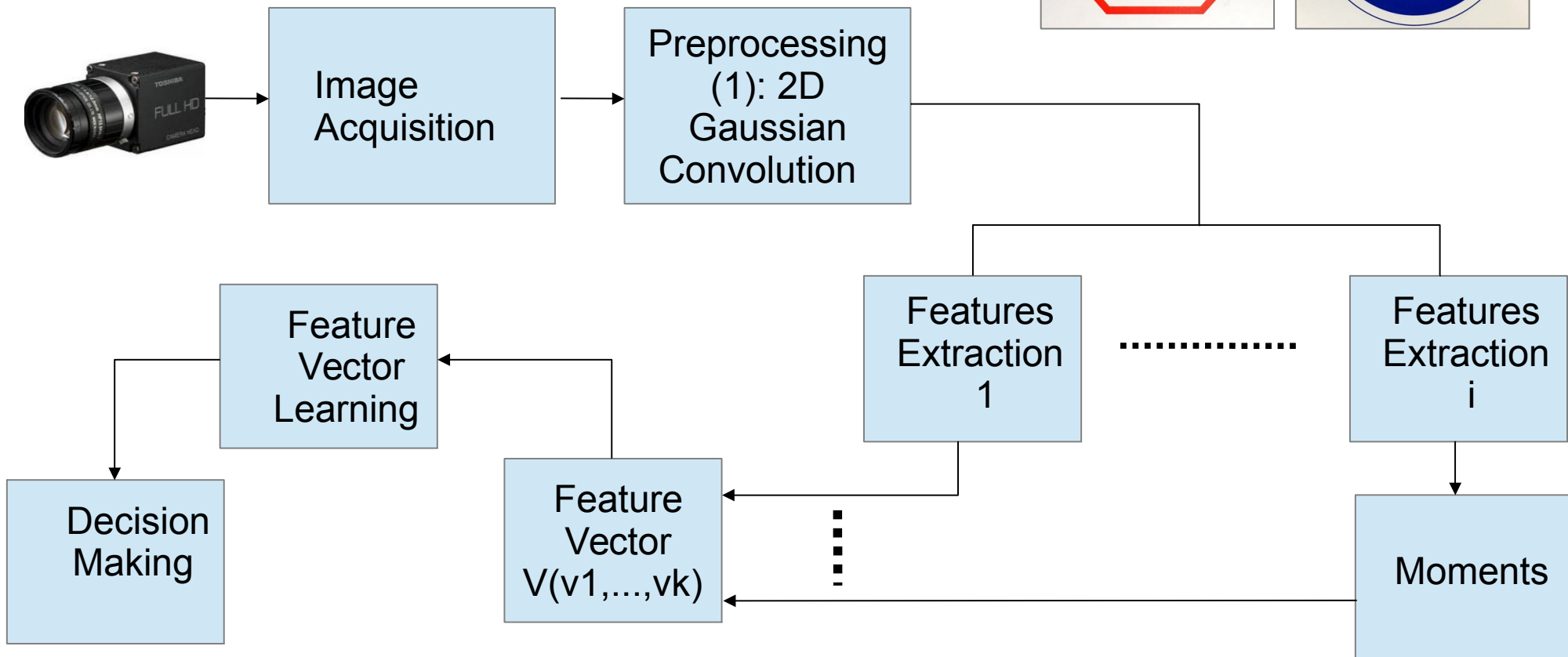


Separation of Floor Track Example With Practical Challenge



Intro to Moments for Objects Recognition

Objectives: Develop a technical to detect different shaped, different color, different size objects



Pattern Recognition For Binary Images

The tool box for pattern recognition for binary images

1. Size
2. Moments

\bar{x}

\bar{y}

\bar{x}^k

\bar{y}^k etc.

3. Perimeter
4. Orientation
5. Compositions of the above

Perimeter and moments: vector

6. Invariant operators
 - size invariant
 - orientation invariant
 - illumination invariant

Note: Starting from binary images, extended to color images

Biologically inspired techniques

- Rule 1. Proximity
- Rule 2. Similarity
- Rule 3. Closure
- Rule 4. Good continuation
- Rule 5. Symmetry
- Rule 6. Simplicity

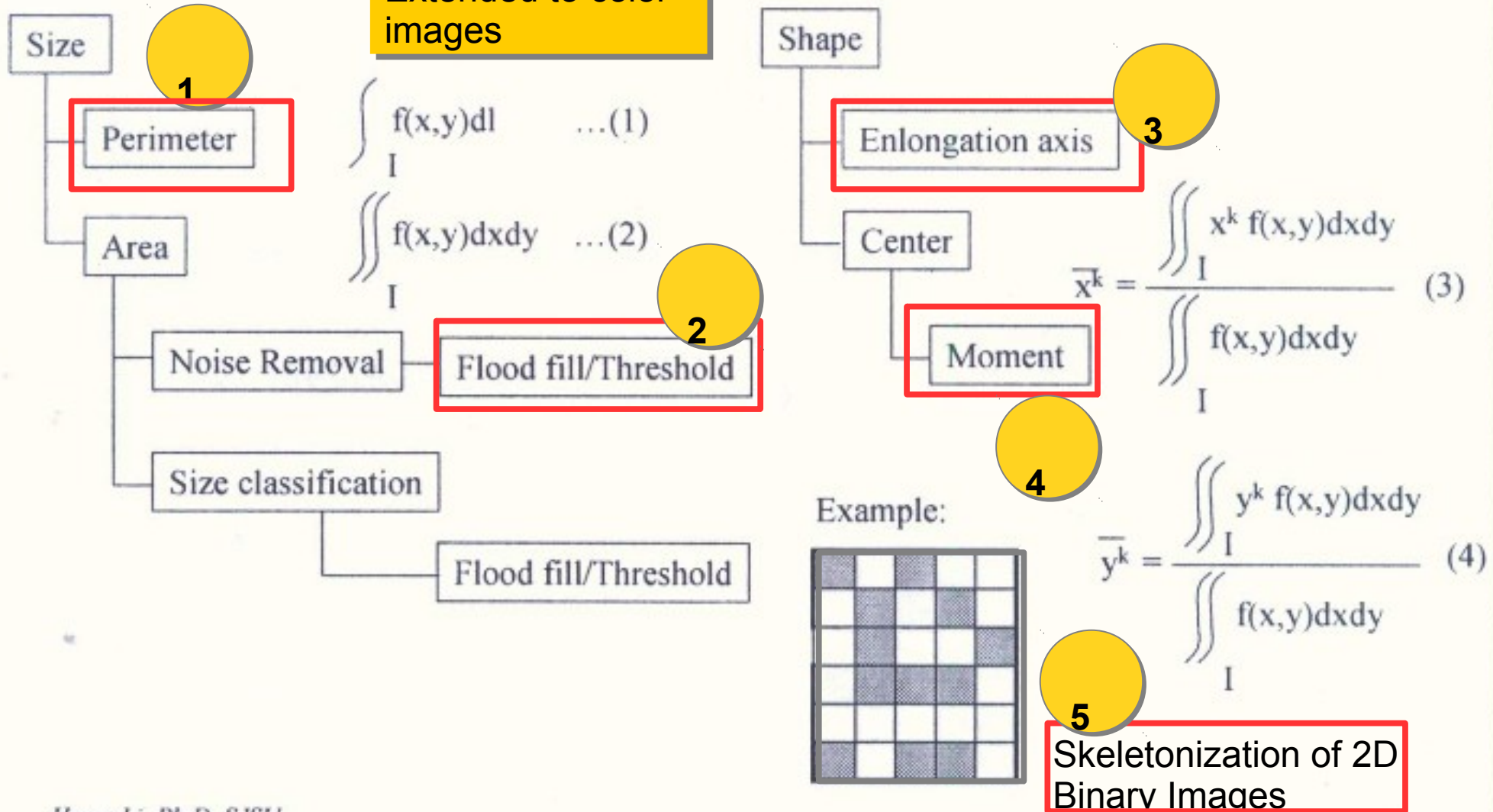
Note: 'Proximity' usage for clean up binary image and remove noise, as well as growing boundary points per 'good continuation' rule to form a better edge map.

Note: Similarity defines a interesting question, how to describe one object is similar, or somewhat similar to others, neural network and fuzzy logic may help.

Ground rule: signature of a image, tools including 3 invariant characteristics

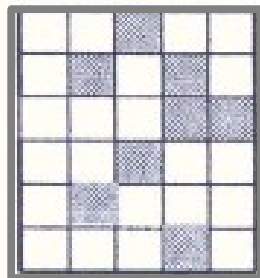
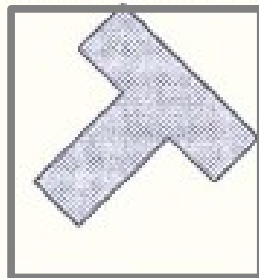
Binary Image Processing

Extended to color images



Example On Simple Pattern Recognition

Given two binary images, derived from two objects, T and O, design a technique to identify them



Example: Computation of
 (1) Area (size);
 (2) X-bar;
 (3) Y-bar;
 (4) Orientation, theta angle
 (5) Perimeter of an object

Fig1(a),(b)

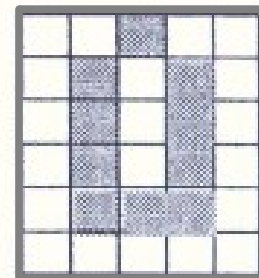
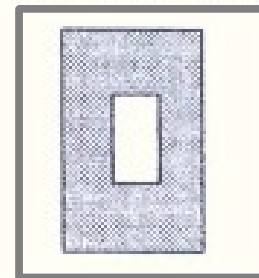


Fig2(a),(b)

Good continuation or noise? What to do with this noise?

Feature Vector		Size	X-bar	Y-bar	Orientation	Perimeter	
V_1(v1,..., v5)	T	v11	v12	v13	v14	v15	From Fig1(b)
V_2(v1,..., v5)	L	v21	v22	v23	v24	v25	From Fig2(b)

Intro Feature Characterization

Example: Fill out this table based on the characteristics of each feature

	Perimeter v1	Area v2	x_bar v3	y_bar v4	Theta v5	Moments v6-vi	Hu-Moments v(i+1)-vk
Illumination invariant							
Scale invariant			Y	Y	Y		Y
Orientation Invariant							Y

Perimeter:

$$P = \int_{\Omega} f(x,y) dl$$

Or,

$$P = \sum_{k_1=1}^N \sum_{k_2=1}^M B'(x,y)$$

Where $B'(x,y)$ from object whose neighboring pixels belong to background

x_bar:

$$\bar{x} = \frac{\iint_{\Omega} x B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy}$$

y_bar can be defined similarly

Moments:

$$M_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x,y) dx dy$$

Central moments:

And

$$\mu_{pq} = \frac{\iint_{\Omega} (x-\bar{x})^p (y-\bar{y})^q B(x,y) dx dy}{A}$$

Orientation Computation

$$\tan 2\phi \triangleq \frac{b}{a-c}$$

$$a = \iint_{\Omega} (x - \bar{x})^2 B(x, y) dx dy \quad \dots (2)$$

$$b = \iint_{\Omega} 2(x - \bar{x})(y - \bar{y}) B(x, y) dx dy \quad \dots (3)$$

$$c = \iint_{\Omega} (y - \bar{y})^2 B(x, y) dx dy \quad \dots (4)$$

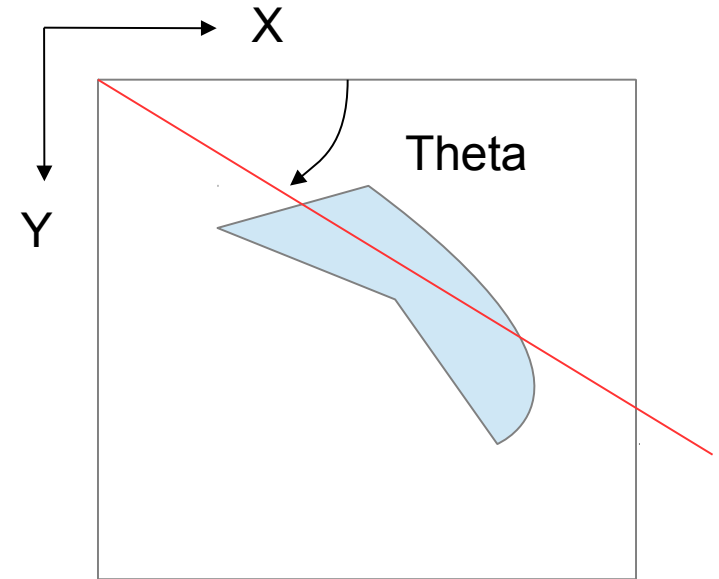
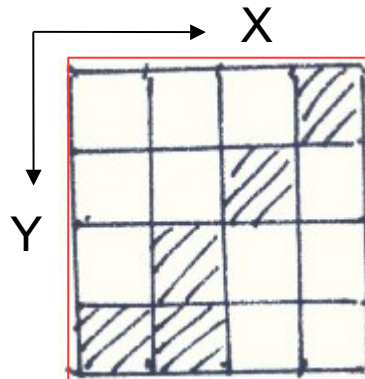
Example: See my handout

$$a = 7$$

$$b = -8$$

$$c = 6$$

$$\text{Theta} = -41.4375$$



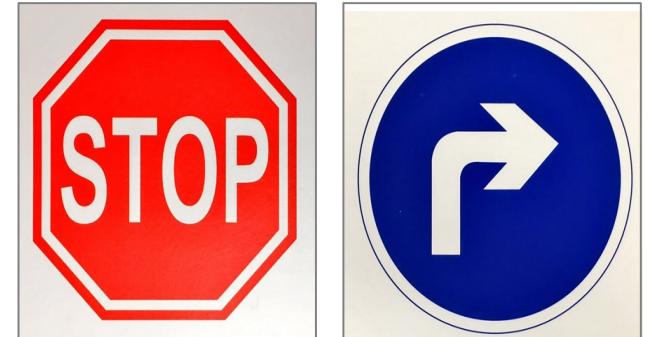
Reference: Robot Vision, by
BPK, Horn, Chapter 3, pp. 46-
64

Note: my hand calculation use
integer, when have access to
computer, use Float!
(x_bar = 2.8 changed to 3, and
y_bar = 2.4 changed to 2)

Raw Moments

The "raw moment" of order $(p + q)$ for image $f(x,y)$ is defined as:

$$M_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy \quad (1)$$



For the discrete function, we have:

$$M_{ij} = \sum_x \sum_y x^i y^j I(x, y) \quad (2)$$

Note: image $I(x,y)$ can be binary image or gray scale images. But we start the discussion from the binary images first.

We can treat image intensity as its probability density function

$$\sum_x \sum_y I(x, y) \quad (3)$$

Reference: Robot Vision, by BPK, Horn, Chapter 3, pp. 46-64

Color Flood Fill Testing

CMPE247 Video Array, March 8, 2018 Harry Li.

1° March 22nd midterm Exam.

2° Homework ON Floodfill

Rubrics

II.1. Testing Pattern
(1+1) Color Image

Part II (Color Images)

3 pts

Part I (GrayScale Images)

2 pts

Numpy 2D Array Definition → Convert to
(See P.P.T. from the Class) MAT

OpenCV Data Type

→ 3 color image
ImagePlane.

cv.imshow()

Result1 Result2 Result3

cv.imshow("res1")...

cv.imshow("res1")...

II.2. Color floodfill
Check the results.

II.2. Input (res1, res2, res3)

User Input: 1° Color?

2° Threshold = ?

Input Thr. < Total Pixels (b, u, b2)

cv.imshow("res1")...

cv.imshow("res1")...

Output of the 1st image:
For 'res1' → Black (all 0's)
'res2' → Black (all 0's)
'res3' →

Submission:

1° CANVAS

2° E-mail: huali@sisu.edu

Due Sat. 11:59pm

Source Code
Walk Through
after Submission

II.2.3. Test Binary Images (Labels)

(1+1)
Test Image: 5x5

Numpy &
MAT (OpenCV)

Input

Output

1° Then, user input: Threshold L = 2

2° Filtering Operation? Threshold H = 4

which Region?

Threshold H
Threshold L

Note: Scanning
the image left,
TAB so "b3"
shown & included.

Note: Color Part II should Allow Any meaningful
Size color Image to be processed;

Part I (2pts): I.1 Any 5x5 Image (Binary Image)
I.2 Any Size Binary Image.

Binary Image Features

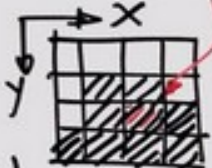
CMPE297 Video Analytics / March 8, 2018 2/74L

Size (AREA)

1. Perimeter $\int_L B(x,y) dx \dots (1)$

Note: "Complexity" Describe
1st Shape of A given
Binary Pattern:
Consider 2 patterns.
Below.

"8" Connected, "Contour":
 $B(x,y)$, Find its $P(x,y) = ?$

Fig 1. 

$\sum_{Q \in \text{Contour}} B(x,y) = P(B(1,1)) + P(B(1,2))$
 $P(B(2,1)) + P(B(3,2)) + P(B(3,3)) +$
 $P(B(2,3)) + P(B(1,3)) + P(B(0,3)) +$
 $P(B(2,2)) = 9 = P_{\Sigma}$

"4" Connected Neighbours, w/o Counting $B(2,2)$
Hence, $P_{\Sigma} = 8 = P_{\Sigma}$

2. AREA, $A = \iint_{\alpha} B(x,y) dx dy \dots (2)$

Example: $A = \sum_y \sum_x B(x,y) \dots (2^*) = 9$

Given $B(x,y)$ in
Fig. 1. Find $A = ?$
 $A = A(B(1,1)) + A(B(2,1)) + A(B(1,2))$
 $+ A(B(2,2)) + A(B(2,2)) + A(B(0,3)) + \dots$

$A_1 = A_2$
 $\hat{=} \iint_{\alpha} B(x,y) dx dy.$

Index $\hat{=} \frac{P}{A} \dots (3)$

2nd "Signature" texture w/ unique
mapping a Binary
Image.
 $\hat{=} \text{Oriental Computation.}$
 $\hat{=} \text{First moments.}$

Moments

CMPE297 Vision Analytic March 8, 2018 Harry Li. 3/ Generalize Egn (3-1), (3-2)

$$\bar{x}^k = \frac{\iint_{\Omega} x^k B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy} \quad \dots (3-1)$$

Now, Feature Vectors,

$$\vec{V} = (P, A, \bar{x}, \bar{y}) = (V_1, V_2, V_3, V_4)$$

$$m_{pq} = \frac{\iint_{\Omega} (x-\bar{x})^p (y-\bar{y})^q B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy} \quad \dots (4)$$

$p, q = 0, 1, 2$ (3 or bigger Not used often)

$$\bar{y}^k = \frac{\iint_{\Omega} y^k B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy} \quad \dots (3-2)$$

If Adding Index = P/A then 5th Dimension,

$m_{01}, m_{02}, m_{10}, m_{11}, m_{12}, m_{20}, m_{21}, m_{22}$ (8 Features)

Example: Given Image in Fig. I. Compute m_{12}

$$\text{Sol: } m_{12} = \frac{\iint_{\Omega} (x-\bar{x})(y-\bar{y})^2 B(x,y) dx dy}{A}$$

$$= \sum_{y=0}^2 \sum_{x=0}^2 (x-\bar{x})(y-\bar{y})^2 B(x,y) / 2 = \sum_{y=0}^2 \sum_{x=0}^2 (x-1.5)(y-1.5)^2 B(x,y) \cdot \frac{1}{2}$$

$$= (1-1.5)(1-1.5)^2 B(1,1) \cdot \frac{1}{2} + (2-1.5)(2-1.5)^2 B(2,2) \cdot \frac{1}{2}$$

"Hu"

Note: \bar{x}, \bar{y} physical meaning, Spread from (\bar{x}, \bar{y}) . $p=q=1$ (5+8)

2. Not a Signature! 3. Vector Feature Dimension upto 13

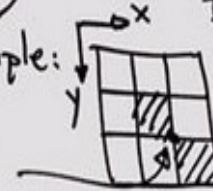
$$\vec{V} = (P, A, \text{Index}, \bar{x}, \bar{y}, m_{01}, m_{02}, m_{10}, m_{11}, m_{12}, m_{20}, m_{21}, m_{22})$$

When $k=1$. (\bar{x}, \bar{y}) center of the Image

$$\vec{V} = (P, A, \text{Index}, \bar{x}, \bar{y})$$

$B(x,y)$

Example:



$$\text{Find } \bar{x} = \frac{\iint_{\Omega} x B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy} = (V_1, V_2, \dots, V_5)$$

$$\text{Sol: } A = \iint_{\Omega} B(x,y) dx dy = \sum_x \sum_y B(x,y)$$

$$= B(1,1) + B(2,2) = 1 + 1 = 2; \text{ and } \iint_{\Omega} x B(x,y) dx dy =$$

$$\sum_{y=0}^2 \sum_{x=0}^2 x B(x,y) = 1 \cdot B(1,1) + 2 \cdot B(2,2) = 1 + 2 = 3 \therefore \bar{x} = \frac{3}{2} = 1.5$$

$$\bar{y} = \frac{\iint_{\Omega} y B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy} = \frac{1}{2} (\sum_x \sum_y y B(x,y)) = \frac{1}{2} (1 \cdot B(1,1) + 2 \cdot B(2,2)) = \frac{3}{2} = 1.5$$

Fig 1

Map To Feature Vectors

IP110 March 10th, 2018 Harry Li.

① 2D Convolution
 ② Kernel Design
 ③ Binarization
 Filtering: Flood Fill
 HW. Algorithm.

BACKGROUND
 Binary Image
 Feature Extraction.
 (Colour Images) " CATI CATI

1) Perimeters.
 $P(x,y) = \int B(x,y) dl \dots (1)$

Example:
 $P(x,y) = \int B(x,y) dl = \sum_i$

① (A): $\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} B(x,y) = A$
 $= A(B(1,1)) + A(B(2,1)) + \dots + A(B(3,3))$
 $= 1 + \dots + 1 = 9$

Features for "Stop" & "Right" Signs.

I: $P_s, A_s \Rightarrow \vec{V}_I = (V_1, V_2) = (V_{I1}, V_{I2}) \dots (3)$
 II: $P_r, A_r \Rightarrow \vec{V}_I = (V_1, V_2) = (V_{I1}, V_{I2}) \dots (4)$

Fig. 1 I(Stop):
 Fig. 2 II(Right):

From (3) $\vec{V}_{Ii} = (V_{Ii1}, V_{Ii2})$
 $i=1,2,3$ Similarly, $\dots (3x)$
 From (4), $\vec{V}_{IIi} = (V_{IIi1}, V_{IIi2})$
 $i=1,2,3$ Similarly, $\dots (4x)$

Map the Feature Vectors.
 For Class I (Stop) $i=1,2,3$
 $i=1$, From (3x)
 $\vec{V}_{I1} = (V_{I11}, V_{I12})$
 $\vec{V}_{I2} = (V_{I21}, V_{I22})$
 $\vec{V}_{I3} = (V_{I31}, V_{I32})$

For Class II (Right)
 $\vec{V}_{II1} = (V_{II11}, V_{II12})$
 $\vec{V}_{II2} = (V_{II21}, V_{II22})$
 $\vec{V}_{II3} = (V_{II31}, V_{II32})$

From Fig. 3 $\vec{V} = (V_1, V_2) \subseteq I?$
 OR $\subseteq II?$
 Map it back to Feature Vector Space.

Then, Engage Machine Learning
 (1) Data Analytics
 (2) Decision Function.

Complexity of A Binary Image.
 Index = $P/A \Rightarrow 3rd Dimension \dots (5)$
 $\vec{V}_{Ii} = (V_{Ii1}, V_{Ii2}, V_{Ii3})$

Moments. $\bar{X}^k = \frac{\iint_{\Omega} x^k B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy}$, $\bar{Y}^k = \frac{\iint_{\Omega} y^k B(x,y) dx dy}{\iint_{\Omega} B(x,y) dx dy}$

Flood Fill
 MAT i SRC
 2D Log
 Video Capture
 Preprocessing Fig. 3.
 $P, A?$
 $(V_1, V_2) =$

8-Connectivity
 Features:
 Class I (Stop) P_s
 Class II (Right) P_r
 2. AREA (Size)
 $A = \iint_{\Omega} B(x,y) dx dy \dots (c)$

Table:

N	N	E
W		E
S	S	S