Lecture 21: Texture Analysis

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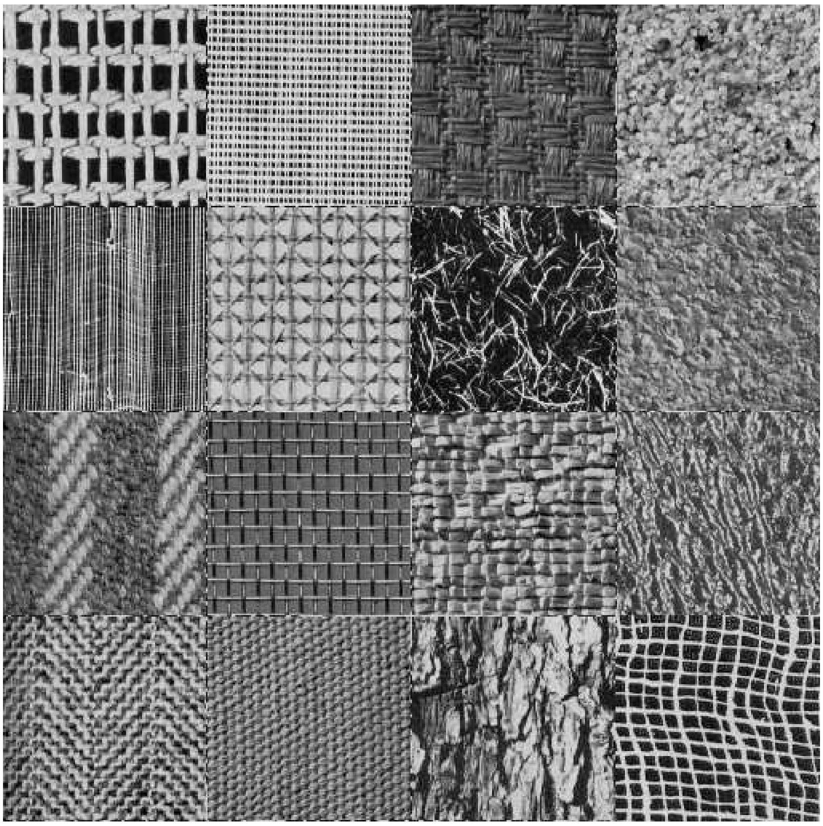
What is Texture? (1)



16 different textures. Author: P. Brodatz (1966).

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What is Texture?

- no general formal definition
- only intuitive notion of texture:
  structured region that appears in a spatially homogeneous way
- often with local stochastic fluctuations:
  size, shape, colour, orientation of the underlying pattern *(textons)* may vary
- Texture analysis often applies a combination of empirically successful statistic expressions.
- Texture is a scale phenomenon.
- The eye recognises a textured region as a single object and can find segment boundaries between textured regions.

Problems

- How can one discriminate two textures?
  (Traditional edge detectors are not useful for separating two regions with different textures.)
- Is is possible to describe the complex stucture of a texture with a few parameters?

Texture Analysis without Neighbourhood Context

Often the average grey value is not sufficient for distinguishing different textures. Then better descriptors such as statistical moments may be useful.

Statistical Moments:

- Consider an image with N pixels with grey values $f_1,...,f_N$ and mean μ.
  Then its *central moment of order k* is defined as

$$M_k \ := \ \frac{1}{N}\sum_{i=1}^{N}(f_i-\mu)^k.$$

- Equivalent characterisation:
  For a histogram $p(z_1),...,p(z_L)$ where $z_1,...,z_L$ are the different grey values and p their relative frequency of occurrence, the k-th central moment is given by

$$M_k \ := \ \sum_{i=1}^{L}(z_i-\mu)^k p(z_i).$$

Important Examples:

- $k=2$: *Variance (Varianz)*

$$\sigma^2 \ := \ M_2 \ = \ \frac{1}{N}\sum_{i=1}^{N}(f_i-\mu)^2$$

  measures the fluctuations around the mean

- $k=3$: *Skewness (Schiefe)*

$$V \ := \ \frac{1}{N}\sum_{i=1}^{N}\left(\frac{f_i-\mu}{\sigma}\right)^3$$

  measures the assymmetry:
  $V<0$: skewness towards left side.
  $V>0$: skewness towards right side.
  The normalisation by σ makes different distributions comparable.

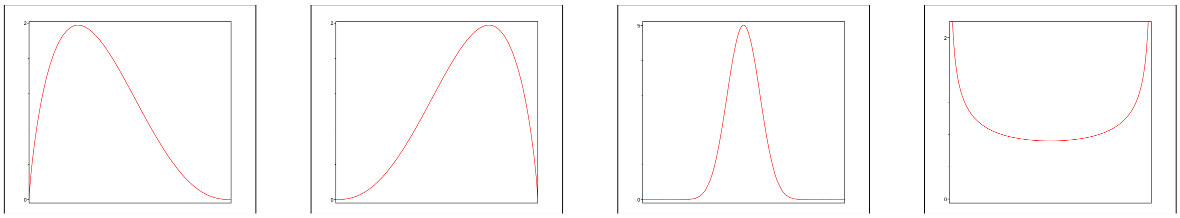
Texture Analysis without Neighbourhood Context (3)

- $k = 4$: *Excess, Kurtosis (Exzess, Kurtosis)*

$$\varepsilon := \frac{1}{N}\sum_{i=1}^{N}\left(\frac{f_i-\mu}{\sigma}\right)^4 - 3$$

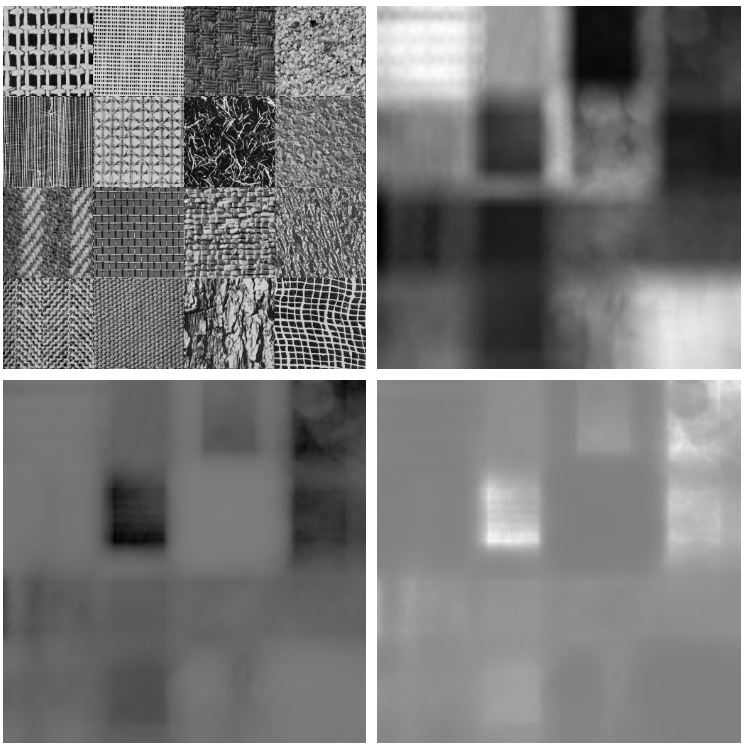
  measures the flatness of the distribution:
  Subtraction by 3 gives $\varepsilon = 0$ for a Gaussian distribution.

- Examples of distributions with



(a) positive skewness, **(b)** negative skewness, **(c)** positive kurtosis, **(d)** negative kurtosis. Author: B. Burgeth (2005).

Texture Analysis without Neighbourhood Context (4)



(a) Top left: Original image, 512×512 pixels. **(b) Top right:** Variance, averaged within a disk-shaped neighbourhood of radius 30, and rescaled to [0,255]. **(c) Bottom left:** Skewness, rescaled. **(d) Bottom right:** Kurtosis, rescaled. Author: J. Weickert (2008).

Texture Discrimination

- Replace every grey value by a texture attribute (e.g. a statistical moment) within some window.
- Apply a classical edge detector to the resulting image (Lectures 18 and 19).

Disadvantage of All Texture Descriptors So Far

- If one uses them for a *global* description of an image or a region, then the spatial ordering of the pixels does not matter:
  A checkerboard image has the same texture descriptor as an image with a black and a white half.
- Statistics with features that ignore the spatial context is called *first-order statistics*.
- Incorporating the neighbourhoud context would be desirable *(second-order statistics)*.

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Texture Analysis with Neighbourhood Context

Possibility 1: Multiscale Representation

- Chararcterise the image on different scales, e.g. using
  - pyramids (Lecture 5)
    Example: Analysing the cloudiness in fabrics
  - scale-space concepts (Lecture 18)
    Example: Convolving the image with Gaussians of increasing standard deviation (Gaussian scale-space)
- Afterwards a texture descriptor based on first-order statistics can be used.

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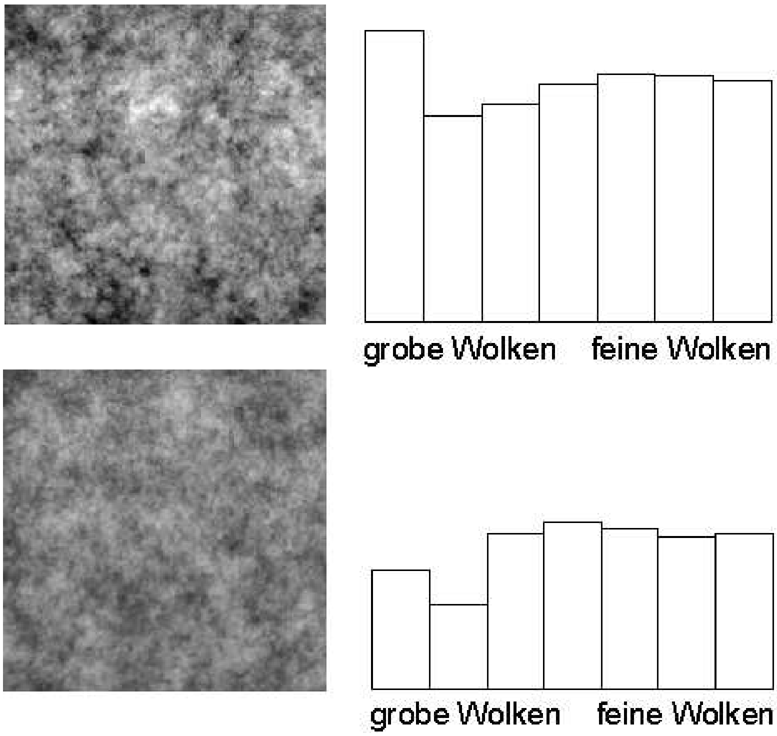
Texture Analysis with Neighbourhood Context (2)



(a) Top: Fabric image with standard deviation σ at different scales of a pyramid representation. **(b) Bottom:** The same representation for another fabric image. Authors: J. Weickert, R. Rösch (1999).

Texture Analysis with Neighbourhood Context (3)

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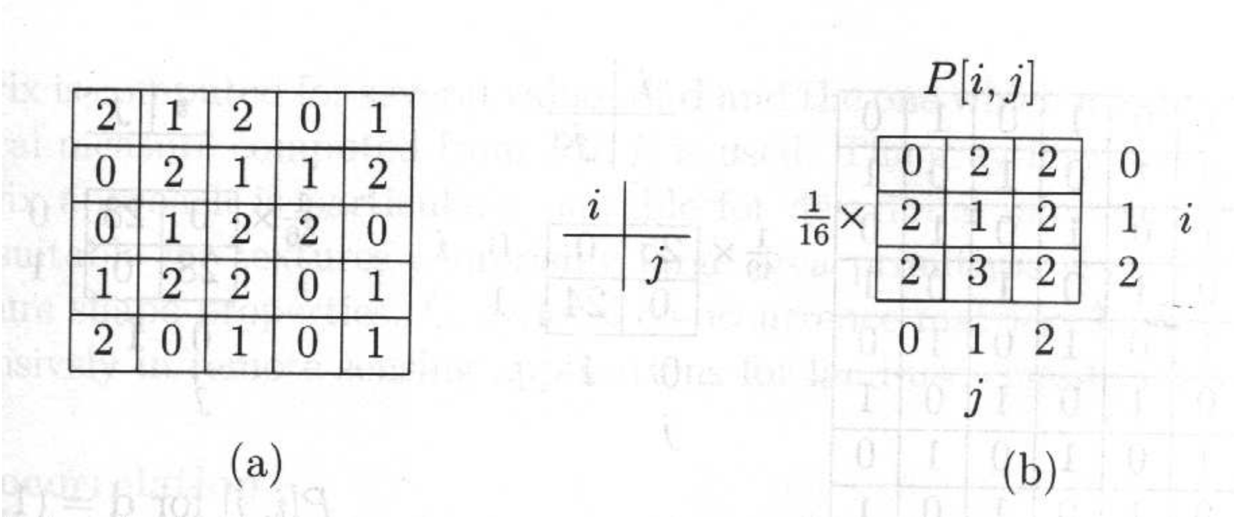
Possibility 2: Cooccurrence Matrices (Grauwertübergangsmatrizen, Kookkurenzmatrizen)

(Haralick et al. 1973)

- Basic idea: histogram of neighbourhood relations
- Specify some displacement vector $\mathbf{d} = (d_1, d_2)^\top$ that identifies a pair of points that is to be compared.
  Example: Using $\mathbf{d} = (1, 0)^\top$ compares every pixel with its right neighbour.
- Create a bivariate grey value histogram $p_{i,j}$. It specifies the relative frequency for which some grey value i occurs together with some grey value j in direction $\mathbf{d}$.

Texture Analysis with Neighbourhood Context (4)



(a) Left: A 5×5 image with three greyscales 0, 1 and 2. **(b) Right:** The cooccurrence matrix with $d = (1,1)^\top$, i.e. one considers the lower right neighbour (x axis points to the right, y axis points downwards). Example: A grey value 2 having a grey value 1 as lower right neighbour occurs in 3 out of 16 cases. Therefore, $p_{2,1} = \frac{3}{16}$. Authors: R. Jain, R. Kasturi, B. G. Schunck (1995).

Texture Analysis with Neighbourhood Context (5)

Characteristic Expressions for Cooccurrence Matrices

Many heuristically motivated expressions:

- *Largest Probability*

  The maximal $p_{i,j}$ gives the most frequent grey value configuration with respect to $\mathbf{d}$.
  Example: In the previous image with $\mathbf{d} = (1,1)^\top$, the configuration (2, 1) was most frequent ($p_{2,1} = \frac{3}{16}$).

- *Contrast*

$$\sum_{i,j} (i-j)^2 \, p_{i,j}$$

  attains small values, if many grey values in the neighbourhood are similar.

Texture Analysis with Neighbourhood Context (6)

- *Homogeneity*

$$\sum_{i,j} \frac{p_{i,j}}{1+|i-j|}.$$

is small, if many different grey values exist in the neigbourhood.

- *Entropy*

$$-\sum_{i,j} p_{i,j} \log p_{i,j}$$

is a measure of randomness. It is maximal, if all possible configurations are equally probable.

Texture Analysis with Neighbourhood Context (7)

Possibility 3: Texture Analysis in the Fourier Domain

- well-suited for (almost) periodic textures
- One wants to characterise the rich information in the Fourier domain with a few parameters.
- One considers the Fourier spectrum of the textured image f in polar coordinates: $|\hat{f}(r,\phi)|$
- By integrating in circular,

$$g(r) := \int_0^{2\pi} |\hat{f}(r,\phi)|\, d\phi$$

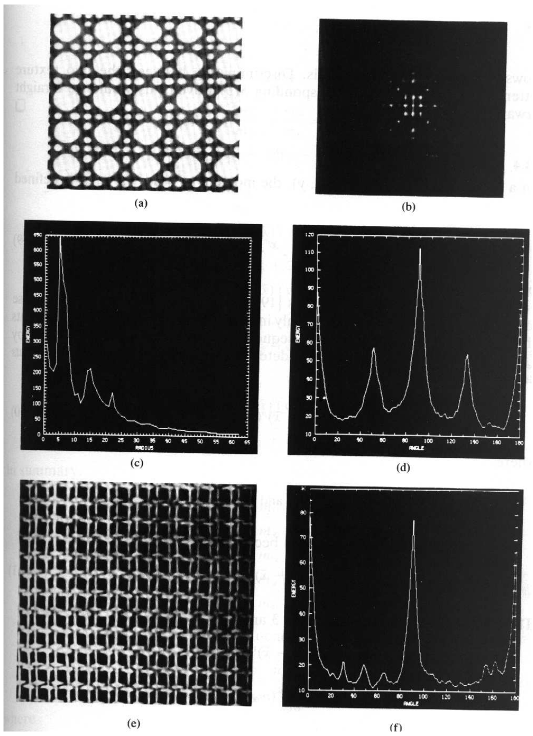
and radial direction,

$$h(\phi) := \int_0^{R} |\hat{f}(r,\phi)|\, dr$$

one obtains two functions in one variable: $g(r)$ and $h(\phi)$.
They characterise the radial behaviour and the angular dependency in the Fourier spectrum.

- By computing simple expressions (e.g. maximum, mean, variance) for these functions, many textures can be discriminated.

Texture Analysis with Neighbourhood Context (8)



(a) Image with periodic texture. (b) Fourier spectrum. (c) Plot of $g(r)$. It is less conclusive. (d) Plot of $h(\phi)$. One observes diagonal structures at 45 and 135 degrees. (e) Another textured image. (f) Its $h(\phi)$ plot. Here one cannot find characteristic diagonal structures. Authors: R. C. Gonzalez, R. E. Woods (1992).

Summary (1)

Summary

- Texture characterises reoccurring patterns, often with stochastic fluctuations.
- There is no fundamental theory for analysing textures, only several classes of heuristically motivated strategies.
- First-order statistics (e.g. moments) is usually not sufficient since neighbourhood structures are important in texture analysis.
- Simple remedy: embedding into a multiscale representation
- Cooccurrence matrices are grey value histograms of neighbourhood structures. With first-order statistics one obtains characteristic texture descriptors.
- For periodic structures, one should consider texture descriptors in the Fourier domain.

Literature

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