KLS Vishwanathrao Deshpande Institute of Technology

(Accredited by NAAC with "A" Grade)
(Approved by AICTE, New Delhi, Affiliated to VTU, Belagavi)
(Recognized Under Section 2(f) by UGC, New Delhi)
Udyog Vidya Nagar, Haliyal - 581 329, Dist.: Uttara Kannada
Phone: 08284 - 220861, 220334, 221409, Fax: 08284 - 220813
www.klsvdit.edu.in | principal@klsvdit.edu.in | hodece@klsvdit.edu.in

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

University / Model Question Paper Scheme & Solution

Faculty Name	:	Prof. Plavin Francis Dias.
Course Name	:	Digital Image Processing
Course Code	:	18EC733
Year of Question Paper	:	June / July 2024
Date of Submission	:	22.10.2024

Faculty Member HoD Dean (Acad.)

Head of the Department
Dept. of Electronic & Communication Engg.
KLS V.D.I.T., HALIYAL (U.K.)

Dean Academics
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CBCS SCHEME

18EC733

USN

Seventh Semester B.E. Degree Examination, June/July 2024
Digital Image Processing

Time: 3 hrs. Max. Marks: 100

Note: Answer any FIVE full questions, choosing ONE full question from each module.

Important Note : 1. On completing your answers, compulsorily draw diagonal cross lines on the remaining blank pages.
2. Any revealing of identification, appeal to evaluator and /or equations written eg, 42+8 = 50, will be treated as malpractice.

Module-1

1 a. With the help of a neat figure, explain the main elements of the human eye. **(10 Marks)**

b. Consider the image segment shown in Fig.Q1(b). Let V = {1, 2, 3, 4}, compute the lengths of the shortest 4, 8 and m-path between p and q. If a particular path does not exist between the two points, explain why.

(p)	4	1	2	6	8	3	5	
	8	6	5	1	4	6	3	
	4	6	5	2	5	8	7	
	2	3	4	8	3	7	2	
	4	5	3	2	3	8	7	
	2	2	5	4	3	2	1	(q)

Fig.Q1(b) **(10 Marks)**

OR

2 a. Explain D_m distance with example. **(08 Marks)**

b. What is image sampling and quantization? What are the different parameters which will decide the number of storage bits of the image in the discrete domain? **(12 Marks)**

Module-2

3 a. Write a short note on unsharp masking and high boost filtering. **(08 Marks)**

b. Perform histogram equalization for the 8-level 64 × 64 image. The histogram of which is given as:

r	0	1	2	3	4	5	6	7
n_r	790	1023	850	656	329	245	122	81

(12 Marks)

OR

4 a. Explain some basic gray level transformation used for image enhancement. **(10 Marks)**

b. Explain image sharpening in spatial domain using second order Laplacian derivative. **(10 Marks)**

Module-3

5 a. Briefly explain any four properties of 2D-DFT. **(08 Marks)**

b. List and explain any three high pass filters in frequency domain and comment on ringing effect. **(12 Marks)**

OR

6 a. Briefly explain ideal lowpass filtering in frequency domain. **(08 Marks)**

b. Explain homomorphic filtering in image processing with neat block diagram. **(12 Marks)**

Module-4

7 a. Comment on various methods used in estimation of degradation model. (10 Marks)
b. Write a short note on inverse filtering and its drawbacks. (10 Marks)

OR

8 a. With neat block diagram explain image degradation and restoration model. (10 Marks)
b. Explain the need for adaptive median filters and its working. (10 Marks)

Module-5

9 a. With necessary diagram explain the RGB and CMY colour models. (08 Marks)
b. Explain and illustrate Erosion and dilation operations used in morphological image processing. (12 Marks)

OR

10 a. Explain with necessary diagram the HSI colour model. (08 Marks)
b. Explain and illustrate opening and closing operations used in morphological image processing. (12 Marks)

* * * * *

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1a. Main Elements of the human eye:

The human eye is nearly a sphere enclosed by three membranes. The cornea and sclera outer cover, the choroid and retina. The cornea is a tough, transparent tissue that covers the anterior surface of the eye. The sclera is an opaque membrane that encloses the remainder of the optic globe. The choroid lies directly below the sclera. This membrane contains a network of blood vessels that serve as the major source of nutrition to the eye. The choroid coat is heavily pigmented, which helps reduce the amount of extraneous light entering the eye and the back-scatter within the optic globe. The choroid is divided into ciliary body and the iris. The iris contracts and expands to control the amount of light that enters the eye.

The Lens consists of concentric layers of fibrous cells and is suspended by fibers that attach to the ciliary body. The Lens helps focus light on the retina. The lens changes shape to focus on objects at different distances. The central opening in the iris called Pupil varies in diameter from approximately 2 to 8 mm. It controls the light entering eye. The pupil appears black because the tissues in the eye absorbs light rays.

The innermost membrane of the eye is the retina, which lines the inside of the walls entire posterior portion. When the eye is focused, light from an object is imaged on the retina. There are two types of receptors cones and rods.

There are between 6 and 7 million cones in each eye. They are located in the central portion of the retina called fovea and highly sensitive to color. Humans can resolve fine details because each cone is connected to its own nerve end. Muscles rotate the eye until the image of the region of interest falls on the fovea. Cone vision is called photopic or bright light vision. The 75 to 150 million Rods are distributed over the retina. Rods capture an overall image of the field of view. They are not involved in color vision and are sensitive to low levels of illumination. The front of the iris contains the visible pigment of the eye, where as the back contains a black pigment.

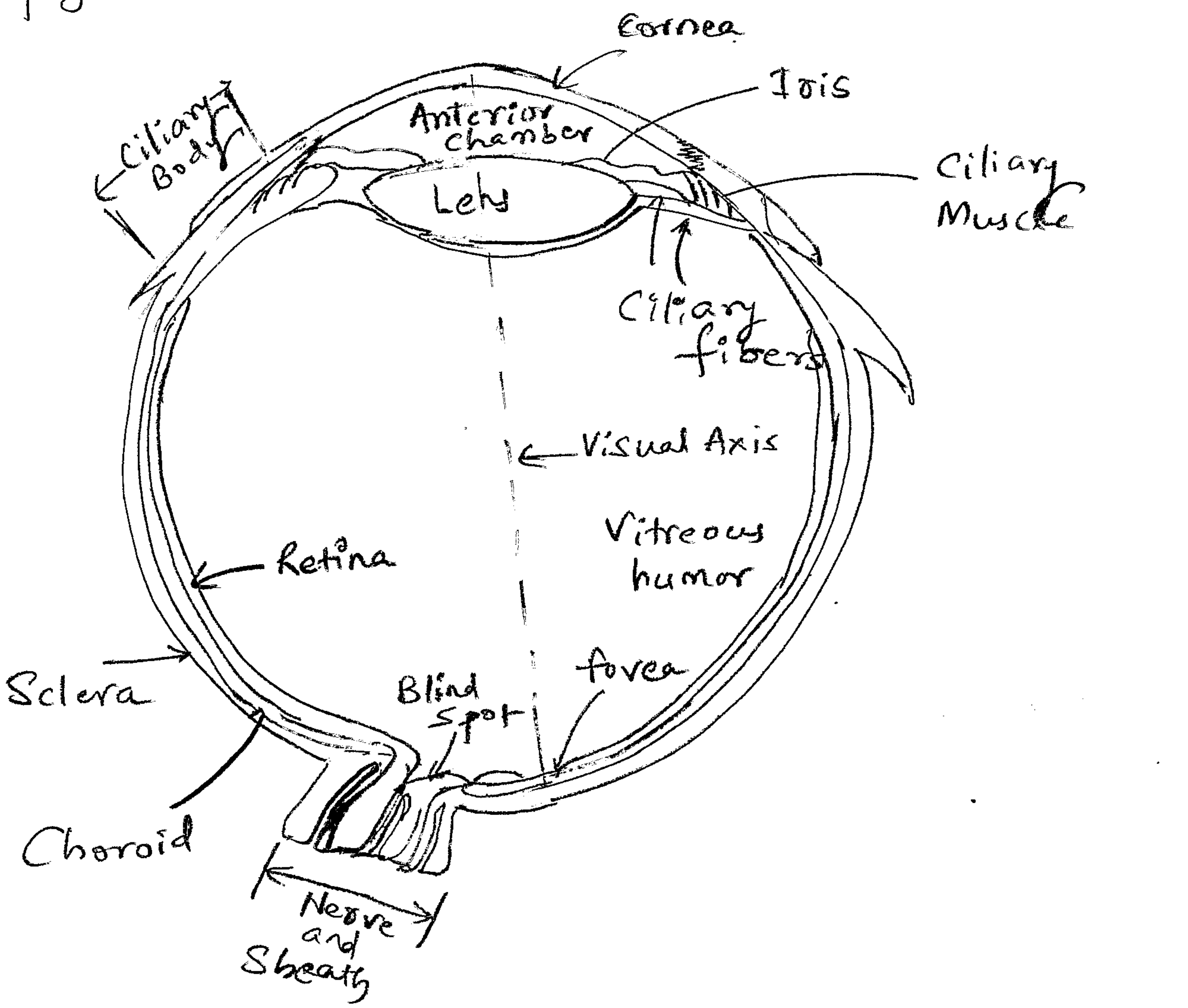


Fig 1.a Cross section of human Eye.

(b) $V = \{1, 2, 3, 4\}$

Lengths of the shortest 4, 8 and m paths, between p and q.

(p)	4	1	2	6	8	3	5
	8	6	5	1	4	6	3
	4	6	5	2	5	8	7
	2	3	4	8	3	7	2
	4	5	3	2	3	8	7
	2	2	5	4	3	2	1 (q)

fig 1.b.

$p(1, 1)$

$q(6, 7)$

$$D_4(p,q) = |x_p - x_q| + |y_p - y_q|$$
$$= |1-6| + |1-7|$$
$$= 5 + 6$$

$$D_4(p,q) = 11$$

$$D_8(p,q) = \max(|x_p - x_q|, |y_p - y_q|)$$
$$= \max(|5| + |6|)$$
$$= 6$$

$D_m = 10$

This is the only path available with given all set values.

2 a) Dm distance with Example:

In case of m adjacency, the Dm distance between two points is defined as the shortest m path between the points. In this case the distance between two pixels will depend on the values of the pixels along the path, as well as the values of their neighbors.

For instances consider following arrangement of pixels and assume the p, p_2 and p_4 have a value of 1 and that p_1 and p_3 can be 0 or 1.

$$\begin{array}{cc} & p_3 \quad p_4 \\ p_1 & p_2 \\ p & \end{array}$$

Suppose that we consider adjacency of pixels value (ie $V = \{1\}$). If p_1 and p_3 are 0, the length of the shortest m path (the Dm distance between p and p_4 is 2. If p_1 is 1 then p_2 and p will no longer be m adjacent and the length of the shortest m path becomes 3. (the path goes through the points $p, p_1, p_2 p_4$)

If p_3 is 1 (& p_1 is 0), in this case the length of the shortest m path also is 3.

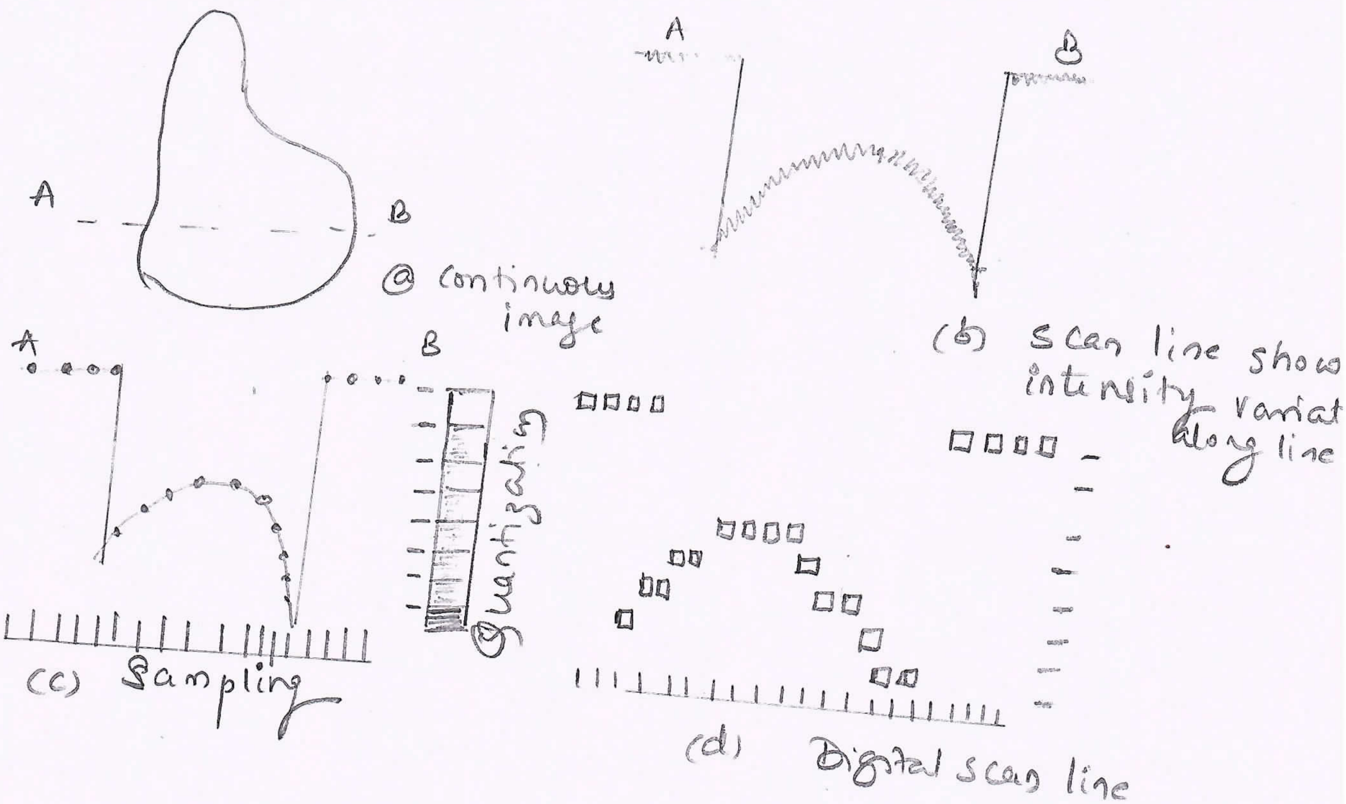
Finally if both p_1 and p_3 are 1, the length of the shortest m path between p and p_4 is 4. In this case, the path goes through the sequence of points $p\, p_1\, p_2\, p_3\, p_4$.

2b Image Sampling and Quantization and the different parameters which will decide the number of storage bits of the image in the discrete domain:

To create a digital image, we need to convert the continuous sensed data into digital format. This requires two processes: Sampling and quantization. An image may be continuous with respect to the x and y coordinates and also in amplitude. To convert it into digital form or to digitize it we have to sample the function in both coordinates and in amplitudes

Digitizing the co-ordinate values is called sampling. Digitizing the amplitude values is called quantization. Consider there is a continuous image along the line segment AB. To sample this function, we take equally spaced samples along line AB. The location of each samples is given by a vertical tick mark in the bottom part. The samples are shown as dark squares constitutes the sampled function. The values of the samples still span (vertically) a continuous range of intensity values.

In order to form a digital function, the intensity values also must be converted (quantized) into discrete quantities. So we divide the gray level scale into eight discrete levels ranging from black to white. The continuous gray levels are quantized simply by assigning one of the eight discrete gray levels to each sample. The assignment is made depending on the vertical proximity of a sample to a vertical tick mark. Starting at the top of the continuous image and carrying out this procedure line by line downward produces a two dimensional digital image.



3 a Unsharp masking and high Boost filtering

Subtracting an unsharp (smoothed) version of an image from the original image is process that has been used since the 1930's by the printing and publishing industry to sharpen images. This process, called unsharp masking consists of following steps.

1. Blur the original image
2. Subtract the blurred image from the original (the resulting difference is called the mask)
3. Add the mask to the original

Letting $\bar{f}(x,y)$ denote the blurred image, the mask in equation form is given by,

$$g_{mask}(x,y) = f(x,y) - \bar{f}(x,y)$$

Then we add weighted portion of the mask back to the original image

$$g(x,y) = f(x,y) + k\, g_{mask}(x,y)$$

where we included a weight, k ($k \geq 0$), for generality

When $k=1$, we have unsharp masking.

When $k>1$, the process is referred to as highboost filtering. Choosing $k<1$ reduces the contribution of the unsharp mask.

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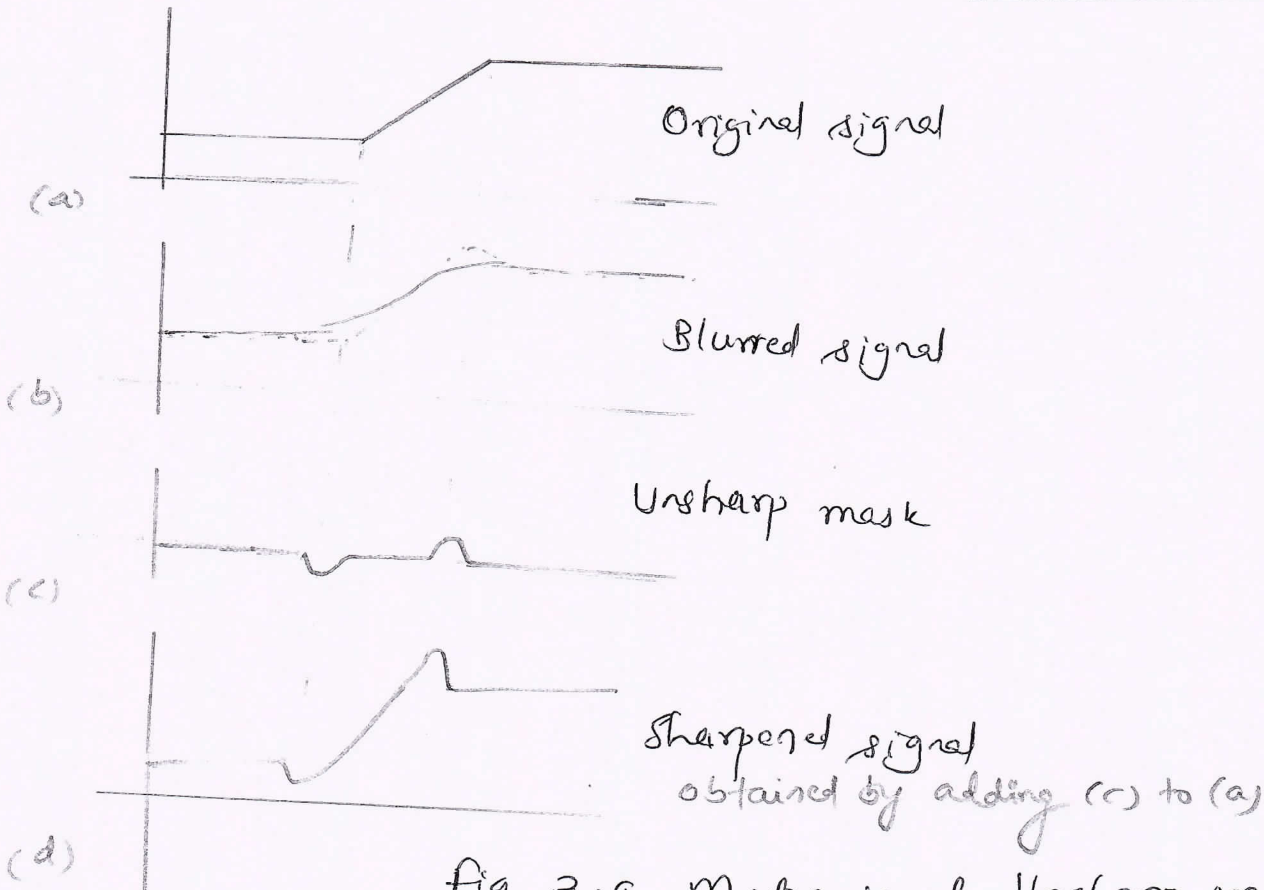


fig 3.a Mechanics of Unsharp masking

(a) Part (a) is horizontal intensity profile across a vertical ramp edge that transitions from dark to light.

(b) fig (b) shows the blurred scan line superimposed on the original signal.

(c) fig (c) is the mask obtained by subtracting the blurred signal from the original.

(d) fig (d) is the final sharpened result, obtained by adding the mask to the original signal.

Negative values cause dark halos around edges that can become objectionable if k is too large.

3 b) Histogram Equalization for the 8 level 64 × 64 image

Histogram

r	0	1	2	3	4	5	6	7
n_r	790	1023	850	656	329	245	122	81

3 bit image ($L=8$) of size 64 × 64 pixels ($MN = 4096$)

r_k	n_k	$p_r(r_k) = n_k / MN$
$r_0 = 0$	790	0.19
$r_1 = 1$	1023	0.25
$r_2 = 2$	850	0.21
$r_3 = 3$	656	0.16
$r_4 = 4$	329	0.08
$r_5 = 5$	245	0.06
$r_6 = 6$	122	0.03
$r_7 = 7$	81	0.02

$$S_0 = T(r_0) = 7 \sum_{j=0}^{0} P_r(r_j) = 7 \times 0.19 = 1.33 \longrightarrow 1$$

$$S_1 = T(r_1) = 7 \sum_{j=0}^{1} P_r(r_j) = 7 \times (0.19 + .25) = 3.08 \rightarrow 3$$

$$S_2 = T(r_2) = 7 \sum_{j=0}^{2} P_r(r_j) = 7 \times (0.19 + 0.25 + 0.21)$$
$$= 4.55 \longrightarrow 5$$

$$S_3 = T(r_3) = 7 \sum_{j=0}^{3} P_r(r_j) = 7 \times (0.19 + 0.25 + 0.21 + 0.16)$$
$$= 5.67 \longrightarrow 6$$

$$S_4 = T(r_4) = 7 \sum_{j=0}^{4} P_r(r_j) = 7 \times (0.19 + 0.25 + 0.21 + 0.16 + 0.08)$$
$$= 6.23 \longrightarrow 6$$

$$S_5 = T(r_5) = 7 \sum_{j=0}^{5} P_r(r_j) = 7 \times (0.19 + 0.25 + 0.21 + 0.16 + 0.08 + 0.06)$$

$$S_6 = T(r_6) = 7\sum_{j=0}^{6} p_r(r_j)$$

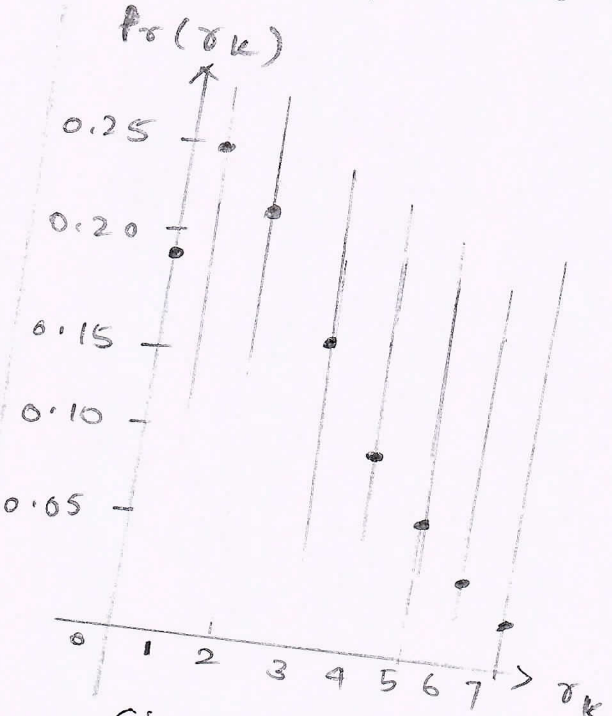
$$= 7 \times (0.19 + 0.25 + 0.21 + 0.16 + 0.08 + 0.06 + 0.03)$$

$$S_6 = 6.86 \longrightarrow 7$$

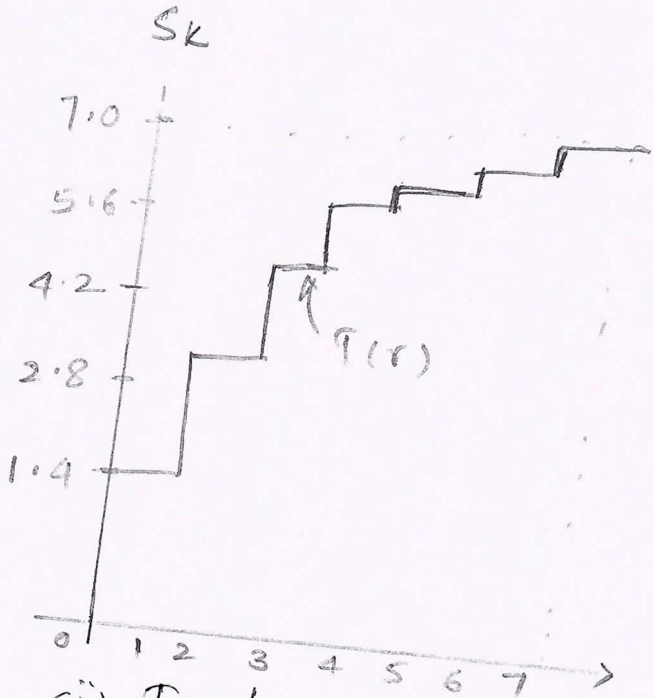
$$S_7 = T(r_7) = 7\sum_{j=0}^{7} p_r(r_j)$$

$$= 7 \times (0.19 + 0.25 + 0.21 + 0.16 + 0.08 + 0.06 + 0.03 + 0.02)$$

$$S_7 = 7.00 \longrightarrow 7$$



(i) Original Histogram



(ii) Transformation function
Equalized Histogram

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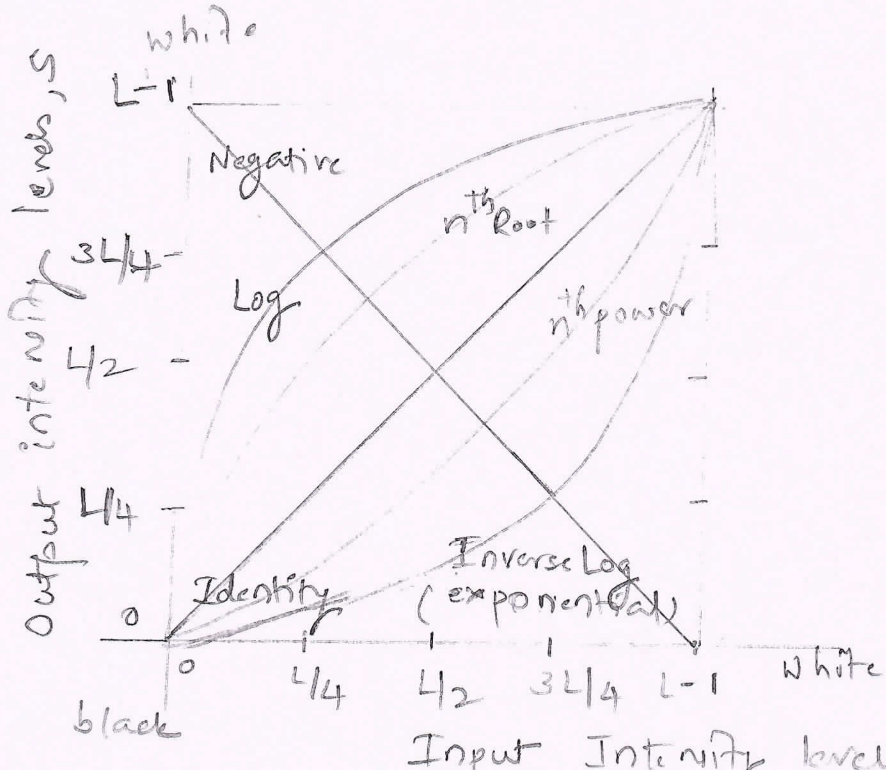
Power Law (Gamma) Transformations

General form:

$$s = c r^{\gamma} \quad \text{--- (3)}$$

where c and γ are positive constants. The equation (3) can be written as $s = c(r+\varepsilon)^{\gamma}$ to account for offsets. (That is measurable output when the input is zero). The power law curves with fractional values of γ map a narrow range of dark input values into a wider range of output values, with the opposite being true for higher values of input levels. Curves generated with values of $\gamma > 1$ have exactly the opposite effect as those generated with values of $\gamma < 1$. When $c = \gamma = 1$ equation (3) reduces to the identity transformation.



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4a Some basic gray level transformation used for image enhancement.

Intensity transformations are simplest of all image processing techniques. The three basic types of functions used frequently in image processing are i) Linear (negative and identity transformation)
ii) Logarithmic (Inverse log and Log transformation)
iii) Power Law (nth power and nth root transformations)

Image negatives:

The negative of an image with intensity levels in the range [0, L−1] is obtained by using the negative transformation function.

$$s = L-1-r \quad \text{——} \quad (1)$$

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

Log Transformation:

$$s = c \log(1+r) \quad \text{——} \quad (2)$$

where c is a constant and it is assumed that $r \geq 0$.
This transformation maps a narrow range of low intensity values in the input into a wider range of output levels. This type of transformations are used to expand the values of dark pixels in an image, while compressing the higher-Level values. The higher values of input levels are mapped to a narrower range in the output.

4b Image sharpening in spatial domain using second order Laplacian derivative.

The simplest isotropic derivative operator (kernel) is the Laplacian, which for a function (image) $f(x,y)$ of two variables, is defined as,

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad \text{——— (1)}$$

The derivates of any order are linear operation. The Laplacian is a linear operator. To express this equation in discrete form, we use the definition in Equation $\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x)$, which has second variable.

In the x direction,

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

and $|||^{ly}$ in the y direction,

$$\frac{\partial^2 f}{\partial y^2} = f(x,y+1) + f(x,y-1) - 2f(x,y) \quad \text{——— (3)}$$

From the preceding three equations, the discrete Laplacian of two variables is,

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

This equation can be implemented using convolution with the kernel in fig 4.6. The kernel is isotropic for rotations in increments of 90° with respect to the x and y axis.

Laplacian is a derivative operator, it highlights sharp intensity transitions in an image and deemphasizes regions of slowly varying intensities.

Laplacian for image sharpening is,

$$g(x,y) = f(x,y) + c\left[\nabla^2 f(x,y)\right]$$

where $f(x,y)$ and $g(x,y)$ are the input and sharpened images. Let $c=-1$, if the Laplacian kernel in fig 4.8 (a) or (b) is used and $c=1$ if either of the other two kernels is used.

0	1	0
1	-4	1
0	1	0

fig 4.8 (a)

1	1	1
1	-8	1
1	1	1

(b)

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

(c)

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

(d)

(a) Laplician kernel used to implement Equation (4)

(b) Kernel used to implement an extension of this equation that includes the diagonal terms.

(c), (d) Two other Laplacian kernels.

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5 a four Properties of 2D DFT

2-D discrete fourier transform (DFT):

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

where $f(x,y)$ is a digital image of size $M \times N$.

Translation and Rotation:

$$f(x,y)\, e^{j2\pi(u_0x/M + v_0y/N)} \Leftrightarrow F(u-u_0, v-v_0)$$

and

$$f(x-x_0, y-y_0) \Leftrightarrow F(u,v)\, e^{-j2\pi(x_0u/M + y_0v/N)}$$

That is multiplying $f(x,y)$ by the exponential shown shifts the origin of the DFT to (u_0, v_0) and conversely multiplying $F(u,v)$ by the negative of that exponential shifts the origin of $f(x,y)$ to (x_0, y_0). Translation has no effect on the magnitude (spectrum) of $F(u,v)$

Using the polar co-ordinates

$x = r\cos\theta$ $y = r\sin\theta$. $u = \omega\cos\varphi$ $v = \omega\sin\varphi$

results in the following transform pair,

$$f(r, \theta+\theta_0) \Leftrightarrow F(\omega, \varphi+\theta_0)$$

which indicates that rotating $f(x,y)$ by angle θ_0 rotates $F(u,v)$ by the same angle. Rotating $F(u,v)$ rotates $f(x,y)$ by the same angle.

Periodicity:

2D fourier transform and its inverse are infinitely periodic in the u and v directions.

$$F(u,v) = F(u+k_1M, v) = F(u, v+k_2N)$$
$$= F(u+k_1M, v+k_2N)$$

and

$$f(x,y) = f(x+k_1M, y) = f(x, y+k_2N)$$
$$= f(x+k_1M, y+k_2N)$$

where k_1, k_2 are integers. Periodicities of the transform and its inverse are important issues in the implementation of DFT based algorithms.

Symmetry Properties:

Any real or complex function $w(x,y)$ can be expressed as the sum of an even and odd part each of which can be real or complex.

$$w(x,y) = w_e(x,y) + w_o(x,y) \quad \text{——— (1)}$$

where even and odd parts are defined as

$$w_e(x,y) \triangleq \frac{w(x,y) + w(-x,-y)}{2} \quad \text{——— (2)}$$

and

$$w_o(x,y) \triangleq \frac{w(x,y) - w(-x,-y)}{2} \quad \text{——— (3)}$$

for all valid values of x and y.

Substitute Eqn (2) and (3) in (1) gives the identity $w(x,y) \equiv w(x,y)$

$$w_e(x,y) = w_e(-x,-y)$$

and $$w_o(x,y) = -w_o(-x,-y)$$

Even functions are said to be symmetric and odd functions are antisymmetric.

Symmetry (antisymmetry) about the centre point of a sequence, in which case the definitions of even and odd become

$$w_e(x,y) = w_e(M-x, N-y)$$

and $$w_o(x,y) = -w_o(M-x, N-y)$$

for $x = 0,1,2,\ldots M-1$ and $y = 0,1,2\ldots N-1$

M and N are number of rows and columns of 2D array

5b List and explanation of three high pass filters in frequency domain, comments on ringing effect.

1. Ideal High Pass filter
2. Gaussian High Pass filter
3. Butterworth High Pass filters.

Subtracting a low pass filter transfer function from 1 yields the corresponding High pass filter transfer function, in the frequency domain.

$$H_{HP}(u,v) = 1 - H_{LP}(u,v)$$

where $H_{LP}(u,v)$ is the transfer function of a lowpass filter.

Ideal low pass filter (ILPF) transfer function

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

where D_0 is a positive constant. $D(u,v)$ is the distance between a point (u,v) in the frequency domain.

∴ Ideal High pass filter (IHPF) transfer function is given by

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

where $D(u,v)$ is the distance from the center of the $P \times Q$ frequency rectangle.

Gaussian Highpass filter (GHPF) transfer function

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

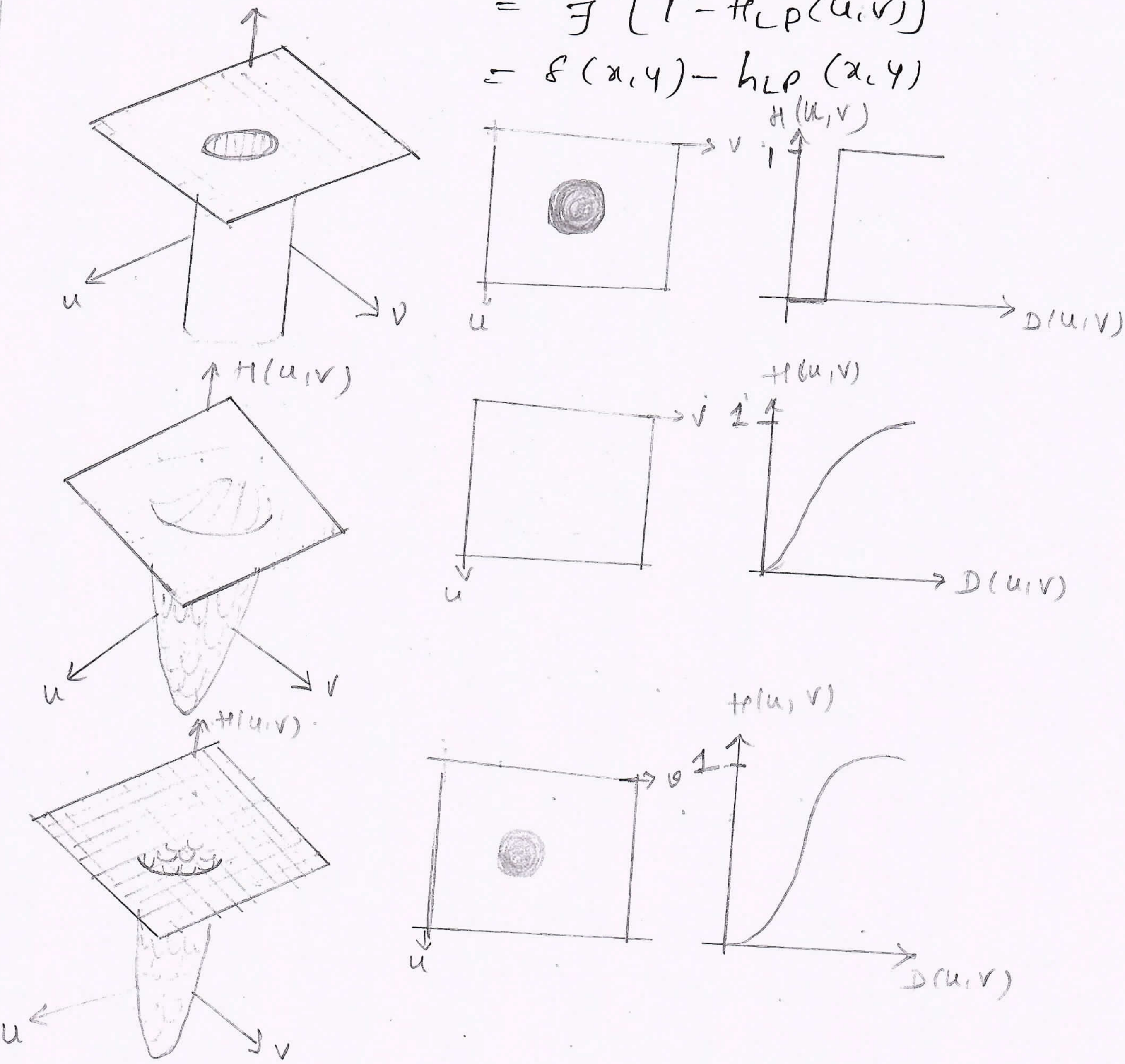
Transfer function of Butterworth high pass filter (BHPF)

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

BHPF transfer function represents a transition bet
the sharpness of the IHPF and broad smoothn
of the GHPF transfer function.

High Pass filter transfer function in the frequency domain is given by,

$$h_{HP}(x,y) = \mathcal{F}^{-1}[H_{HP}(u,v)]$$
$$= \mathcal{F}^{-1}[1 - H_{LP}(u,v)]$$
$$= \delta(x,y) - h_{LP}(x,y)$$



6 a) Ideal Low pass filtering in frequency domain

A 2D lowpass filter that passes without attenuation all frequencies within a circle of radius from the origin and "cuts off" all frequencies outside this circle is called an ideal low pass filter ILPF. It is specified by the transfer function

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

Where D_0 is a positive constant and $D(u,v)$ is the distance between a point (u,v) in the frequency domain and center of the $P \times Q$ frequency rectangle

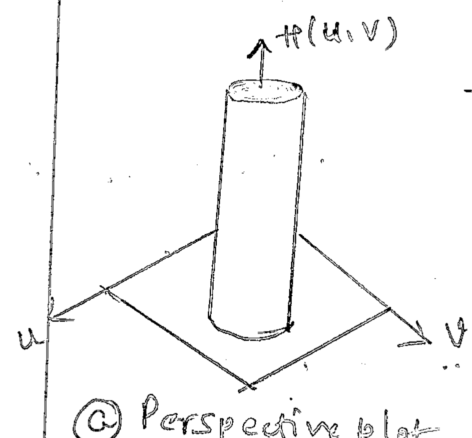
$$D(u,v) = \left[(u - P/2)^2 + (v - Q/2)^2 \right]^{1/2}$$

where P, Q are the padded sizes, $P = 2M$, $Q = 2N$.

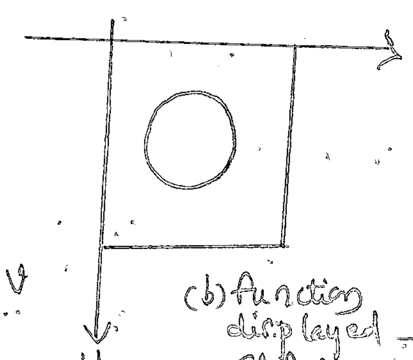
For an ILPF cross section, the point of transition between the values $H(u,v) = 1$ and $H(u,v) = 0$ is called the cut off frequency. In figure 6a cut off frequency is D_0 and total image power P_T obtained by summing the components of the power spectrum of the padded images at each point (u,v) for $u = 0, 1, 2, \dots P-1$ and $v = 0, 1, 2, \dots Q-1$

$$P_T = \sum_{u=0}^{P-1} \sum_{v=0}^{Q-1} P(u,v)$$

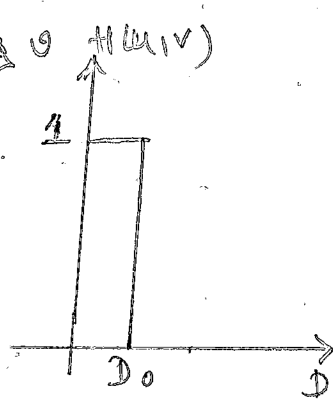
where $P(u,v)$ is given by $P(u,v) = |F(u,v)|^2 = R^2(u,v) + I^2(u,v)$



(a) Perspective plot of ILPF transfer functio[n]



(b) function displayed as image



(c) Radial cross section.

6 b) Homomorphic filtering in image processing

An image $f(x,y)$ can be expressed as the product of its illumination $i(x,y)$ and reflectance $r(x,y)$ components.

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

This cannot be used directly to operate on the frequency components of illumination and reflectance because the fourier transform of a product is not the product of the transforms.

$$\mathcal{F}[f(x,y)] \neq \mathcal{F}[i(x,y)]\, \mathcal{F}[r(x,y)]$$

We define $z(x,y) = \ln f(x,y)$

$$= \ln i(x,y) + \ln r(x,y)$$

Then $\mathcal{F}[z(x,y)] = \mathcal{F}[\ln f(x,y)]$

$$= \mathcal{F}[\ln i(x,y)] + \mathcal{F}[\ln r(x,y)]$$

$$Z(u,v) = F_i(u,v) + F_r(u,v) \quad \text{——— (A)}$$

$F_i(u,v)$ and $F_r(u,v)$ are the fourier transforms of $\ln i(x,y)$ and $\ln r(x,y)$ respectively.

We can filter $Z(u,v)$ using filter transfer function $H(u,v)$, so that

$$S(u,v) = H(u,v)\, Z(u,v)$$

$$= H(u,v)\, F_i(u,v) + H(u,v)\, F_r(u,v) \quad \text{——— (B)}$$

The filtered image in the spatial domain is then

$$s(x,y) = \mathcal{F}^{-1}[S(u,v)] \quad \text{——— (D)}$$

$$= \mathcal{F}^{-1}[H(u,v)\, F_i(u,v)] + \mathcal{F}^{-1}[H(u,v)\, F_r(u,v)]$$

By defining $i'(x,y) = \mathcal{F}^{-1}[H(u,v)\, F_i(u,v)]$

and $r'(x,y) = \mathcal{F}^{-1}[H(u,v), F_r(u,v)]$

We can express equation (1) in the form

$$s(x,y) = i'(x,y) + r'(x,y)$$

$z(x,y)$ is formed by taking the natural logarithm of the input image.

We reverse the process by taking the exponential of the filtered result to form the output image.

$$g(x,y) = e^{s(x,y)}$$

$$= e^{i'(x,y)} e^{r'(x,y)}$$

$$= i_0(x,y)\, r_0(x,y)$$

where

$$i_0(x,y) = e^{i'(x,y)}$$

and

$$r_0(x,y) = e^{r'(x,y)}$$

are the illumination and reflectance components of the output (processed) image. This method is based on a special case of a class of systems known as homomorphic systems.

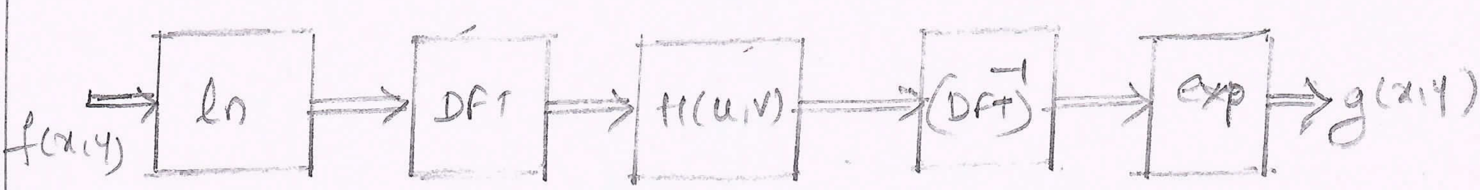


fig 68. Steps in Homomorphic filtering

Separation of illumination and reflectance components achieved in the form of Eqⁿ (A). The homomorphic filter transfer function $H(u,v)$, then can operate on these components separately, by Eqⁿ (B)

7a Methods used in estimation of degradation model.

There are three principal ways to estimate the degradation function for use in image restoration 1). Observation 2). Experimentation 3) Mathematical modeling. The process of restoring an image by using a degradation function that has been estimated by any of these approaches sometimes is called "blind deconvolution".

(i) Estimation by Image Observation:

Suppose given a degraded image without any knowledge about the degradation function H. Based on the assumption that the image was degraded by a linear position invariant process, one way to estimate H is to gather information from the image itself.

Let the observed subimage be denoted by $g_s(x,y)$ and let the processed subimage which in reality is our estimate of the original image in that area be denoted by $\hat{f}_s(x,y)$. Then assuming that the effect of noise is negligible because of our choice of a strong signal area.

$$H_s(u,v) = \frac{G_s(u,v)}{\hat{F}_s(u,v)} \quad \text{———} ①$$

from the characteristics of this function, we then deduce the complete degradation function $H(u,v)$ based on assumption of position invariance

Estimation by Experimentation:

If equipment similar to the equipment used to acquire the degraded image is available, it is possible in principle to obtain an accurate estimate of the degrad. Images similar to the degraded image can be acquired with various system settings until they are degraded as closely as possible to the image we wish to restore. The idea is to obtain the impulse response of the degradation by imaging an impulse using the same system settings.

An impulse is simulated by a bright dot of light as bright as possible to reduce the effect of noise to negligible values. The fourier transform of an impulse is constant, it follows from Equation $G(u,v) = H(u,v)F(u,v) + N(u,v)$ that,

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

where $G(u,v)$ is the fourier transform of the observed image. A is a constant, describing the strength of the impulse.

Estimation by Modeling:

This degration model takes into account environmental conditions, that cause degradation. A degradation model proposed by Hufnagel and Stanley is based on the physical characteristics of atmospheric turbulence. This model has familiar form

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

where k is constant that depends on the nature of the turbulence. Another approach used frequently in modeling is to derive a mathematical model starting from basic principles.

Head of the Department
Dept. of Electronic & Communication Engg.
KLS V.D.I.T., HALIYAL (U.K.)

Inverse filtering and its drawback.

The simplest approach to restoration is direct inverse filtering, where we compute an estimate $\hat{F}(u,v)$ of the transform of the original image by dividing the transform of the degraded image, $G(u,v)$ by the degradation transfer function,

$$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)} \quad \text{—— (1)}$$

Substitute the right side of Equation (A)

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

in Equation (1),

$$\hat{F}(u,v) = F(u,v) + \frac{N(u,v)}{H(u,v)}$$

This expression, tells that even if we know the degradati-on function we cannot recover the undegraded image [the inverse fourier transform of $F(u,v)$] exactly because $N(u,v)$ is not known.

If the degradation function has zero or very small values, then the ratio $N(u,v)/H(u,v)$ could easily dominate the term $F(u,v)$. One approach to get around the zero or small value problem is to limit the filter frequencies to values near the origin. $H(0,0)$ is usually the highest value of $H(u,v)$ in the frequency domain. Thus by limiting the analysis to frequencies near the origin, we reduce the likelihood of encountering zero values.

8a Image degradation and restoration model.

The principal sources of noise in digital images arise during image acquisition and/or transmission. The performance of imaging sensors is affected by a variety of environmental factors during image acquisition, and by the quality of the sensing elements themselves. In acquiring images with a CCD camera, light levels and sensor temperature are major factors affecting the amount of noise in the resulting image. Images are corrupted during transmission principally by interference in the transmission channel. An image transmitted using a wireless network might be corrupted by lightning or other atmospheric disturbance.

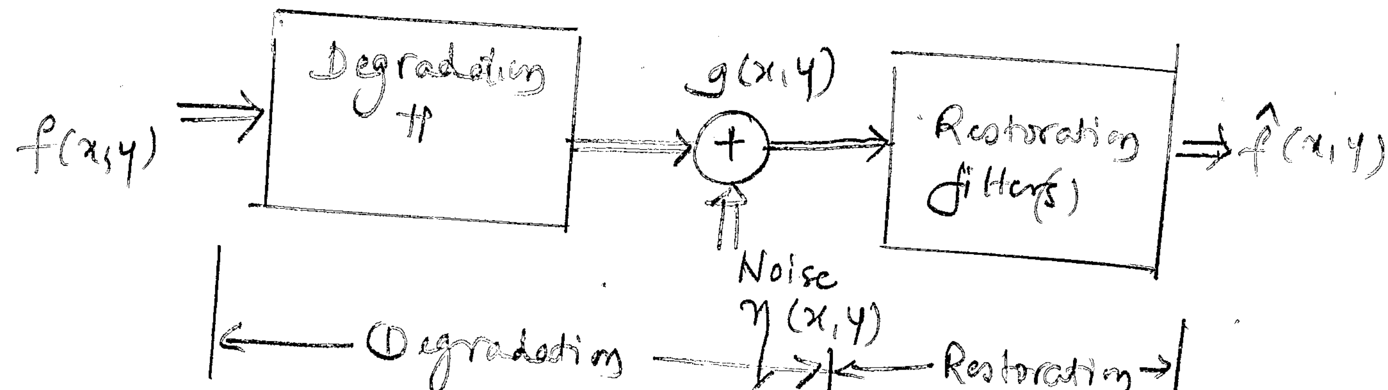


fig (8a). Model of image degradation/restoration process

Image degradation is modeled as an operator H that, together with additive noise term, operates on input image $f(x,y)$ to produce a degraded image $g(x,y)$, as in fig 8(a).

Given $g(x,y)$, some knowledge about H, and some knowledge about the additive noise term $\eta(x,y)$ the objective of restoration is to obtain an estimate $\hat{f}(x,y)$ of the original image. We want the estimate to be as close as possible to the original image. and in general the more we know about H and η, the closer $\hat{f}(x,y)$ will be $f(x,y)$

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

$$g(x,y) = (h * f)(x,y) + \eta(x,y) \quad \text{——— (1)}$$

where $h(x,y)$ is the spatial representation of the degradation function. The * indicates convolution. It follows from the convolution theorem that the equivalent of equation (1) in the frequency domain is

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

where the terms in capital letters are the fourier transform of the corresponding terms in Eqn (1)

8b. Need for Adaptive Median filters and its working

Adaptive filters behaviour changes based on statistical characteristics of the image inside the filter region defined by the $m \times n$ rectangular neighborhood S_{xy}. Adaptive filters are capable of performance superior to that of other filters. The price paid for improved filtering power is an increase in filter complexity.

Median filter replaces the value of a pixel by the median of the intensity levels in a predefined neighborhood of that pixel,

$$\hat{f}(x,y) = \underset{(r,c)\in S_{xy}}{\text{median}} \{g(r,c)\} \quad \text{——— (1)}$$

S_{xy} is a subimage (neighborhood) centered on point (x,y). Median filter in Eqn (1) performs well if the spatial density of the salt & pepper noise is low

86 (P_s and P_p less than 0.2). The adaptive median filtering can handle noise with probabilities larger than these. Adaptive filters seeks to preserve detail while simultaneously smoothing non impulse noise, which traditional median filter does not do. The adaptive median filters also works in a rectangular neighborhood, S_{xy}. The adaptive median filter changes (increases) the size of S_{xy} during filtering, depending on certain conditions. The output of the filter is a single value used to replace the value of the pixel at (x,y), the point on which region S_{xy} is centered at a given time.

Z_{min} = minimum intensity value in S_{xy}

Z_{max} = maximum intensity value in S_{xy}

Z_{med} = median of intensity values in S_{xy}

Z_{xy} = intensity at coordinates (x,y).

S_{max} = maximum allowed size of S_{xy}.

The adaptive median filtering algorithm uses two processing levels, denoted level A and level B, at each point (x,y):

Level A : If $Z_{min} < Z_{med} < Z_{max}$, go to Level B
Else, increase the size of S_{xy}
If $S_{xy} \leq S_{max}$, repeat level A
Else output Z_{med}.

Level B : If $Z_{min} < Z_{xy} < Z_{max}$, output Z_{xy}
Else output Z_{med}.

where S_{xy} and S_{max} are odd, positive integers greater than 1. Another option in last step of level A is to output Z_{xy} instead of Z_{med}. This produces a slightly less blurred result.

This algorithm has three principal objectives: to remove salt and pepper (impulse) noise, to provide smoothing of other noise that may not be impulsive and to reduce distortion, such as excessive thinning or thickening of object boundaries. The values of Z_{min} and Z_{max} are considered statistically by the algorithm to be "impulse like" noise components in region S_{xy}, even if these are not the lowest and highest possible pixel values in the image.

The purpose of level A is to determine if the median filter output, Z_{med} is an impulse (salt or pepper) or not. If the condition $Z_{min} < Z_{med} < Z_{max}$ holds, then Z_{med} cannot be an impulse for the given reason. We go to level B and test to see if the point in the center of the neighborhood is itself an impulse ((x, y) is the location of the point being processed and Z_{xy} is its intensity. If the condition $Z_{min} < Z_{xy} < Z_{max}$ is true, then the pixel at Z_{xy} cannot be the intensity of an impulse for the same reason that Z_{med} was not. In this case, algorithm outputs the unchanged pixel value Z_{xy}. By not changing these "intermediate level" points, distortion is reduced in the filtered image. If the condition $Z_{min} < Z_{xy} < Z_{max}$ is false, then either $Z_{xy} = Z_{min}$ or $Z_{xy} = Z_{max}$. In either case, the value of the pixel is an extreme value and the algorithm outputs the median value Z_{med}, which we know from level A is not a noise impulse.

Head of the Department
Dept. of Electronic & Communication Engg.
KLS V.D.I.T., HALIYAL (U.K.)

9(a) The RGB and CMY Colour Models

The purpose of a color model also called a color space or color system is to facilitate the specification of colors in some standard way. A color model is a specification of i) a co-ordinate system (ii) subspace within that system such that each color in the model represented by a single point contained in that subspace.

In terms of digital image processing, the hardware oriented models most commonly used in practice are the RGB (Red, Green, Blue) model for color monitors and broad class of color video cameras, the CMY (cyan, magenta, yellow) and CMYK (cyan, magenta, yellow, black) models for color printing and HSI (hue, saturation, intensity) model, which corresponds closely with the way humans describe and interpret color.

RGB Color model: In the RGB model, each color appears in its primary spectral components of red, green and blue. This model is based on a cartesian co-ordinate system. The color subspace is the cube as shown in fig 9a, in which RGB primary values are at three corners, the secondary colors are cyan, magenta and yellow are at three other corners, black is at the origin and white is at the corner farthest from the origin. In this model the gray scale (points of equal RGB values) extends from black to white along the line joining these points. The different colors in this model are points on or inside the cube and are defined by vectors extending from the origin.

All values of RGB are assumed to be in the range [0, 1]. RGB primaries can be interpreted as unit vectors emanating from the origin of the cube. Images represented in RGB color model consists three component images, one for each primary color. When fed into RGB monitor, these three images combine on the screen to produce a composite color image. The number of bits used to represent each pixel in RGB space is called the pixel depth. Consider an RGB image in which each of the red, green and blue images is an 8 bit image. Under these condition, each RGB color pixel has depth of 24 bits. The term full color image is used to denote a 24 bit RGB color image. The total number of possible colors in a 24 bit RGB image is $(2^8)^3 = 16,777,216$

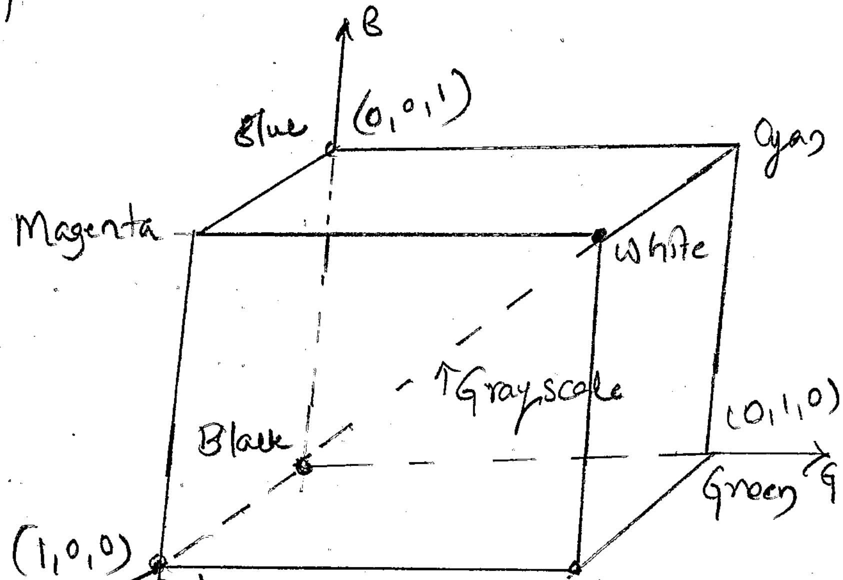


Fig 9a. Schematic of RGB color cube.

Points along the main diagonal have gray values from black at the origin to white at point (1,1,1)

CMY color model: Cyan, magenta and yellow are the secondary colors of light or alternatively they are the primary colors of pigments.

$$\begin{bmatrix} C \\ M \\ Y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad \text{——— (1)}$$

RGB color values have been normalized to the range [0, 1]

9 b. Erosion and Dilation in Morphological Image Processing

Erosion and Dilation operations are fundamental to morphological processing.

Erosion: Morphological expressions are written in terms of structuring elements and a set A, of foreground pixels, or in terms of structuring elements and an image I that contains A. With A and B as sets in Z^2, the erosion of A by B, denoted $A \ominus B$, is defined as

$$A \ominus B = \{ z \mid (B)_z \subseteq A \}$$

where A is a set of foreground pixels, B is a structuring element and the z's are foreground values (1's). Erosion of A by B is the set of all points z such that B, translated by z, is contained in A.

For complete image, I,

$$I \ominus B = \{ z \mid (B)_z \subseteq A \text{ and } A \subseteq I \} \cup \{ A^c \mid A^c \subseteq I \}$$

where I is a rectangular array of foreground and background pixels.

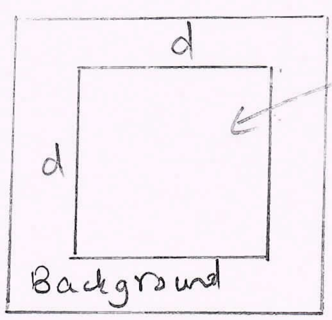
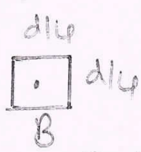


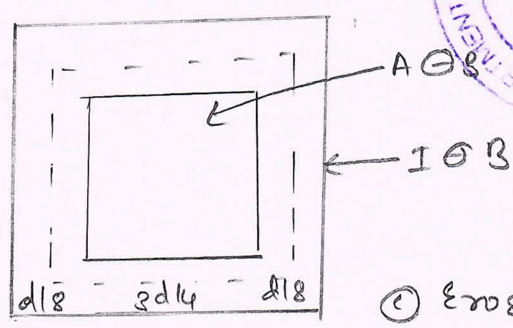
Image I

(a) Image I with set A and Background

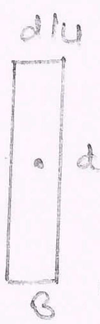


(b) Square SE, B

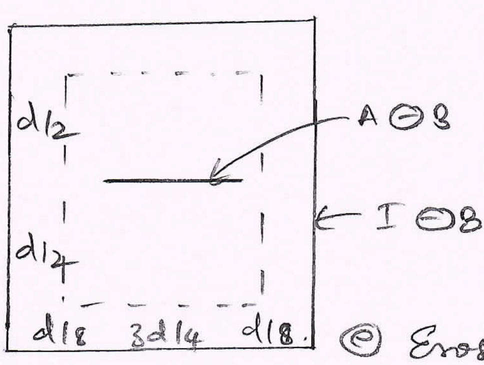
dot is origin



(c) Erosion of A by B



(d) Elongated SE.



(e) Erosion of A by B,

Dilation:

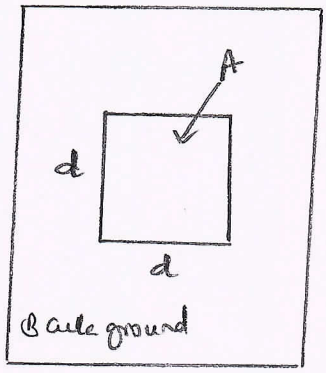
With A and B as sets in Z^2, the dilation of A by B, denoted as $A \oplus B$, is defined as

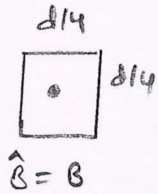
$$A \oplus B = \{ z \mid (\hat{B})_z \cap A \neq \emptyset \}$$

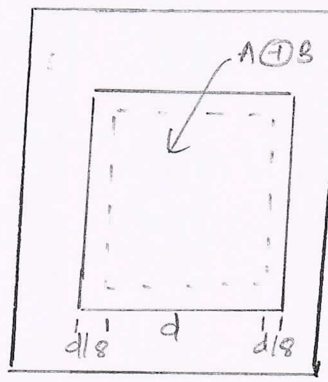
This equation is based on reflecting B about its origin and translating the reflection by z, as in erosion. The dilation of A by B then is the set of all displacements z such that the foreground elements of $\hat{B}$ overlap at least one element of A. z is the displacement of the origin of $\hat{B}$.

$$A \oplus B = \{ z \mid [(\hat{B})_z \cap A] \subseteq A$$

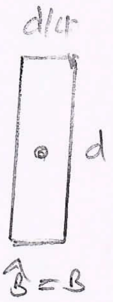
Erosion, which is a shrinking or thinning operation, dilation "grows" or "thickens" objects in a binary image.

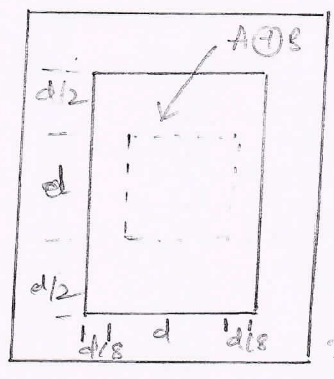






$A \oplus B$





$A \oplus B$

10 a ## HSI Colour model

Hue, Saturation, intensity color model decouples the intensity component from the color carrying information (hue and saturation) in a colour image. HSI model is useful tool for developing image processing algorithms based on color descriptions that are natural and intuitive to humans. The important components of HSI color space are the vertical intensity axis, the length of the vector to a color point and the angle this vector makes with the red axis.

RGB to HSI :

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

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

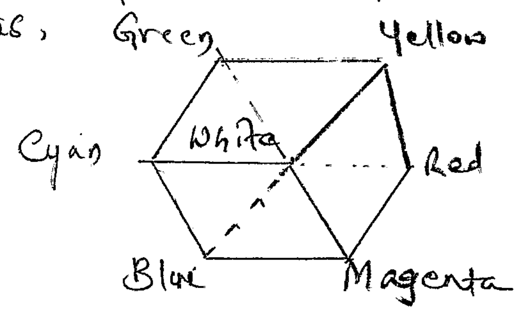
Saturation component

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

Intensity component

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

HSI space is represented by a vertical intensity axis and the locus of colour points that lie on planes perpendicular to that axis,



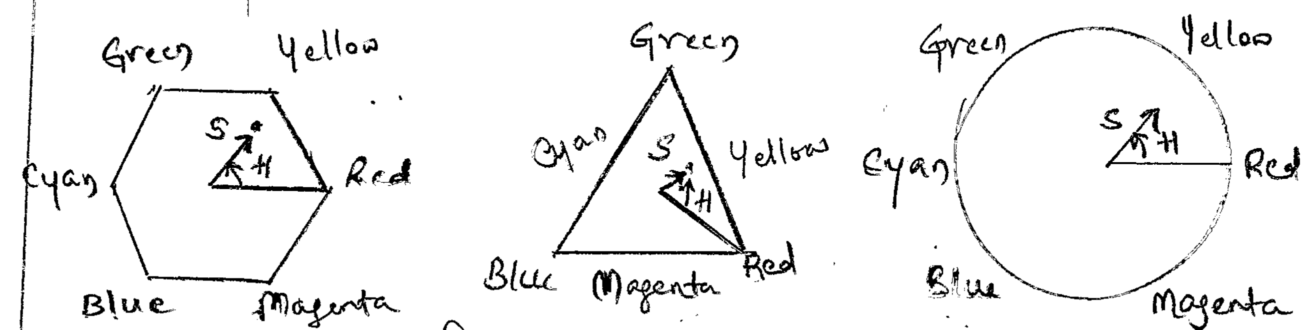


fig 10a. Hue & Saturation in the HSI color model.

10 b Opening and closing operations used in Morphological image processing

Opening and Closing are the other two important morphological operations. Opening generally smoothes the contour of an object, breaks narrow isthmuses and eliminates thin protrusions. Closing also tends to smooth sections of contours, but as opposed to opening it generally fuses narrow breaks and long thin gulfs eliminates small holes and fills gaps in the contour.

The opening of set A by structuring element B, denoted by $A \circ B$, is defined as

$$A \circ B = (A \ominus B) \oplus B$$

Thus the opening A by B is the erosion of A by B, followed by dilation of result by B.

Similarly the closing set A by structuring element B denoted $A \bullet B$ is defined as

$$A \bullet B = (A \oplus B) \ominus B$$

which says that the closing of A by B is simply the dilation of A by B, followed by erosion of the result by B.

The opening of A by B is the union of all the translations of B such that B files entirely within A can be written in equation form as,

$$A \circ B = \cup \{ (B)_z \mid (B)_z \subseteq A \}$$

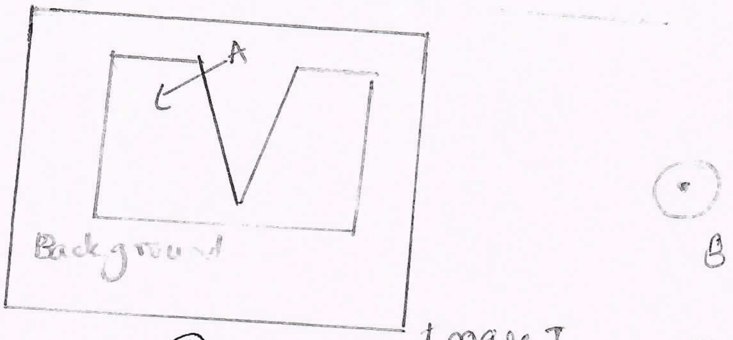
'$\cup$' denotes the union of the sets inside the braces.

Opening and closing are duals of each other with respect to set complementation and reflection.

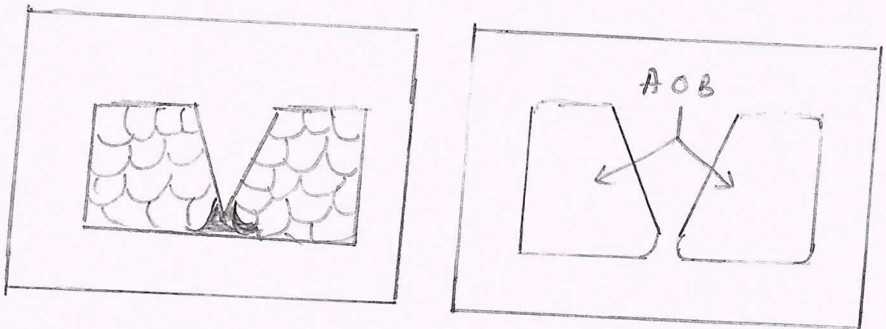
$$(A \circ B)^c = (A^c \bullet \hat{B})$$

and $$(A \bullet B)^c = (A^c \circ \hat{B})$$

10 b. Openings:



(a) Image I (b)



(c) (d)

(a). Image I composed of set (object) A and background.

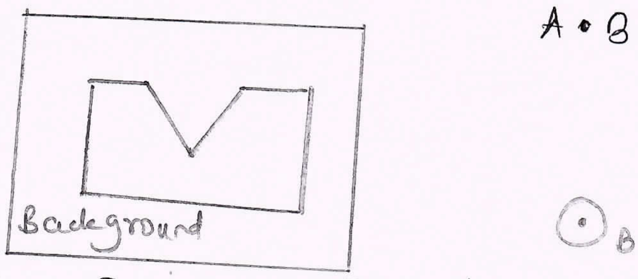
(b) Structuring element B.

(c) Translations of B while being contained in A (dark area)

(d) opening of A by B.

Closing :- Closing is complement of the union of all translations of B that donot overlap.

$$A \bullet B = \left[\cup \{ (B)_z \mid (B)_z \cap A = \emptyset \} \right]^c$$



(a) Image I, with set A and background Image I (b) structuring element B.

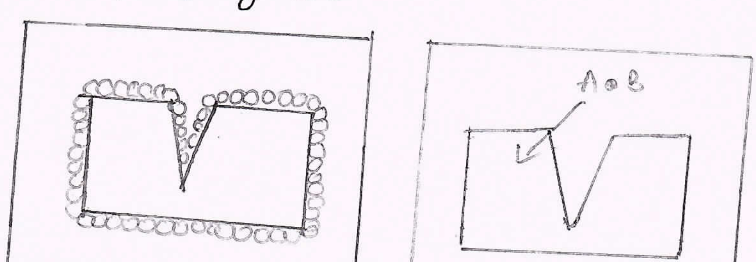


Image I

(c) Translation of B, does not overlap in A. (d) closing of A by B.

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