Moving avg = $ap(a) + b\,p(b) + c\,p(c)$

where $p(a) \neq p(b) \neq p(c)$

& $p(a) + p(b) + p(c) \neq 1$

$E[x] = \sum x$

↓

randomly changing

pdf = probability density function

vdf = velocity density funct

Gdf

Rdf

Ndf

~~Bdf~~

BDF

If data size is increased to enormous limits the behaviours of profile will always be gaussian density function [GDF]

↓

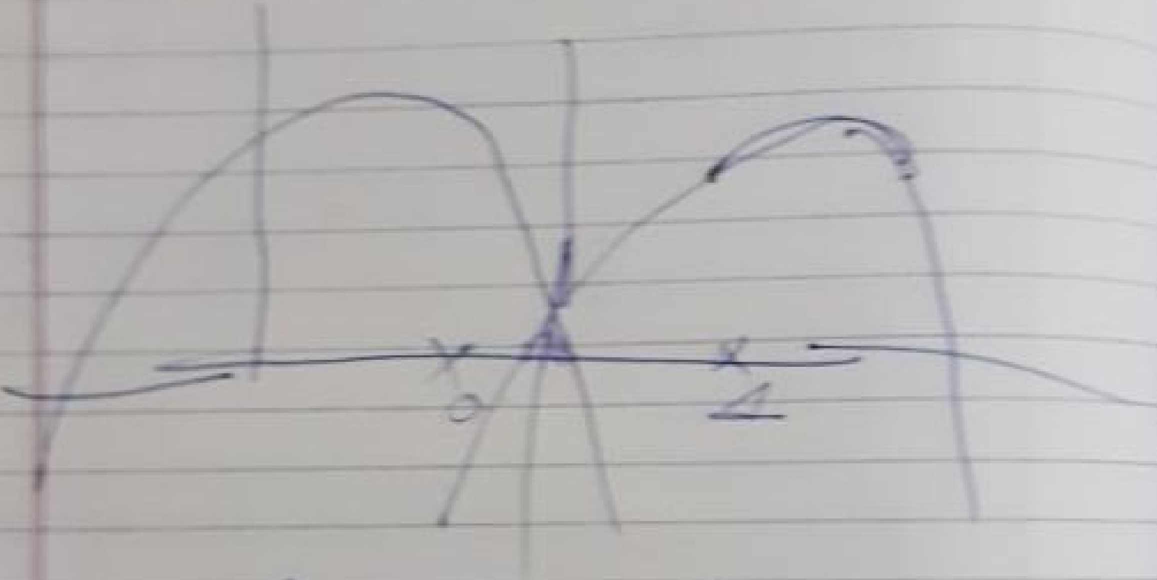
central limit theorem

$gdf = pdf_1 \cdot pdf_2 \cdot pdf_3 \ldots pdf_n$

convolved around them

$f(y/1) \frac{1}{\sqrt{2\pi N_0}} e^{(-y-A)^2/N_0}$

Space Diagram



P_{01} = Probability that zero becomes 1

$$P_{01} = \int_{0}^{\infty} f(y/0)\, dy$$

$$P_{10} = \int_{-\infty}^{\infty} f(y/1)\, dy$$

probability that 1 becomes 0

→ error

Average error probability to minimum $= E[P_{01}, P_{10}]$

Bayes law

Edge Detection

#

Data vs Model Generalization

let the data be

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

$$g_{0^\circ} = A(c+i-a-g)+B(f-d$$

$$g_{90} = A(a+c-g-i)+B(b-h)$$

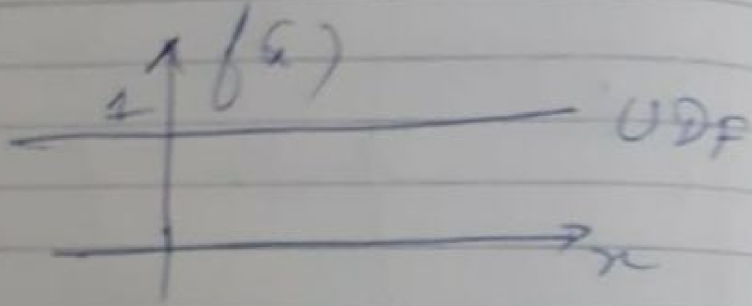
$$g_{45} = C(b+f-d-h)+D(c-g$$

$$g_{45^\circ} = \frac{g_{0^\circ}+g_{90^\circ}}{\sqrt{2}}$$

$$C = \frac{B}{\sqrt{2}}, \quad \boxed{D = \frac{A}{\sqrt{2}}}$$

why these gradients are so important

↳ use of gradients to other latest techniques f(x) is a uniformly distributed function [UDF]



SA = EA

statistical average = Ensemble average

$$y = A(x - m_x)$$

transformation matrix which is orthonormal matrix

Transformational - orthonormal matrix

$\downarrow$

all values less than o

$$A.\ \underbrace{\sigma_x}_{\downarrow\ \text{eigen values}} .\ A^T = \text{Diagonal matrix}$$

$\downarrow$

all diagonals will be eigen values of standard deviation autto corelation

$$\sum_{t=0}^{\infty} x(t).x(t-\tau) = R(\tau)$$

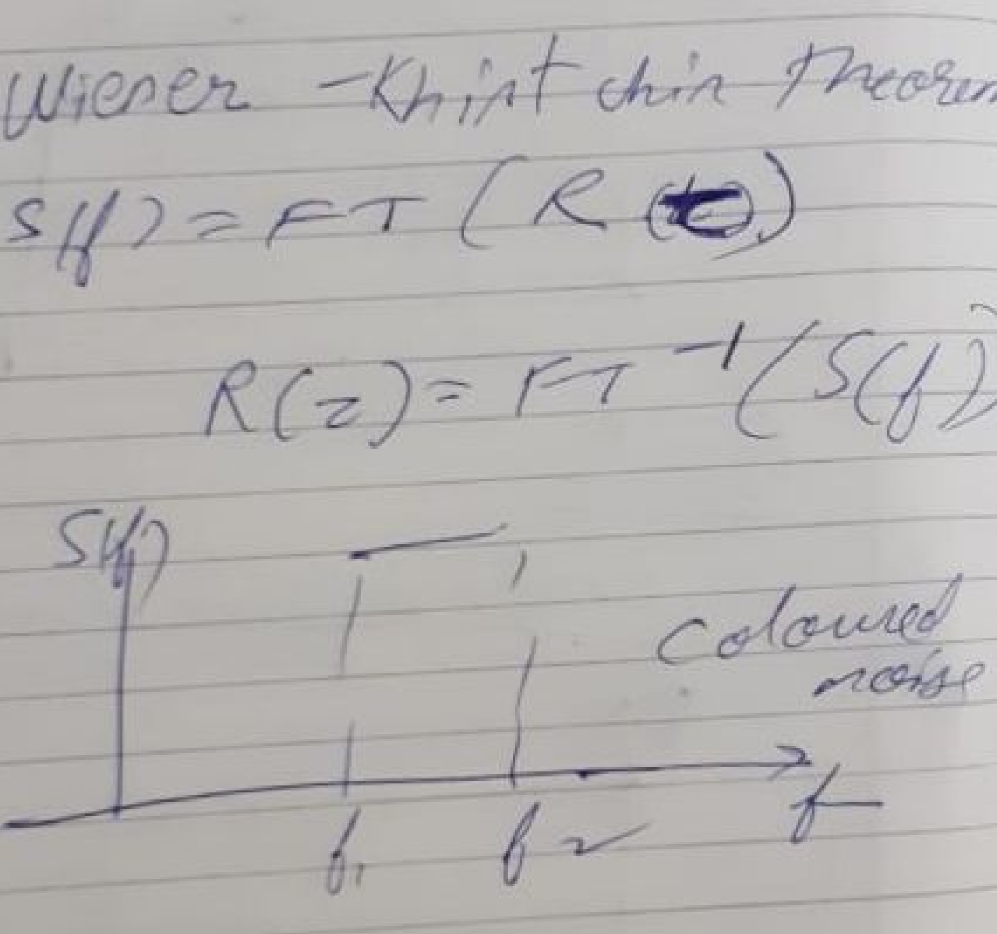
$f(\tau)$

$r(\tau)$

Wiener -Khintchin theorem.

$$S(f) = FT(R(\tau))$$

$$R(\tau) = FT^{-1}(S(f))$$



20.8.19
8C3B3

$$\text{OTF} = \frac{F(\omega)}{|F(\omega)|_{max}}$$

Optimal
transfer
function

signal processing + vision
+ AI

$$F(\omega) = \int_{-\infty}^{\infty} f(t)\, \underbrace{e^{-j\omega t}}_{\text{basis function}}\, dt$$

F ← matrix

basis function
A

$B = AFA^T$

A = orthogonal matrix

$B = AFA^T \Rightarrow$ Diagonal [illegible]

⇓

eigen
~~values~~
vectors

+ve definite
or semi +ve definite
matrix

generalized matrices

$$\begin{array}{cc} 0^\circ & 45^\circ \\ \begin{bmatrix} -A & 0 & A \\ -B & 0 & B \\ -A & 0 & A \end{bmatrix} & \begin{bmatrix} 0 & C & D \\ -C & 0 & C \\ -D & -C & 0 \end{bmatrix} \end{array}$$

1) step edge

~~response for 0° mask~~

→ 0° response using 0° mask having step edge

~~$0^\circ = 2A+B$~~

0° response $= 2A+B$ (add vertically)

→ 45° response using 0° mask for step edge

45° response $= A+B$ (add upper triangle) above diagon

→ 0° response using 45° mask for step edge

$\cdot 0^\circ$ response $= C+D$ (add all vertically

→ 45° response using 45° mask for step edge

45° response $= 2C+D$ (Add upper t above

$b_k(z) = b_k(101)$

~~$z = 5$~~ k^{th} bit of binary representation of z

101

$b_0(5) = 1$
$b_1(5) = 0$
$b_2(5) = 1$

Kernel matrix

$n = 3$ $\quad W(x, u)$ $\quad N=8$

$N = 8$ $\quad W(0,0) = \frac{1}{8} \prod_{i=0}^{n-1} (-1)^{b_i(0) b_{2-\ldots}}$

u \ x	0	1	2	3	4	5	6	7
0	+1	+1	+1	+1	+1	+1	+1	+1
1	+1	+1	+1	+1	-1	-1	-1	-1
2								
3								
4								
5								
6								
7								

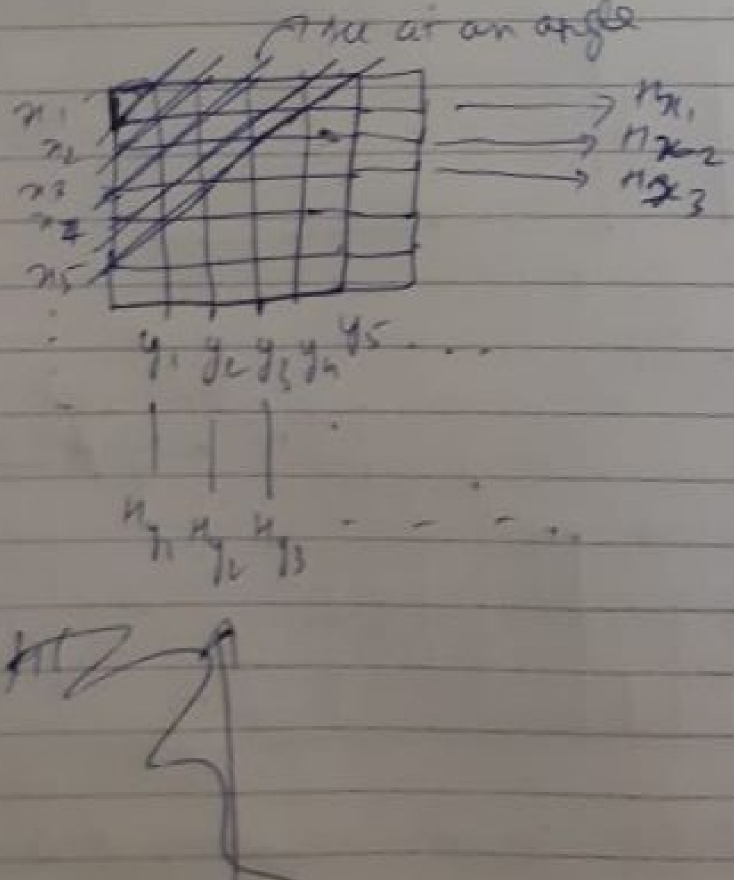
f(p) = more or [illegible]
what it says theoretically
difficult to implement ~~and a~~
practically/

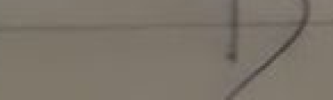
Advantage: No gray level
for which the image is biased

Dis-advantage { bright image + small areas
with darkness : image ~~be~~ [illegible]
darken

Lateral Histogram

The way of projecting an image on
two or more than ~~three~~ axes.





Date : / /
Page No.

Assignment -1

Q1 | Take an image, apply translation scaling & rotation on it

Q2, Compare all the transform implied on given data - where the redundancy

Unitary Transforms ↳ is the least best compression transform

↳ only once on the data set, cannot be applied a number of times

Discrete wavelength Transform

↳ apply a number of times

Unitar Transform

⇓

Walsh transform

↳ digital transform nothing imaginary)

$N = 2^n$

N ↙ #symbols

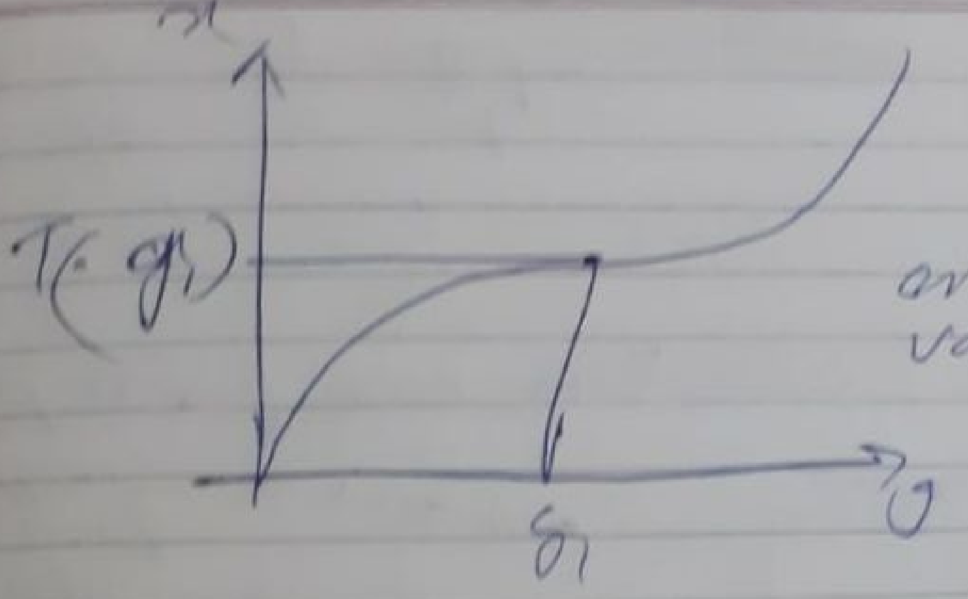
n ↘ #bits

$$W(x, u) = \frac{1}{N} \prod_{i=0}^{n-1} (-1)^{b_i(x) b_{n-1-i}(u)}$$

x ↓ data

u ↓ transformed variable

W ↙ Kernel of Transform

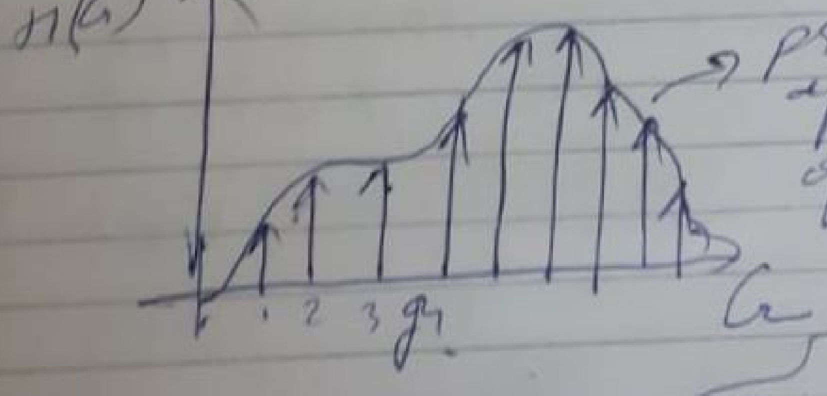


every value is diff

$r = T(g)$

Prob. Density fn (PDF)

Cumulative Density fn (CDF]



probability of occurrence of grey level

[if histogram normalized]

$$\int_{0}^{g_1} H(g)\,dg = CDF$$

→ If differentiate = PDF

If we integrate = CDF

Date : / /
Page No.

Hotelling Transform

$$\{X\} = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ \vdots \\ x_{N-1} \end{bmatrix}$$

$$m_x = E[X]$$

co-variance of data ← $C_x = [(x - m_x)(x - m_x)^T]$

$$\Downarrow$$

1) Real
2) Symmetrical / Toeplitz

Correlation can make data into info

Toeplitz ~~\$~~ $A(i) = A(i-j)$

x_i & x_j are uncorrelated

covariance = 0

$$c_{ij} = c_{ji}$$

statistical mean ← $m_x = \frac{1}{m} \sum_{i=0}^{m-1} x$

ensemble average ← $m_x = \frac{1}{m} \sum_{i=0}^{m-1} x f(x)$

$$0 < g < 1$$

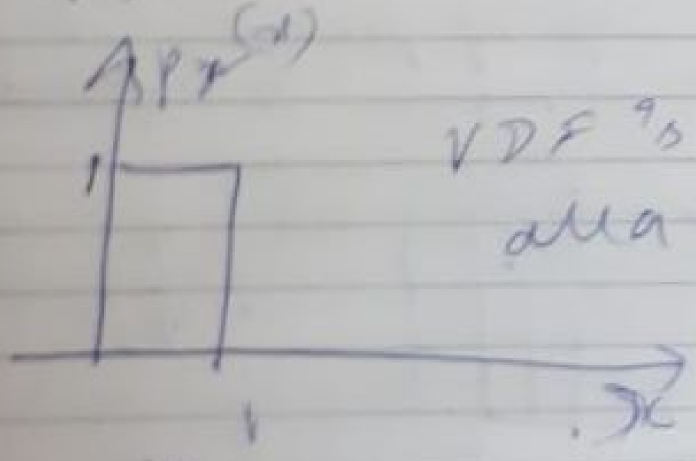
$$\frac{dx}{dg} = P_g(g) \quad \text{— ③}$$

$$P_x(x) = \left| P_g(g)\, \frac{dg}{dx} \right|_{g = T^{-1}x}$$

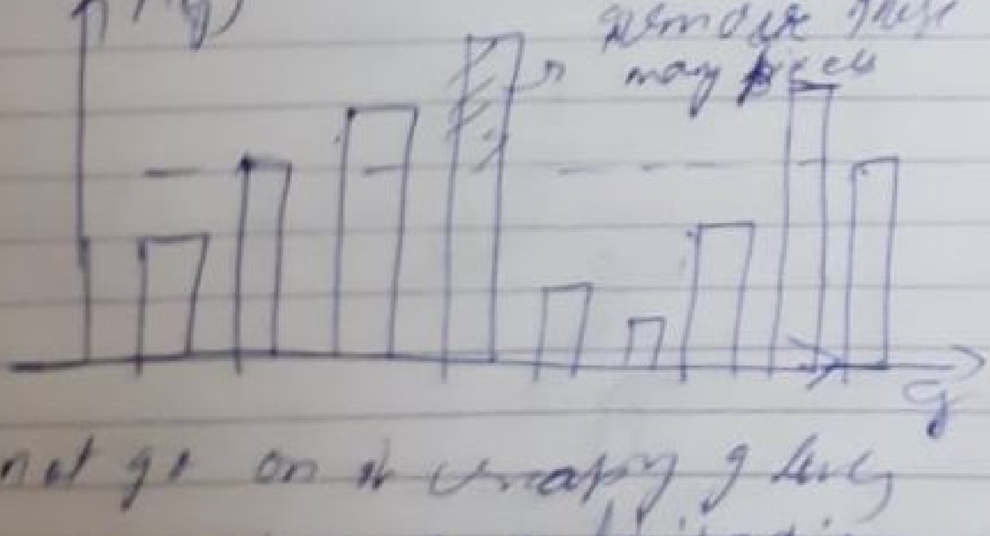
PDF of ~~[illegible]~~ the histogram equalized/transformed image should be 1

$$= |1| = \underline{1}$$

VDF → $\underline{1}$



VDF is property
area = $\underline{1}$



not go on remapping g levels
beyond a limitation

~~α^3~~ ~~$\frac{p^2 n^{\alpha}}{\alpha^3}$~~ [illegible]

$$\alpha^3 = \frac{p^2 n}{N}$$

$$\alpha = \sqrt[3]{\frac{p^2 n}{N}}$$

If $\alpha = \underline{1}$

~~$N = p^3 n$~~

discriminant comes out to be +ve

for $p = \sqrt{2} \cdot \frac{N}{n}$

Adjust α such that

$\overline{N} = n . \overline{p}$

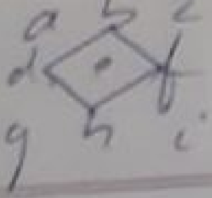
object size

If $\overline{p} = 1$

$\overline{N} = n$

atleast accomodate 1 object

$$\alpha = \frac{np}{N}$$



have to go beyond eight connected

↳ generally four or eight conn
to process any kind of ima

→ In other replacement of edge correction is the con of <u>labeling ⇒ clustering</u>

much more complicated

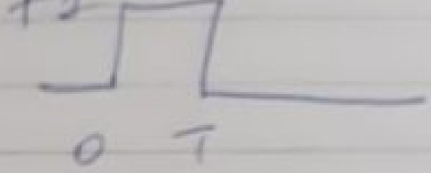
<u>MRI</u> : tissues spread over

Segmentation

$$\left.\begin{array}{l} G_1 \rightarrow \theta_1 \\ G_2 \rightarrow \theta_2 \\ \vdots \\ G_n \rightarrow \theta_n \end{array}\right]$$ Data matrix

$[e_1, e_2, e_3]$

$$y(t) = \int_0^T x(t) \cdot \underline{1}\, dt$$



$$= \int_0^T s(t)\, dt + \int_0^T w(t)\, dt$$

Let's take $s(t) = -A$
Assume 0 as original signal

$$= \int_0^T -A\, dt + \int_0^T w(t)\, dt$$

$$y(t) = -AT + \int_0^T w(t)\, dt$$

$$y(T) = y(t)\Big/_{t=T} = -A + \frac{1}{T}\int_0^T w(t)\, dt$$

slicing

$$m_x = -A$$

$$\sigma_y^2 = E\left(y - m_x\right)^2$$

Ensemble

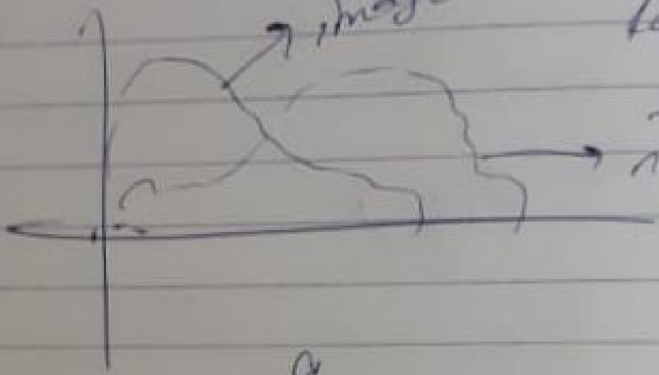
y is not deterministic

dark g levels

$\nearrow$

~~p~~ $\int_0^{g_0} p_g(g)\,dg$ = CDF of $p_g(g)$

x = T(g) // histogram normalized ⇒ PDF



images are dark same grey levels are more

normal

$$x = T(g) = \int_0^{g_0} p_g(g)\,dg \quad \text{— ②}$$

CP ⇒ cumulative probability

The CP of the original grey levels some ppl might use a dummy variable for ex,

$$T(g) = \underbrace{\int_0^{g_0} p_g(a)\,da}$$

PDF belonging to original image but a is random variable

Transformation function is the cumulative view of probability

$h(n) \cdot s(n)$

[illegible] function

$g(x,y) = H[s(x,y)] + \eta(x,y)$

Let $\eta(x,y) = 0$

$g(x,y) = H[s(x,y)]$

$H \Rightarrow$ Linear transfer function

$= H[K_1 s_1(x,y) + K_2 s_2(x,y)]$

$= K_1 H[s_1(x,y)] + K_2 H[s_2(x,y)]$

~~$h(n) * s(n)$~~

Assume $K_1 = K_2$

$= H[s_1(x,y)] + H[s_2(x,y)]$

assume s_2 to be zero homogeneity?

$= H[s_1(x,y)]$

given function can be space invariant, if

$= K_1 H(s_1(x-\alpha, y-\beta)) \Rightarrow g(x-\alpha, y-\beta)$

$s(x,y) = \iint s(\alpha,\beta) \cdot \delta(x-\alpha, y-\beta)\, d\alpha\, d\beta$

why additive?

2. **Scaling**

$$T = \begin{bmatrix} S_x & 0 & 0 & 0 \\ 0 & S_y & 0 & 0 \\ 0 & 0 & S_z & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

A →

algorithm "B splines" to fill the gaps

3. **Rotation (along z axis)**

$$T = \begin{bmatrix} \cos\theta & \sin\theta & 0 & 0 \\ -\sin\theta & \cos\theta & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

↳ **Along x-axis**

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\theta & \sin\theta & 0 \\ 0 & -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Shannon theorem

$$C = B\log\left(1 + \frac{P}{N_0 B}\right) \text{ bits/sec}$$

Computer vision

Geometrical Transforms

1. Translation

$$\underset{\text{coordinates after translation}}{X^*} = \underset{\text{original coordinate}}{X} + \underset{\text{the translation}}{\Delta X}$$

$$Y^* = Y + \Delta Y$$

$$Z^* = Z + \Delta Z$$

$$\underset{\text{transformed coordinates}}{\begin{bmatrix} x^* \\ y^* \\ z^* \\ 1 \end{bmatrix}} = \underset{\text{transformation matrix}}{\begin{bmatrix} 1 & 0 & 0 & \Delta X \\ 0 & 1 & 0 & \Delta Y \\ 0 & 0 & 1 & \Delta Z \\ 0 & 0 & 0 & H \end{bmatrix}} \underset{\text{original coord}}{\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}}$$

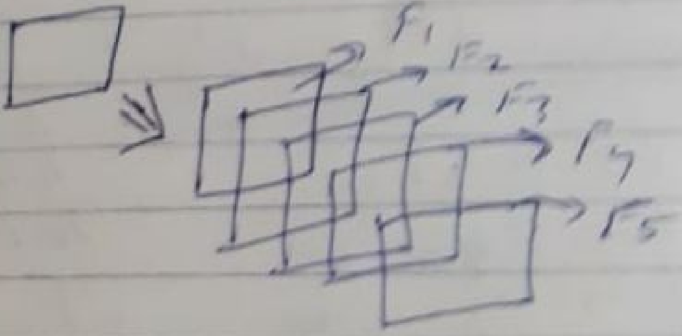
② → ④ → ⑯ → [illegible]

Squaring function

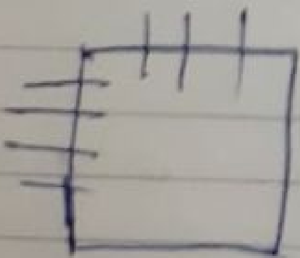
& [illegible]

a molecular latt

(discrete mathemat



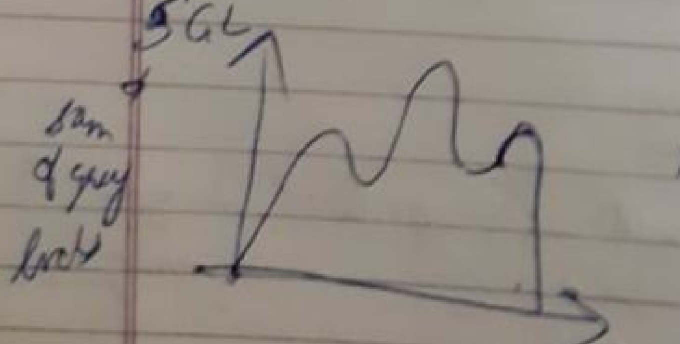
$$F_1\underbrace{(\hat{x},\hat{y},\hat{z})}_{\text{tensor}} \rightarrow F_2(\ ) \rightarrow F_3(\ ).$$



scan along x

& scan along y

Ⓐ



method of projectio
transformation

$$R_{LAT} = 2aN'^2 + 2bN_n + c^2\rho^2 n^2$$

$$= \alpha\left[\frac{2N'^2}{\alpha^2} + \frac{2N'\cdot n}{\alpha} + \frac{\rho^2 n^2}{\alpha^2 \alpha^2}\right]$$

$$= \frac{\alpha}{\alpha^2}\left[2N^2 + 2Nn\alpha + \frac{\rho^2 n^2}{\alpha^2}\right]$$

1. Too big $\alpha \Rightarrow$ loss of info

2.

complexity reduced $\Rightarrow$ loss of info
as $\rho \Rightarrow 0$
becomes nearly 0

3. α should be such that it accomodates the size of the data

optimum size.

$$\overline{R_{LAT}} = \alpha\left[2N^2 + 2\alpha Nn + \frac{\rho^2 n^2}{\alpha^2}\right]$$

$$\frac{d\overline{R_{LAT}}}{d\alpha} = 2Nn - \frac{2\rho^2 n^2}{\alpha^3} = 0$$

Enhancement →

||

Histogram Equilization

g → No. of grey levels of an image
↓
Normalized
to $\{0\ 1\}$

$T(g)$ ⇒ Monotonically ↑ fn
→ single valued fn
⇒ $0 < T(g) < 1$
$0 < g < 1$

$x = T(g)$ → enhanced image
$g = T^{-1}(x)$

x → when I put transformation on grey levels
↳ enhanced image

T^{-1}: should also follow the same properties which $T(g)$ meets

x & g both are random - let us assume

$P_g(g)$ → pdf of probability density function of original image

9.2.19

Computer vision

Morphological operators / functions / Transforms

Morphological operators:

- → Dilation
- → Erosion
- → Opening
- → Closing

→ help you to take up a small task & it becomes a function

$(t_k - s_m)^2 p_0(t_k) = 0$

dog → transforms into a lion
→ change in the morphology

image processing
→
changes

opening: o → circle

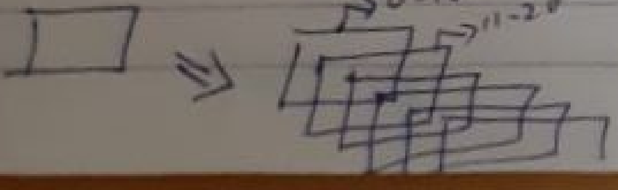
image: need to enhance it

Enhancement via function

H. transform:

→ Take a GLI (grey level image)
→ Break the grey levels into groups
(0-10, 11-20, - - -)

direction of facial features



⇒ small sub images

→ Template matching uses local edge gradient magnitude by approximating the maximum of the responses of the edge mass

$$\underset{\text{gradient mass}}{\underset{\swarrow}{g}} = \max[g_i], \; i = 1, \ldots, N$$

N : 8 – 12
to be more effective

⇒ Different gradient based edge detection method the local edge gradient magnitude is computed vectorially as a vector using non-linear transformation.

$$g_{Dc} = \sqrt{g_x^2 + g_y^2}$$

where g_x & g_y

$$g_x = \max[g_{xi}], \; i = 1, \ldots, N$$

$$g_y = \max(g_{yi}], \; i = 1, \ldots, N$$

$$\theta = \arctan\left(\frac{g_y}{g_x}\right)$$

$$C_k(u) = \alpha(u) \sum_{x=0}^{N-1} f(x) \cos\left[\frac{(2x+1)u\pi}{2N}\right]$$

point of trst

; where $U = 0, \dots N-1$

if you remove $f(x)$] → then its a kernel

if you add $f(x)$] → then its a transform

$$\alpha(u) = \frac{1}{\sqrt{N}} \; ; \; u = 0$$

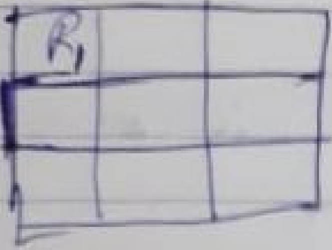
N = # symbols

$$= \sqrt{\frac{2}{N}} \; ; \text{ else}$$

from $U = 1, \dots N-1$

u \ x	0	1	2	3	4	5	7	8
0	1	1	1	1	1	1	1	1
1	1	0.8	0.5	0.2	-0.2	-0.5	-0.8	-1
2								
3								
4								
.								

Sub-image Analysis



= n parts

objects in sub-image $\propto$ (Part size)

$= K(\text{Part size})^{\alpha}$

related to energy of image $= K(\text{Part size})^2$

↗ sub image size

size => $\overline{N} \times \overline{N}$; $\overline{N} < N$ → image size

$$\alpha = \frac{N}{\overline{N}} > 1$$

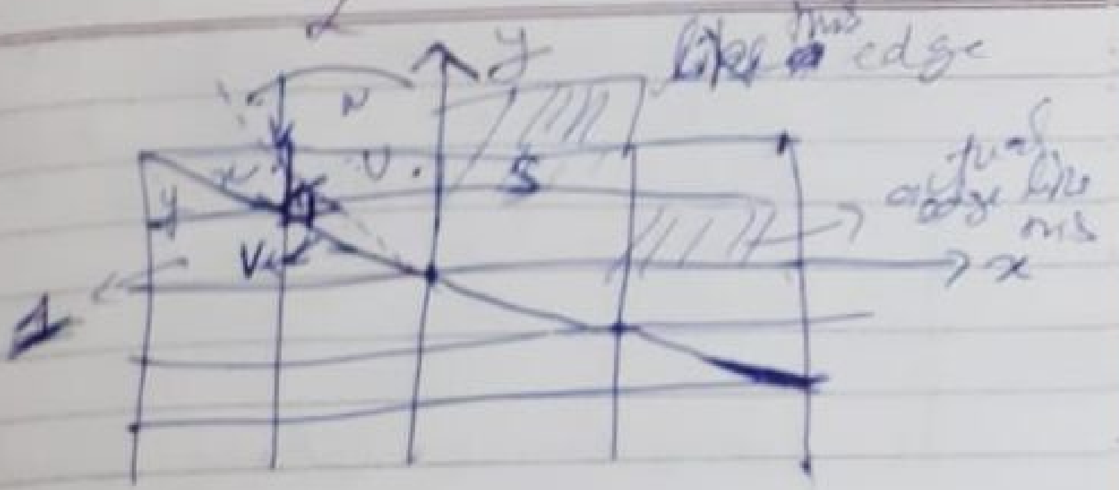
$$\overline{P} = \frac{P}{\alpha^2}$$

How many parts should we define in

R_{LAT} $\overline{N} = \frac{N}{\alpha}$

↙ complexity of Lateral

$$\overline{R_{LAT}} = \alpha\left(2\overline{N}^2 + 2\overline{N}n + \overline{P}^2 n^2\right)$$



area of one individual cell is one

x-axis response = (using for step edge

$(1+x+y-w)A+B$

$x+y+w=1$

$x+y=1-w$

$(1+1-w-w)A+B$

$2(1-w)A+B$

tically)

upper triangle)
above diagonal

α° response for step edge using 45° mask

α° respons $= (1+T ~~+V~~ -U)C+D$

vertically

(add upper triangle
above diagonal

≠ P(C)

n(c) ≠ 1

rated

limits

always

ear

PDF]

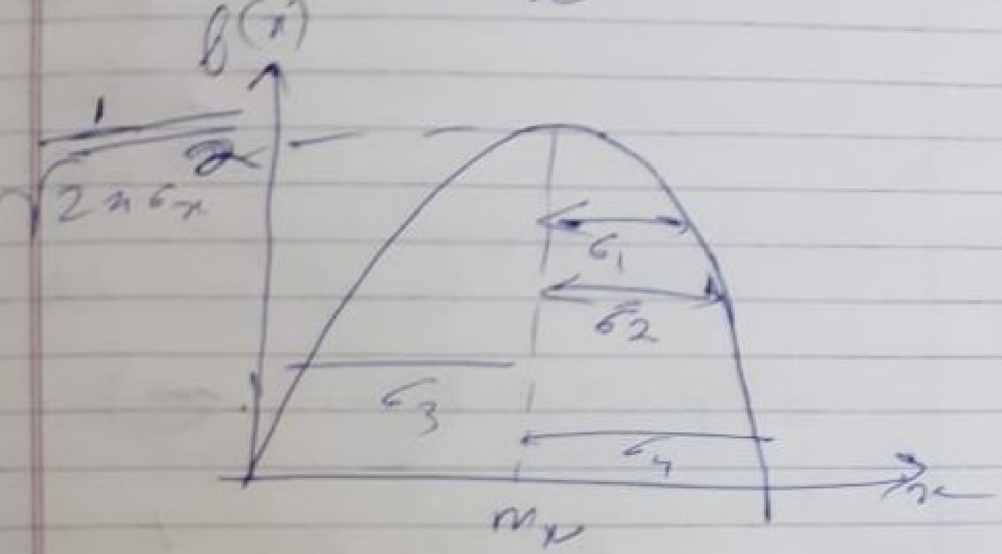
t problem

f3 .... ff4

blem

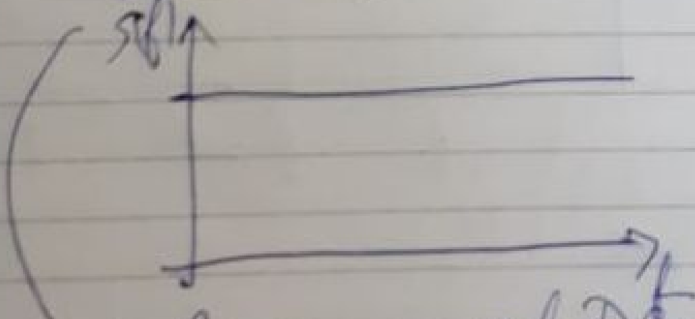
density function $= f_{gdf}(x)$

$$= \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-(x-m_x)^2/(2\sigma_x^2)}$$



GMM

White Noise / Coloured Noise



→ Power spectral Density

auto correlation

cross correlation

MSE : mean square error ~~mean square error~~

x & $\bar{x}$

~~$\sum_{i=1}^{n} \lambda_i$~~

$$\underbrace{\sum_{j=1}^{n} \lambda_j}_{\text{error}} - \sum_{j=1}^{k} \lambda_j$$

, when $K < n$

$$= \underbrace{\sum_{j=k+1}^{n} \lambda_j}$$

mean square error

K

to make data rate faster because 90% useful info on top.

K-L Transform

let $\underset{\text{matrix co-variance}}{C_x} = E\left[(x-m_x)(x-m_x)'\right]$

$A \rightarrow$ transformation Matrix
orthogonal

001 0010 001

10 0 001 110 011 0010

x u 111 001

$w(0,1) = \frac{1}{8}\prod_{i=0}^{2}(-1)^{b_i(0)\,b_{2-i}(1)}$

-1

u \ x	0	1	2	3	4	5	6	7
0	+1	+1	+1	+1	+1	+1	+1	+1
1	+1	+1	+1	+1	-1	-1	-1	-1
2								
3								
4								
5								
6								
7								

remove ← row 0 & row 1 = 0
↳ then orthogonal

$(-1)^{b_i(0)\,b_{2-i}(0)}$

basis function or kernel function has to be orthogonal if not then it will be a distructive transform

jpg = compress
↓
by a transform

behind every jpg there is a transform

// every transform by default compresses //

~~Haar~~ HAAR Tr
SLANT TR
Sine TR

Cosine Tr
↓
jpeg

technique

$\downarrow$

without this $\downarrow$ Dimension Reduction
cannot reduce : Amount of data

Poupalis

Innovation Process

$$N(t) = S(t) = S_1(t) + S_2(t) + \cdots + S_N(t)$$

$$\text{Avg.} = \frac{a+b+c}{3} = \frac{1}{3}a + \frac{1}{3}b + \frac{1}{3}c$$

$$\text{Sample Avg.} = a.p(a) + b.p(b) + c.p(c)$$

$$p(a) = p(b) = p(c) \rightarrow ①$$

$$p(a) + p(b) + p(c) = 1 \rightarrow ②$$

$$\text{Ensemble Avg} = a.p(a) + b.p(b) + c.p(c)$$

where $p(a) \neq b(b) \neq p(c)$

but $p(a) + p(b) + p(c) = 1$

$) = R(\tau)$

$f(\tau)$

$n(\tau)$

n theorem

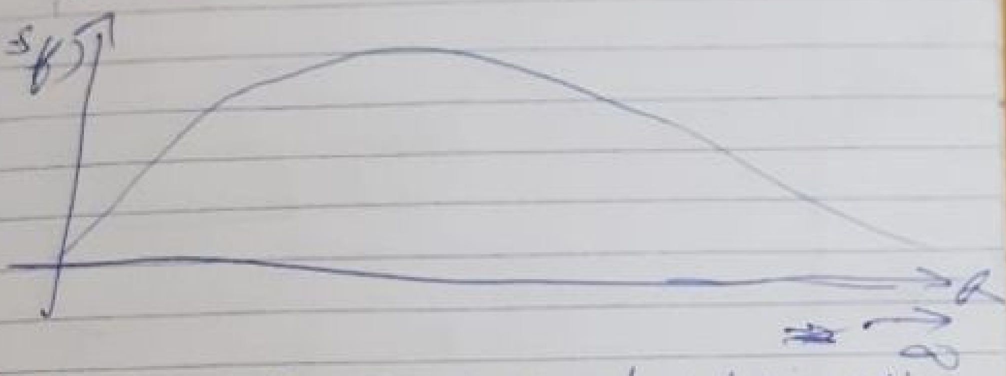
$\tau)$

$^{-1}(S(f))$

coloured noise

$\rightarrow f$

Gaussian white noise



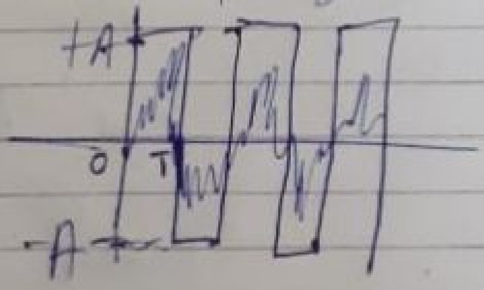
Entropy = measure of information content

whatever manner you can make max entropy to be max for the given noise when evaluated comes out to be a gaussian expression!

$x(t) = s(t) + w(t)$

↓ digital signal = +A, = −A } NRZ Not return to zero signal

↓ white noise

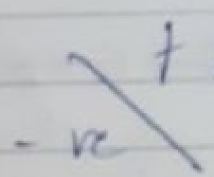


Prewitt 0° 45°

to change the mask

0° 45°

$$\begin{bmatrix} -1 & 1 & 1 \\ -1 & 2 & 1 \\ -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ -1 & 2 & 1 \\ -1 & -1 & 1 \end{bmatrix}$$



→ edge towards 45°

Kirsch:

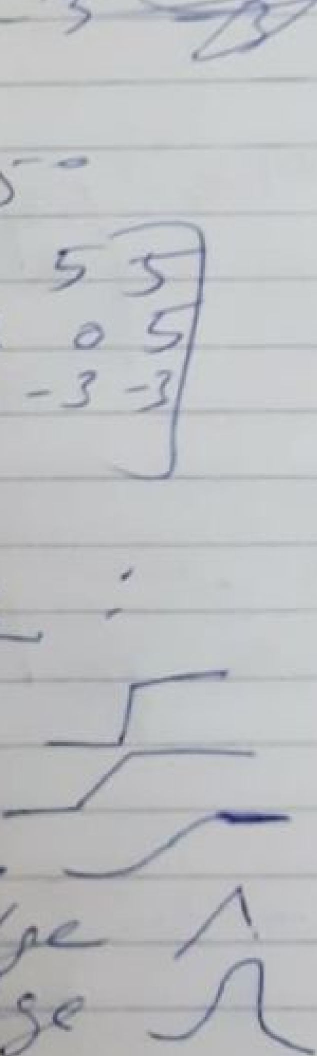
$$\begin{bmatrix} -3 & 3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}$$

0° 45°

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}$$

5 kinds of edges:

1) step edge
2) slant edge
3) ~~[illegible]~~ planar edge
4) Roofline edge
5) impulse edge



→ Let the image be of size N×N

→ Let there be an obj inside the img of size (n×n) pixels

$$TM \rightarrow N_n$$

~~→ objects this~~

$$R_{LAT} = 2aN^2 + 2bN_n + cp^2$$

Lateral histogram complexity

$a \approx b \approx c$

p = # of objects in the image

256×256 | 7 × ~~7~~

p = 20 objects

$$= \cancel{a}\, a\left[2N^2 + 2N_n + p^2 n^2\right]$$

$$= a\left[2\times256^2 + 2\times256\times7 + 20^2\times7^2\right]$$

normal image: N^2

template matching: even less

~~do~~ decrease complexity

(pdf) of transformed

$p_x(x) \Rightarrow$ probability density function of transform image.

pdf : UDF, [illegible], GDF, BDF, RDF

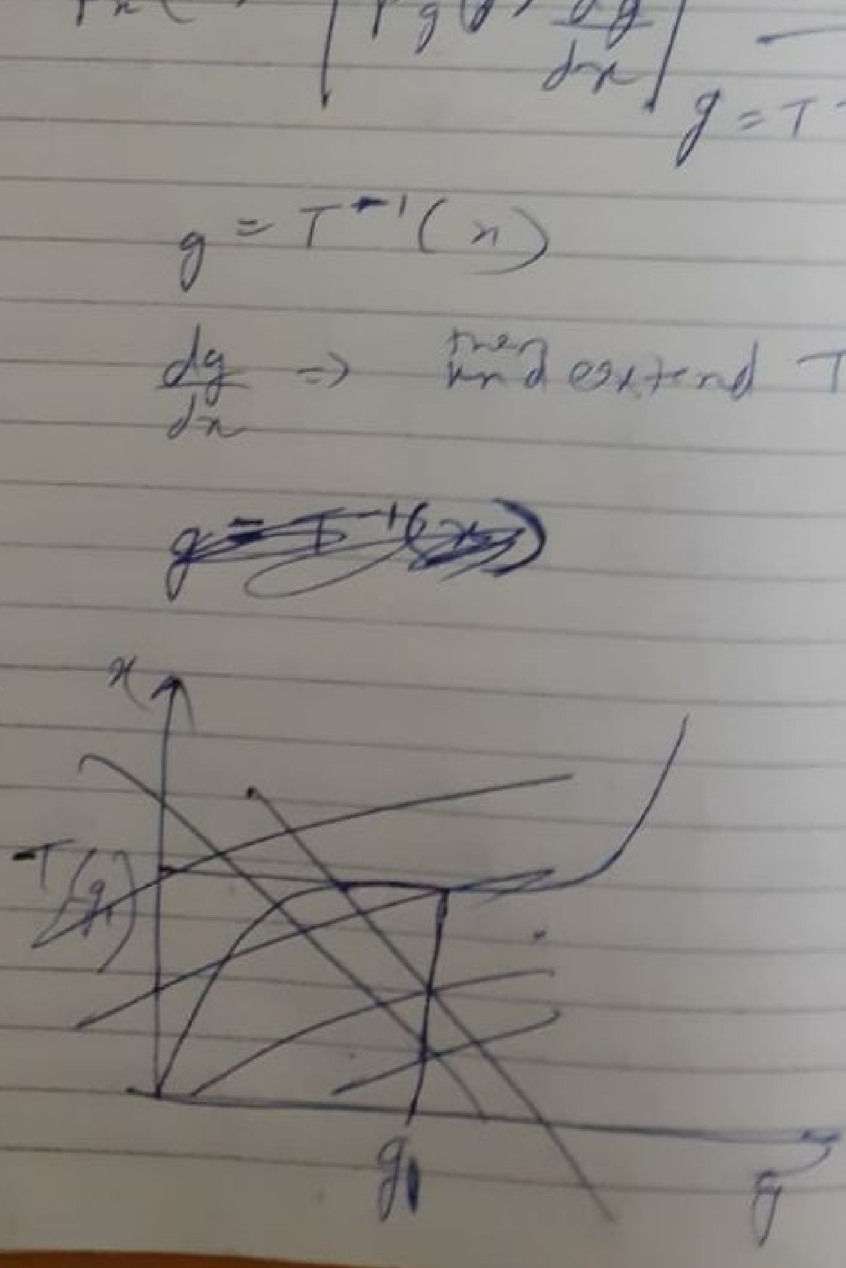
$p_x(x) =$ in terms of $p_g(g)$

$$p_x(x) = \left| p_g(g) \frac{dg}{dx} \right|_{g = T^{-1}(x)} \quad ①$$

$g = T^{-1}(x)$

$\frac{dg}{dx} \Rightarrow$ then ind extend T^{-1}

~~$g = T^{-1}(x)$~~



Metric properties

Reynold transform → MRT

→ Distence {Finds} the distance

Euclidean distance

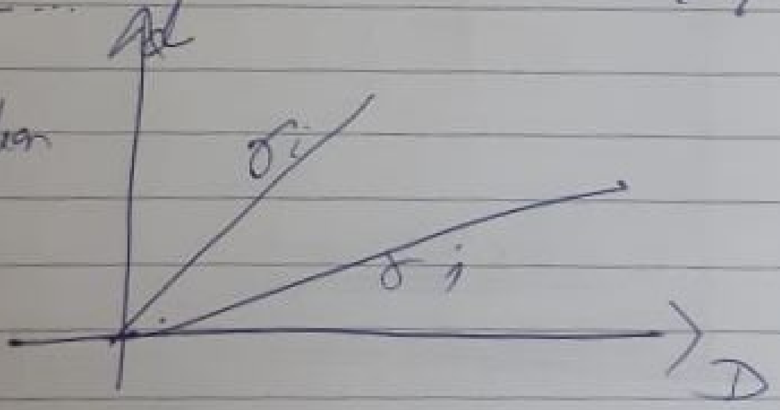
distance compute w.r.t to origin ⇒ normalized distance ("norm")

$d(i, j) = d(\delta_i, \delta_j) > 0$

$i \neq j$

Qu'est ce qu'elle parle ...

Euclidean



① $d(\delta_i, \delta_j) > 0$, $i \neq j$

② $d(\delta_i, \delta_j) = d(\delta_j, \delta_i)$

③ distances must follow the triangular rule

$$d(\delta_i, \delta_j) + d(\delta_j, \delta_k) \geq d(\delta_i, \delta_k)$$

(t), dt

d signal

t)dt

dt

(t)dt $\Big] \rightarrow ①$

$n)^2$

t

ristic

Date :

Page No. 3

$\sigma_y^2 = E(y - m_x)^2$

$\sigma_y^2 = \left(-A + \frac{1}{T}\int_0^T w(t)\,dt + A\right)^2 \rightarrow ②$

$\sigma_y^2 = E\left[\frac{1}{T}\int_0^T w(t)\,dt\right]^2$

$\sigma_y^2 = E\left\{\frac{1}{T^2}\int_0^T\int_0^T w(t).w(u)\,dt\,du\right\}$

$= \frac{1}{T^2}\int_0^T\int_0^T E(w(t).w(u))\,dt.du$

$= \frac{1}{T^2}\int_0^T\int_0^T R(t-u)\,dt\,du$

$= \frac{1}{T^2}\int_0^T\int_0^T \frac{N_0}{2}\,\delta(t-u)\,dt\,du$

$\sigma_y^2 = \frac{N_0}{2T^2}\int_0^T 1\,dt$

$= \frac{N_0}{2T^2}.T = \frac{N_0}{2T}$

$f(y/0) = \frac{1}{\sqrt{2\pi\frac{N_0}{2T}}}\, e^{-(y+A)^2 / \frac{N_0}{2T}}$

$= \frac{1}{\sqrt{\pi N_0}}\, e^{-(y+A)^2/N_0}$ At $T = 1$

$y(\beta)\, d\alpha\, d\beta$ makes resonates into 2D

$d\beta$

to degrading transfer function

or

point spread function

[PSF]

Wiener Filter

posterior vs prior learning

worked on prior knowledge

Case 1 $d(n) = s(n) \rightarrow$ original signal

desired signal

Case 2 $d(n) = s(n+D)$

delayed version

Case 3

$d(n) = s(n-D)$ [illegible]

↳ Priority worked on this case

⇒ convex ~~[illegible]~~ hull algorithm / Image
to use this

→ Morphological operators

→ Structuring element → (patch)

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \rightarrow \text{smaller}$$

bigger 3

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Histograms

ML

$$E = - \sum_{i} p_i \log p_i$$

2.9.19 Information gain (IG)

$$IG(S, A) = H(S) - \underbrace{\sum_{t \in T} p(t)\,(t)}_{\text{avg entropy}}$$

H(t) = entropy of subset

Sobel operator

Sobel : edge detection matrix as sobel operator

transfor is operator
(Ecis) (comp)

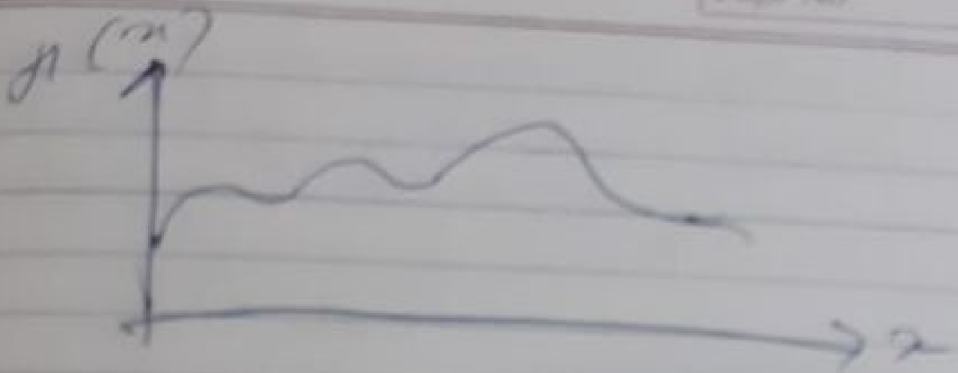
$$S_x = \begin{bmatrix} -1 & 0 & -1 \\ -2 & 0 & 2 \\ -1 & 0 & -1 \end{bmatrix}$$

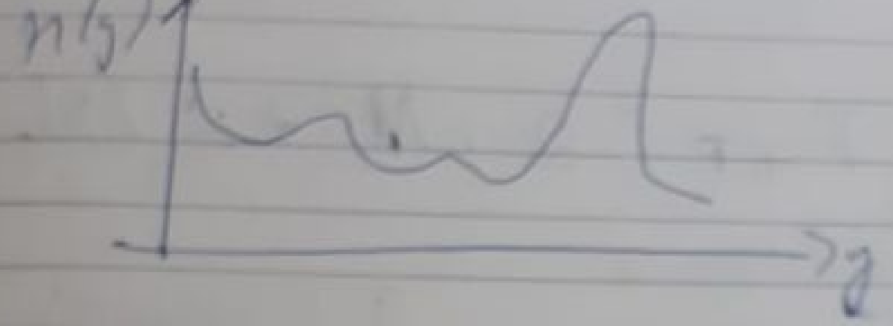
$$S_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

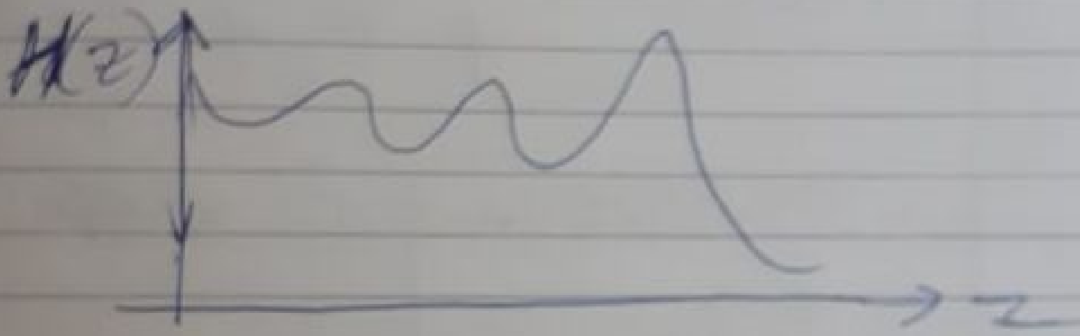
Prewitt operator

$$P_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$P_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$







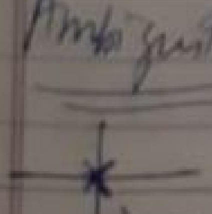
1. Discrete analysis
2. Complexity

Lateral Histogram

3. Object Identification

Huff transfo
to identify
a [illegible] line
to
(or make 2D→3D)
can identify circle

Ambiguities/ Drawbacks of Lateral Histogram



we cannot identify the intersecting points

$A . C_x . A^T$ ⇒ Diagonal matrix

↓

eigen vector

↓

~~[illegible]~~

&

99%

have equivalent of the energy of info

Considering few top eigen vectors

↓

principal components | PCA

PCA is used until
Dimension reduction

MDS
ICA
ISOMAP
LLE
] intelligent transformation

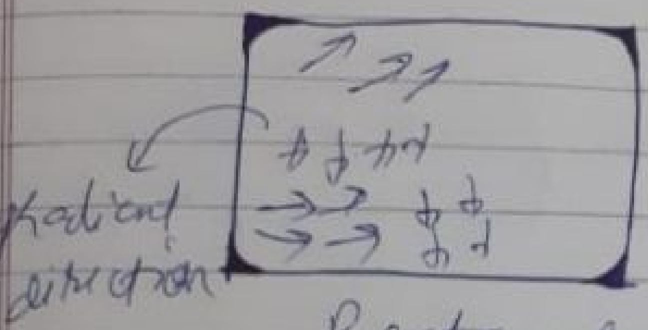
Edge Detection : video signals

Edge Detection

→ Template matching

→ Differential Gradient based

→ basis of both technique is gradient



Rectangular

Circular kind of Marking

→ If we use the step edge orientation in the neighbourhood of central pixel.
Earlier approach is fine.
→ In practical gives an error of 6.6° on an average
error → $E(Avg) = 6.6°$

→ To avoid this go for a circular ~~kind~~ operators

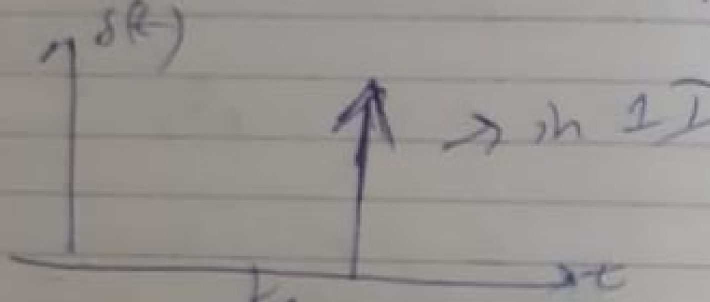
Circular operators:

→ One of the way to limit the error and restrict the observations of the edge to a circular neighbourhood

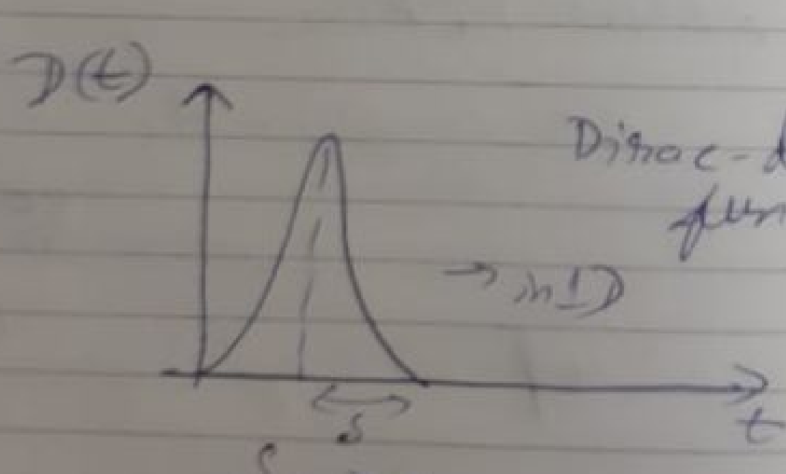
→ If we need to increase # of pixels in neighbourhood, we assume $\eta(x, y) = 0$

$$g(x,y) = H[s(x,y)] = H\left[\int_{-\infty}^{\infty}\int s(\alpha,\beta).\delta(x-\alpha, y-\beta)\,d\alpha\,d\beta\right]$$

$$= \int_{-\infty}^{\infty}\int s(\alpha,\beta)\underbrace{H.[\delta(x-\alpha, y-\beta)]}_{\text{point spread fn [PSF]}}\,d\alpha\,d\beta$$



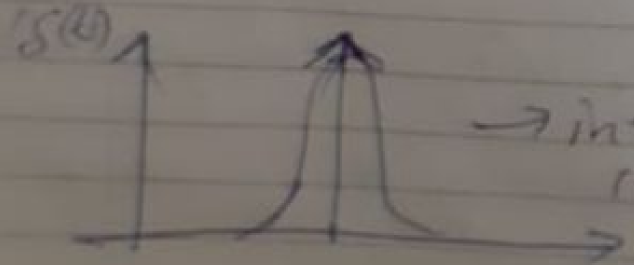
Kronecker delta function



Dirac-delta function

$\delta \to 0$

when in 2D kronecker gets for



(loading effect

& causing rep

Wi

positi

work

case 1

desired
figure

case 2

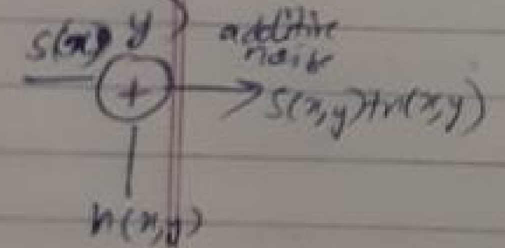
case 3

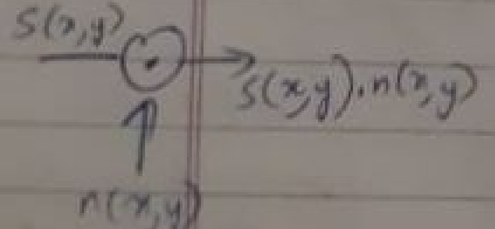
d

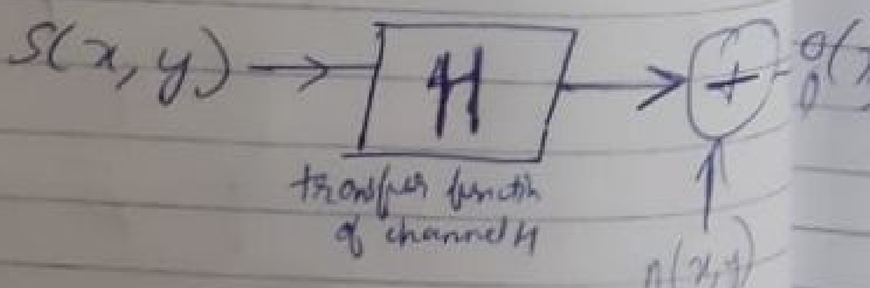
1) Regular addressing
2) Immediate Addressing
3) Direct Addressing
4) Register Indirect Addressing
5) Based Addressing
6) Indexed Addressing
7) Based Index Addressing
8) String Addressing
9) Direct I/O port Addressing
10) Indirect I/O port Addressing
11) Relative Addressing
12) Implied Addressing

4.9.19 CV

Original image ⇒ Fog, smog, smoke, dust, fire, blur
⇓
Degradation Model
(there is noise in the image)







generally at time noise is additive in nature

To reduce freq → use multiplication
additive → spectrum doesn't change
multip → spectrum changes, new type of freq introduced