3. Characterization: Colour, Texture & Shape

IMAGE CHARACTERIZATION

Characterization

- Contents
  - Texture
    - Co-ocurrence matrices
    - Law Masks
    - Local Binary Patterns
  - Colour
    - Physical properties
    - Colour Spaces
  - Shape
    - Statistical

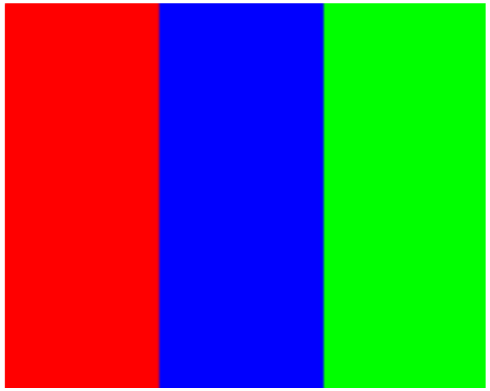
Characterization

Introduction

- Visual information (visual cues)
  - Shape
  - Texture
  - Colour

Characterisation

- Sometimes a single characteristic is not enough to characterise a region…



They are the same images based on just colour characteristics!!

- Shape and Texture information is needed

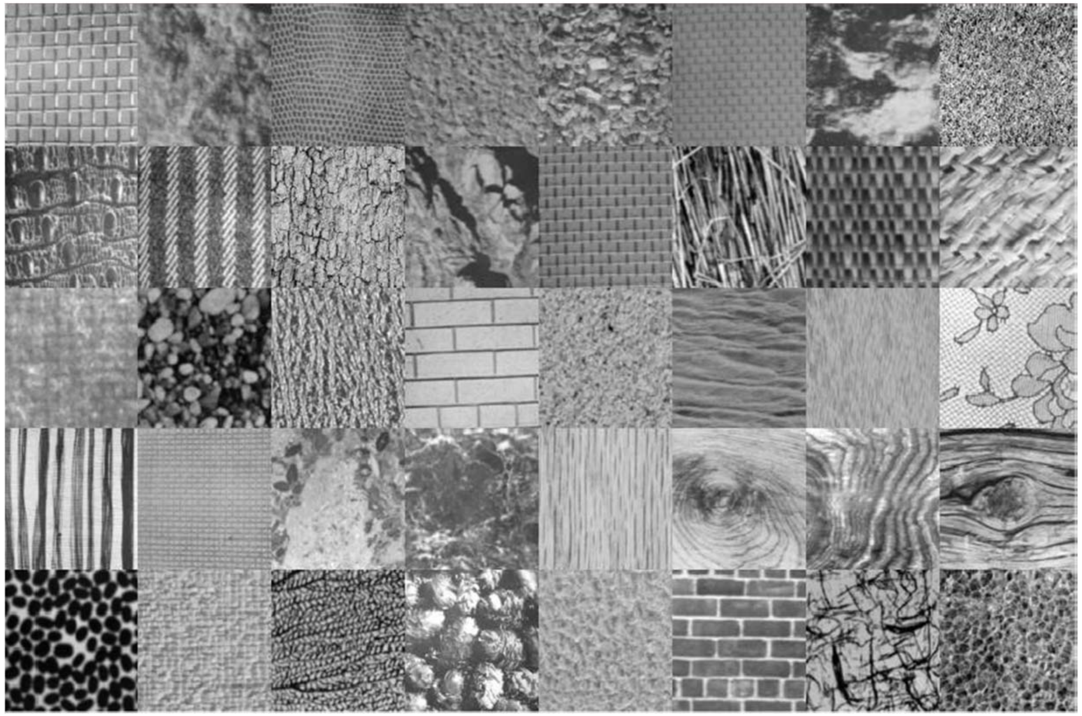
Texture

Texture

What is texture?

Texture

There is not **an accepted definition** for this visual cue



It is the property of some surfaces

Texture. Introduction

What is texture?

- Is it something related to the touch?
- Can we extract information from images? has it got color?
- Is a property of the surface of an object, and can not be defined by a single point
- A given texture depends on the scale at which is regarded

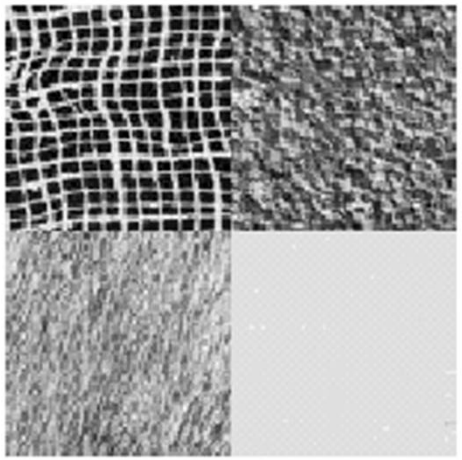


Image with 4 textures

Texture. Introduction

Everyday texture terms - *rough, silky, bumpy* - refer to touch.

A texture that is ***rough*** to touch has:

- a large difference between high and low points, and
- a space between highs and lows approximately the same size as a finger.

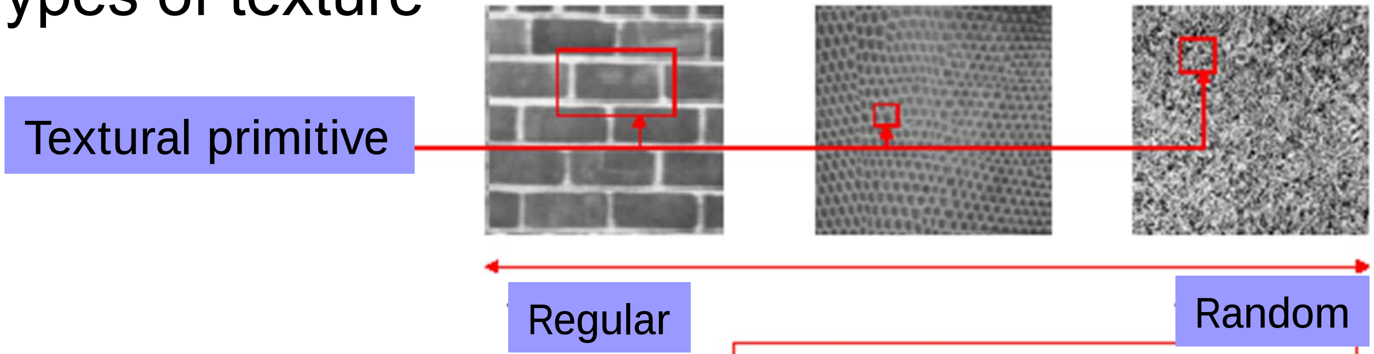
Silky would have

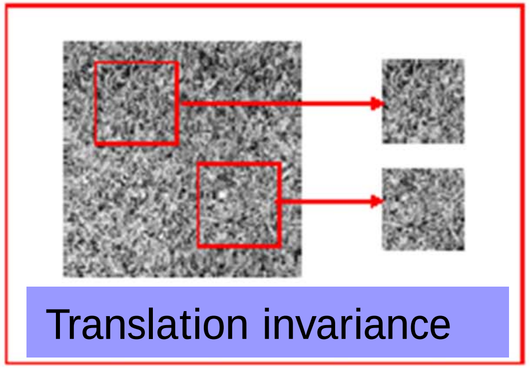
- little difference between high and low points, and
- the differences would be spaced very close together relative to finger size.

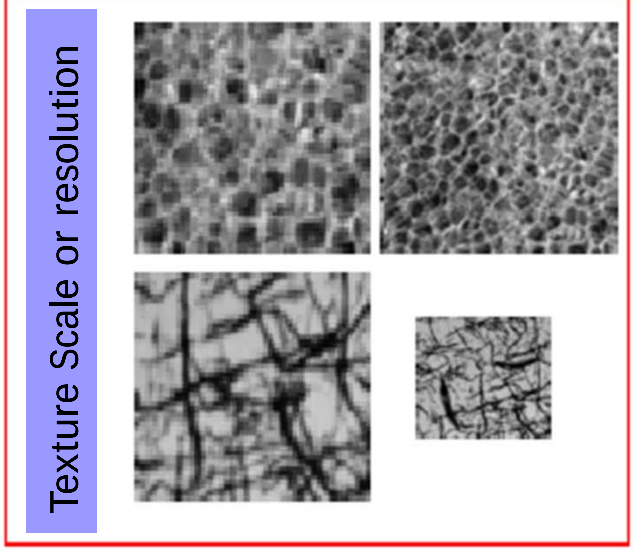
Image texture works in the same way, except the highs and lows are brightness values instead of elevation changes. Instead of probing a finger over the surface, a "window" box is used.

Texture. Introduction

Types of texture



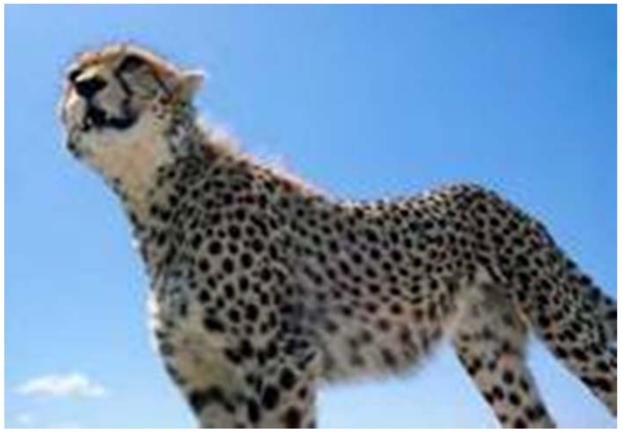




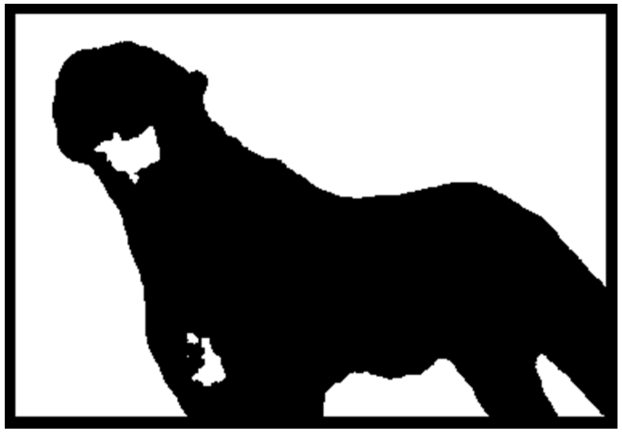
From Maria Vanrell at the Universitat Autònoma de Barcelona

Texture. Introduction

- Most of the existing image segmentation algorithms assume uniform regions related to intensity or colour (non textured regions)
- The surface of the object, illumination and other factors affect this intensity or colour information



Original Image



Segmented Image

Texture. Operators

- Statistical methods
  - Co-occurrence matrices
  - Energy (Laws masks)
  - Parametric masks
  - Local Binary Patterns (LPB)
- Structural methods
- Modelization methods
  - Markov Random Fields
- Space-frequency filtering methods
  - Gabor filters
  - Wavelets

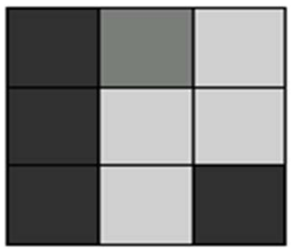
Texture. Co-occurrence Matrices

What is it? **The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image.**

A position in the matrix (i,j) corresponds to the number of pixels of intensity i and j separated by a given distance and angle. They are always square matrices with the same dimensionality as the number of grey-levels

<u>GLCM:</u>

<u>Input image:</u>



Texture. Co-occurrence Matrices

- The GLCM is used for a series of "**second order**" texture calculations.
- **First order** texture measures are statistics calculated from the original image values, like variance, and *do not consider pixel neighbour relationships.*
- **Second order** measures consider the relationship between *groups of two (usually neighbouring) pixels* in the original image.
- **Third** and higher **order** textures (considering the *relationships among three or more pixels*) are theoretically possible but not commonly implemented due to calculation time and complexity.

Texture. Co-occurrence Matrices

The matrix (when normalized) represents the probability that two points with grey-levels ***i*** and ***j*** exist in a distance ***d*** and orientation θ.

(orientations: 0º, 45º, 90º and 135º)

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

$$M_V = M(1, 90^o) = \begin{pmatrix} 6 & 0 & 2 & 0 \\ 0 & 4 & 2 & 0 \\ 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 0 \end{pmatrix}$$

Texture. Co-occurrence Matrices

Energy $= \left(\sum_{i,j=0}^{N-1} m_{ij}^2\right)^{1/2}$

Entropy $= \sum_{i,j=0}^{N-1} m_{ij} \times \log(m_{ij})$

Probability $= \max_{i,j=0}^{N-1} (m_{ij})$

Contrast $= \sum_{i,j=0}^{N-1} (i-j)^2 \times m_{ij}$

Measures related to orderliness (how regular the pixel values are within the window)

Measures related to the distance from the GLCM diagonal

Inverse $= \sum_{i,j=0}^{N-1} \frac{m_{ij}}{(i-j)^2} \quad i \neq j$

Homogeneity $= \sum_{i,j=0}^{N-1} \frac{m_{ij}}{1+|i-j|^2}$

Correlation $= \sum_{i,j=0}^{N-1} \frac{(i-\mu)\times(j-\mu)\times m_{ij}}{\sigma^2}$

$$\mu = \sum_{i,j=0}^{N-1} i \times m_{ij}$$

$$\sigma = \sqrt{\sum_{i,j=0}^{N-1} (i-\mu)^2 \times m_{ij}}$$

Statistics derived from the GLCM

Texture. Co-occurrence Matrices

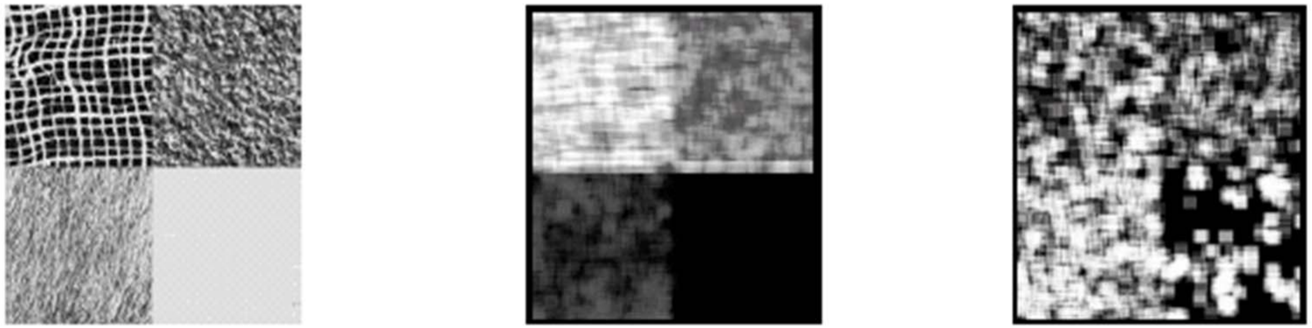
- **Contrast:** indication of the local variation in the image
  (big value → large variation
  small value → uniform)

- **Homogeneity**: values concentrated/located in the diagonal of the matrix
  (big value → homogeneity)

- **Energy $(\sum m_{ij}^2)^{1/2}$**: indication of the uniformity of the image
  (big values → few entries in the matrix with large values,
  small values → entries in the matrix with similar values)

Texture. Co-occurrence Matrices

How are these images obtained?



Texture. Co-occurrence Matrices

Activity

Given the following 2 images (2bits), compute the co-occurrence matrix **M(1,0º)**, and extract the **contrast feature** for both images

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

Image 1

2	2	2	2	2
2	2	2	2	2
2	2	2	2	2
1	1	1	1	1
1	1	1	1	1

Image 2

$$\text{Contrast} = \sum_{i,j=0}^{N-1} (i-j)^2 \times m_{ij}$$

Texture. Co-occurrence Matrices

Activity

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

Image 1

2	2	2	2	2
2	2	2	2	2
2	2	2	2	2
1	1	1	1	1
1	1	1	1	1

Image 2

Contrast $= \sum_{i,j=0}^{N-1} (i-j)^2 \times m_{ij}$

0	0	12	0
0	8	0	4
12	0	0	0
0	4	0	0

M(1,0º)

0	0	0	0
0	16	0	0
0	0	24	0
0	0	0	0

M(1,0º)

Contrast Image 1 = 2^2*12 + 2^2*4+ 2^2*12 + 2^2*4 = **128**

Contrast Image 2 = **0**

Texture. Co-occurrence Matrices

Questions:

- What is the texture of a pixel?
- What is the texture of a region?

Variables...

- Matrix size
- Computational cost
- Parameters
  - Distance?
  - Orientation?
  - Statistic?

Texture. Operators

- Statistical methods
  - Co-occurrence matrices
  - Energy (Laws masks)
  - Parametric masks
  - Local Binary Patterns (LPB)
- Structural methods
- Modelization methods
  - Markov Random Fields
- Space-frequency filtering methods
  - Gabor filters
  - Wavelets

Texture. Energy (Laws Masks)

- Laws masks are the result of applying certain masks which represent features such as edges, holes, etc

- 2 steps are needed:
  - Mask convolution over the image
  - Obtain statistic measures from the convolution results

    - Statistics: mean, abs mean, standard deviation

Texture. Energy (Laws Masks)

- Developed by Laws (1979) as a set of two-dimensional masks derived from three simple one-dimensional filters:

L3 = (1, 2, 1)	Level detection
E3 = (-1, 0, 1)	Edge detection
S3 = (-1, 2,-1)	Spot detection

Convolving these with each other a set of symmetric and anti-symetric centre-weighted masks with all but the level filters being zero sum is got.

Texture. Energy (Laws Masks)

1	2	1
2	4	2
1	2	1

L3L3

-1	0	1
-2	0	2
-1	0	1

L3E3

-1	2	-1
-2	4	-2
-1	2	-1

L3S3

-1	-2	-1
0	0	0
1	2	1

E3L3

1	0	-1
0	0	0
-1	0	1

E3E3

1	-2	1
0	0	0
-1	2	-1

E3S3

-1	-2	-1
2	4	2
-1	-2	-1

S3L3

1	0	-1
-2	0	2
1	0	-1

S3E3

1	-2	1
-2	4	-2
1	-2	1

S3S3

Laws masks 3x3

-1	-4	-6	-4	-1
-2	-8	-12	-8	-2
0	0	0	0	0
2	8	12	8	2
1	4	6	4	1

E5L5

1	-4	6	-4	1
-4	16	-24	16	-4
6	-24	36	-24	6
-4	16	-24	16	-4
1	-4	6	-4	1

R5R5

-1	0	2	0	-1
-2	0	4	0	-2
0	0	0	0	0
2	0	-4	0	2
1	0	-2	0	1

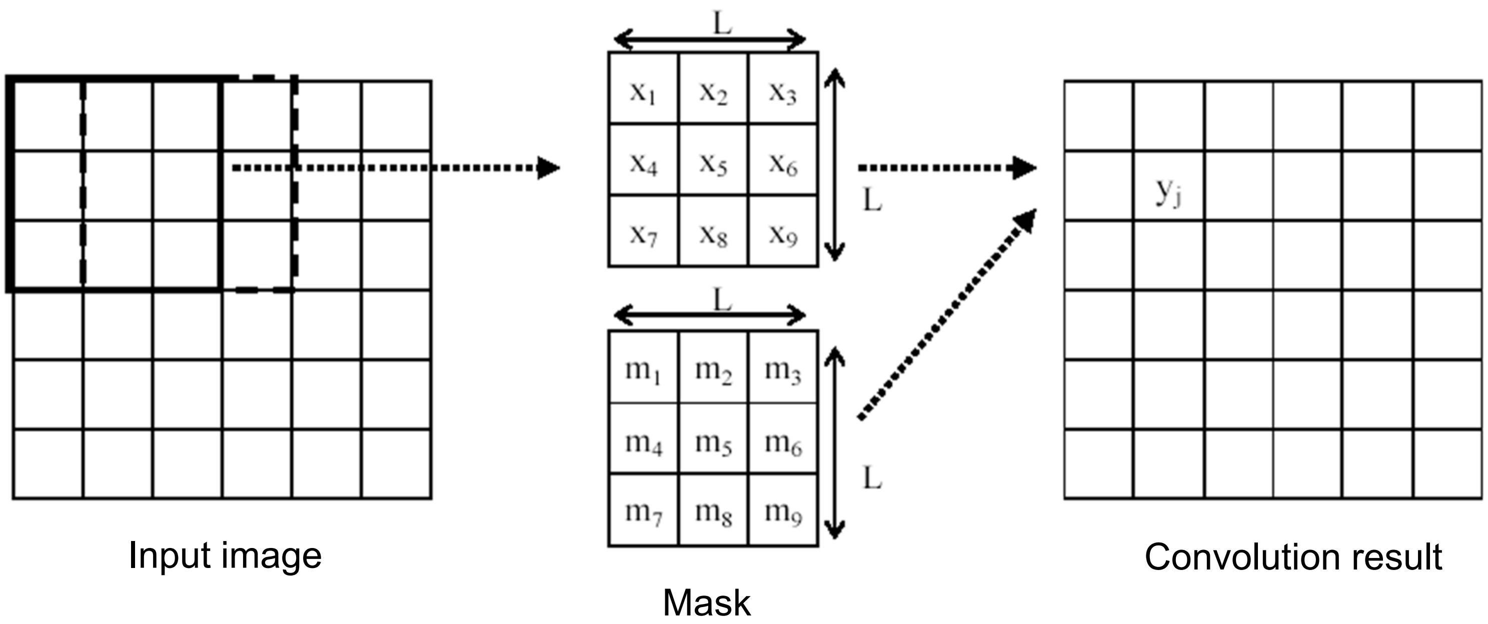
E5S5

-1	0	2	0	-1
-4	0	8	0	-4
-6	0	12	0	-6
-4	0	8	0	-4
-1	0	2	0	-1

L5S5

Laws masks 5x5

Texture. Energy (Laws Masks)

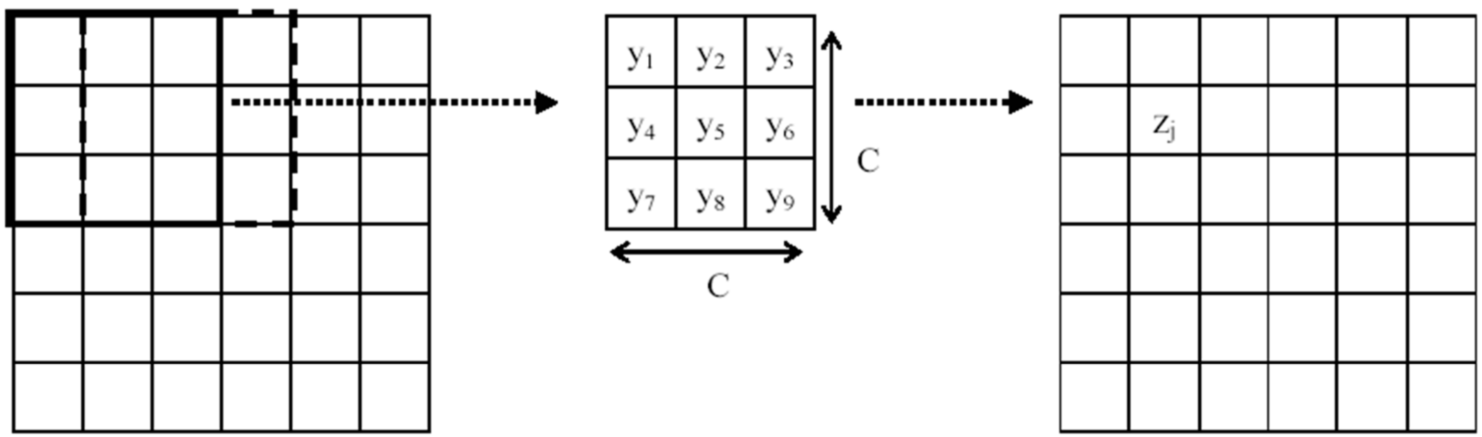


$$Pixels = N = L \times L$$

$$y_j = \sum_{i=1}^{N} x_i \times m_i$$

STEP 1. Mask Convolution

Texture. Energy (Laws Masks)



Convolution result

$$Pixels = N = C \times C$$

$$z_j = f(y_1, y_2, \ldots, y_N)$$

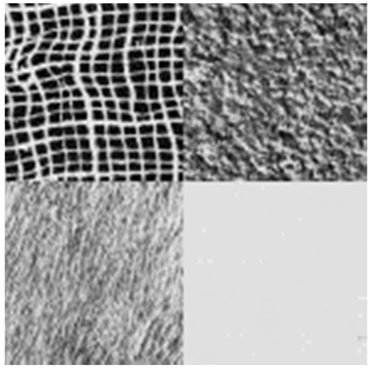
STEP 2. Statistic computation

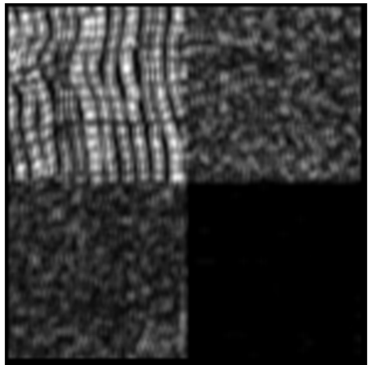
Mean $= \mu = \dfrac{\sum_{i=1}^{N} y_i}{N}$

Standard deviation $s = +\sqrt{\sum_{i=1}^{N} \dfrac{(y_i - \mu)^2}{N}}$

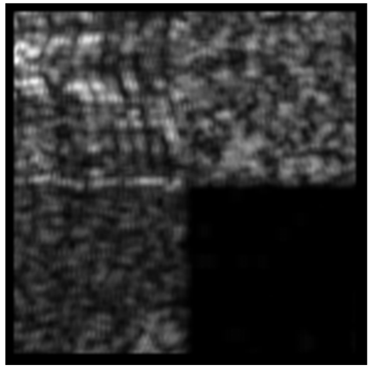
Absolute mean $= \dfrac{\sum_{i=1}^{N} |\, y_i \,|}{N}$

Texture. Energy (Laws Masks)

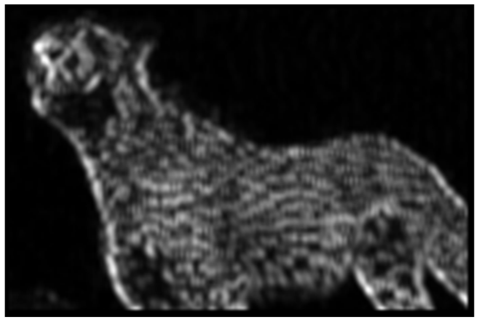




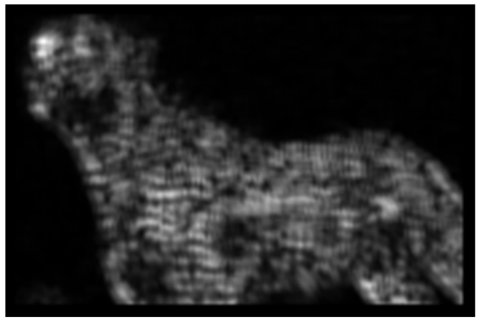
Mask 3x3



Mask 5x5



Mask 3x3



Mask 7x7

Texture. Operators

- Statistical methods
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- Structural methods
- Modelization methods
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  - Gabor filters
  - Wavelets

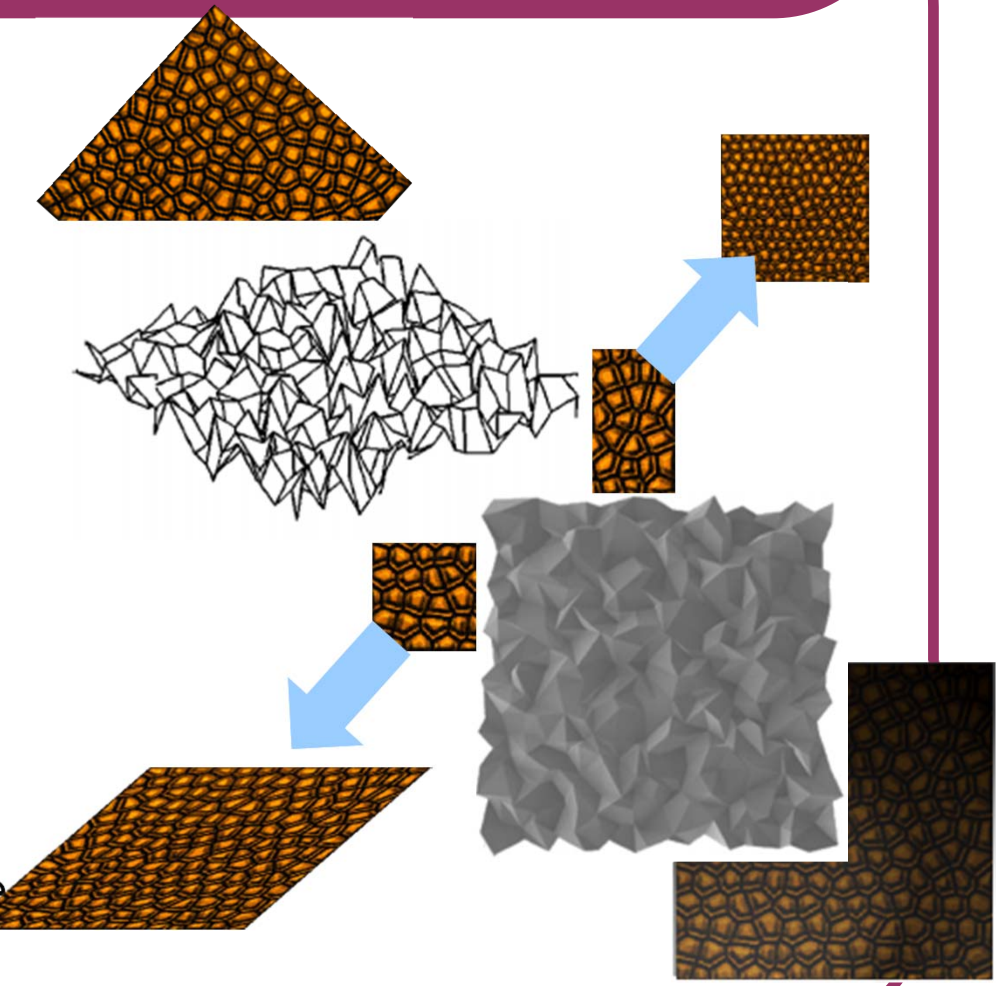
Local Binary Patterns

Luca Giancardo
Alonso Sánchez Secades

Texture: LBP(Local Binary Patterns)

Characteristics of a good texture classifier

- Invariant to:
  - Scale
  - Rotation
  - Illumination
  - Other homographies
- Unique
- Computationally inexpensive
- Multi-dimensional



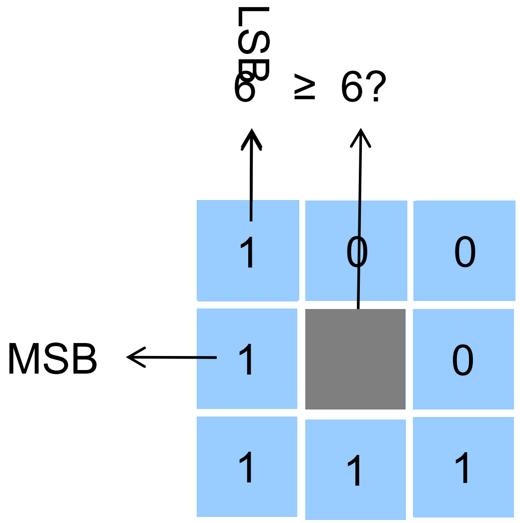
Texture: LBP(Local Binary Patterns)

- A texture measure
- Originally developed by Timo Ojala and Matti Pietikäinen
- Based on simple ideas:
  - Each texture is composed of micro-structures
  - These micro-structure repeat themselves
  - They can be represented with binary patterns easily computed
- …how does it work?

Texture: LBP(Local Binary Patterns)

Binary patterns derivation

- The LBP operator:



PATTERN = 11110001b = 241d

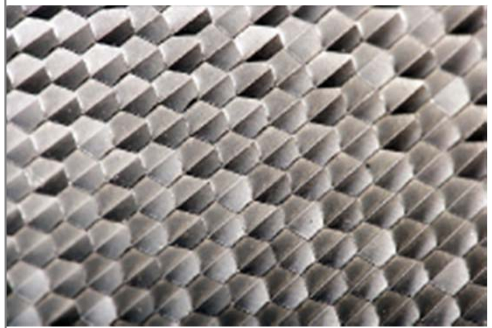
Texture: LBP(Local Binary Patterns)

Textures Classification

- Each texture is classified using the LBP codes derived for each pixel
- A LBP histogram is employed as a measure

Texture: LBP(Local Binary Patterns)

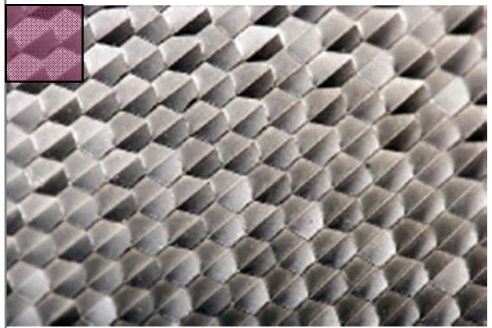
Textures Classification



Occurrence	LBP Codes	Occurrence
0	0000000	0
0	0000001	0
0	0000011	0
0	0000111	0
0	0001111	0
0	0011111	0
0	0111111	0
0	1111111	0

Texture: LBP(Local Binary Patterns)

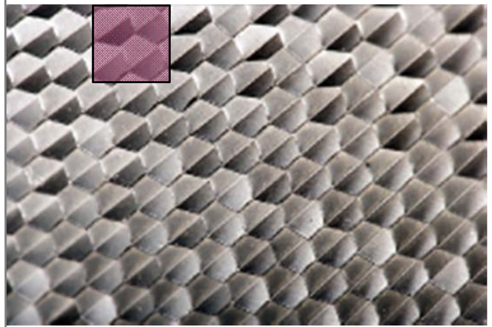
Textures Classification



Occurrence	LBP Codes	Occurrence
0	0000000	0
0	0000001	1
1	0000011	0
0	0000111	0
0	0001111	0
0	0011111	0
0	0111111	0
0	1111111	0

Texture: LBP(Local Binary Patterns)

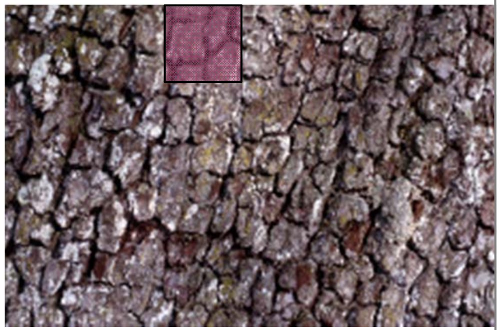
Textures Classification

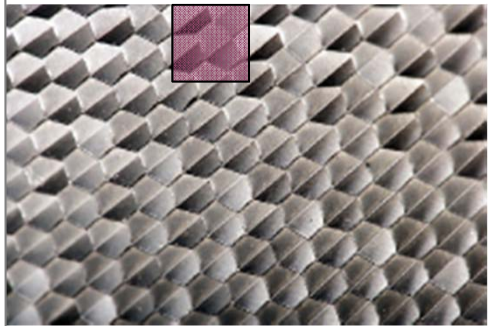


Occurrence	LBP Codes	Occurrence
0	0000000	0
0	0000001	1
1	0000011	1
0	0000111	0
1	0001111	0
0	0011111	0
0	0111111	0
0	1111111	0

Texture: LBP(Local Binary Patterns)

Textures Classification

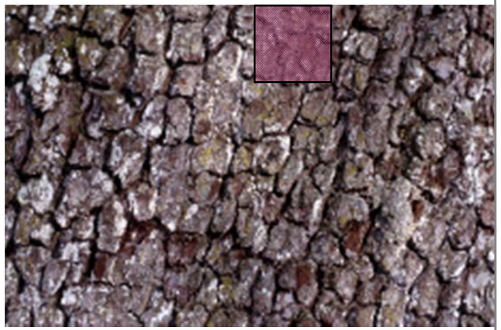


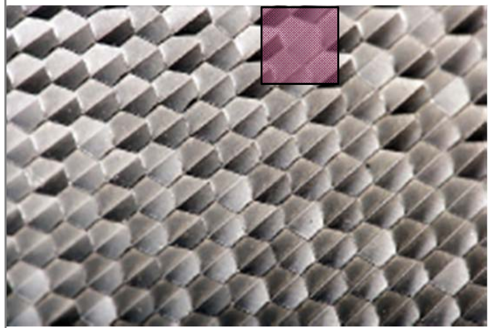


Occurrence	LBP Codes	Occurrence
0	0000000	0
0	0000001	1
1	0000011	1
0	0000111	0
2	0001111	1
0	0011111	0
0	0111111	0
0	1111111	0

Texture: LBP(Local Binary Patterns)

Textures Classification



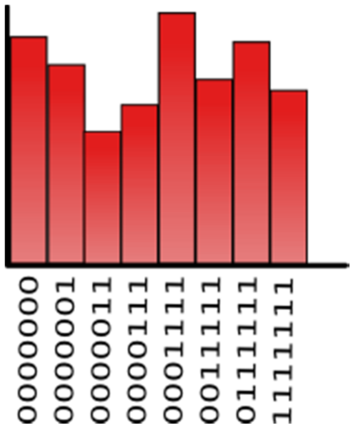


Occurrence	LBP Codes	Occurrence
0	0000000	0
0	0000001	1
1	0000011	1
0	0000111	0
2	0001111	1
1	0011111	1
0	0111111	0
0	1111111	0

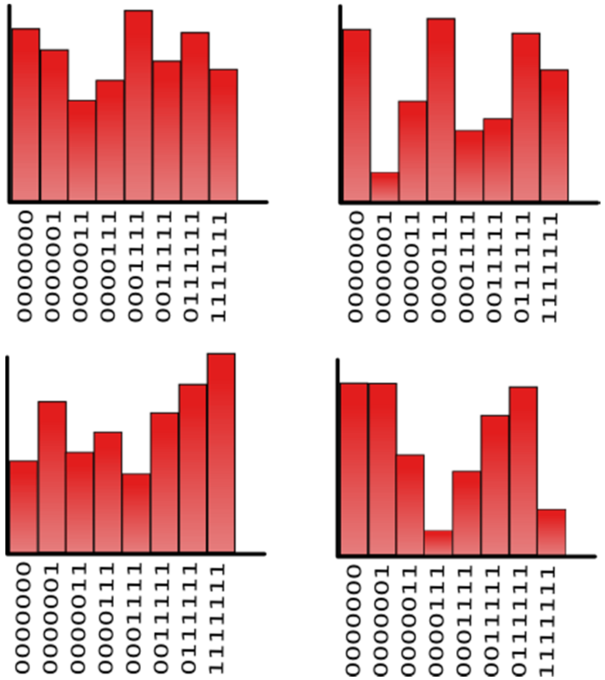
Texture: LBP(Local Binary Patterns)

Textures Classification

New LBP Histogram



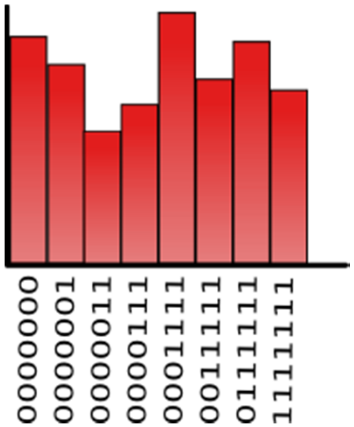
Textures Database



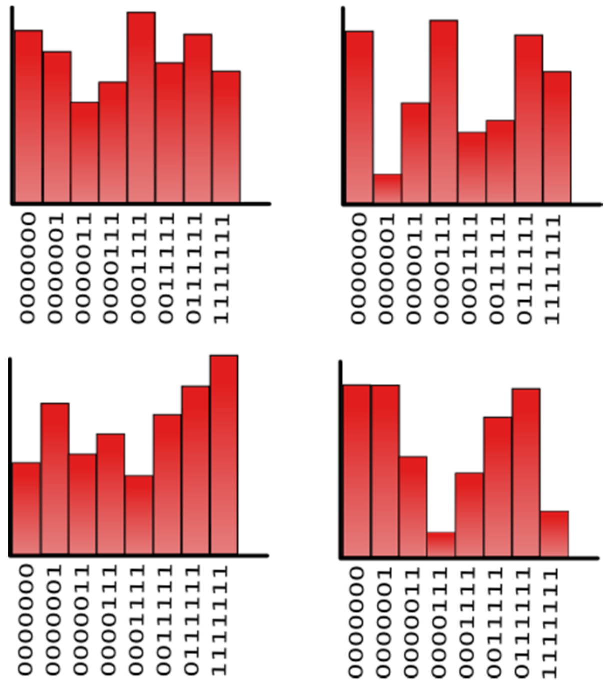
Texture: LBP(Local Binary Patterns)

Textures Classification

New LBP Histogram



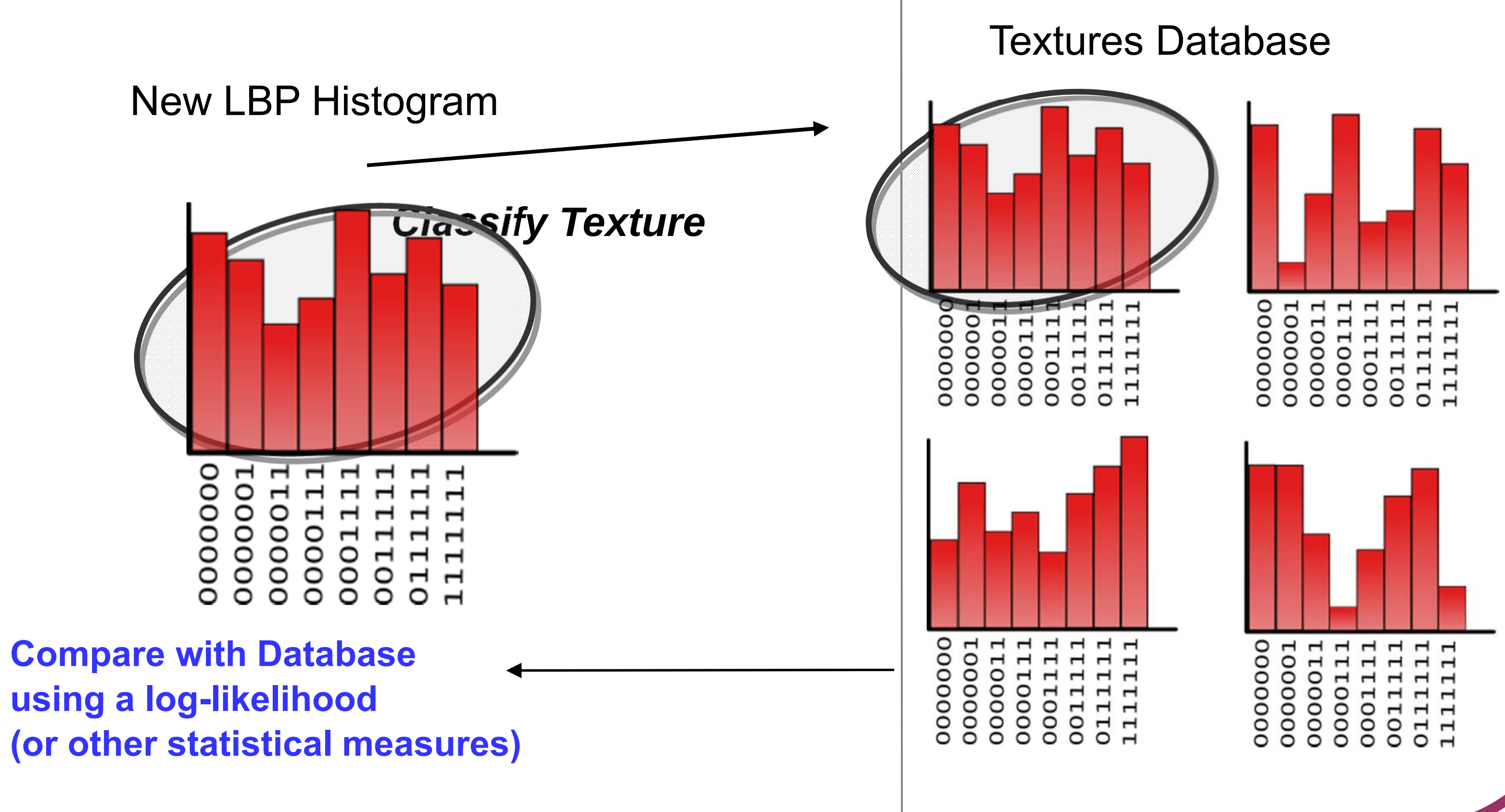
Textures Database



Compare with Database using a log-likelihood (or other statistical measures)

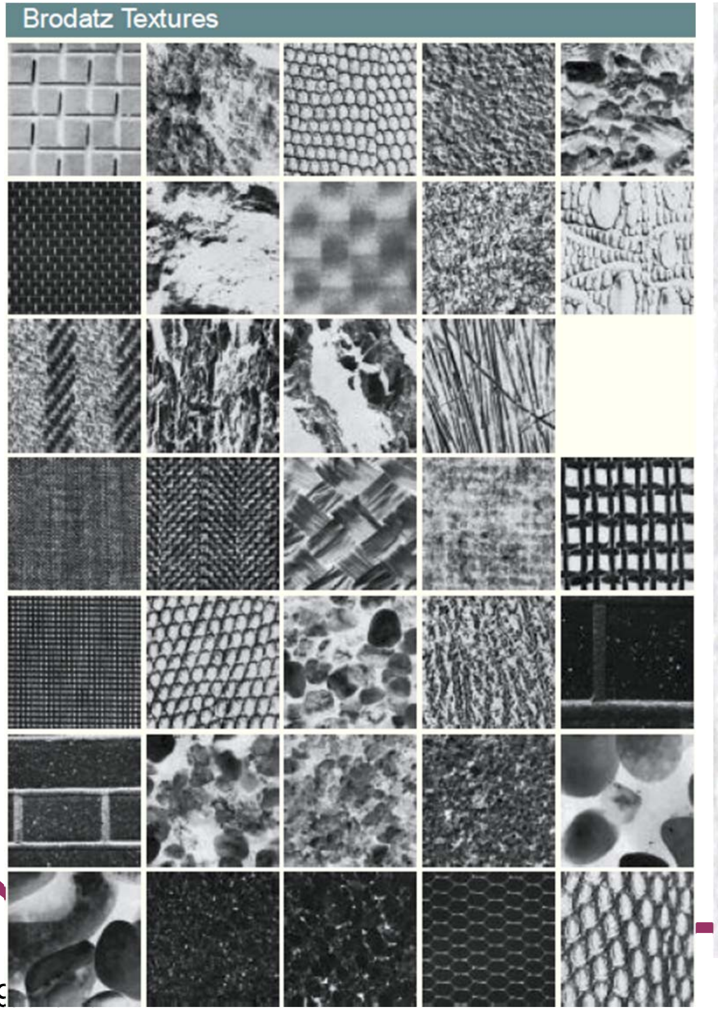
Texture: LBP(Local Binary Patterns)

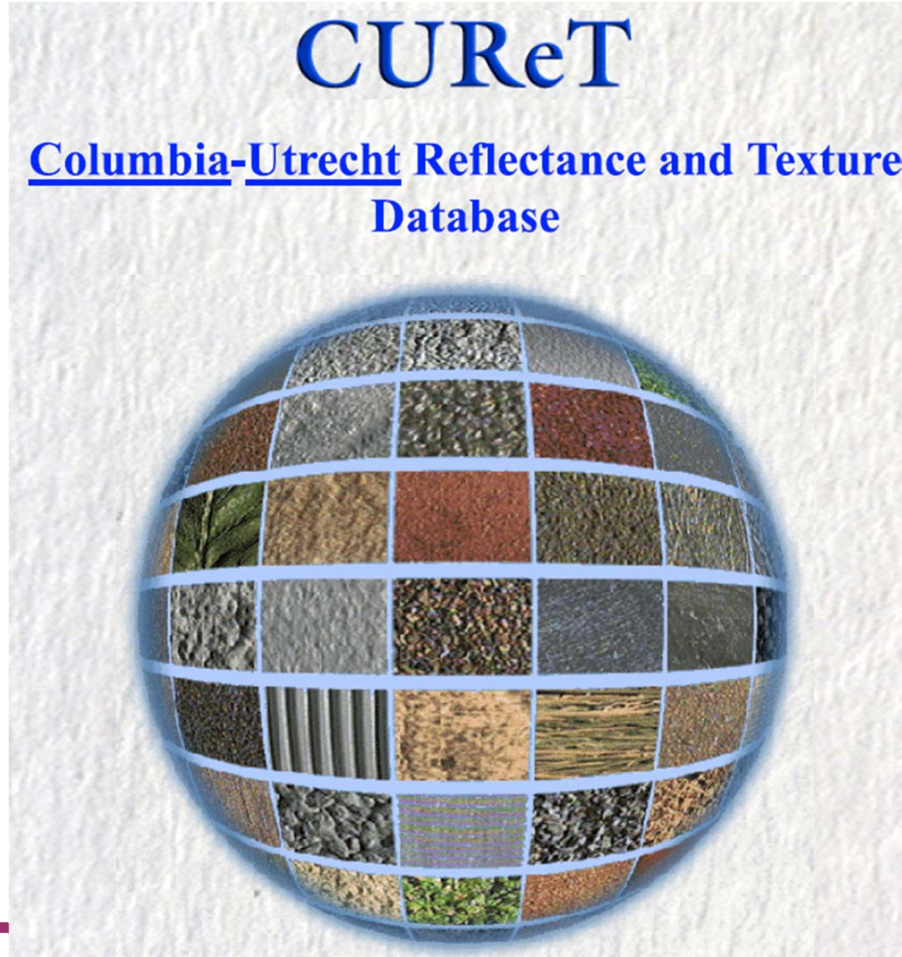
Textures Classification



Texture: LBP(Local Binary Patterns)

Textures Classification



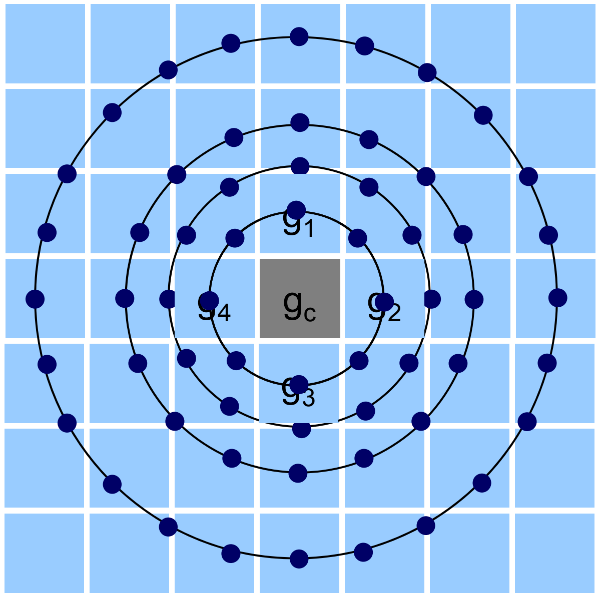


Texture: LBP(Local Binary Patterns)

The Circular Extension

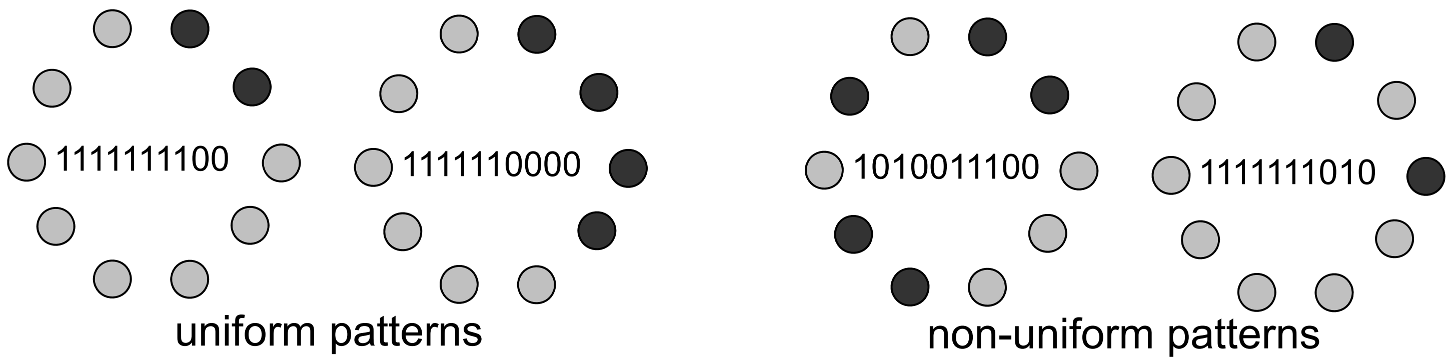
- LBP codes can be derived considering a circular neighbourhood

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



Texture: LBP(Local Binary Patterns)

Uniform LBP Patterns



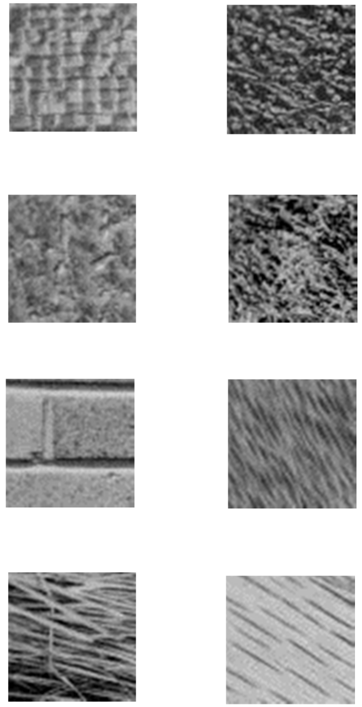
- Through empirical experiments it was discovered that *uniform patterns* are:
  - More stable to transformations
  - So common that can be used as the only LBP descriptors for textures

Texture: LBP(Local Binary Patterns)

Uniform LBP Patterns

Texture	P=8,R=1	P=16,R=2	P=24,R=3
canvas	84.8	58.5	41.2
cloth	91.8	74.2	52.8
cotton	88.9	67.0	46.3
grass	85.5	63.3	45.6
leather	87.7	66.6	49.1
matting	89.5	72.0	55.8
paper	89.2	70.9	52.9
pigskin	87.6	67.9	50.9
raffia	91.4	76.4	59.1
rattan	86.1	68.5	52.4
reptile	88.4	70.9	55.6
sand	89.1	70.7	53.4
straw	83.8	56.6	40.7
weave	76.6	50.9	32.1
wood	86.1	65.1	46.1
wool	88.9	71.0	55.0
AVERAGE	87.2	66.9	49.3

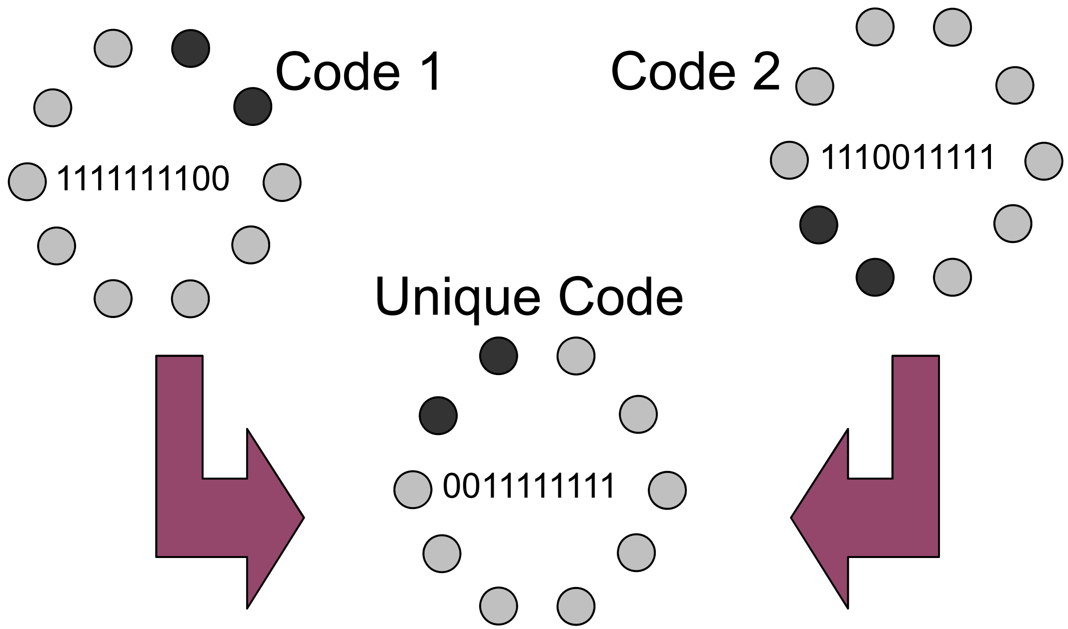
Examples of textures tested



Texture: LBP(Local Binary Patterns)

Rotation Invariance

- Each LBP code can be binary shifted to achieve rotation invariance

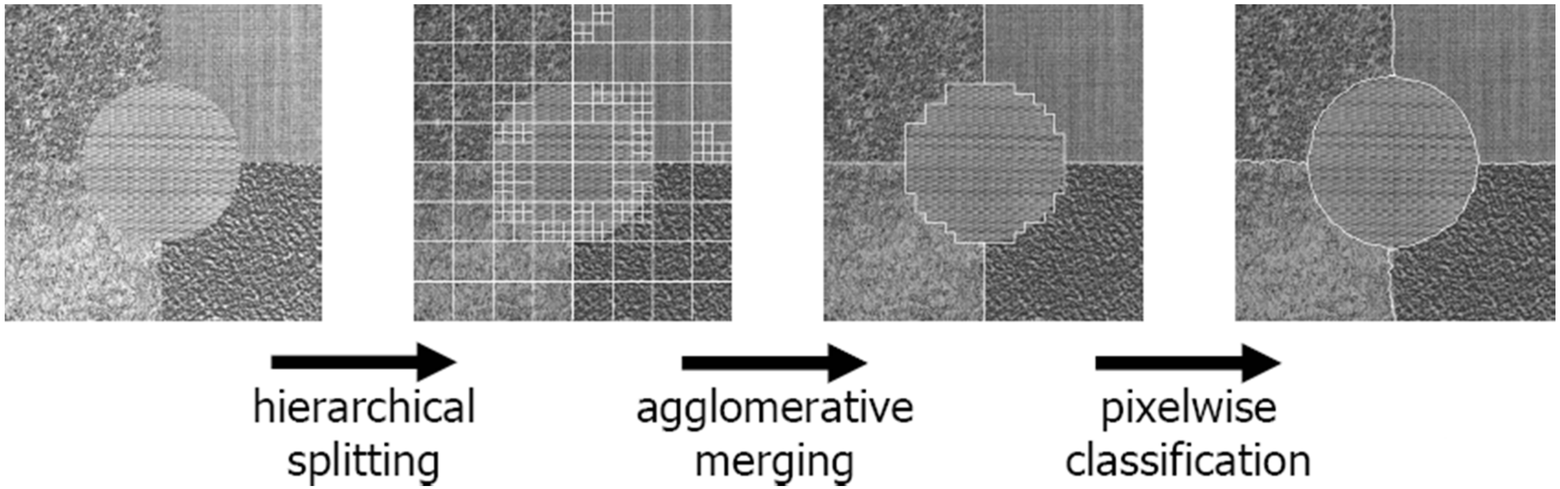


- All the possible transformations are stored in a look-up table

Texture: LBP(Local Binary Patterns)

Applications

- Textures segmentation

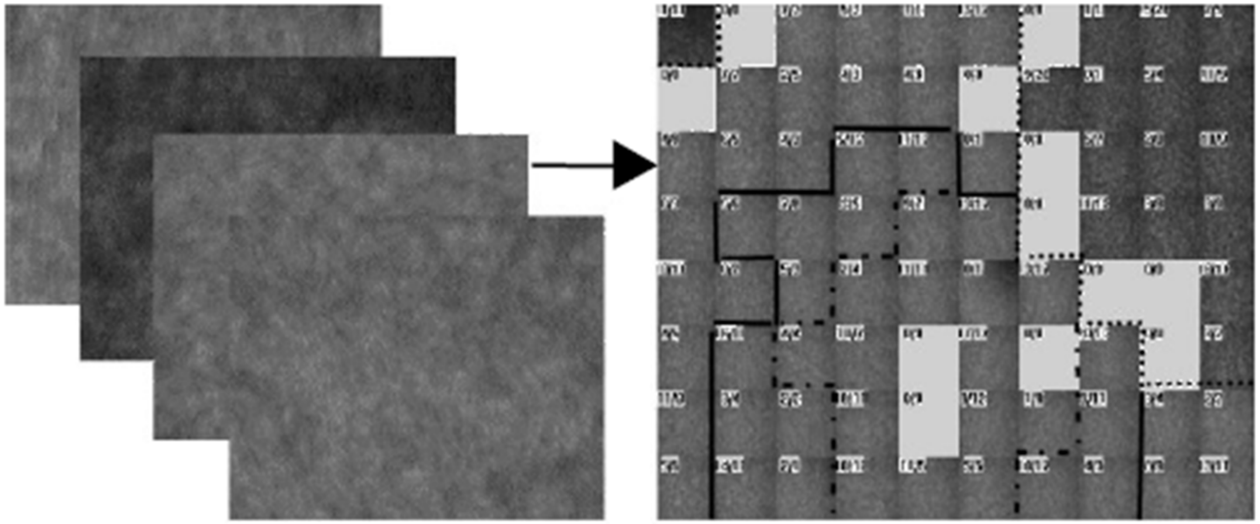


Timo Ojala & Matti Pietikäinen (1999)
Unsupervised texture segmentation using feature distribuition.

Texture: LBP(Local Binary Patterns)

Applications

- Visual Inspection
  - Wood, Paper Inspection
  - Metal, Automotive Parts Inspection

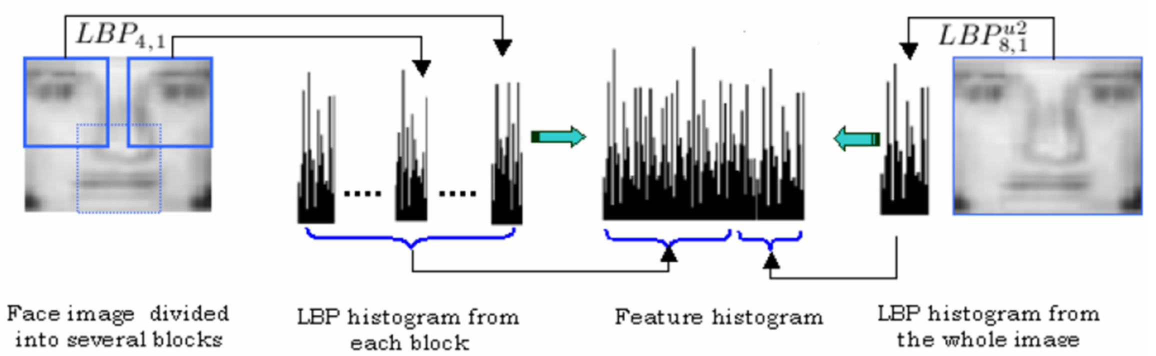


Turtinen et al. (2003)
Paper characterization using visual-based training. IJAMT 22

Texture: LBP(Local Binary Patterns)

Applications

- Face Recognition



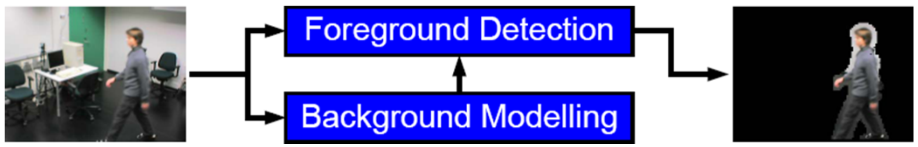
Method	Face detected	False detections	Detection rates
Schneiderman-Kanade(1.0, 1.0) [14]	218	41	96.0 %
BDF Method [17]	221	1	97.4 %
Normalized Pixel features [5]	213	6	93.83%
LBP representation : $LBP^{u2}_{8,1}$ (59 bins)	47	184	20.70 %
LBP representation : $LBP_{4,1}$ (144 bins)	211	9	92.95 %
LBP representation : $LBP_{4,1}$+$LBP^{u2}_{8,1}$ (203 bins)	**221** 222	**0** 13	97.4 % 97.8 %

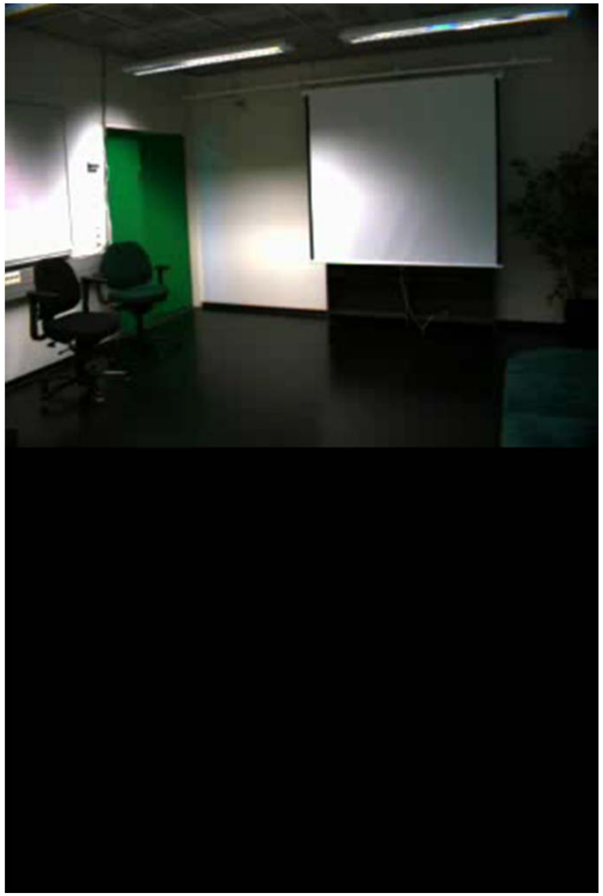
Ahonen T et al. (2004) Face Recognition with local binary patterns

Texture: LBP(Local Binary Patterns)

Applications

- Movement Detection
  - Background dynamically updated
  - Real Time





Heikkilä M, et al. (2004)
A texture-based method for detecting moving objects.

Texture: LBP(Local Binary Patterns)

References

- Timo Ojala, Matti Pietikäinen “A comparative study of texture measures with classification based on feature distribution ” *Pattern Recognition*, vol. 29 (1), 1996, pp. 51-59.
- Timo Ojala, Matti Pietikäinen and Topi Mäenpää “Texture Analysis with Local Binary Patterns” in *Chen and Wang (eds) Handbook of Pattern Recognition and Computer Vision*, 3rd ed., Singapore: Wold Scientific Press, 2005.
- Timo Ojala, Matti Pietikäinen and Topi Mäenpää “Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 24 (7), Jul. 2002, pp. 971-987.
- Machine Vision Group. “Local Binary Pattern” [online]. Finland: University of Oulu. Available at:

http://www.ee.oulu.fi/research/imag/texture/lbp/about/Texture Analysis with Local Binary Patterns.pdf (accessed 18/12/2010)

Summary. Texture

- Texture operator depends on the application and images
- Usually, there's a need to use various operators, and therefore fuse the results (feature vectors)
- Need to integrate with other features (shape, colour)
- No texture operator close to human texture perception

Texture characterization