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Global & regional features

Multimodal
Classification
* Structural - micro texture patterns (texels)
eg: fabric, grass, water

gradient → first ~~derivative~~ derivative

* ~~Statistical~~ Statistical - Gray level statistical moments.

* Model based: fractal, stochastic, semi-random field
* Transform or basis based - fouriers, Gabor, zoneric, wavelets, statistical moments.

History (1960, 1970, 1980)
- Whole ~~image~~ object approaches
- Early 1990s, partial object approach
- Mid 1990s, local feature approaches.
- Late 1990s
classified invariant
local feature approaches.
- Early 2000
Scene & object modelling
approaches
SIFT, HAAR
OpenCV → Bradski

- Mid 2000s

fine grain feature
metric composition
app composition

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Computer V
(Global & regional features)

8 bit → Half fold
↳ 4 bits
Mouthful
↳ 2 bit

Edge metrics

Edge density = $\frac{gm(d) \text{ kernal size}}{\text{pixels in region}}$ gradient magnitude

Edge contrast = $\frac{\Sigma d}{\text{max pixel value}}$

Edge entropy

$$E_e = \sum_{i=0}^{n} gm(x_i) \log_b gm(x_i)$$

$\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right)$

edge directivity

$$E_e = \sum_{i=0}^{n} g_d(x_i) \log_b g_d(x_i)$$

edge linearity

E_l = Cooccurrence of collinear edge pairs

* edge periodicity,

$E_p = a, b, c$

* edge size,

$E_s \cdot a, d / b, d / c, d$

Exam * edge primitive length total

4x4

= total length of gradient magnitude with same direction.

	0	1	2	3
0	0	0	1	1
1	0	0	1	1
2	0	2	2	2
3	2	2	2	3

0°, 90°, 135°, 45°

	0	1	2	3
0	4	2	1	0
1	2	4	0	0
2	1	0	6	1
3	0	0	1	2

	0	1	2	3
0	6	0	2	0
1	0	4	2	0
2	2	2	2	2
3	0	0	2	2

	0	1	2	3
0	2	1	3	0
1	1	2	1	0
2	3	1	0	2
3	0	0	2	0

	0	1	2	3
0	4	1	0	0
1	1	2	2	0
2	0	2	4	1
3	0	0	1	0

SDM

Area
small ~ large
64X64
Always start with smaller areas

Haralick matrices

$p(i,j)$ — $(i,j)^{th}$ entry in a normalized gray-tone SDM, $= \frac{P(i,j)}{R}$

$P_x(i)$ — i^{th} entry in marginal probability matrix obtained by summing the rows of $p(i,j) = \sum_{j=1}^{N_g} p(i,j)$

N_g : No. of distinct gray levels in the quantized image.

$\sum_i \quad \sum_j \quad \sum_{i=1}^{N_g} \quad \sum_{j=1}^{N_g}$

$$P_y(j) = \sum_{i=1}^{N_g} p(i,j)$$

$$P_{x+y}(k) = \sum_{\substack{i=1 \\ i+j=k}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \quad k=2,3\ldots 2N_g$$

$$P_{x-y}(k) = \sum_{\substack{i=1 \\ |i-j|=k}}^{N_g} \sum_{j=1}^{N_g} p(i,j) \quad k=0,1,\ldots N_g-1$$

$p(\bar{x})$

fig - second largest eigen values

$$\boxed{|A - \lambda I| = 0}$$

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Object Recognition :

~~(Chapter 11)~~

Feature = = Pattern = = descriptors

Pattern class = ω_i = similar properties

Pattern

↳ Vectors (quantitive descriptions)

Strings & trees (structural ")

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$x_i \rightarrow$ i^{th} descriptor out of total n descriptors

Ex: Iris flowers. → sentosa (ω_1)

↳ virginica (ω_2)

↳ versicolor (ω_3)

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

↳ for each flower

$x_1, x_2 \rightarrow$ petal width & ~~petal~~ length. parameters

4 moments → mean

→ ~~median~~ median

→ kurtosis

→ skewness

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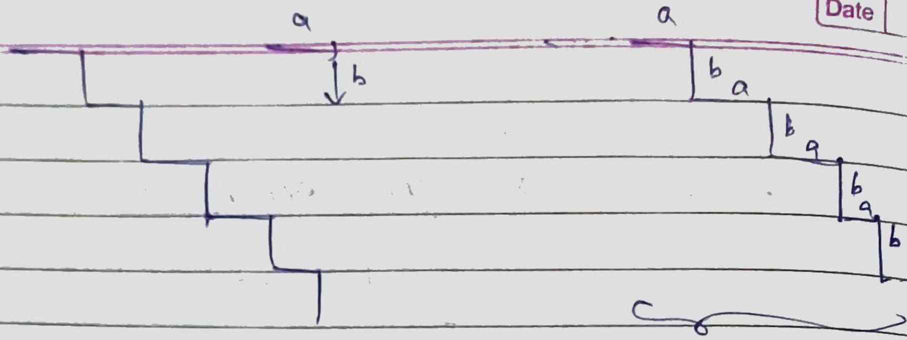
structural based pattern :
↳ basic structure is repeated



representing as string

$w = ab \cdot bab$

~~we identified the structure that is being repeated &~~ hence ~~we convert it to pattern.~~

~~(string descriptors)~~ $\xrightarrow{\text{more complex version}}$ True descriptors

Recognition

↳ uses decision functions

$x = (x_1, x_2, \dots x_n)^T$

W pattern classes : $\omega_1, \omega_2, \dots, \omega_W$

Task → to find W decision function $d_1(x), d_2(x) \dots d_W(x)$ with a property, if a pattern x belongs to class then $d_i(x) > d_j(x)$; $j = 1, 2 \dots W$ & $j \neq i$

* decision boundary ~~where~~ seperating w classes w_i & w_j is given by where

$$\boxed{d_{ij}(x) = d_i(x) - d_j(x) = 0}$$

> 0 if class belongs ~~of~~ to w_i

< 0 if class belongs to w_j

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Recognition technique based on matching:

represent each class by a prototype pattern vector
class is assigned a pattern vector to which it is closest to.

(1) distance
(2) Correlator

4/4/24 (writing)

Matching (Min distance classifier)

the prototype of each pattern class is defined as the mean vector of the patterns in that class.

$$\bar{m}_j = \frac{1}{N_j} \sum_{x \in \omega_j} \bar{x}_j \qquad j = 1, 2, \ldots \omega \qquad (5)$$

No. of pattern vector from class w_j.
To determine class membership through euclidean dist.

$$D_j(\bar{x}) = \|\bar{x} - \bar{m}_j\| \qquad j = 1, 2, 3 \ldots \omega \qquad (6)$$

$$\|a\| = (a^T a)^{1/2}$$

Selection of smallest class can be represented as a single function of the form:

$$d_j(\bar{x}) = \bar{x}^T \bar{m}_j - \frac{1}{2} \bar{m}_j^T \bar{m}_j \qquad j = 1, 2, 3 \ldots \omega \qquad (7)$$

$\begin{array}{r} 30 \\ 152 \\ +\ 450 \end{array}$

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eqⁿ 4 & eqⁿ 7, the decision boundary between classes w_i & w_j from min dist classifier is

$$d_{ij}(\bar{x}) = d_i(\bar{x}) - d_j(\bar{x})$$
$$= \bar{x}^T(\bar{m}_i - \bar{m}_j) - \frac{1}{2}(\bar{m}_i - \bar{m}_j)^T(\bar{m}_i - \bar{m}_j) = 0$$

(8)

$n=2$, ⊥r bisector is a line
$n=3$, ⊥r " " " plane.
$n>3$, ⊥r " " hyperplane

q

w_1	w_2
Iris versicolor	Iris setosa

mean vector

$\bar{m}_1 = (4.3, 1.3)^T$ $\quad \bar{m}_2 = (1.5, 0.3)^T$

~~$\bar{m}_2 = ($~~

$$d_1(\bar{x}) = \bar{x}^T\bar{m}_1 - \frac{1}{2}\bar{m}_1^T m_1$$

$$= \overset{(x_1, x_2)}{\begin{pmatrix} \cancel{x_1} \\ x_2 \end{pmatrix}} \begin{pmatrix} 4.3 \\ 1.3 \end{pmatrix} - \frac{1}{2}(4.3, 1.3)\begin{pmatrix} 4.3 \\ 1.3 \end{pmatrix}$$

$$= 4.3x_1 + 1.3x_2 - \frac{1}{2}(18.49 + 1.69)$$

$$\boxed{d_1(\bar{x}) = 4.3x_1 + 1.3x_2 - 10.09}$$

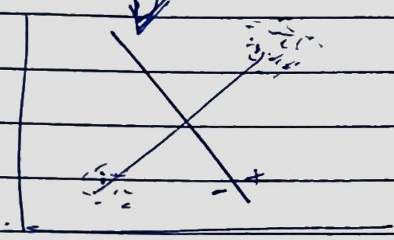
$$d_2 = (x_1, x_2)\begin{pmatrix} 1.5 \\ 0.3 \end{pmatrix} - \frac{1}{2}\cancel{(4.3\ 1.3)}\,(1.5\ 0.3)\begin{pmatrix} 1.5 \\ 0.3 \end{pmatrix}$$

$$= 1.5x_1 + 0.3x_2 - \frac{(2.25 + 0.09)}{2}$$

$$\boxed{d_2(\vec{x}) = 1.5x_1 + 0.3x_2 - 1.17}$$

eq^n 8

$$4.3x_1 + 1.3x_2 - 10.09 = 1.5x_1 + 0.3x_2 - 1.17$$
$$2.8x_1 + x_2 - 8.92 = 0$$



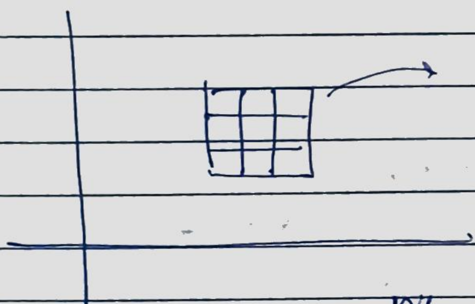
Correlation

$$\boxed{C(x,y) = \sum_s \sum_t f(s,t) \times w(x+s, y+t)}$$

8/4/24 Matching by correlation :

$w(x,y)_{J \times K}$ $f(x,y)_{M \times N}$

$$C(x,y) = \sum_s \sum_t f(s,t)\, w(x+s, y+t)$$



Multiply the corresponding points of mask and image & add them.

we get $C(x_0, y_0)$

We get many C values for all points, the max^m match is max^m (x_0, y_0)

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Correlation coeff. we calculate,
(r)

$$\cancel{\frac{f(s,t) - \bar{f}(s,t)}{f(s,t) - \bar{f}(s,t)}}$$

$$= \frac{\sum_s \sum_t [f(s,t) - \bar{f}(s,t)]\,[w(x+s, y+t) - \bar{w}(x+s, y+t)]}{\left\{ \sum_s \sum_t [f(s,t) - \bar{f}(s,t)]^2 \sum_s \sum_t [w(x+s, y+t) - \bar{w}(x+s, y+t)]^2 \right\}^{1/2}}$$

$$\sum_s \sum_t (f(s,t) - \bar{f}(s,t)) \times \sum_s \sum_t (w(x+s, y+t) - \bar{w}(x+s, y+t))$$

* that is Normalization of correlation process against scaling

Classifiers
- probabilistic approach
- reduce the classification error

W
w_θ

$p(w_i/\bar{x})$

L_{ij} → error in classifying
Avg. loss is assigning $\bar{x}$ to class w_j is

$$r_j(\bar{x}) = \sum_{k=1}^{W} L_{kj}\, p(\omega_k/\bar{x}) \quad \text{--- (1)}$$

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$$p(A/B) = \frac{p(A)\, p(B/A)}{p(B)}$$

$$r_j(\bar{x}) = \frac{1}{p(x)} \sum_{k=1}^{w} L_{kj}\, p(\bar{x}/w_k)\, p(w_k) \quad (12)$$

scaling factor
which is common for all
dropped
(13)

$~~r_j(\bar{x}) = \sum~~$

Base Classifier (when scaling factor is dropped)

$r_i > r_j$

then it belongs to class i

$$\sum_{q=1}^{w} L_{qj}\, p(x/w_j)\, p(w_k) \quad (14)$$

* $L_{ij} = 1 - \delta_{ij} \quad (15)$

* $\delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$

wakad

* $r_j(\bar{x}) = \sum_{k=1}^{w} (1 - \delta_{kj})\, p(\bar{x}/w_k)\, p(w_k)$

$= p(\bar{x}) - p(\bar{x}/w_j)\, p(w_j) \quad (16)$

$$p(\bar{x}) - p(\bar{x}/w_i)\,p(w_i)$$
$$< p(\bar{w}) - p(\bar{x}/w_j)\,p(w_j)$$

(17)

Equivalently

$$p(\bar{x}/w_i)\,p(w_i) > p(\bar{x}/w_j)\,p(w_j)$$

(18)

$$d_j(\bar{x}) = p(\bar{x}/w_j)\,p(w_j)$$
$$j = 1, 2, \ldots w$$

(18)