Texture analysis

Image Processing — scc0251

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2020

Agenda

1. Basic concepts
2. Texture analysis
3. Grey-level co-ocurrence matrices (GLCM)
4. Local Binary Patterns (LBP)

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Texture

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- Image textures is a concept related to local differences in the intensity levels, in which important elements are:
  - Differences in the pixel levels (contrast)
  - Size of regions to be considered (window)
  - Direction (ou lack of direction)

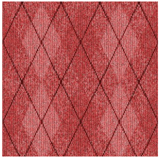
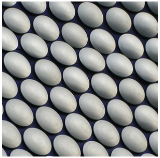
Texture

- Represent details in an image

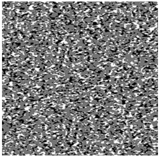
Texture with repeated local patterns

Local pattern

Texture — characteristics

Repetition

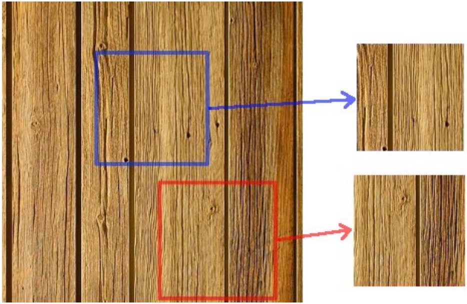



Stochastic


Both

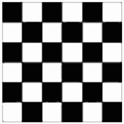
Texture Analysis

- Compare textures to look for similar or different patterns:



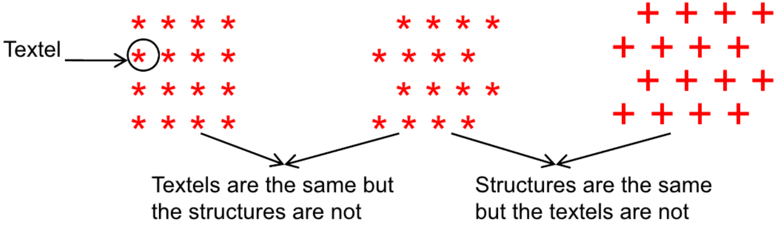
Texture Analysis: approaches

1. Structural (top–down)
   - decompose image in basic elements: texels (*texture elements*) / textons
   - adequate for artificial texture or well-behaved patterns
2. Statistical (bottom–up)
   - characterize texture as a series of statistical properties in a small group of pixels
   - often adequate for natural texture




Structural: textel

- Texture represented via primitives with regular repeated patterns: textels
  - textel is a group of pixels with similar intensity properties: average value, contrast, flat regions, etc.
  - the granularity of the texture is given by the size of the "primitive".



Statistical approach

- Define and segment regions of textels can be a challenge for natural scenes
  - textures look similar but it is hard to extract their structure.

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    - textures look similar but it is hard to extract their structure.
    - compare **statistics** can be an alternative

- Compute numerical/statistical measures to describe texture to be computed in greylevel or color.
    - computationally efficient

Statistical approach: first order

Measures computed over the values or the histogram.

- Fixing a window (region) of pixels, compute the mean, standard deviation, skewness and kurtosis
- Other methods such as uniformity and entropy are often computed using the histogram

Statistical approach: other

Let z represent indices of pixels in a given window, $p(z_i)$, $i = 0..L-1$ is the frequency of intensity z_i, in which p is a normalized histogram.

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$$U(z) = \sum_{i=0}^{L-1} p(z_i)^2, \tag{1}$$

Statistical approach: other

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- Uniformity:

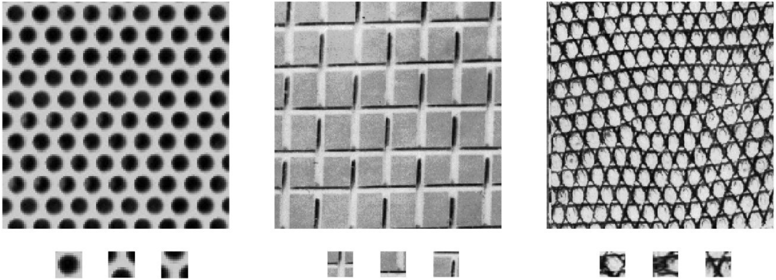
$$U(z) = \sum_{i=0}^{L-1} p(z_i)^2, \tag{1}$$

- Entropy

$$e(z) = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i), \tag{2}$$

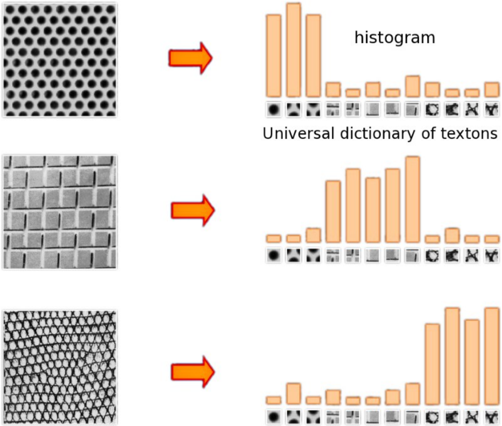
Textons

- Textons can be extracted from images using small *patches*, and then form a dictionary of textures for differente geometric and photometric configurations.
  - based on a study showing that human perception of texture is based on texture atoms (Julesz, 1981)
  - there are several ways to extract textons: sparse coding over-complete basis (Olshausen; Field, 1997), micro-image patches (Lee et al., 2000).



Histogram of textons

- After building a dictionary of textons, count the frequency of the most similar textons in a given image.
- The resulting distribution defines the image texture pattern.



Texture: co-ocurrence matrix

- Capture relationships between a pair of pixels.
- The co-ocurrence matrix considers a fixed distance Q between two pixels: **reference** and **neighbour**.

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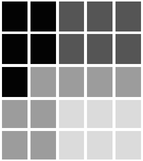
- The co-ocurrence matrix considers a fixed distance Q between two pixels: **reference** and **neighbour**.
- Ex: $Q = (0, 1)$ means that the neighbour is shifted by 0 pixels in the x direction (row) and 1 pixel in y direction (column). In this particular case we are looking at the pixel on the right hand side.

Texture: co-ocurrence matrix



- Consider $Q = (0, 1)$.

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

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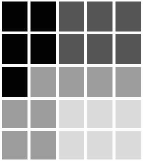

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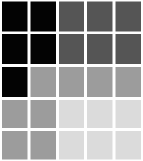
- Consider $Q = (0, 1)$.
- Compute the co-ocurrence at every pixel of an image with L graylevels.
  In this example we cannot compute the co-ocurrence at the right border.

Texture: co-ocurrence matrix



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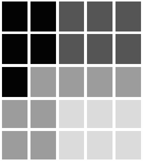
- Consider $Q = (0, 1)$.
- Compute the co-ocurrence at every pixel of an image with L graylevels.
  In this example we cannot compute the co-ocurrence at the right border.
- Build a matrix G given by a shift $Q = (dx, dy)$, and all pairs of intensities $i, j \in \{0, \cdots L - 1\}$:

$$G(i,j) = |\{(x,y)|f(x,y) = i, f(x+dx, y+dy) = j\}|$$

Texture: co-ocurrence matrix



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0	2	2	2	2
2	2	3	3	3
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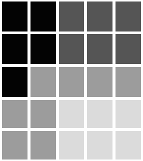
Considering the configuration of relative position as $Q = (dx, dy) = (0, 1)$:

pixel	n. 0	n. 1	n. 2	n. 3
ref. 0	2	2	1	0
ref. 1	0	4	0	0
ref. 2	0	0	5	2
ref. 3	0	0	0	4

Texture: co-ocurrence matrix



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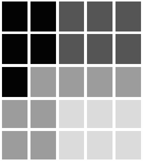
G is usually sparse. It is common to re-quantize the image with less number of intensities before computing the GLCM.

Texture: co-ocurrence matrix



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

$P_{i,j} = G_{i,j}/n$ can be seen as a probability estimate of a given pair of intensities to be observed in an image.

pixel	n. 0	n. 1	n. 2	n. 3
ref. 0	0.100	0.100	0.050	0.000
ref. 1	0.000	0.200	0.000	0.000
ref. 2	0.000	0.000	0.250	0.100
ref. 3	0.000	0.000	0.000	0.200

Texture: Haralick descriptors

Let m_r, m_c be the mean and σ_r^2, σ_c^2 be the variances of, respectively, the rows and columns of the CM G:

$$m_r = \sum_{i=1}^{L} i \sum_{j=1}^{L} p_{i,j} \qquad m_c = \sum_{j=1}^{L} j \sum_{i=1}^{L} p_{i,j}$$

$$\sigma_r^2 = \sum_{i=1}^{L} (i - m_r)^2 \sum_{j=1}^{L} p_{i,j} \qquad \sigma_c^2 = \sum_{j=1}^{L} (j - m_c)^2 \sum_{i=1}^{L} p_{i,j}$$

Texture: Haralick descriptors

- In order to extract relevant information to compare textures, we often use **Haralick** descriptors — by Robert Haralick et al. (1973). Although there are many descriptors, there are 6 often used due to be uncorrelated with each other:
- Maximum probability: strongest response of P, in the range $[0, 1]$

$$\max_{i,j} p_{i,j} \tag{3}$$

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- Maximum probability: strongest response of P, in the range $[0, 1]$

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- Correlation: between pixels reference and neighbour, in the range $[-1, 1]$

$$\sum_{i=1}^{L} \sum_{j=1}^{L} \frac{(i - m_r)(j - m_c) p_{i,j}}{\sigma_r \sigma_c}, \tag{4}$$

requires $\sigma_r \neq 0$, $\sigma_c \neq 0$,

Texture: Haralick descriptors

- Contrast: between the intensities of the pixels, range $[0, (L-1)^2]$

$$\sum_{i=1}^{L}\sum_{j=1}^{L}(i-j)^2 p_{i,j} \tag{5}$$

- Energy: range $[0, 1]$, will be 1 for a constant image.

$$\sum_{i=1}^{L}\sum_{j=1}^{L} p_{i,j}^2 \tag{6}$$

Texture: Haralick descriptors

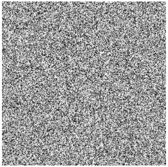
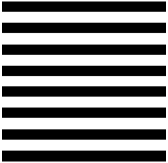
- Homogeneity: spatial auto-correlation measure, range $[0, 1]$, it is 1 for a diagonal G.

$$\sum_{i=1}^{L}\sum_{j=1}^{L}\frac{p_{i,j}}{1+|i-j|} \tag{7}$$

- Entropy: randomness of G, range $[0, 2\log_2 L]$, max for $p_{i,j}$ and 0 for $p_{i,j} = \mathbf{0}$.

$$-\sum_{i=1}^{L}\sum_{j=1}^{L} p_{i,j}\log_2 p_{i,j} \tag{8}$$

Texture: Haralick descriptors — example

	P.Max	Corr.	Cont.	Unif.	Homog.	Entrop.
	0.099	0.007	1273.68	0.019	0.328	5.741
	0.437	0.884	230.71	0.445	0.512	1.320
	0.330	0.802	99.97	0.130	0.639	4.323

Local Binary Patterns (LBP)

- Ojala (1996): based on the idea that texture is described by two complementary information:
  - local spatial patterns;
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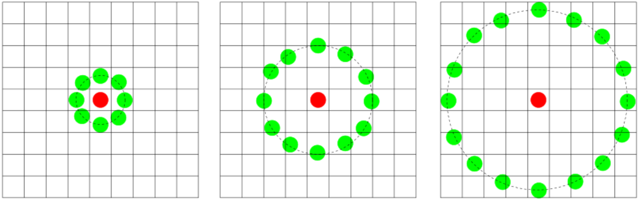
- Ojala (1996): based on the idea that texture is described by two complementary information:
  - local spatial patterns;
  - greylevel contrast.
- Let P, R be the neighbourhood of a pixel with P sampling points and a circle of radius R.



$P = 8, R = 1$ $P = 12, R = 2$ $P = 16, R = 4$

Local Binary Patterns (LBP)

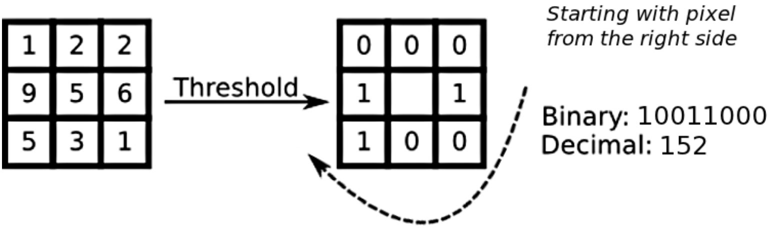
- Produces a code (LBP code) for a central pixel c, with coordinates (x_c, y_c), sampling P pixels in a radius R:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{9}$$

$$s(x) = \begin{cases} 1, & \text{if } x > 0; \\ 0, & \text{otherwise,} \end{cases} \tag{10}$$

g_p and g_c are the greylevels of points in the neighbourhood p and the central pixel c

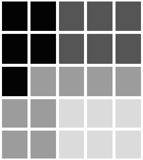
Local Binary Patterns (LBP)



http://www.bytefish.de/blog/local_binary_patterns/

Local Binary Patterns (LBP)

For $c = (1,1)$, with $g_c = 0$, we have:



$$LBP_{8,1} = s(1-0)2^0 + s(2-0)2^1 + s(2-0)2^2 + s(0-0)2^3 + s(0-0)2^4 + s(0-0)2^5 + s(0-0)2^6 + s(1-0)2^7$$

0	0	1	1	1
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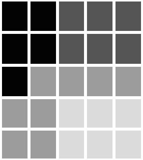

$$
\begin{aligned}
LBP_{8,1} =& s(1-0)2^0 + s(2-0)2^1 + s(2-0)2^2 + s(0-0)2^3 + \\
& s(0-0)2^4 + s(0-0)2^5 + s(0-0)2^6 + s(1-0)2^7 \\
=& 1 \cdot 1 + 1 \cdot 2 + 1 \cdot 4 + 0 + 0 + 0 + 0 + 1 \cdot 128 = \mathbf{135}
\end{aligned}
$$

0	0	1	1	1
0	0	1	1	1
0	2	2	2	2
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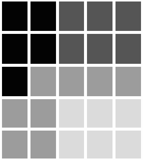
Local Binary Patterns (LBP)



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For $c = (1,1)$, with $g_c = 0$, we have:

$$\begin{aligned} LBP_{8,1} =& s(1-0)2^0 + s(2-0)2^1 + s(2-0)2^2 + s(0-0)2^3 + \\ & s(0-0)2^4 + s(0-0)2^5 + s(0-0)2^6 + s(1-0)2^7 \\ =& 1\cdot 1 + 1 \cdot 2 + 1 \cdot 4 + 0 + 0 + 0 + 0 + 1 \cdot 128 = \mathbf{135} \end{aligned}$$

For $c = (2,3)$, with $g_c = 2$, we have:

Local Binary Patterns (LBP)

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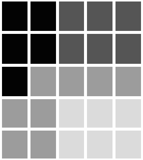

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LBP_{8,1} =& s(1-0)2^0 + s(2-0)2^1 + s(2-0)2^2 + s(0-0)2^3 + \\
& s(0-0)2^4 + s(0-0)2^5 + s(0-0)2^6 + s(1-0)2^7 \\
=& 1 \cdot 1 + 1 \cdot 2 + 1 \cdot 4 + 0 + 0 + 0 + 0 + 1 \cdot 128 = \mathbf{135}
\end{aligned}
$$

For $c = (2, 3)$, with $g_c = 2$, we have:

$$LBP_{8,1} = 0 + 2 + 4 + 8 + 0 + 0 + 0 + 0 = \mathbf{14}$$

0	0	1	1	1
0	0	1	1	1
0	2	2	2	2
2	2	3	3	3
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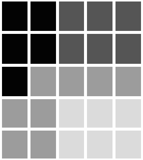
Local Binary Patterns (LBP)



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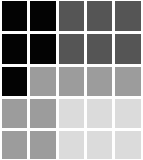
For $c = (2,3)$, with $g_c = 2$, we have:

$$LBP_{8,1} = 0 + 2 + 4 + 8 + 0 + 0 + 0 + 0 = \mathbf{14}$$

For $c = (3,3)$, with $g_c = 3$, we have:

Local Binary Patterns (LBP)



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0	0	1	1	1
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For $c = (1,1)$, with $g_c = 0$, we have:

$$\begin{aligned} LBP_{8,1} = & s(1-0)2^0 + s(2-0)2^1 + s(2-0)2^2 + s(0-0)2^3 + \\ & s(0-0)2^4 + s(0-0)2^5 + s(0-0)2^6 + s(1-0)2^7 \\ = & 1 \cdot 1 + 1 \cdot 2 + 1 \cdot 4 + 0 + 0 + 0 + 0 + 1 \cdot 128 = \mathbf{135} \end{aligned}$$

For $c = (2,3)$, with $g_c = 2$, we have:

$$LBP_{8,1} = 0 + 2 + 4 + 8 + 0 + 0 + 0 + 0 = \mathbf{14}$$

For $c = (3,3)$, with $g_c = 3$, we have:

$$LBP_{8,1} = 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 = \mathbf{0}$$

Local Binary Patterns (LBP)

- A code can be uniform or non-uniform, given the number of transitions $0, 1$
- Uniform patterns:
  - 11111111 : no transition
  - 11110000 : 1 transition
  - 11000111 : 2 transitions
- Non-uniform patterns:
  - 11001101 : 4 transitions
  - 01010010 : 6 transitions

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- Uniform patterns:
  - 11111111 : no transition
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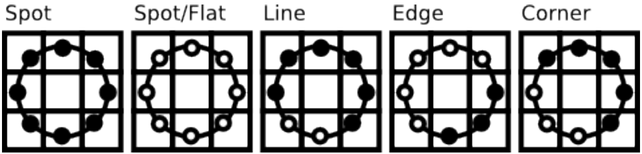
- Non-uniform patterns:
  - 11001101 : 4 transitions
  - 01010010 : 6 transitions
- Ojala recommends the use of a code for each uniform pattern, and a single bin/label for all non-uniform patterns
  - uniform patterns represent $\sim 90\%$ of the total with $LBP_{8,1}$, and $\sim 70\%$ with $LBP_{16,2}$
- For $LBP_{8,R}$, there are 256 possible codes, 58 are uniform, totaling **59**.

Local Binary Patterns (LBP)

- Feature vector can be produced by a histogram of LBP codes
- Each LBP can be considered a micro-texton.
- Local primitives codified by each position of the histogram can define different shapes and characteristics:



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