Texture Representation and Analysis

Samia Ainouz

Overview

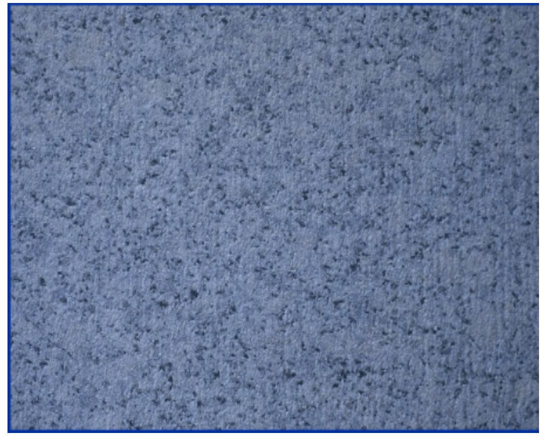
What’s a texture
Examples of textured images
Texture representation
Texture analysis

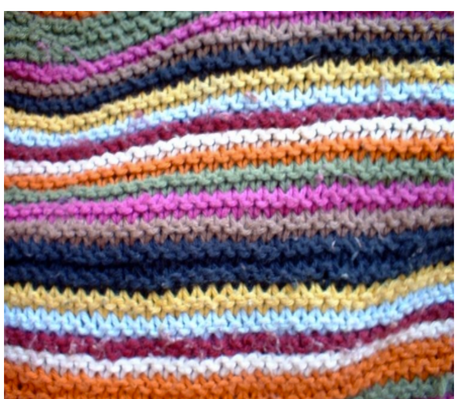
What’s a texture

- Definition not sharp
- Image of stationary statistics
- Pattern repeatted in an image
- Whenever I see, too many
- Extreme variability
- How to describe them?

What’s a texture

It could be homogeneous and regular, stochastic, non regular/non homogenous, strog reflectance variation&warping, stochastique scale variation and stoch. scale, shape and reflectance variation





…and more

flower

food

water

quito

machu

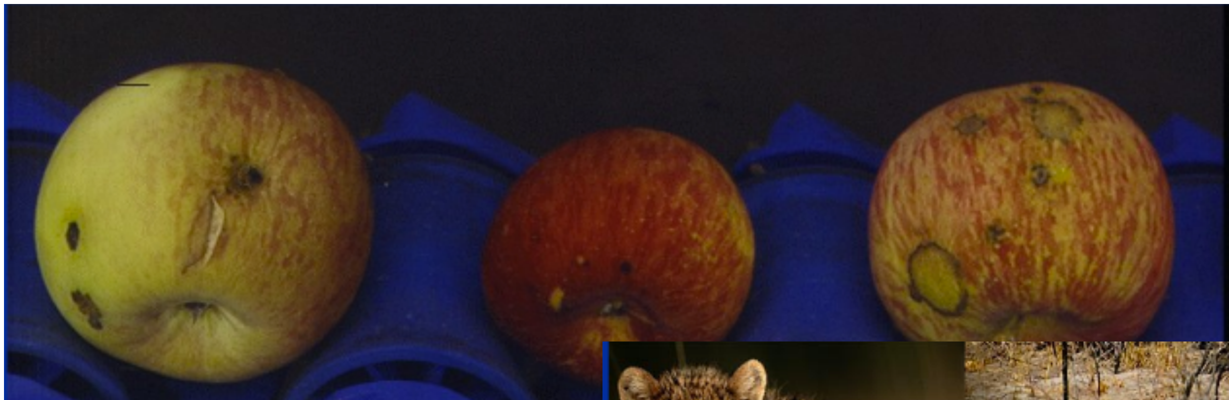
crowd

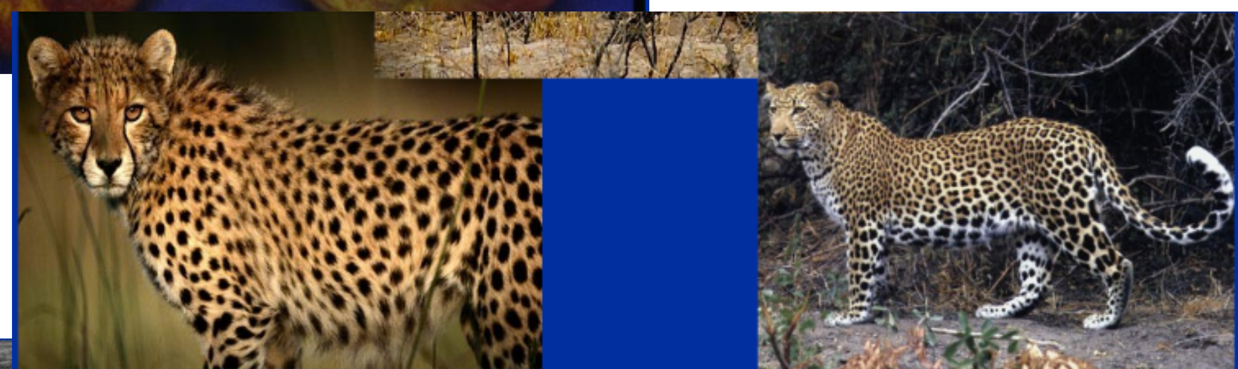
Texure and structure

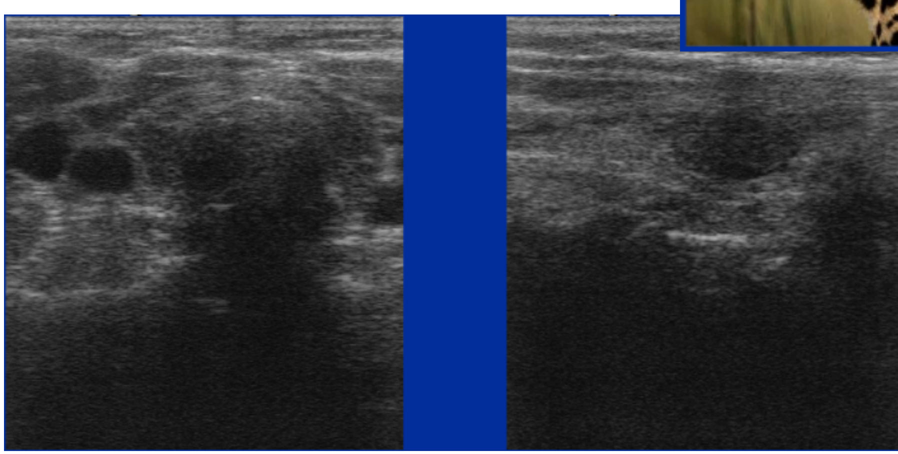
Application

- Assessment quality of :
- Food
- Matérials
- Healtheness

Application





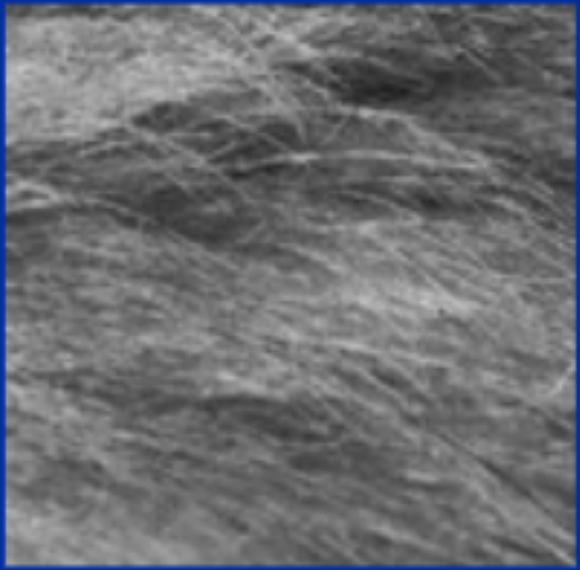


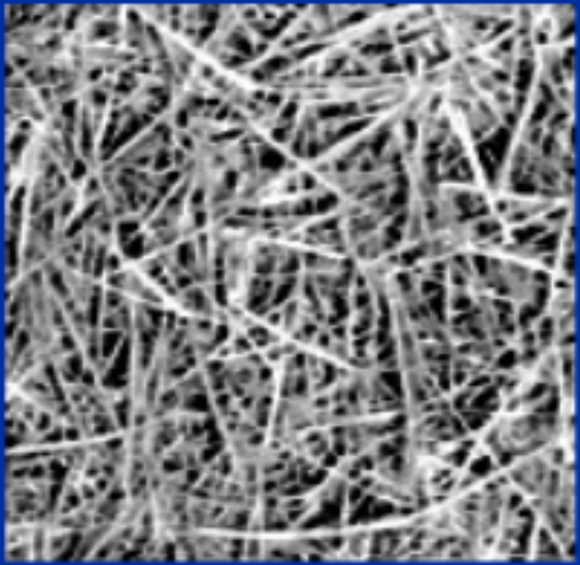
So a texture is

- Patterns of structure from
  - changes in surface albedo (eg printed cloth)
  - changes in surface shape (eg bark)
  - many small surface patches (eg leaves on a bush)
- Hard to define; but texture tells us
  - what a surface is like
  - (sometimes) object identity
  - (sometimes) surface shape

Description

- **primitives (texels)**
- spatial structure → statistical properties





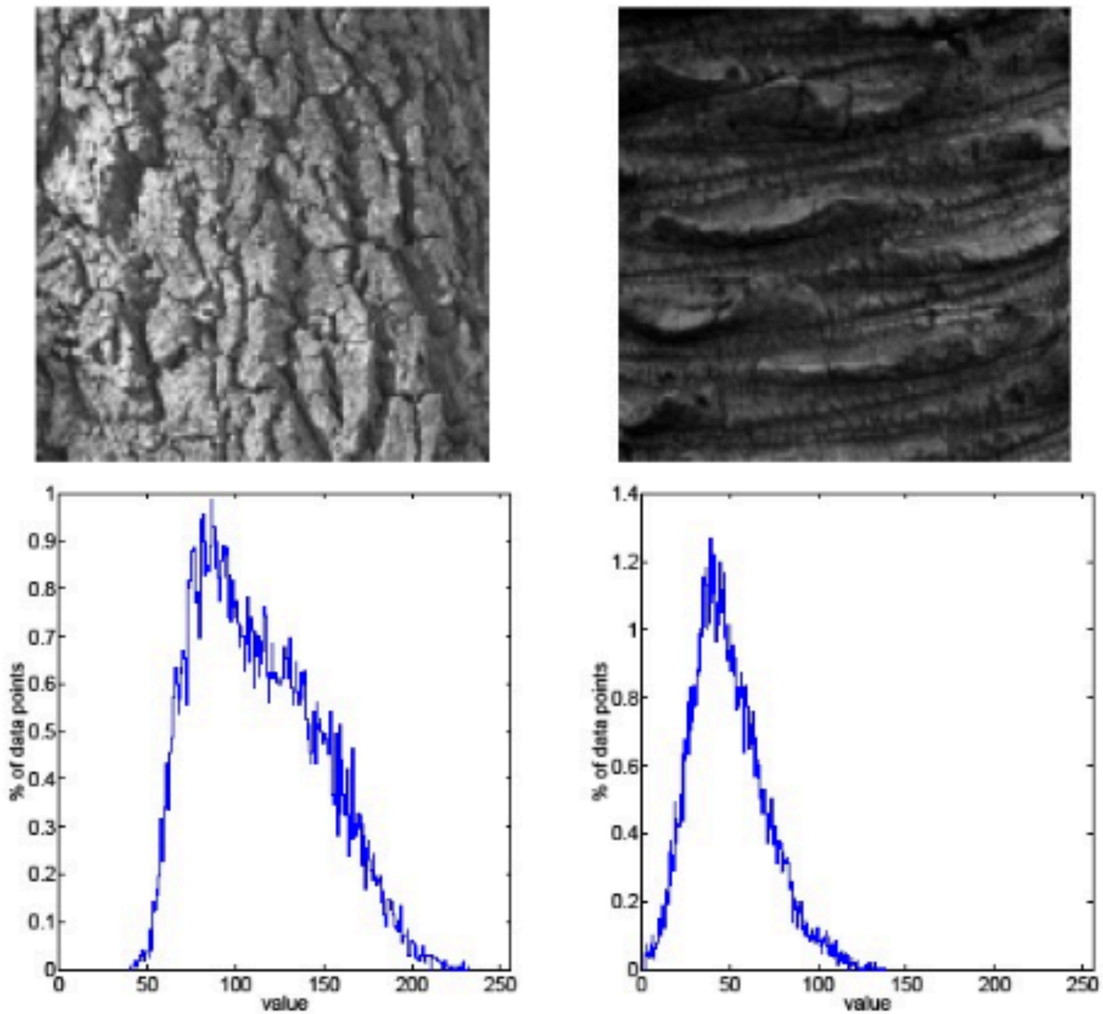
Texture representation

- Usually depends in regards to the task
- Recognition methods tend to use simple and more robust features. Aim at discriminability (Intra-class vs. Inter-class variability)
- Synthesis methods sometimes sample from the source image itself, thus arguably overfitting

Texture recognition

- Marginal statistics of filter responses (Review: Randen & Hussoy, PAMI 1999)
- Joint statistics of filter responses (Leung & Malik, ICCV'99)
- Filter, cluster, make histogram, compare using chi-sq (Leung & Malik, Varma & Zisserman, Forsyth 2004, ..)
- Extract affine-covariant regions, SPIN/SIFT, cluster, compare using EMD (Lazebnik, Schmid, Ponce)

Texture sample

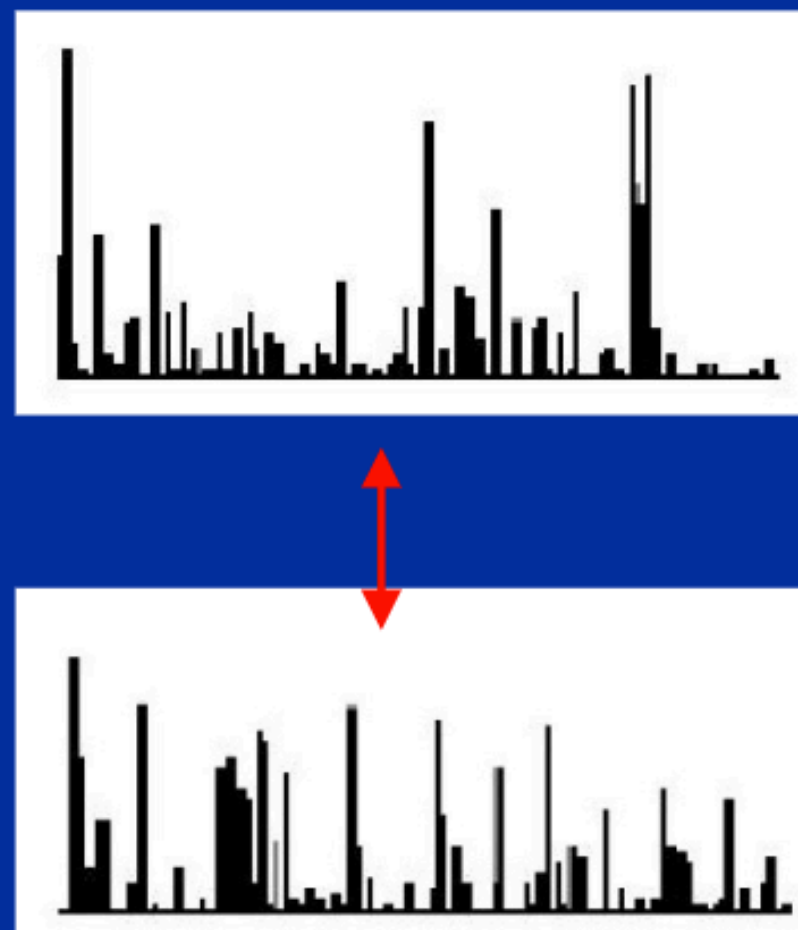


$E(I) = 113.2$
$\text{std}(I) = 46.3$

$E(I) = 49.4$
$\text{std}(I) = 25.0$

Histogram comparison

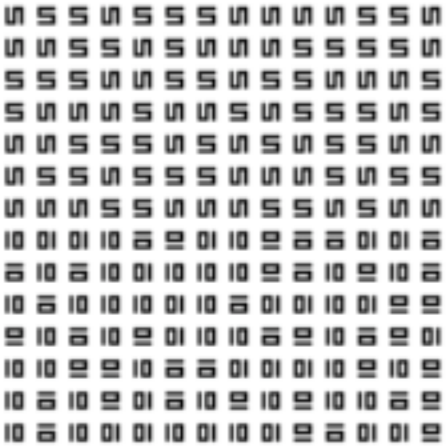
$$\chi^2 = \sum_i \frac{(R_i - S_i)^2}{R_i + S_i}$$



Some fields of application

Inspection :

Defect detection in images of textiles, automated inspection of carpet wear and automobile paints



What is wrong in this image

Some fields of application

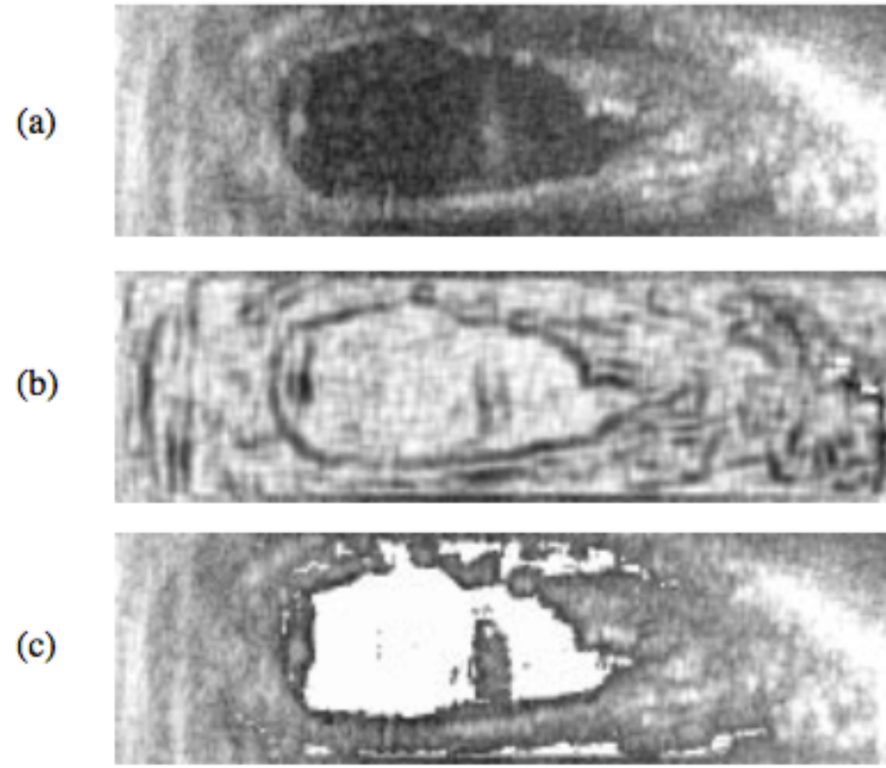
Medical images analysis :

Distinguish normal from abnormal tissues

Differentiate types of white blood

Analyse ultrasons images of the heart

Analyse X-rays images of some lesions



(a) Utrason image of the left ventricle hart
(b) Textures fractal representation
(c) Segmentation (blood in white)

Some fields of application

Document processing

Document analysis

Character recognition

Postal adress recognition

Bare code inspection


Bar Codes, an Added Dimension

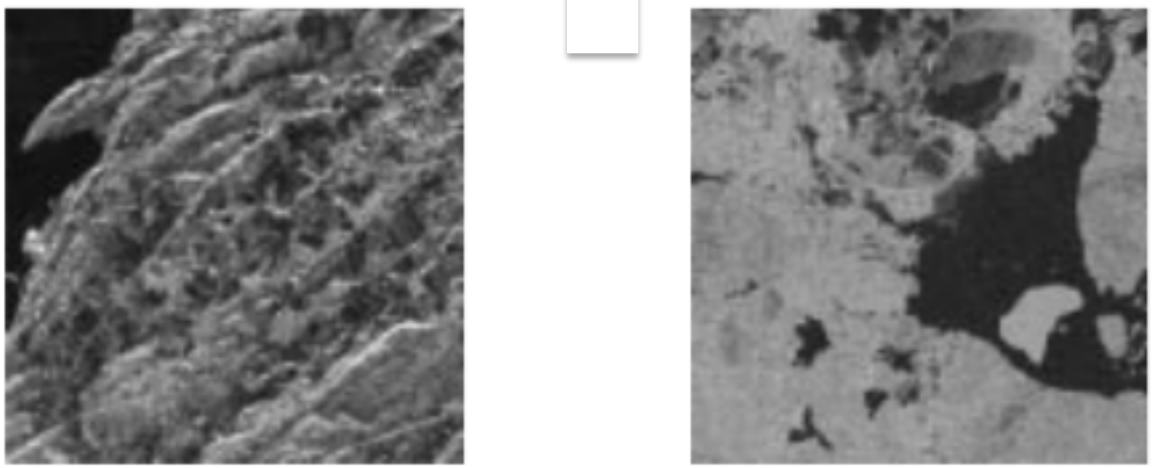
Bar code localization by textures, features segmentation

Some fields of application

Remote sensing

Classify different types of terrains

Segmentation of SAR images



Aerial SAR images

Some fields of application

In sum, there are a number of intuitive properties of texture :

- Texture is a property of areas; the texture of a point is undefined. So, texture is a contextual property and its definition must involve gray values in a spatial neighborhood. The size of this neighborhood depends upon the texture type, or the size of the primitives defining the texture.

- Texture involves the spatial distribution of gray levels. Thus, two-dimensional histograms or co-occurrence matrices are reasonable texture analysis tools.

- Texture in an image can be perceived at different scales or levels of resolution [10]. For example, consider the texture represented in a brick wall. At a coarse resolution, the texture is perceived as formed by the individual bricks in the wall; the interior details in the brick are lost. At a higher resolution, when only a few bricks are in the field of view, the perceived texture shows the details in the brick.

- A region is perceived to have texture when the number of primitive objects in the region is large. If only a few primitive objects are present, then a group of countable objects is perceived instead of a textured image. In other words, a texture is perceived when significant individual "forms" are not present.

Textures representation

There is different methods to represent and analyse a texture

- Statistical methods
- Geometrical methods
- Model based methods
- Signal processing methods

Textures representation

Statistical methods

First order statistics :

- histogram, average variance, skewness, Kurtosis, SNR, std…

Second order statistics :

- Co-occurrence matrix : energy, entropy, contrast, homogeneity, correlation
- Auto-correlation

Textures representation

Statistical methods

First order statistics : histogram, average variance, skewness, Kurtosis, SNRstd…

Given
$$P(I) = \frac{\text{number of pixels with gray level } I}{\text{total number of pixels in the region}}$$

We define the first order statistics by :

$$m_1 = E\left[I^1\right] = \sum_{I=0}^{N_g-1} I^1 P(I)$$

Is the mean

$$\mu_k = E\left[\left(I - E[I]\right)^k\right] = \sum_{I=0}^{N_g-1} (I - m_1)^k P(I),$$

$$k = 2, 3, 4$$

K=2 :the variance measuring the deviation of the graylevels from the mean
K=3: the skewness measuring the histogram assymetrie arround the mean
K=4 the Kurtosis measuring the histogram Sharpness

Textures representation

First order Statistical methods

$$m_1 = E\left[I^1\right] = \sum_{I=0}^{N_g-1} I^1 P(I)$$

$$\mu_k = E\left[\left(I - E[I]\right)^k\right] = \sum_{I=0}^{N_g-1} (I - m_1)^k P(I),$$

$$k = 2, 3, 4$$

m_I is the mean
μ_2 is the variance measuring the deviation of the graylevels from the mean
μ_3 is the skewness measuring the histogram assymetrie arround the mean
μ_4 is the Kurtosis measering the histogram Sharpness

Textures representation

Statistical methods : second order statistical methods

Co-occurrence matrix : the most used texture feature introduced by Haralick

We use $\left\{I(x,y), 0 \le x \le N-1, 0 \le y \le N-1\right\}$ to detone an NxN image of G gray levels

Pd is a GxG gray level matrix called a co-occurrence matrix defined as :

$$P_d(i,j) = \left|\left\{\left((r,s),(t,v)\right) : I(r,s) = i, I(t,v) = j\right\}\right|$$

- (i,j) is the gray levels entry at a distance $d = (dx, dy)$
- It gives the numbrer of co-occurrence of the pair of gray levels i and j separed by a distance d
- The Co-occurrence matrix may give an idea about the pattern of the texture

Textures representation

Statistical methods : second order statistical methods

Co-occurrence matrix : example

$$P_d(i,j) = \left|\left\{\left((r,s),(t,v)\right) : I(r,s) = i, I(t,v) = j\right\}\right|$$

- Give a co-occurence matrix of the following patch at a distance d=(1,0) and then for d=(1,1)

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

Textures representation

Statistical methods : : second order statistical methods

Co-occurrence matrix :

Other strongly useful statistics with μ_x, μ_y the means and σ_x, σ_y the std of $P_d(x),\ P_d(y)$

Texture Feature	Formula
Energy	$\sum_i \sum_j P_{\mathbf{d}}^2(i, j)$
Entropy	$-\sum_i \sum_j P_{\mathbf{d}}(i, j) \log P_{\mathbf{d}}(i, j)$
Contrast	$\sum_i \sum_j (i-j)^2 P_{\mathbf{d}}(i, j)$
Homogeneity	$\sum_i \sum_j \frac{P_{\mathbf{d}}(i, j)}{1 + \lvert i-j \rvert}$
Correlation	$\frac{\sum_i \sum_j (i-\mu_x)(j-\mu_y) P_{\mathbf{d}}(i, j)}{\sigma_x \sigma_y}$

$$P_d(x) = \sum_j P_d(x, j)$$

$$P_d(y) = \sum_i P_d(i, y)$$

Textures representation

Statistical methods

Co-occurrence matrix : example

Efter compoting the co-occurence matrix of the patch at a distance d=(1,0), Compute for the same matrix P(1,0) the second order statistics.

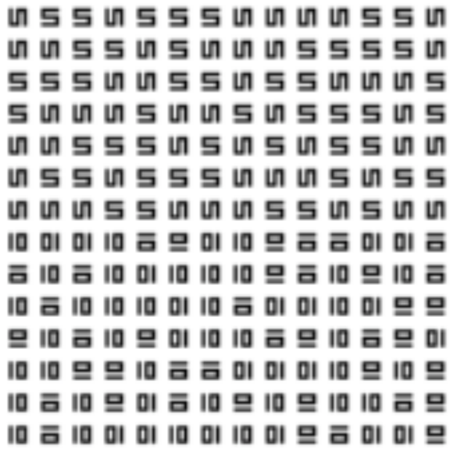
2	**1**	**0**	**4**
0	2	1	0
0	4	0	4
3	4	0	0

Textures representation

Statistical methods

Co-occurrence matrix :

- The co-occurrence patrix has some difficulties, there is no well established method for selecting the displacement vector d
- The folowing two images has the same second statistices order



- Feature selection method is necessary to select the most relevant features (and directions)

Textures representation

Statistical methods

Autocorrelation features:

- Used to assess the amount of regularity , the finess or coarsness of the texture.
- The autocorrelation function of an image I(x,y) is defined as :

$$\rho(x, y) = \frac{\sum_{u=0}^{N} \sum_{v=0}^{N} I(u, v) I(u + x, v + y)}{\sum_{u=0}^{N} \sum_{v=0}^{N} I^2(u, v)}$$

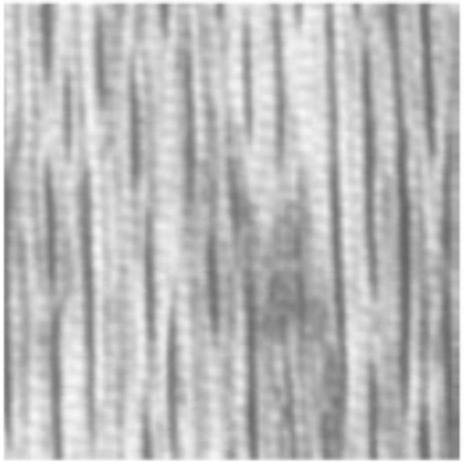
- The autocorreclation function is related to the finess of the texture
- If the texture is coarse, the function will drop of slowly, otherwise, it will dropp of rapidily
- For regular textures, the autocorrelation function exibits pics and valleys

Textures representation

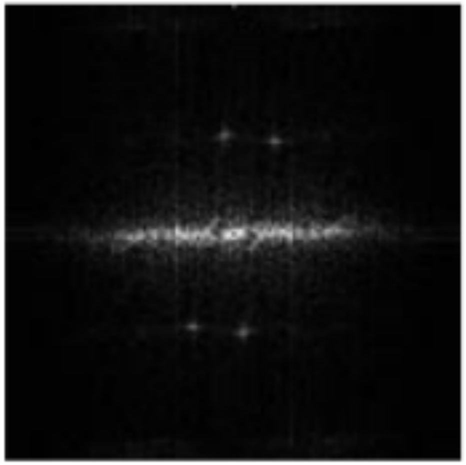
Statistical methods

Autocorrelation features:.

- The autocorrelation function is related to the power spectrum of the Fourrier transform (PSF)
- The following image shows the effects of the directionalyty of the texture on the distribution of energy of the PSF



(a)



(b)

(a) Textured image
(b) Its PSF

Textures representation

Statistical methods

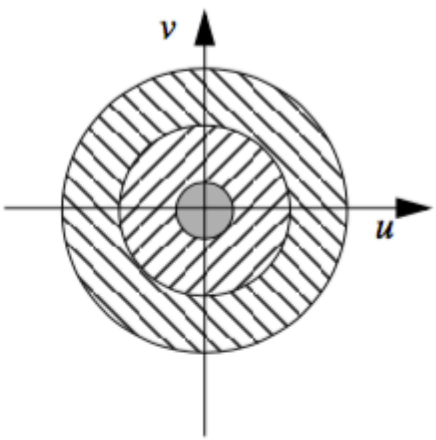
Autocorrelation features:.

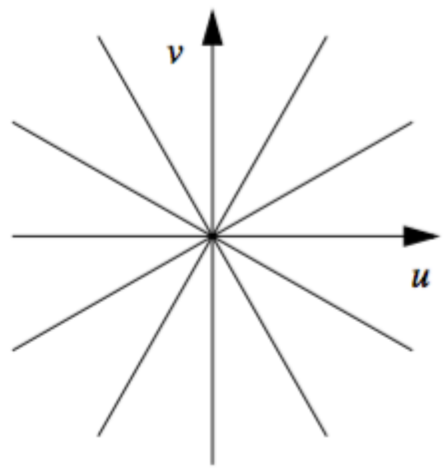
- To get the textures feature, the PSF image is devided into regions,
- The following image shows the effects of the directionalyty of the texture on the distribution of energy of the PSF
- The energy function is deveded into rings (for frequency content) and wedges (for orientation contents

Textures representation

Statistical methods

Autocorrelation features:.





Texture features computed from the PSF image

a) The energy computed in each shadded bound is a feature indicating coarsness/fitness
b) The energy computed in each wedge is a feature indicating the directionality

$$f_{r_1,r_2} = \int_0^{2\pi}\int_{r_2}^{r_1} |F(u,v)|^2 dr d\theta$$

$$r = \sqrt{u^2+v^2} \qquad \theta = \operatorname{atan}(v/u)$$

(a)

$$f_{\theta_1,\theta_2} = \int_{\theta_1}^{\theta_2}\int_0^{\infty} |F(u,v)|^2 dr d\theta$$

$$r = \sqrt{u^2+v^2} \qquad \theta = \operatorname{atan}(v/u)$$

(b)

Textures representation

- **Geometrical methods :**
  - Veronoi tesselation features
  - Structural methods

Textures representation

- **Model based methods:**
  - Random field models
  - Fractals

Textures representation

- **Signal processing methods:**
  - Spatial domain filtering
  - Fourrier domain filtering
  - Gabor and wavelets models

Textures Analysis problems

- Texture segmentation
- Texture analysis
- Texture synthesis
- Shape from textures

References

- Texture Analysis, team 5, A. Belgaru et al
- Medical image analysis, Chapter 2.1, M. Tuceyran and A. K. Jain