Computer Vision

Bayes Law

$X \rightarrow$ original Data

$Y \rightarrow$ Noisy Data

$$p(X)\, p(Y/X) = p(Y)\, p(X/Y)$$

MA $\rightarrow$ Filters — Moving Average Models

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

Only numerator : zeros

Denominator : Poles

$\Downarrow$

Autoregressive Systems (AR systems)

ARMA Models (Autoregressive Moving Average)

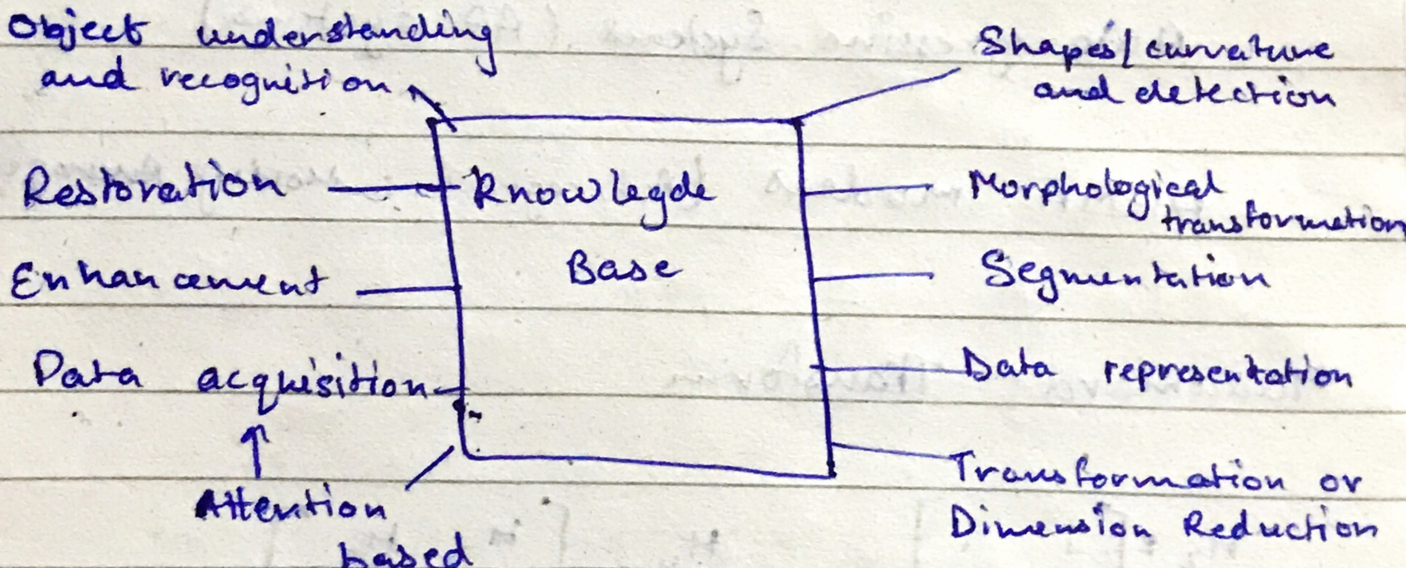
Hadamard Transform

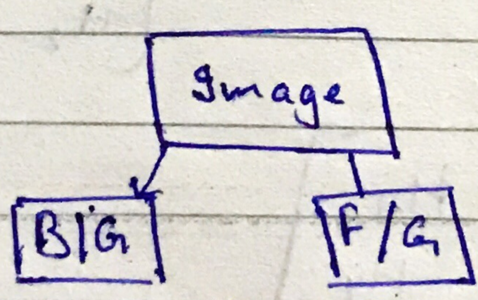
$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \qquad H_4 = \begin{bmatrix} H_2 & H_2 \\ H_2 & -H_2 \end{bmatrix}$$

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

$$H_4 = \begin{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} & \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \\ \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} & \begin{bmatrix} -1 & -1 \\ -1 & 1 \end{bmatrix} \end{bmatrix}$$

$$H_4 = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \begin{array}{l} \\ \}\,0 \\ \}\,0 \quad 0 \\ \}\,0 \end{array}$$





Computer Vision

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

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

(Z-axis)

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

Unitary Transform

$\Downarrow$

Walsh Transforms

$N = 2^n$, $8 = 2^3 \Rightarrow n = 3$

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

$\downarrow$

Kernel of Transform

$b_k(z) = b_k(101)$

$\downarrow$

k^{th} bit of binary value.

$n = 3$

$N = 8$

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

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								

Haar Transform

Slant Transform

Sine Transform

Cosine Transform.

COSINE TRANSFORM

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

$u = 0 \dots n-1$

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{N}} & ; u = 0 \\ \sqrt{2/N} & ; u \text{ is something else.} \end{cases}$$

u \ x	0	1	2	3	4	5
0	1	1	1	1	1	1
1						
2						
3						

HOTELLING Transform

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

$$m_x = E[x]$$

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

$$\Downarrow$$

1. Real
2. Symmetrical

x_i and x_j are uncorrelated

$$C_{ij} = C_{ji}$$

If $f(x)$ is uniformly distributed function.

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

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

$\downarrow$

Transform ortho-normal matrix.

KL - transforms

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

$A \rightarrow$ Transformation Matrix

$A C_x A^T \Rightarrow$ Eigen vectors

$\Downarrow$

Considering few top eigen vectors

$\Downarrow$

Principal Components (PCA)

Transforms you require to compress da

EDGE DETECTION

Template matching

Differential Gradient Based.

It uses the local edge gradient magnitude by approximating the max of the responses of the edge masks.

$$g = \max [g_i] \quad i = 1 \ldots n$$

In differential gradient edge detection the local edge gradient magnitude is computed vectorly using some non-linear transformation.

$$g_x = \max [g_{x_i}] \quad i = 1 \ldots n$$

$$g_y = \max [g_{y_i}] \quad i = 1 \ldots n$$

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

Sobel Operator

It is one of the edge detection technique

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

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

Prewitt Operators.

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

Prewitt at 0°

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

Prewitt at 45°

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

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

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