# Gray Level Co-occurance Matrix

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### **GLCM**

#### **Gray Level Co-occurance Matrix**

#### **Asymmetric GLCM**

$$C_{ASYM}(i, j, \Delta x, \Delta y) = \begin{cases} \text{The number of pixels where} \\ I_{Q}(x, y) = i \text{ and } I_{Q}(x + \Delta x, y + \Delta y) = j \end{cases}$$

 $I_o(x, y)$ : Quantized Image i, j: Intensity Levels (after quantization)

(x, y): Pixel Coordinate  $(\Delta x, \Delta y)$ : Offset of Neighboring Pixel

## **GLCM**

#### **Gray Level Co-occurance Matrix**

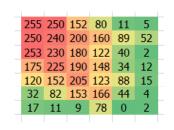
R. M. Haralick, K. Shanmugam, I. Dinstein (1973)

- Textural feature
- Using joint probability distributions of pairs of pixels (Second-order histogram)
- Time-consuming

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# GLCM [Asymmetric]





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

Label	0	1	2	3	
Intensity Range	0-63	64-127	128-191	192-255	

**STEP 1:** Quantize Intensity Level

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$$C_{ASYM}(\Delta x = 0, \Delta y = 1) = \begin{bmatrix} 7 & 2 & 3 & i \\ 7 & 2 & 0 & 0 \\ 5 & 2 & -1 \\ 2 & 2 & 2 \\ 0 & 4 & 4 \end{bmatrix} = \begin{bmatrix} (x, y) = i & (x, y + 1) = j \\ 1 & 3 & -1 \end{bmatrix}$$

**STEP 2:** Count number of occurrence of each pattern of pixel pair

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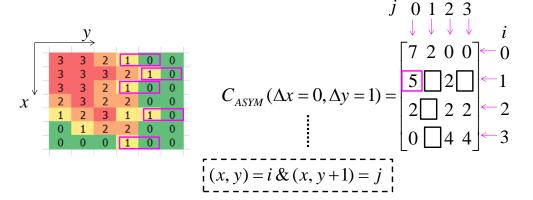
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*j* 0 1 2 3  $C_{ASYM}(\Delta x = 0, \Delta y = 1) = \begin{vmatrix} 5 & \boxed{2} & \boxed{2} \\ 2 & \boxed{2} & 2 & \boxed{4} \\ 0 & \boxed{4} & 4 & \boxed{4} \end{vmatrix}$ i(x, y) = i & (x, y+1) = j

> **STEP 2:** Count number of occurrence of each pattern of pixel pair

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GLCM [Asymmetric]



**STEP 2:** Count number of occurrence of each pattern of pixel pair

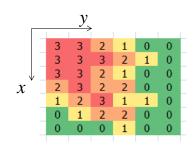
GLCM [Asymmetric]

$$C_{ASYM} = \begin{bmatrix} 7 & 2 & 0 & 0 \\ 5 & 1 & 2 & 0 \\ 2 & 3 & 2 & 2 \\ 0 & 1 & 4 & 4 \end{bmatrix} \Rightarrow \frac{1}{\sum_{i,j} C} \begin{bmatrix} 7 & 2 & 0 & 0 \\ 5 & 1 & 2 & 0 \\ 2 & 3 & 2 & 2 \\ 0 & 1 & 4 & 4 \end{bmatrix} = \begin{bmatrix} 0.20 & 0.06 & 0 & 0 \\ 0.14 & 0.03 & 0.06 & 0 \\ 0.06 & 0.09 & 0.06 & 0.06 \\ 0 & 0.03 & 0.11 & 0.11 \end{bmatrix}$$

**STEP 3:** Normalize with  $\sum_{i,j} C_{i,j}$ 

(optional)

# GLCM [Asymmetric]



$$C_{ASYM}(\Delta x = 1, \Delta y = -1) = ?$$

$$C_{ASYM}(\Delta x = -1, \Delta y = 1) = ?$$

# **GLCM**

#### **Gray Level Co-occurance Matrix**

#### **Symmetric GLCM**

$$C_{SYM}(\Delta x, \Delta y) = C_{ASYM}(\Delta x, \Delta y) + C_{ASYM}(-\Delta x, -\Delta y)$$
$$= C_{ASYM}(\Delta x, \Delta y) + \left[C_{ASYM}(\Delta x, \Delta y)\right]^{T}$$

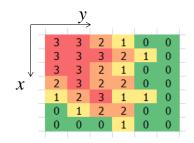
Note that  $C_{ASYM}(-\Delta x, -\Delta y) = \left[C_{ASYM}(\Delta x, \Delta y)\right]^T$ 

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# GLCM [Symmetric]



$$C_{SYM} (\Delta x = 0, \Delta y = 1)$$
$$= C_{ASYM} (0,1) + [C_{ASYM} (0,1)]^T$$

$$= \begin{bmatrix} 7 & 2 & 0 & 0 \\ 5 & 1 & 2 & 0 \\ 2 & 3 & 2 & 2 \\ 0 & 1 & 4 & 4 \end{bmatrix} + \begin{bmatrix} 7 & 5 & 2 & 0 \\ 2 & 1 & 3 & 1 \\ 0 & 2 & 2 & 4 \\ 0 & 0 & 2 & 4 \end{bmatrix} = \begin{bmatrix} 14 & 7 & 2 & 0 \\ 7 & 2 & 5 & 1 \\ 2 & 5 & 4 & 6 \\ 0 & 1 & 6 & 8 \end{bmatrix}$$

$$= \begin{bmatrix} 0.20 & 0.10 & 0.03 & 0 \\ 0.10 & 0.03 & 0.07 & 0.01 \\ 0.03 & 0.07 & 0.06 & 0.09 \\ 0 & 0.01 & 0.09 & 0.11 \end{bmatrix}$$
 (Normalized)

# GLCM [Polar Notation]

 $C(d,\theta)$ 

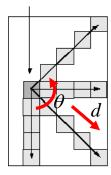
$$C(d, \theta = 0^\circ) = C(\Delta x = d, \Delta y = 0)$$

$$C(d, \theta = 45^{\circ}) = C(\Delta x = d, \Delta y = d)$$

$$C(d, \theta = 90^\circ) = C(\Delta x = 0, \Delta y = d)$$

$$C(d, \theta = 135^\circ) = C(\Delta x = -d, \Delta y = d)$$

Point of interest



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#### **Statistical Properties of GLCM**

**1.** Maximum probability  $\max_{i,j} C(i,j)$ 

Measure the strongest response of GLCM.

2. Angular Second Moment  $\sum_{i,j} C^2(i,j)$  [Uniformity, Energy]

Measure of uniformity. Uniformity is 1 (maximum) for a constant image

3. Contrast  $\sum_{i,j} (i-j)^2 C(i,j)$ 

Measure of intensity contrast between a pixel and its neighbor.

Note that C(i, j) is a normalized GLCM

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### **Statistical Properties of GLCM**

**4. Correlation**  $\sum_{i,j} \frac{(i-\mu_1)(j-\mu_2)C(i,j)}{\sigma_1\sigma_2}$ 

Measure of how correlated a pixel is to its neighbor. Range of correlation is [-1,1].

$$C = \begin{bmatrix} 7 & 2 & 0 & 0 \\ 5 & 1 & 2 & 0 \\ 2 & 3 & 2 & 2 \\ 0 & 1 & 4 & 4 \end{bmatrix} \qquad \mu_1 = \sum_{i} \left( i \cdot \sum_{j} C(i, j) \right) \qquad \sigma_1^2 = \sum_{i} \left( (i - \mu_1)^2 \sum_{j} C(i, j) \right) \qquad \mu_2 = \sum_{j} \left( j \cdot \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{j} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_$$

## **Statistical Properties of GLCM**

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Measure of how correlated a pixel is to its neighbor. Range of correlation is [-1,1].

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$$\mu_2 = \sum_{j} \left( j \cdot \sum_{i} C(i, j) \right) \qquad \sigma_2^2 = \sum_{j} \left( (j - \mu_2)^2 \sum_{i} C(i, j) \right)$$

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## **Statistical Properties of GLCM**

5. Homogeneity 
$$\sum_{i,j} \frac{C(i,j)}{1+|i-j|}$$

Measure spatial closeness. Homogeneity is maximum when GLCM is a diagonal matrix.

**6. Entropy** 
$$-\sum_{i,j} C(i,j) \log_2 C(i,j)$$

Measure a randomness. Entropy is maximum when all elements in GLCM are equal

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7. Variance

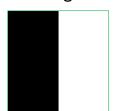
- **13.** Inverse Difference Moment
- 8. Sum Average
- 14. Information Measure of Correlation
- 9. Sum Variance
  - ntropy 15. Maximal Correlation Coefficient
- 10. Sum Entropy
- 11. Difference Variance
- 12. Difference Entropy

http://www.cis.rit.edu/~cnspci/references/dip/segmentation/haralick1973.pdf

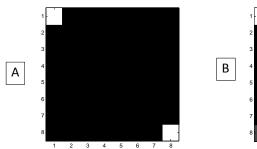
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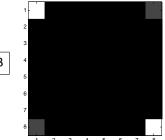
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- $\begin{vmatrix} 1 \end{vmatrix} \quad C_{SYM} \left( \Delta x = 1, \Delta y = 0 \right)$
- $\boxed{2} \quad C_{SYM} (\Delta x = 0, \Delta y = 1)$

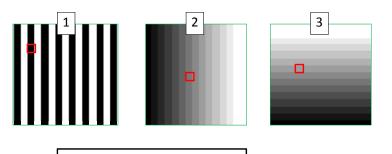


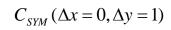


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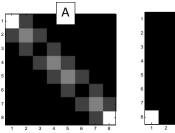
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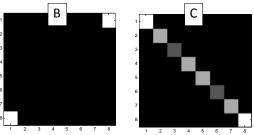


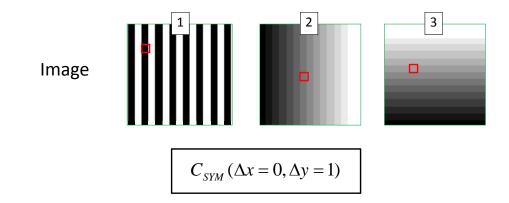


GLCM

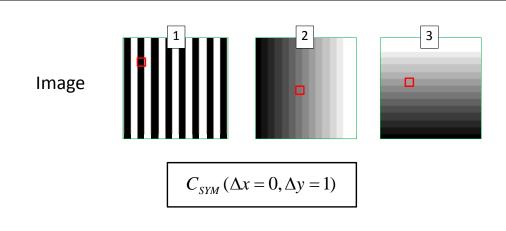
Image







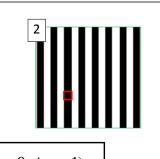




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**Images** 

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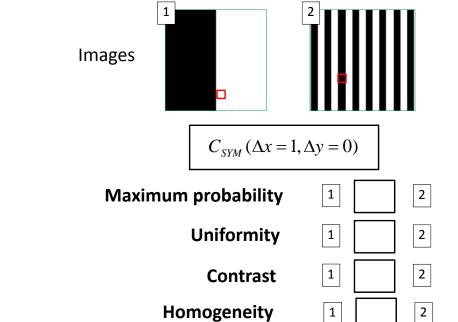
 $C_{SYM} (\Delta x = 0, \Delta y = 1)$ 

Maximum probability 1 2

Uniformity 1 2

Contrast 1 2

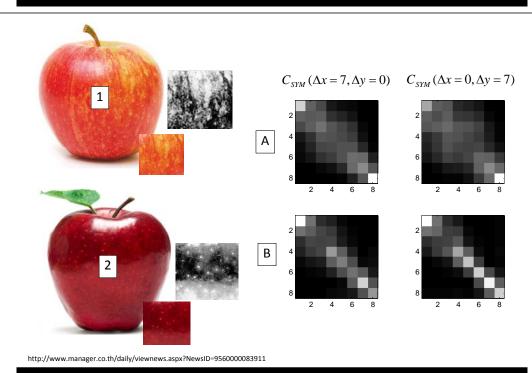
Homogeneity 1 2



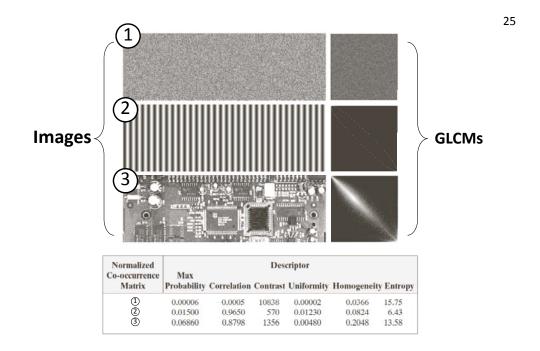
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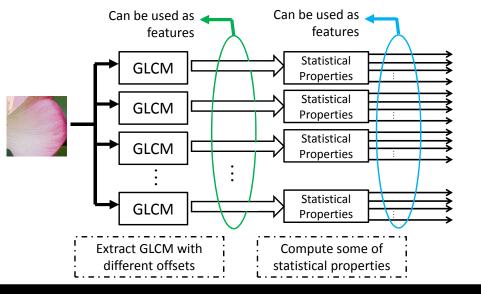
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#### **GLCM Based Feature Extraction**



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