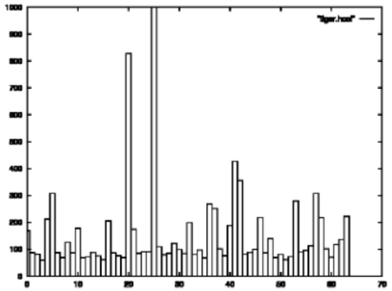
Image Features

Color Histogram

Color Histogram

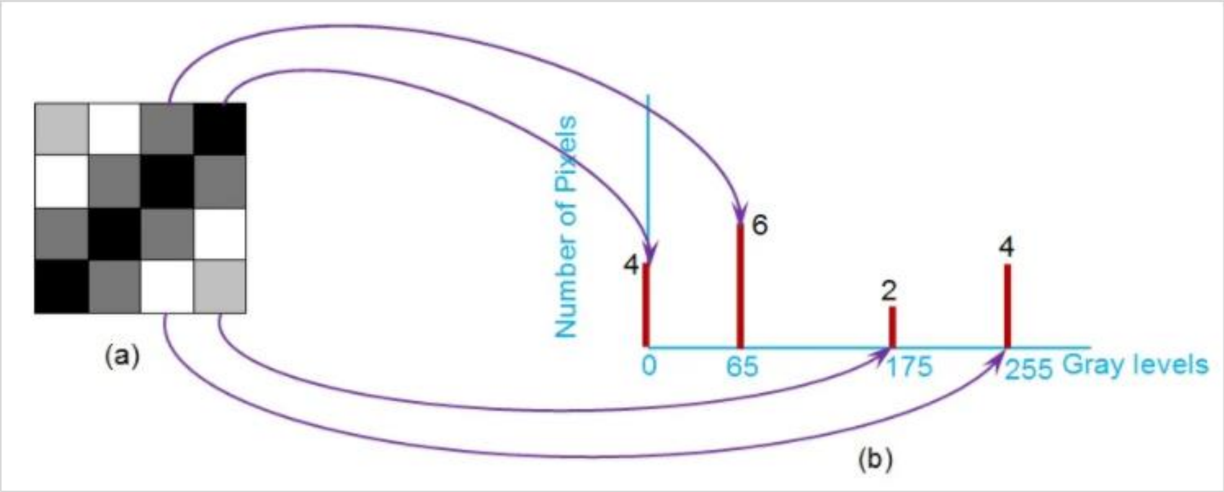


- A color histogram represents the number of pixels that have colors in each of a fixed list of color ranges, that span the image's color space, the set of all possible colors.

- The color histogram can be built for any kind of color space, although the term is more often used for three-dimensional spaces like RGB or HSV.

Intensity Histogram

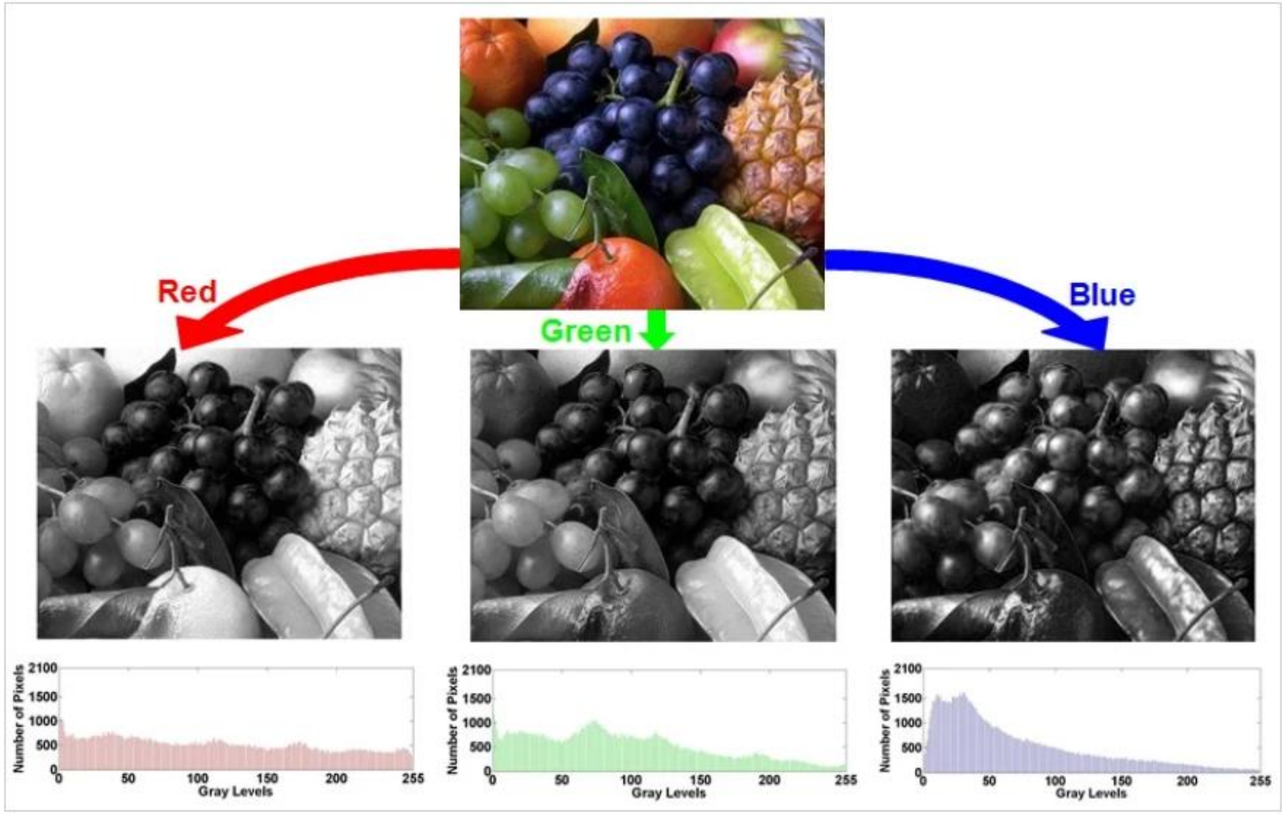
- In the intensity histogram, the x-axis has all available gray levels, and the y-axis indicates the number of pixels that have a particular gray-level value.
- For an 8-bit grayscale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values.



8-bit grayscale image and its histogram.

Histogram of a Colored (RGB) Image

- The histogram of an RGB image can be displayed in terms of three separate histograms—one for each color component (R, G, and B) of the image.



Colour image and the histograms corresponding to its red, green and blue monochrome channels.

How to make a color histogram

Option A:

- Make 3 histograms (each for the RGB channels) and concatenate them
- Discretize each color channel into a number of bins and count the number of image pixels in each bin.
  - For example, 8 bins for the red channel, 8 bins for the green channel, four bins for the blue channel.
- Can normalize histogram to hold normalized frequencies so that the maximum possible value for a bin is 1.0.

How to make a color histogram

Option B:

- Instead of concatenating 3 histograms, a 3-D histogram whose axes correspond to the red, green, and blue intensities can be constructed.

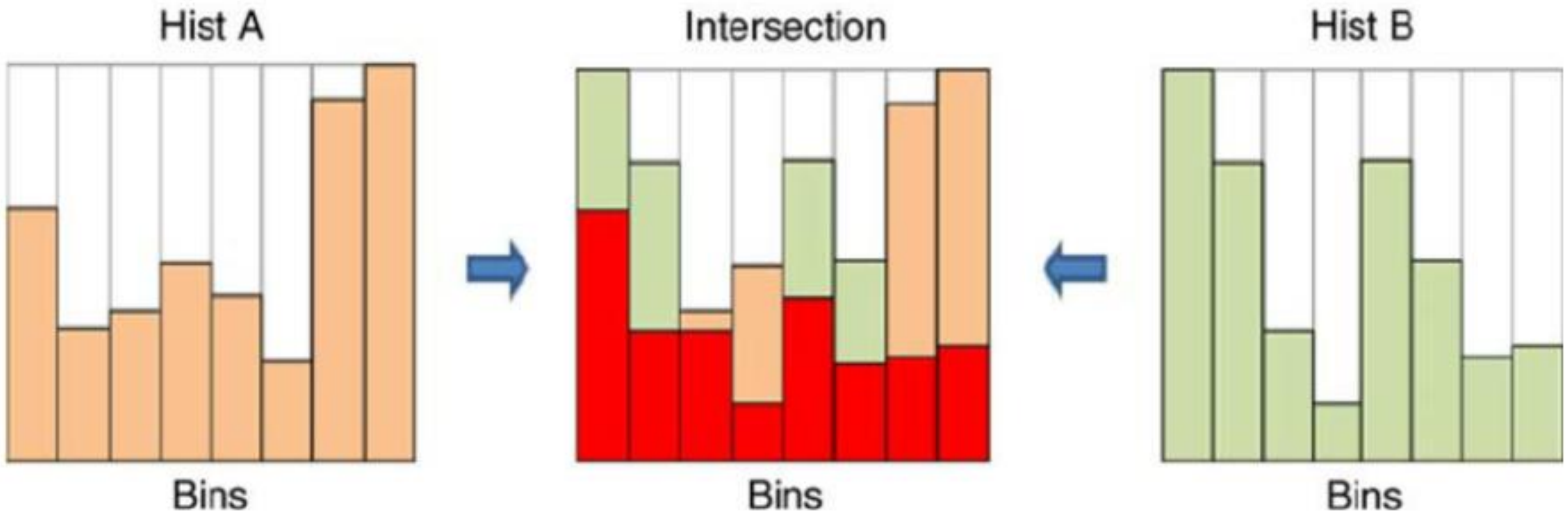
- A two-dimensional histogram of Red-Blue chromaticity divided into four bins (*N*=4) might yield a histogram that looks like this table:

		red			
		0-63	64-127	128-191	192-255
blue	0-63	43	78	18	0
	64-127	45	67	33	2
	128-191	127	58	25	8
	192-255	140	47	47	13

Histogram Intersection Similarity Method

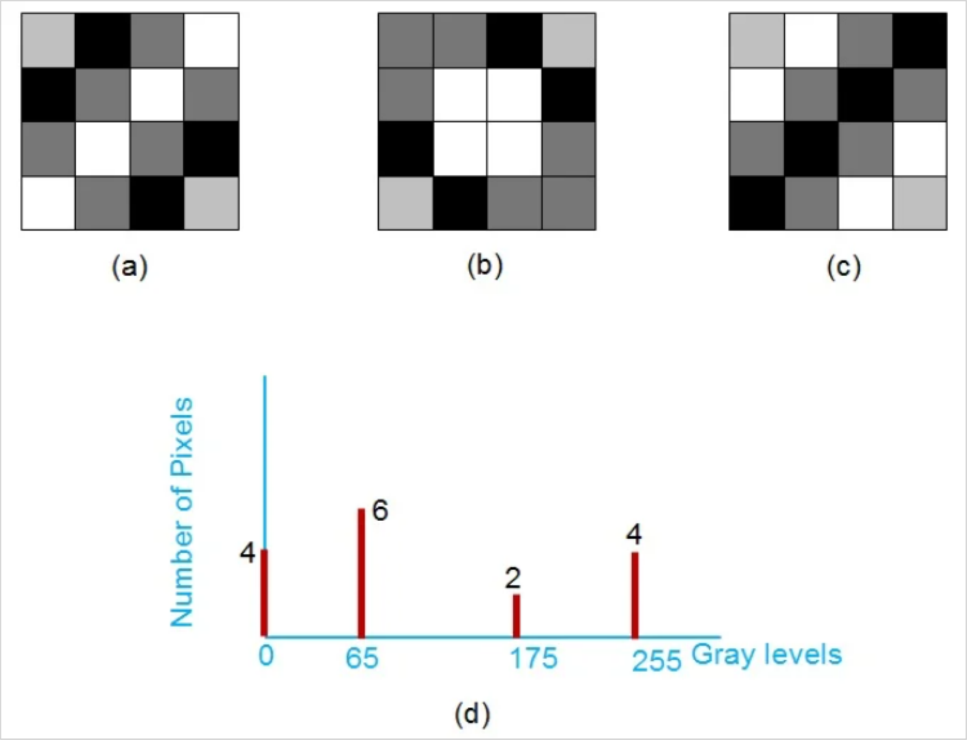
intersection(h(A),h(B)) = $\sum_{j=1}^{num\ bins} \min(\ h(A)[j], h(B)[j])$

Similarity score (h(A),h(B)) = $\frac{intersection\ (h(A),h(B))}{\sum_{j=1}^{num\ bins} h(A)[j]}$



Color Histogram Drawbacks

- One limitation is that a histogram provides no information regarding the spatial distribution of an image's pixel values. Thus, we can have multiple different images that share the same histogram.

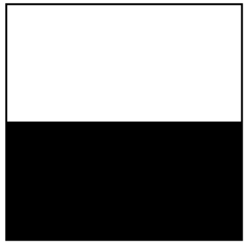


Different images that have the same histogram.

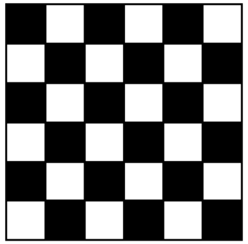
Texture

Why texture?

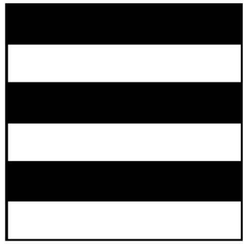
- Texture provides information about the *spatial arrangement* of the colours or intensities in an image
  - spatial distribution beside colour/intensity level distribution
- Texture descriptor provides measures of properties such as smoothness, coarseness, and regularity



block pattern



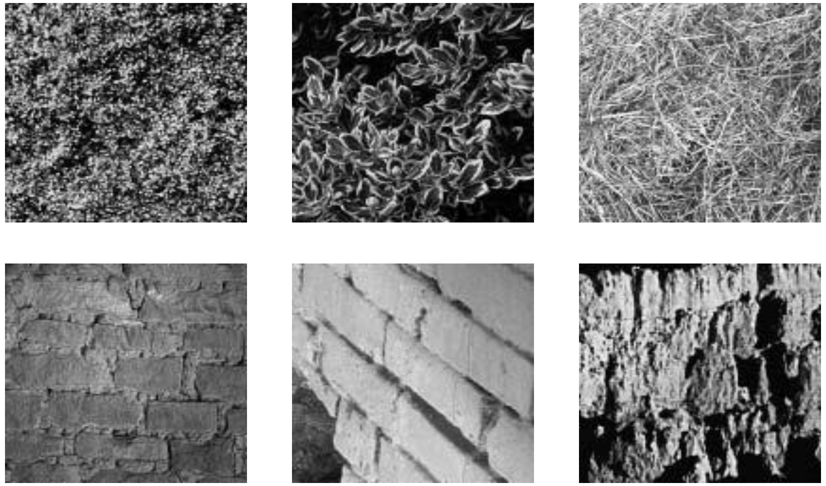
checkerboard



striped pattern

Texture, texels, and statistics

- It is usually difficult to describe the irregular spatial arrangements
- There is some quality of the image that would make on argue that there is a noticeable arrangement in each image
- Properties as playing an important role in describing texture: uniformity, density, coarseness, roughness, regularity, linearity, directionality, frequency, and phase.



Texture, texels and statistics

- Structural approach:
  - Texture is a set of primitive texels in some regular or repeated relationship
- Statistical approach:
  - Texture is a quantitative measure of the arrangement of intensities in a region
  - More general, easier to compute and popular in practice

Structural Texture Description

- A simple “texture primitive” can be used to form more complex texture patterns by means of some rules that limit the number of possible arrangements of the primitives.
- Descriptors:
  - A description of the texels
  - A specification of the spatial relationship
- Suitable for man-made and regular patterns

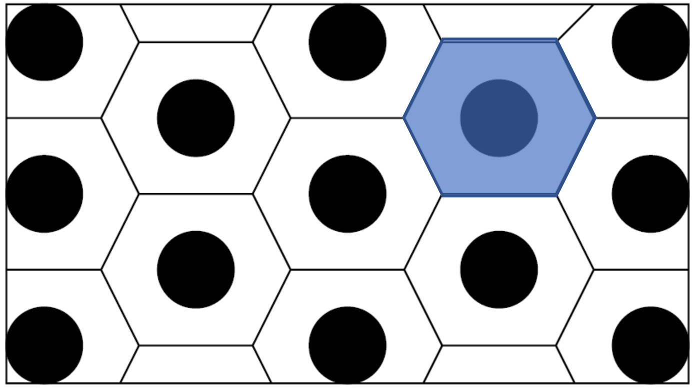
Structural Texture Description

- Geometry-based description (Tuceryan & Jain)
  - The characterisation of the spatial relationships is obtained from a Voronoi tessellation of the texels
  - Process steps:
    1) Segment the image to extract texels
    2) Construct the Voronoi tessellation
    3) Calculate shape feature of the polygons to group the polygons into clusters that define uniformly textured regions

Structural Texture Description

- Construction of Voronoi tessellation
  - Let S be the set of centroids of texels
  - For any pair of points P and Q in S, create the perpendicular bisector of the line joining them
  - Let $H^Q(P)$ be the half plane that is closer to P with respect to the perpendicular bisector of P and Q. The Voronoi Polygon of P is defined by:

$$V(P) = \bigcap_{Q \in S, Q \notin P} H^Q(P)$$



Statistical Texture Description

- Methods for statistical texture description
  - Edge Density and Direction
  - Local Binary Partition
  - Co-occurrence Matrices and Features

Edge Density and Direction

- Use an edge detector as the first step in texture analysis.
- The number of edge pixels in a given fixed-size region gives some indication of the busyness of that region
- The directions of the edges also describe the characteristics of the texture pattern

Edge Density and Direction

- Consider a region of N pixels. Suppose that a gradient-based edge detector is applied to this region producing two outputs for each pixel p:
    1. The gradient magnitude Mag(p)
    2. The gradient direction Dir(p)
- One very simple texture feature is *edgeness per unit area* (EPUA) which is defined by

$$F_{edgeness} = \frac{|\{p \mid Mag(p) \geq T\}|}{N}$$

    - For some threshold T and N pixels in the area of interest.

- EPUA measures the busyness, but not the orientation of the texture

Edge Density and Direction

- Extended to include both busyness and orientation
- Let $H_{mag}(R)$ denote the normalized histogram of gradient magnitudes of region R
- Let $H_{dir}(R)$ denote the normalized histogram of gradient orientations of region R
- The quantitative texture description of region R is

$$F_{mag,dir} = \left(H_{mag}(R), H_{dir}(R)\right)$$

- L_1 distance for comparison

$$L_1(H_1, H_2) = \sum_{i=1}^{n} \left| H_1[i] - H_2[i] \right|$$

Edge Density and Direction Example

- Consider the two 5x5 images shown in Figure 7.5.
- The image on the left is busier than the image on the right.
  - The image on the left has an edge in every one of its 25 pixels, so its edgeness per unit area is 1.0.
  - The image on the right has 6 edges out of its 25 pixels, so its edgeness per unit area is only 0.24.

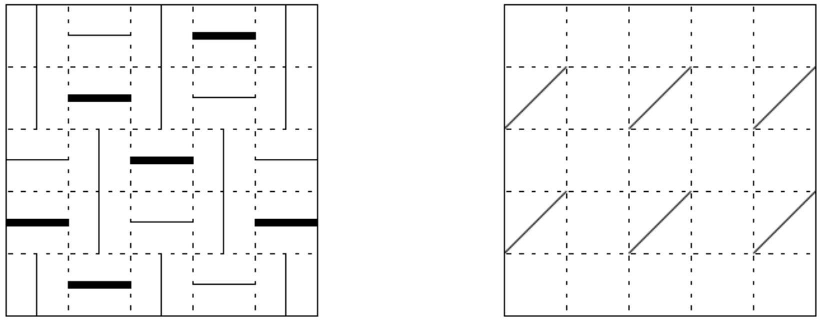


Figure 7.5: Two images with different edgeness and edge-direction statistics.

Edge Density and Direction Example

- Consider the two 5x5 images shown in Figure 7.5.
- For the **gradient-magnitude histograms**, we will assume there are two bins representing dark edges and light edges. For the **gradient-direction histograms**, we will use three bins for horizontal, vertical, and diagonal edges.
- **The image on the left** has 6 dark edges and 19 light edges, so its **normalized gradient-magnitude histogram is (0.24,0.76)**, meaning that 24% of the edges are dark and 76% are light. It also has 12 horizontal edges, 13 vertical edges, and no diagonal edges, so its **normalized gradient-direction histogram is (0.48,0.52,0.0)**, meaning that 48% of the edges are horizontal, 52% are vertical and 0% are diagonal.
- **The image on the right** has no dark edges and 6 light edges, so its **normalized gradient-magnitude histogram is (0.0,0.24)**. It also has no horizontal edges, no vertical edges, and 6 diagonal edges, so its **normalized gradient-direction histogram is (0.0,0.0,0.24)**.

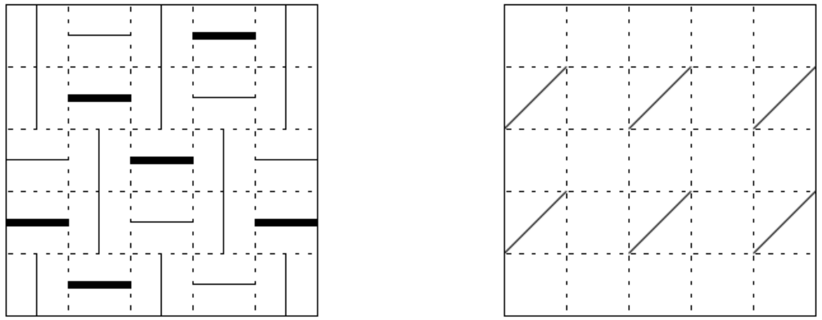


Figure 7.5: Two images with different edgeness and edge-direction statistics.

Edge Density and Direction Example (summary)

- Consider the two 5x5 images shown in Figure 7.5.
- **The image on the left:**
  - Its edgeness per unit is 1.0
  - its normalized gradient-magnitude histogram is (0.24,0.76)
  - its normalized gradient-direction histogram is (0.48,0.52,0.0).
- **The image on the right:**
  - Its edgeness per unit is 0.24
  - its normalized gradient-magnitude histogram is (0.0,0.24)
  - its normalized gradient-direction histogram is (0.0,0.0,0.24).

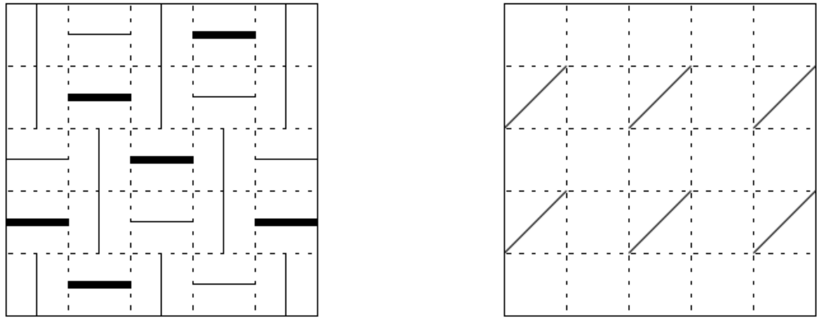


Figure 7.5: Two images with different edgeness and edge-direction statistics.

In the case of these two images, the edgeness-per-unit-area measure is sufficient to distinguish them, but the histogram measure provides a more powerful descriptive mechanism in general.

Local Binary Partition (LBP)

- For each pixel p in the image, create an 8-bit number $B=b_0b_1b_2b_3b_4b_5b_6b_7$

- Check the eight neighbour of p

$$b_i = \begin{cases} 1, I_i > I_p \\ 0, else \end{cases}$$

b_0	**b_1**	**b_2**
b_3	*****	**b_4**
b_5	**b_6**	**b_7**

10	**12**	**9**
6	**7**	**19**
7	**10**	**16**

- Texture is represented by a histogram of B
- L1 distance can be used to compare two images

B=

1	**1**	**1**	**0**	**1**	**0**	**1**	**1**

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Local Binary Partition (LBP)

- An example

110	20	198	30	64
110	147	137	75	64
47	89	56	27	6
9	11	73	112	167
1	3	6	143	186

	01100000	11010000	10010000	
	11100000	11110001	11110111	
	11101000	11001001	00001011	

Co-occurrence Matrix Features

- A co-occurrence matrix is a 2-D array (referred to as the matrix C) in which both the rows and the columns represent a set of possible image values V.
- The value of $\mathbf{C_d(i, j)}$ denotes how many times value i co-occurs with value j in some designated spatial relationships d.
- V can be the set of possible gray tones for gray-level images or the set of possible colours for colour images.

Co-occurrence Matrices

- The spatial relationship is specified by a vector d = (dr,dc).
- Let d = (dr, dc) be a displacement vector where dr is a displacement in rows (downward) and dc is a displacement in columns (to the right).
- Let V be a set of gray tones
- The gray-level co-occurrence matrix C_d for image I is defined by

$$C_d[i,j] = \left|\{[r,c] \mid I[r,c] = i \;\&\; I[r+dr, c+dc] = j\}\right|$$

Co-occurrence Matrices

- An example

0	**1**	**1**	**0**
1	**0**	**0**	**1**
2	**2**	**1**	**1**
2	**2**	**0**	**0**

Gray-tone image I

$C_{[0,1]}$

	0	1	2
0	**2**	**2**	**0**
1	**2**	**2**	**0**
2	**1**	**1**	**2**

i	j

$C_{[1,0]}$

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

i
j

$C_{[1,1]}$

	0	1	2
0	**1**	**2**	**0**
1	**2**	**1**	**1**
2	**1**	**0**	**1**

i	
	j

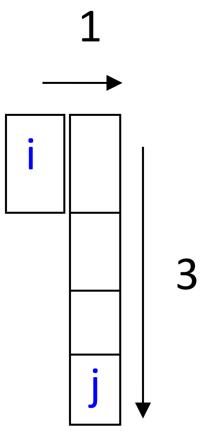
Three different co-occurrence matrices for the gray-tone image I

Co-occurrence Matrices

- An example

1	1	0	0
1	1	0	0
0	0	2	2
0	0	2	2
0	0	2	2
0	0	2	2

gray-tone image



d = (3,1)

$$\begin{array}{c|c} & 0\ 1\ 2 \\ \hline \begin{array}{c}0\\1\\2\end{array} & \begin{bmatrix} 1 & 0 & 3 \\ 2 & 0 & 2 \\ 0 & 0 & 1 \end{bmatrix} \end{array} \quad C_d$$

co-occurrence matrix

Co-occurrence Matrices

- Normalized gray-level co-occurrence matrix

$$N_d[i, j] = \frac{C_d[i, j]}{\sum_i \sum_j C_d[i, j]}$$

From C_d we can compute N_d, the normalized co-occurrence matrix, where each value is divided by the sum of all the values in the matrix C.

Co-occurrence Matrices

- Features based on co-occurrence matrix

$$\text{Energy/Uniform} = \sum_i \sum_j N_d^2[i, j]$$

$$\text{Entropy} = -\sum_i \sum_j N_d[i, j] \log_2 N_d[i, j]$$

$$\text{Constrast} = \sum_i \sum_j (i - j)^2 N_d[i, j]$$

$$\text{Homogeneity} = \sum_i \sum_j \frac{N_d[i, j]}{1 + |i - j|}$$

$$\text{Correlation} = \frac{\sum_i \sum_j (i - \mu_i)(j - \mu_j) N_d[i, j]}{\sigma_i \sigma_j}$$

where $\mu_{i,}$ μ_j are the mean and σ_i, σ_i are the standard deviations of the row and column sums

Co-occurrence Matrices

- Features based on co-occurrence matrix

$$\text{Maximal Probability} = \max_{i,j} N_d[i, j]$$

$$\text{Element difference moment of order k} = \sum_i \sum_j (i-j)^k N_d[i, j]$$

$$\text{Inverse element difference moment of order k} = \sum_i \sum_j N_d[i, j]/(i-j)^k, i \neq j$$

- Maximal probability gives an indication of the strongest response
- The second one has a relatively low value when the high values of N are near the man diagonal
- The third one has the opposite effect

Co-occurrence Matrices

- The co-occurrence matrix features suffer from a number of difficulties
  - There is no well-established method of selecting the displacement vector
  - Computing co-occurrence matrices for different values of *d* is not feasible
  - Some sort of feature selection methods must be used to select the most relevant ones from a large number of features