Introduction to Digital Image Processing

—— Image Features

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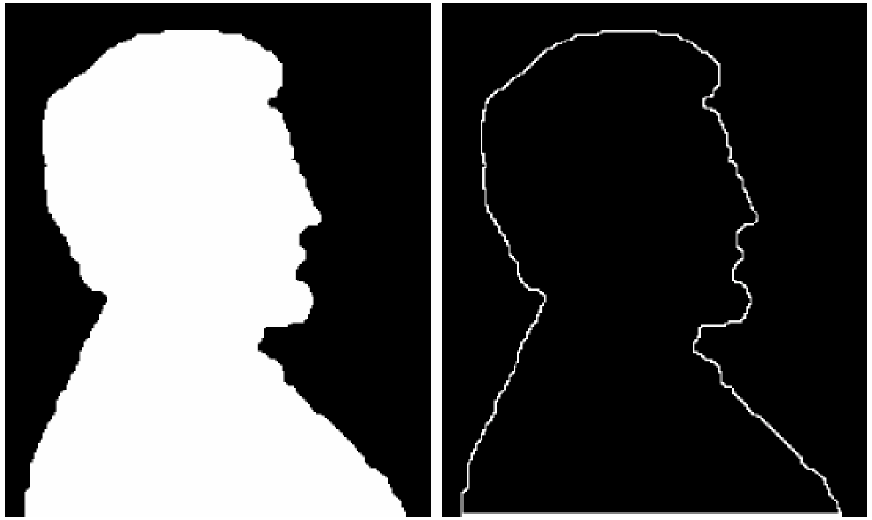
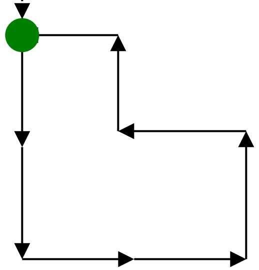
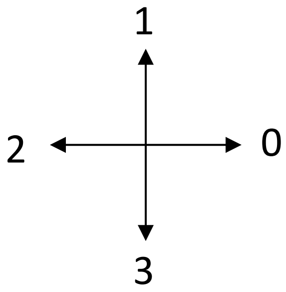
Object Boundary

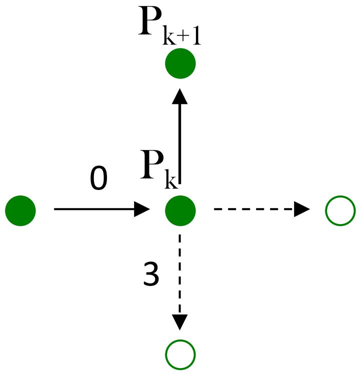
Chain Code (4-Direction)

1. Find the top-left pixel on the boundary; call this P_0. The direction property DIR is initialized as 3.
2. Traverse the four neighborhoods of the current pixel in the counter-clockwise order,
    - Begin the search in the direction calculated as (DIR+3) mod 4.
3. Stop when the current boundary pixel P_k equals to P_1 and P_{k-1} equals to P_0.



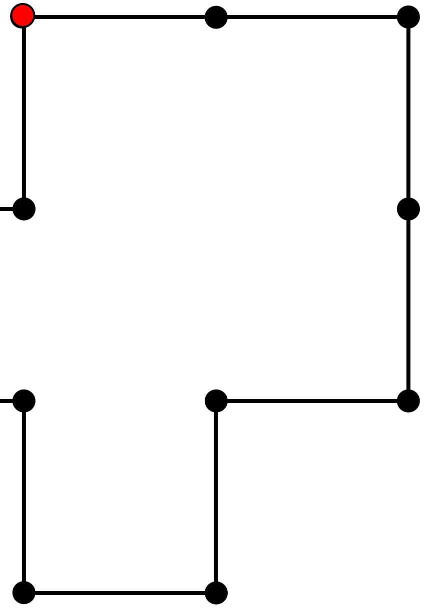




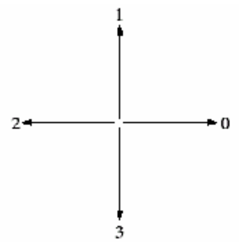


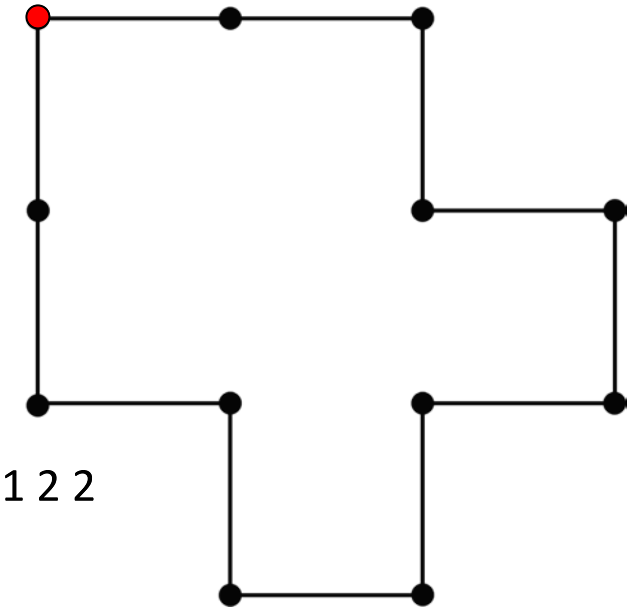
Chain Code (8-Direction)

1. Find the top-left pixel on the boundary (P_0.) The direction property DIR is initialized as 7.
2. Traverse the eight neighborhood of the current pixel in a counter-clockwise order
   - beginning the search at the pixel in direction (DIR+5) mod 8 or in direction
     - (DIR+7) mod 8, if DIR is even
     - (DIR+6) mod 8, if DIR is odd
3. Stop when the current boundary pixel P_n equals to P_1 and P_{n-1} equals to P_0

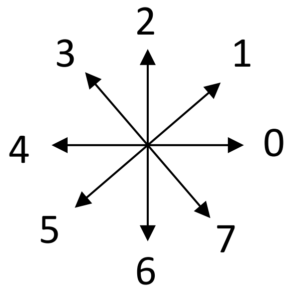


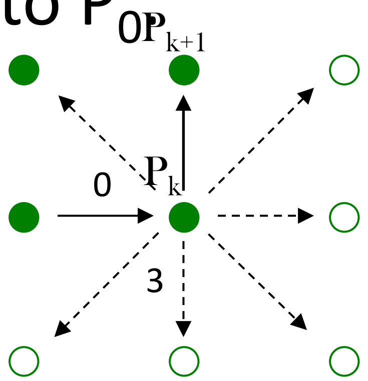
3 2 3 0 3 0 1 0 1 1 2 2





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



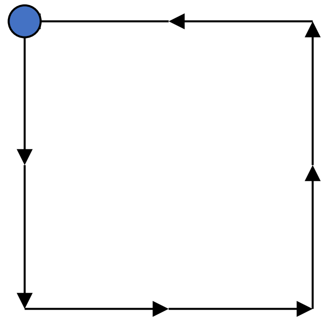


Problems with Chain Code

- Chain code representation is conceptually appealing, but has the following problems
  - Dependent on the **starting point**
  - Dependent on the **object orientation**
- To use boundary representation for recognizing objects, we need to achieve invariance to the starting point and orientation
  - Normalized codes
  - Differential codes

Normalized Chain Code

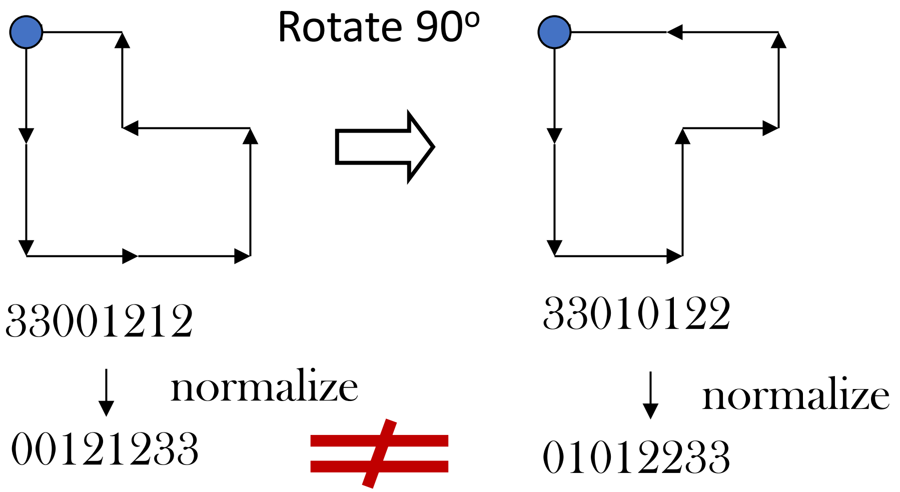
- **We treat the chain code as a cyclic sequence of direction numbers and redefine the starting point so that the resulting sequence of numbers forms an integer of minimum magnitude.**



33001122

Create cyclic matrix $\longrightarrow$		Sort rows $\longrightarrow$		$\longrightarrow$
	33001122		00112233	First row gives the normalized chain code
	30011223		01122330	00112233
	00112233		11223300	
	01122330		12233001	
	11223300		22330011	
	12233001		23300112	
	22330011		33001122	
	23300112		30011223	

Differential Chain Code



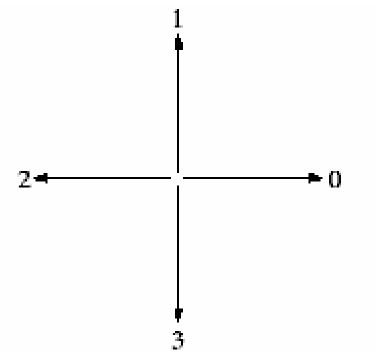
Differential coding is obtained by counting the number of direction changes of the two adjacent elements.

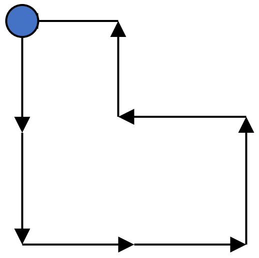
Computation:

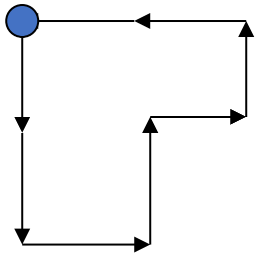
$d_k = (c_k - c_{k-1}) \bmod 4$ for 4-directional chain codes

$d_k = (c_k - c_{k-1}) \bmod 8$ for 8-directional chain codes

Normalized Differential Chain Codes







Differential code:
$d_k = (c_k - c_{k-1}) \bmod 4$

33001212
↓ differentiate
10101131
↓ normalize
01011311

33010122
↓ differentiate
10113110
↓ normalize
01011311

Fourier Descriptor

- The contour of an object is a closed curve described by pixel coordinates (x_0, y_0).
  - The sequence of pixels are encountered in traversing the object contour in the counterclockwise direction: $(x_0, y_0), \dots, (x_{k-1}, y_{k-1})$.
  - Each coordinate pair is treated as a complex number $s = x + iy$.
- The Fourier transform of $s(k)$ results in a set of Fourier coefficients $a(u)$.

$$a(u) = \frac{1}{N} \sum_{k=0}^{N-1} s(k) e^{-j\frac{2\pi uk}{N}}$$

$a(u)$ are called **Fourier Descriptor**.

- With inverse Fourier transform, $s(k)$ can be reconstructed.
  - If the first p terms are used, the reconstruction is an approximation.
  - Two shapes are compared against their Fourier descriptors.

Contour Reconstruction using Fourier Descriptor

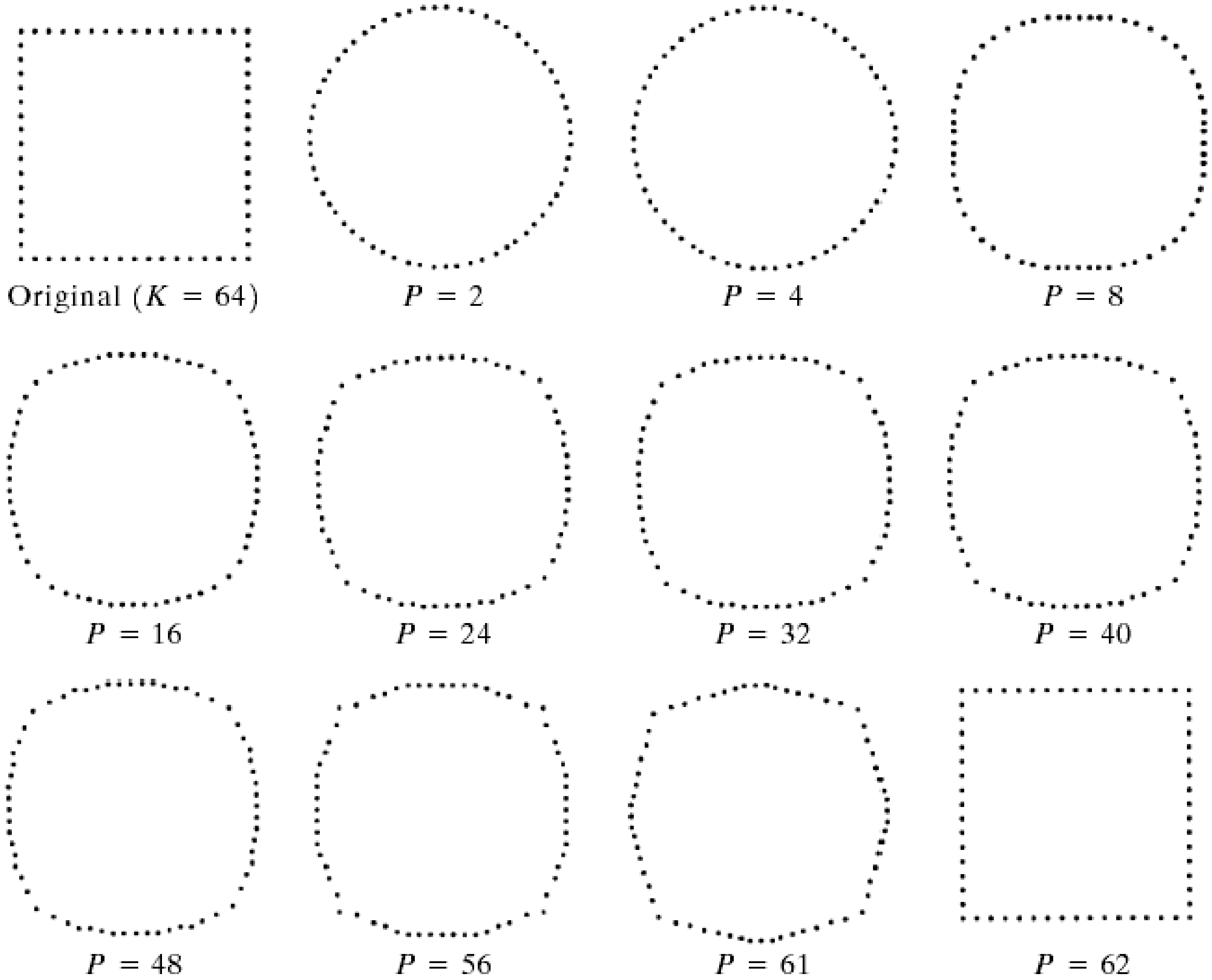
- Varying the number of coefficients used in reconstruction results in different contours.

Normalized Fourier Descriptors

- The first component of the Fourier Descriptor implies the size of the object.
- We use the first component to normalize the rest coefficients:

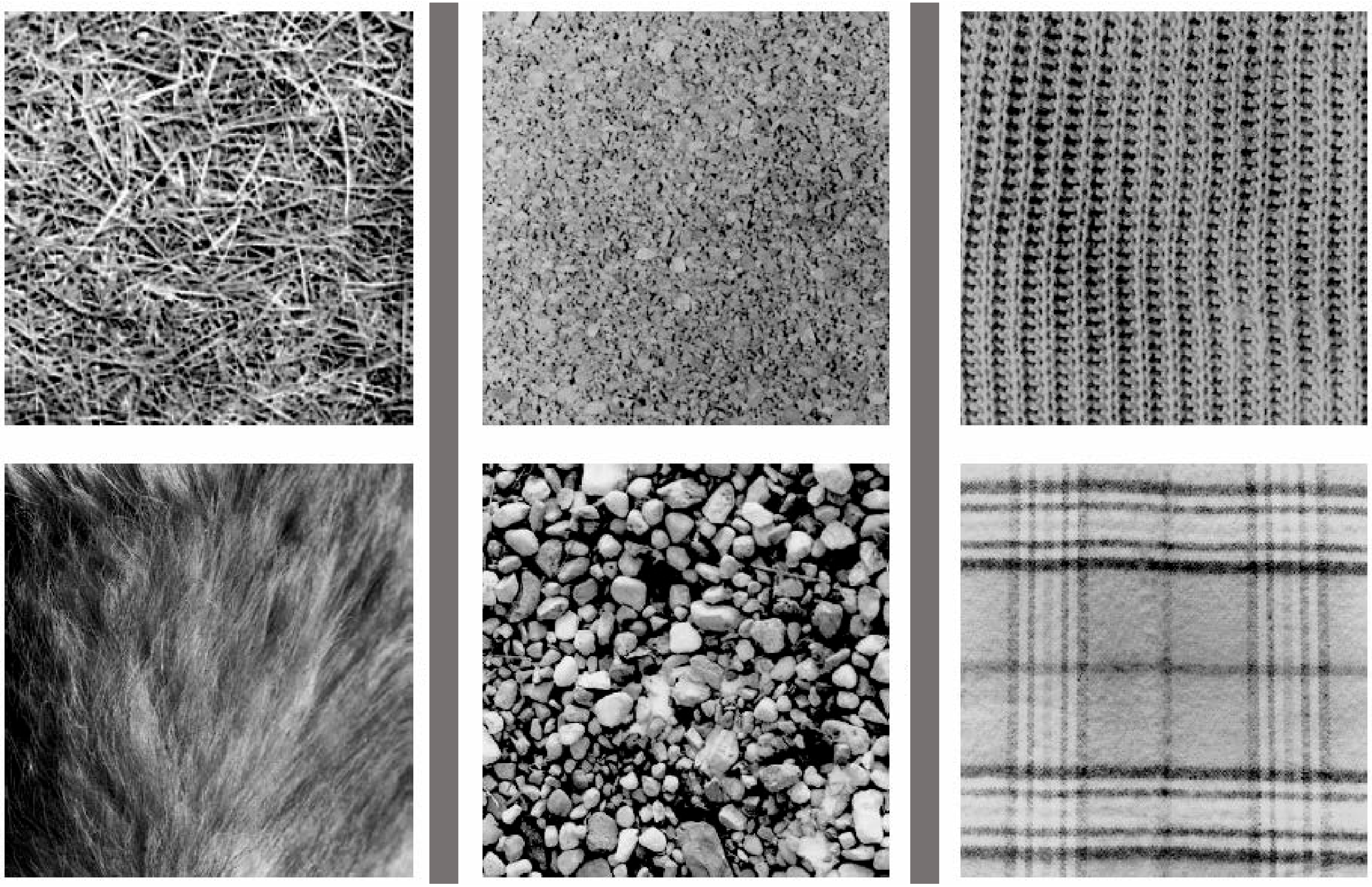
$$FD = \{\frac{FD_1}{FD_0}, \frac{FD_2}{FD_0}, \ldots, \frac{FD_{N-1}}{FD_0}\}$$

- Similarity of the two objects is determined by the distance of FD.



What is Image Texture?

- What is image texture?
- How to measure texture?



Frequency Analysis …

- One possible approach is to perform local Fourier transforms of the image.
- Then we can derive information on
  - the contribution of different spatial frequencies, and
  - the dominant orientation(s) in the local texture.
- For both kinds of information, only the power (magnitude) spectrum needs to be analyzed.

Co-occurrence Matrix

- A simple and popular method for texture analysis is the computation of gray-level co-occurrence matrices.
- (optional) To compute such a matrix, we usually reduce the quantization of the image color depth (i.e., the number of color or gray-levels).
  - For example, by dividing the brightness values ranging from 0 to 255 by 64 and rounding it to the floor, we create the levels 0, 1, 2, and 3.
- By specifying a spatial relationship r (orientation and distance), the co-occurrence matrix C is obtained by counting all pairs of pixels separated by r having gray levels i and j.
  - $C_r(i, j)$ indicates how many times value i co-occurs with value j in a particular spatial relationship r.

Example

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

Image

$$r = (0, 1),\quad C_{(0,1)} = \begin{array}{c|cccc} & 0 & 1 & 2 & 3 \\ \hline 0 & 4 & 2 & 1 & 0 \\ 1 & 2 & 4 & 0 & 0 \\ 2 & 1 & 0 & 6 & 1 \\ 3 & 0 & 0 & 1 & 2 \end{array}$$

$$r = (135, 1),\quad C_{(135,1)} = \begin{array}{c|cccc} & 0 & 1 & 2 & 3 \\ \hline 0 & 2 & 1 & 3 & 0 \\ 1 & 1 & 2 & 1 & 0 \\ 2 & 3 & 1 & 0 & 2 \\ 3 & 0 & 0 & 2 & 0 \end{array}$$

Algorithm for Co-occurrence Matrix

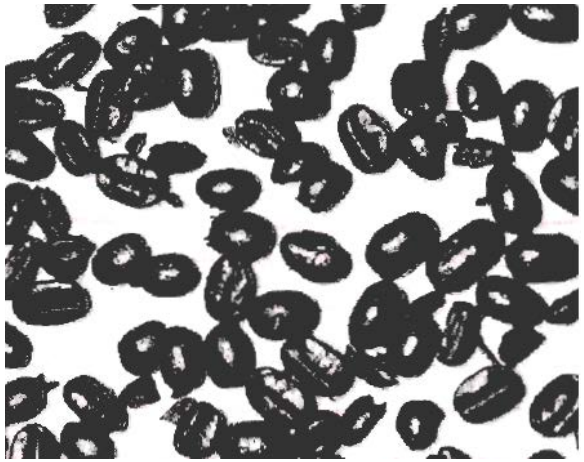
Image
$$\begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 2 & 2 & 2 \\ 2 & 2 & 3 & 3 \end{bmatrix}$$

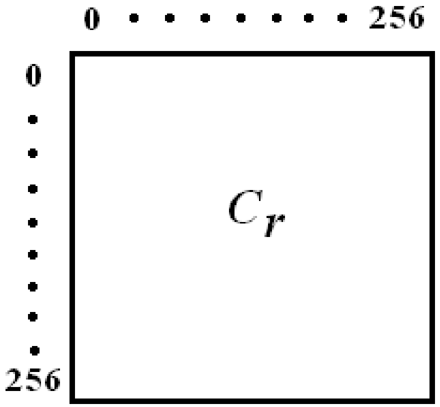
r = (0, 1)

$$C_{(0,\,1)} = \begin{array}{c|cccc} & 0 & 1 & 2 & 3 \\ \hline 0 & 4 & 2 & 1 & 0 \\ 1 & 2 & 4 & 0 & 0 \\ 2 & 1 & 0 & 6 & 1 \\ 3 & 0 & 0 & 1 & 2 \end{array}$$

r = (135, 1)

$$C_{(135,\,1)} = \begin{array}{c|cccc} & 0 & 1 & 2 & 3 \\ \hline 0 & 2 & 1 & 3 & 0 \\ 1 & 1 & 2 & 1 & 0 \\ 2 & 3 & 1 & 0 & 2 \\ 3 & 0 & 0 & 2 & 0 \end{array}$$





r = (orientation, distance)

1. Assign $C_r(i, j) = 0$ for all $i, j \in [0, L]$, where L is the maximum brightness.
2. For all pixels (x_1, y_1) in the image, determine (x_2, y_2) which has the relation r with the pixel (x_1, y_1), and perform
$$C_r[f(x_1, y_1), f(x_2, y_2)] = C_r[f(x_1, y_1), f(x_2, y_2)] + 1 .$$

Using Co-occurrence Matrix

- It is often a good idea to construct a co-occurrence matrix with more than one spatial relation.
- Similar matrices of two textures indicate similar textures.
  - The difference between corresponding elements of these matrices can be taken as a similarity metric.
  - We use texture to enhance the detection of regions and contours in images.
- Additional metrics
  - Energy $\sum_i \sum_j C_r^2(i,j)$
  - Entropy $-\sum_i \sum_j C_r\ (i,j) \log_2 C_r(i,j)$
  - Homogeneity $\sum_i \sum_j \frac{C_r\ (i,j)}{1+|i-j|}$
  - Correlation $\frac{\sum_i \sum_j (i-\mu_i)(j-\mu_j) C_r(i,j)}{\sigma_i \sigma_j}$

μ_i and μ_j are the means and σ_i and σ_j are the STDs of the row and column

Local Binary Pattern

- For each pixel p, create an n-bit number (n=4 or 8) $b_1\ b_2\ b_3\ b_4\ b_5\ b_6\ b_7\ b_8$, where $b_i = 0$ if neighbor i has a value less than or equal to p's value and 1 otherwise.

	1	2	3	
	100	101	103	
8	40	50	80	4
	50	60	90	5
	7	6		

$\longrightarrow$ $\boxed{1\ 1\ 1\ 1\ 1\ 1\ 0\ 0}$

- For 4-neighbor, the range of LBP is 0 - 16
- For 8-neighbor, the range of LBP is 0 - 255
- A histogram or the decimal number is used to represent the LBP results.