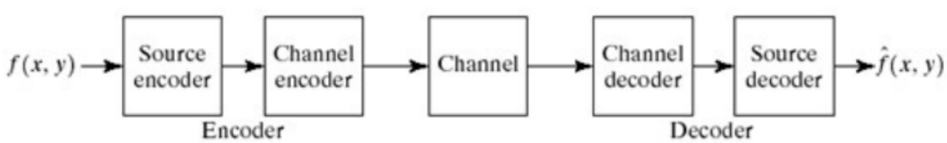


FIGURE 8.5 A general compression system model.

- Source encoder and decoder
  - Reduces or eliminates any coding, interpixel and/or psycho visual redundancies in the input image.
- Channel encoder and decoder
  - Plays an important role when the channel is noisy or prone to error by inserting “controlled redundancy”.

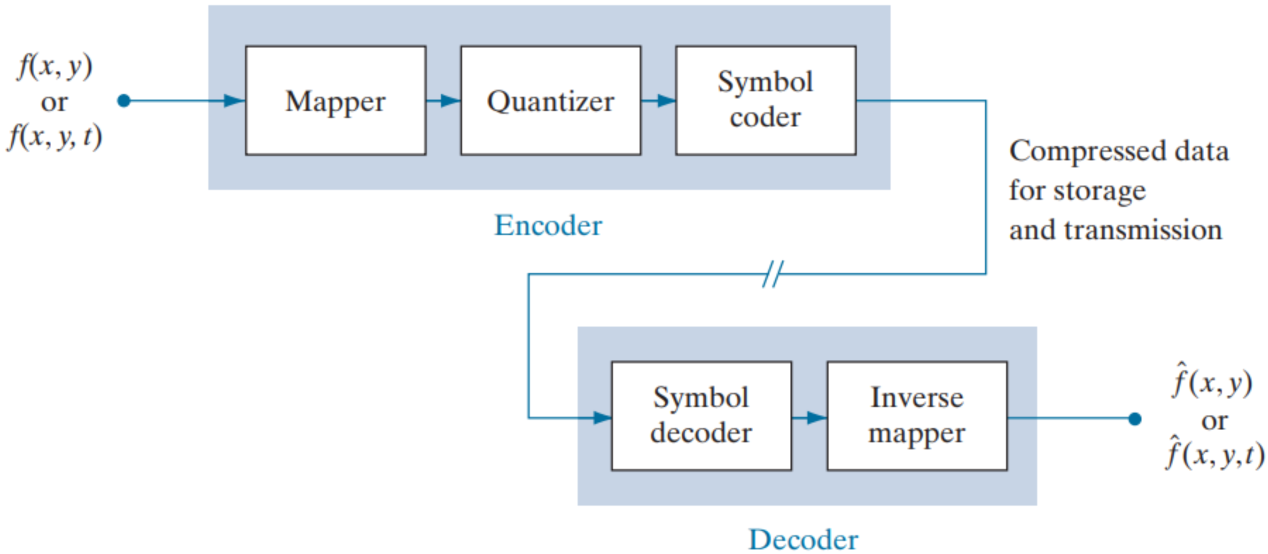
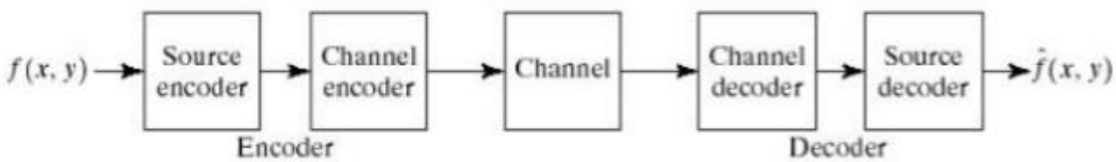


FIGURE 8.5 Functional block diagram of a general image compression system.

Compression Model



The source encoder is responsible for removing redundancy (coding, inter-pixel, psycho-visual)

The channel encoder ensures robustness against channel noise.

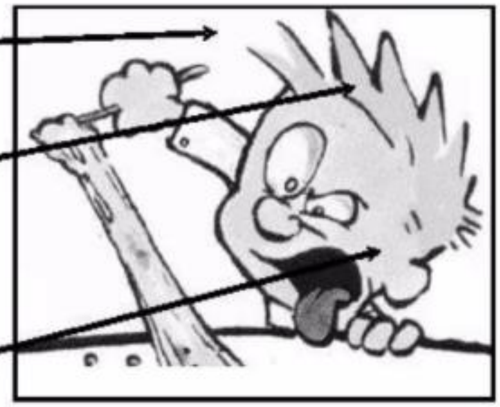
Three basic data redundancies

- Coding Redundancy
- Interpixel Redundancy
- Psychovisual Redundancy

CR: some graylevels are more common than others

IR: the same graylevel covers large areas

PVR: the eye can only resolve 32 graylevels locally



Types of Compression

- Lossless compression
  - Huffman coding
  - Bit-plane coding
  - Run length coding
- Lossy compression
  - Lossy predictive coding
  - Transform coding
  - JPEG

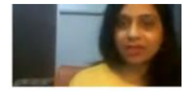
Applicability of various noise models

- Gaussian noise⇨ electronic circuit noise and sensor noise due to poor illumination and/or high temperature
- Rayleigh density⇨ characterize noise phenomena in range imaging
- Exponential and gamma densities⇨ laser imaging
- Impulse noise⇨ occur when quick transients (faulty switching) take place during imaging
- Uniform density⇨ the least descriptive of practical situations

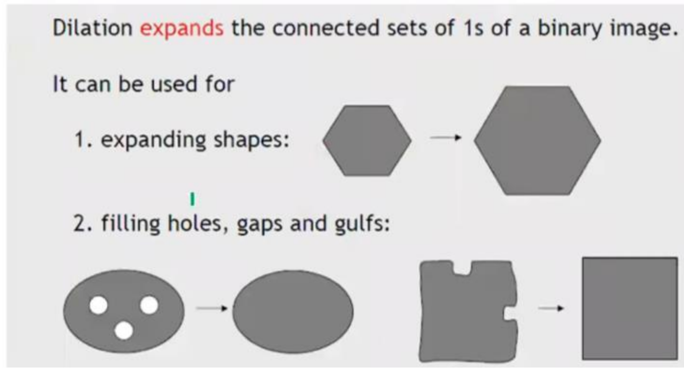
Estimation of noise parameters

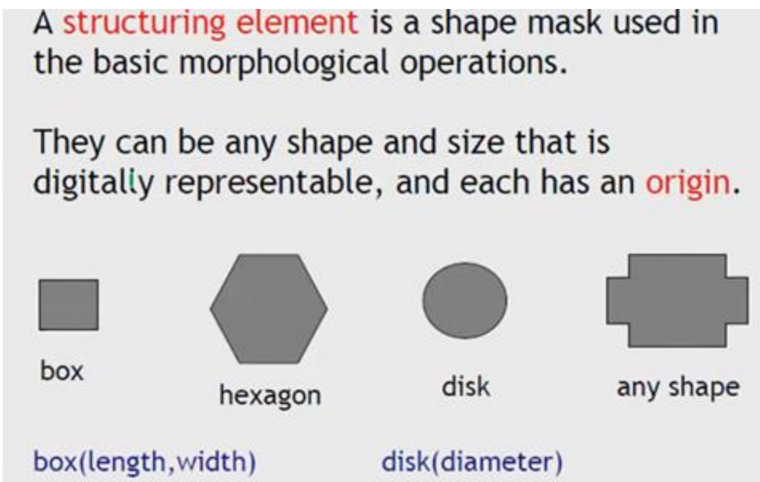
- Periodic noise: Fourier spectral components
- Imaging system is available: study the characteristics of system noise by acquiring a set of images of flat environment under uniform illumination (constant background)
- Only images are available: estimate the noise PDF from small patches of reasonably constant gray level

Dilation:



- Fills in holes.
- Smoothes object boundaries.
- Adds an extra outer ring of pixels onto object boundary, ie, object becomes slightly larger.





Dilation : Adds pixels to the boundaries of objects in an image.
Erosion: Removes pixels on object boundaries.

Structuring element **:**The number of pixels added or removed from the objects in an image depends on the size and shape of the ***structuring element*** used to process the image.