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EC-353 Computer Vision

Topic: Bayes Law.

$x \rightarrow$ original data

$y \rightarrow$ noisy Data

$$p(x) \cdot p\left(\frac{y}{x}\right) = p(y)\, p\left(\frac{x}{y}\right)$$

$p(x)$ - a-priori

$p(y)$ - a-priori

$p\left(\frac{x}{y}\right)$ - a - posteriori

$p\left(\frac{y}{x}\right)$ - a - priori

MA $\rightarrow$ Filters (Moving Avarage)

$\Downarrow$

Zeros

Denominator - Poles

$$H(z) = \frac{N(z)}{D(z)}$$ - Autoregressive Systems

ARMA Models - Auto Regressive Moving average Models

$A A B A^T A^T$

$FT\,(f(t)) = f(w)$

$FT\,(f(w) = f(t)$

$$E[e^{jwt}] = \int_{-\infty}^{\infty} e^{jwt} f(t)\, dt$$

$$E[X] = \sum x \cdot f(x)$$

$$= \int_{-\infty}^{\infty} x \cdot f(x)\, dx$$

Hadamard Transform

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

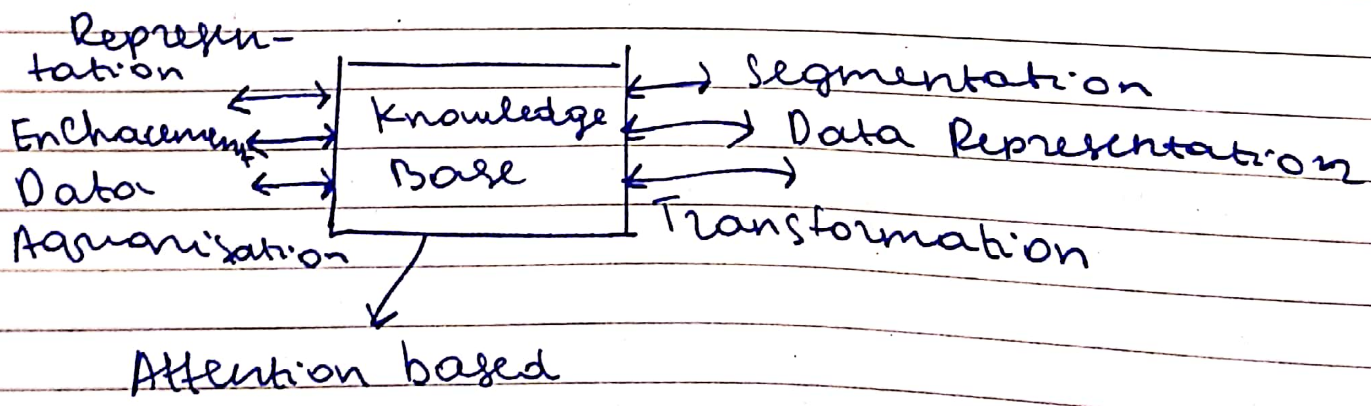
$$H_4 = \begin{bmatrix} H_2 & H_2 \\ H_2 & -H_2 \end{bmatrix}, \quad H_8 = \begin{bmatrix} H_4 & H_4 \\ H_4 & -H_4 \end{bmatrix}$$

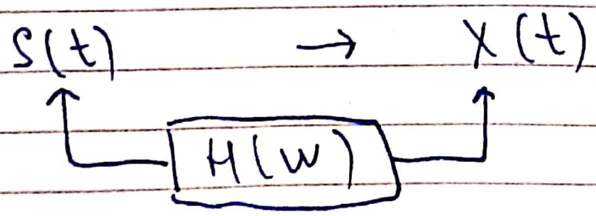
$$= \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & +1 \end{bmatrix}$$

$1 - 1 + 1 - 1 = 0$

$1 + 1 + 1 - 1 = 0$

$1 - 1 - 1 + 1 = 0$





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Topic : Computer vision. Concepts

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

$$R(w) = \int_{-\infty}^{\infty} \underbrace{f(t)}_{F} \; \underbrace{e^{-jwt}}_{A} \, dt$$

$B = AFA^T$ - Diagonal matrix

A - Orthogonal matrix

$B = AFA^T \Rightarrow$ Diagonal matrix

+ve definite. $\Downarrow$

eigen vectors

Every transform is a comprehension technique in itself

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

Statistical avg = $ap(a) + bp(b) + cp(c)$

$p(a) = p(b) = p(c)$ - (1)

$p(a) + p(b) + p(c) = 1$ - (2)

Ensemble avg = $ap(a) + bp(b) + cp(c)$

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

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

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Probabilities are unequal

$MA = ap(a) + bp(b) + cp(c)$

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

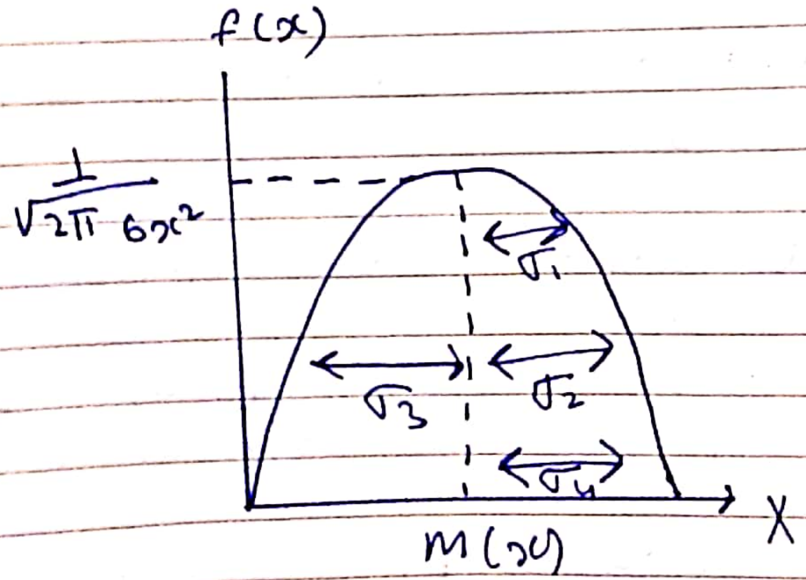
$\& \; p(a) + p(b) + p(c) \neq 1$

Probability density function
Uniform density function
Gaussian density function
RDF
Naragami density function
Binominal density function

GMM $gdf = pdf_1 \cdots pdf_2 \ldots pdf_n$

Gaussian density function

$$f_M(x) = \frac{1}{\sqrt{2\pi 6x^2}} e^{-(x-m_x)^2/2\sigma x^2}$$



White noise / colored noise

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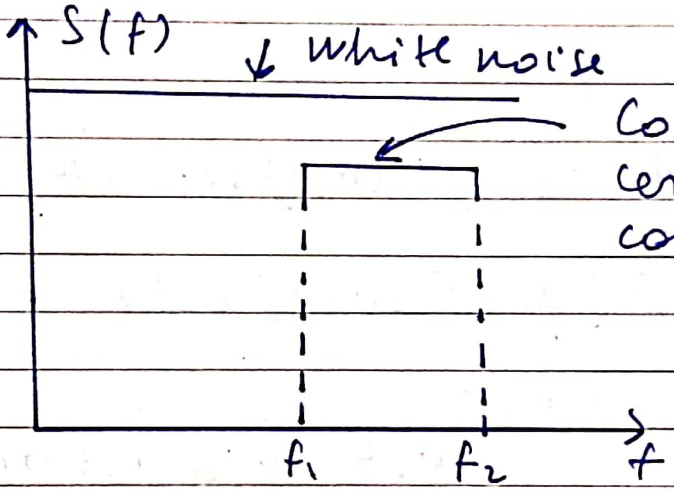
$$\sum_{t=0}^{\infty} x(t)\; x(t-\tau) = R(t)\; v(t)$$

Weiner - Khintchin theorem

$$S(f) = FT(R(T))$$
$$R(T) = F(T)^{-1}(S(f))$$

Power spec density gives behaviour of signal



Consist only for certain range
colored noise

• Enthropy is a measure of info content Whenever and whatever function manner you can make that enthropy to the max for the given noise that condition when evaluated comes out to be gaussian eqn (noise is gaussian)

$$x(t) = s(t) + w(t)$$
$$s(t) = \left.\begin{matrix} +A \\ -A \end{matrix}\right] \; NR\ 2$$

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$$y(t) = \int_0^T (x(t) \,.. 1\, dt$$

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

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

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

$$m_x = -A$$

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

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

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

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

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

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

$$= \frac{1}{T^2}\int_0^T\int_0^T \frac{N_2}{2}\,\delta(t-a)\,dt\,du$$

$$= \frac{N_2}{2T^2}\int_0^T 1 \cdot dt \quad \{t = u\}$$

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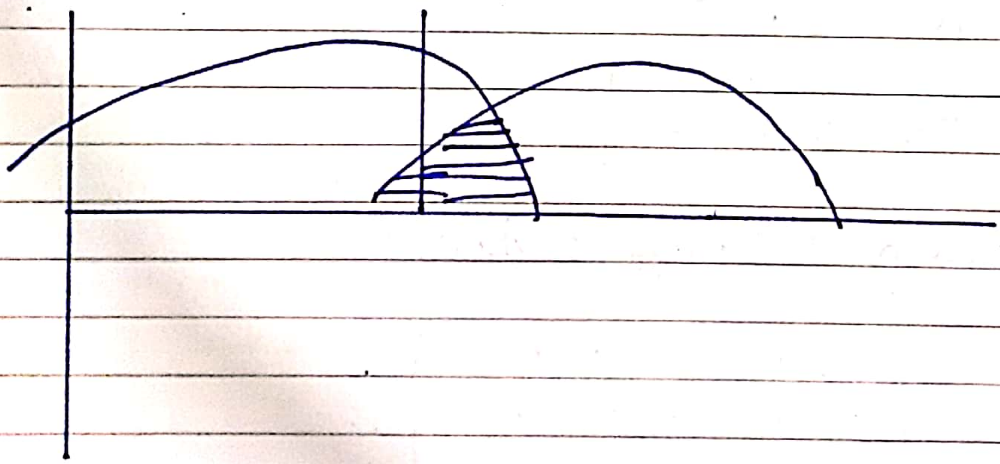
$$= \frac{N_0}{2T^2} \times \cancel{T} = \frac{N_0}{2T}$$

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

Let $T = 1$

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

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



$$P_{01} = \int_0^\infty f(y/0)\, dy$$

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Topic: Geometrical Transforms

Translation:

$x^* = x + \Delta x$

$y^* = y + \Delta y$

$z^* = z + \Delta z$

$$\begin{bmatrix} x^* \\ y^* \\ z^* \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \Delta x \\ 0 & 1 & 0 & \Delta y \\ 0 & 0 & 1 & \Delta z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

Scaling

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

Rotation (Along z Axis)

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

Rotation (Along x-axis)

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

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Unitary Transforms

⇓

Walsh Transform

$N = 2^n$; $8 = 2^3$ $n = 3$

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

Kernel transform

$b_k(z) = b_k(110)$

$z = 6 - (110)$ kth Bit of Binary representation of 2

$b_0 = 0$ $b_1 = 1$ $b_2 = 1$

$n = 3$ $W(0,0) = \frac{1}{8}\left[\prod_{i=0}^{2} (-1)^{b_i(0)\, b_{2-i}(0)}\right.$

$N = 8$

y \ x	0	1	2	3	4	5	6	7
0	+	+	+	+	+	+	+	+
1	+	+	+	+	−	−	−	−
2								
3								
4								
5								
6								

HAAR Transform
Slant Transform
Sine Transform

Cosine Transform

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

$u = 0 \ldots (n-1)$

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

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

u \ x	0	1	2	3	4	5	6	7	8	
0	1	1	1	1	1	1	1	1	1	1
1	1	1								
2										
3										

Hotteling Transform

$$[X] = \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{n-1} \end{bmatrix} \qquad m_x = E[X]$$

$$C_x = \left[(X - m_x)\cdot(x - m_x)^T\right]$$

1) Real
2) Symmetrical

Toeplitz

$A(i) = A(i-j)$

X_i and X_j are uncorrelated

$C_{ij} = C_{ji}$

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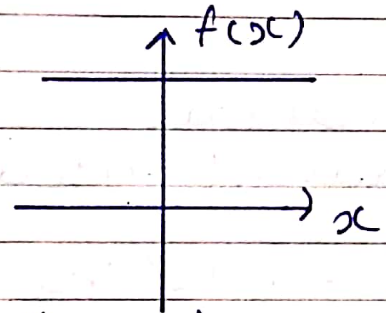
$$m_x = \frac{1}{m}\sum_{i=0}^{m-1} x_i \cdot f(x) \rightarrow \text{UDF}$$

If $f(x)$ is a udf (uniformly distributed function) then statistical average will be = E.A (Ensamble average)



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

Transform - ortho-normal Matrix

$$A \cdot \underbrace{\sqrt{x}}_{\text{Eigenvalues}} \cdot A^T = \text{Diagonal Matrix}$$

<u>MSE</u>

$x \varepsilon \bar{X}$

$$\sum_{y=1}^{n} l_j - \sum_{j=1}^{k} l_j,\ k< = \sum_{j=k+1}^{n} l_j$$

K.L. Transform

Let

$$C_x = E\left[(x - m_x)(x - m_x)^T\right]$$

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$A \rightarrow$ Transformation Matrix

$A C_x A^T \Rightarrow$ Eigen Vectors

$\Downarrow$

Considering few top eigenvectors

$\Downarrow$

Principal Components

Edge Detection

Template Matching

Differential Gradient Based

The template matching uses local edge gradient magnitude by the approximately maximum of the responses of edge mask

$$g = \max[g_i], \quad i = 1 \dots N$$

(gradient mask)

8-12

In differential gradient the local edge magnitude is computed vectorically as a vector using a non-linear transform

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

$$g_x = \max[g_x], \quad i = 1 \dots N$$

$$g_y = \max[g_y], \quad i = 1 \dots N$$

$$\theta = \arctan(g_y / g_x)$$

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Scanned by CamScanner

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Sabel operator

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

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

Prewitt Operators

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

0°

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

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

45°

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

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

45°

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

Types of edges:

1) Step edge
2) Slant edge
3) Signal / Planar edge
4) Triangular edge
5) Impulse Edge

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$0°$

$$\begin{bmatrix} -A & 0 & A \\ -B & 0 & B \\ -A & 0 & A \end{bmatrix}$$

$45°$

$$\begin{bmatrix} 0 & C & D \\ -C & 0 & C \\ -D & -C & 0 \end{bmatrix}$$

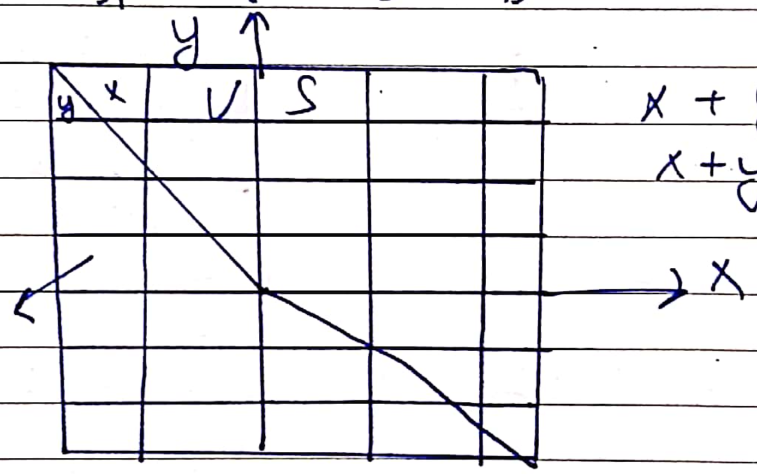
Response for $0°$ mask ($0°$ response) using $0°$ mask for step edge

$= 2A + B$

$45°$ mask using $0°$ response $= A + B$

$0°$ response $- C + D$

$45°$ response $- 2C + D$



$x + y + w = 1$

$x + y = 1 - w$

α-axis response $=$

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

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

$= (1 - w) A + B$

$\alpha°$ response

$= (1 + T + S - V) C + D$

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Topic: Edge detection
Data vs Mask Generalization
Let the data be

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \qquad C = \frac{B}{\sqrt{2}} \quad \Bigg| \quad D = \frac{A}{\sqrt{2}}$$

$$g_{0^\circ} = A((c+i-a-g) + B(f-d)$$
$$g_{90^\circ} = A(a+c-g-i) + B(b-h)$$
$$g_{45^\circ} = C(b+f-d-h) + D(c-g)$$

$$g_{45^\circ} = \frac{g_0 + g_{90}}{\sqrt{2}}$$

If we use the step H edge orientation in the neighbourhood of the central pixel then the earlier approach is fine, if this approach gives an error of 6.6° in average

$$\varepsilon(avg) = 6.6.$$

Circular operator is one of the way to limit the error and restrict the observations of the circular neighbor.

If we need to increase the number of pixels in neighbourhood then we have to go beyond 4 and 8 connected.

Another replacement of edge detec-

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tion is known as labeling or labeling

Segmentation

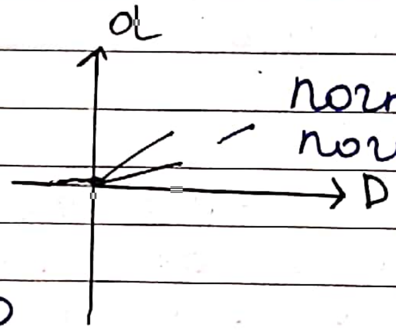
$$\begin{bmatrix} G_1 - & \theta_1 \\ G_2 - & \theta_2 \\ \vdots & \vdots \\ G_n - & \theta_n \end{bmatrix} \text{ - Data matrix}$$

$[e_1, e_2, e_3]$

Metric Properties

$\Downarrow$

Distance $\qquad (d(i,g))$



normalized norm (distance)

$d(r_i, r_g) > 0$

$i \neq 0$

$d(r_i, r_j) = d(r_j, r_i)$

Triangle rule:

$d(r_i, r_j) + d(r_j, r_k) \geq d(r_i, r_k)$

Morphological operations

Structuring element

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