Image Analysis - Lecture 6

Texture

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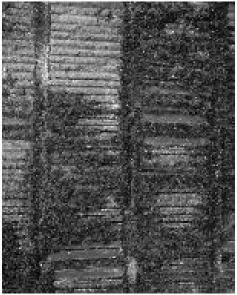
Lecture 6

Contents

Texture



Texture (ctd.)

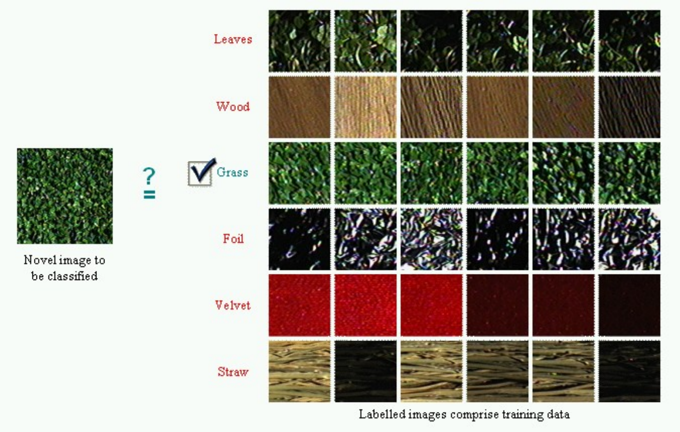
Texture is easy to recognize, but difficult to explain.
A leaf is an object, but foliage is a texture.

- Texture recognition
- Texture synthesis
- Shape from texture

Links

http://www.ux.uis.no/~karlsk/tct/
http://www.alceufc.com/2013/09/
texture-classification.html

Texture Recognition - a classification problem



Images taken from: `http://www.robots.ox.ac.uk/~vgg/research/texclass/`

Repetition: Features

Examples of features in images are

- Edges, where the intensity gradients are large.
- Ridges, the centre of dark or light stripes.
- Corners or other interesting points that can be tracked reliably.

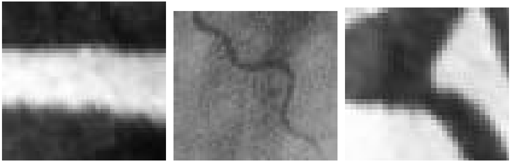
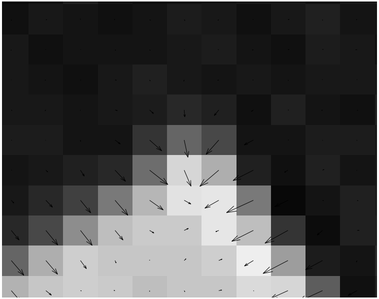


Illustration of orientations



Illustrations of the partial derivatives $\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$

The Orientation Tensor

Construct the matrix

$$M = \begin{bmatrix} W_{xx} & W_{xy} \\ W_{xy} & W_{yy} \end{bmatrix} = \begin{bmatrix} (\frac{\partial f}{\partial x})^2 * G_b & (\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}) * G_b \\ (\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}) * G_b & (\frac{\partial f}{\partial y})^2 * G_b \end{bmatrix} \quad ,$$

where G_b denotes the Gaussian function with parameter b.
M - orientation tensor.
Note: We construct a matrix for every pixel.

Properties of the orientation tensor

The matrix M has the following properties:

- (Flat) Two small eigenvalues in a region - flat intensity.
- (Flow) One large and one small eigenvalue - edges and flow regions.
- (Texture) Two large eigenvalues - corners, interest points, texture regions.

This can be used in algorithms for segmenting the image into (flat, flow, texture).

Textons

Texture often contains regular patterns of parts, often called **textons**.
Idea: If you can detect the textons and measure where they are and how they are distributed?
Problem: There is no useful definition of textons that can be used for detection.
By convolution with small patterns, a strong response signals existence of that small pattern. This could be thought of as texton-detection.
What patterns should we use?

Filter banks: Edge detection

For **edge detection** we used two filters
$\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$.
After non-linear transformation (squaring) and summation we obtained

$$\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2 = |\nabla f|^2 .$$

which is used to detect edges (classify pixels as belonging to the texture 'edge').

Filter banks: Corner detection

For **corner/interest point detection** we used two filters $a_1 = \frac{\partial f}{\partial x}$ and $a_2 = \frac{\partial f}{\partial y}$.
After non-linear transformation (a_1^2, $a_1 a_2$ and a_2^2), further smoothing and another non-linear transformation we obtained

$$f_{cr} = (k + \frac{1}{k})|\det(M)| - |\operatorname{trace}(M)^2 - 2\det(M)|$$

that was used to detect interest points (classify pixels as belonging to the texture 'corner').

Filter banks: Ridge detection

For **ridge detection** we used three filters
$\frac{\partial^2 f}{\partial x^2}$, $\frac{\partial^2 f}{\partial x \partial y}$ and $\frac{\partial^2 f}{\partial y^2}$.
After mean value filtering and a non-linear transformation we obtain a measure that can be used to detect ridges (classify pixels as belonging to the texture 'ridge').

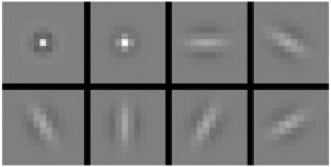
Filter banks: Texture classification

- Several filters $(f * h_1, \ldots, f * h_n)$
- What filters $h_1, \ldots, h_n$ should we use?
- Non-linear transformation, e.g. squares, absolute values, taking the positive or negative part of a signal, thresholding.
- Use machine learning - classification on filter responses.

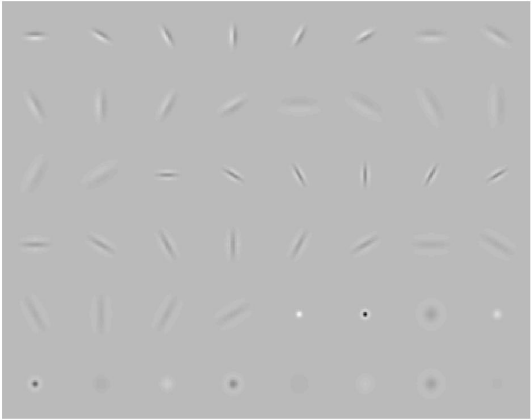
Examples of filters and filter banks

- **Spots:** Gaussian filters
- **Spots:** Difference of Gaussian filters
- **Bars:** Elongated Gaussians
- **Edges:** Derivatives of Gaussians and of elongated Gaussians
- **Ridges:** Second derivatives of Gaussians and of elongated Gaussians
- **Gabor filters:**

Examples of filters and filter banks

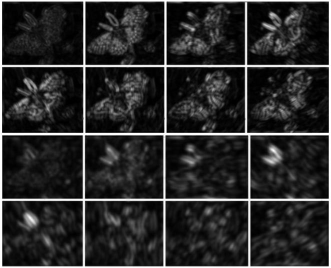


Examples of filters and filter banks

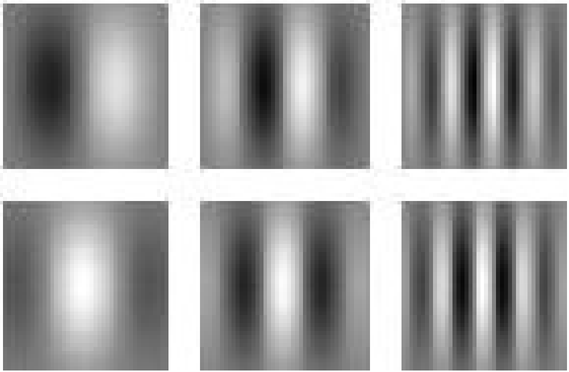


Search (for texture) on different scales

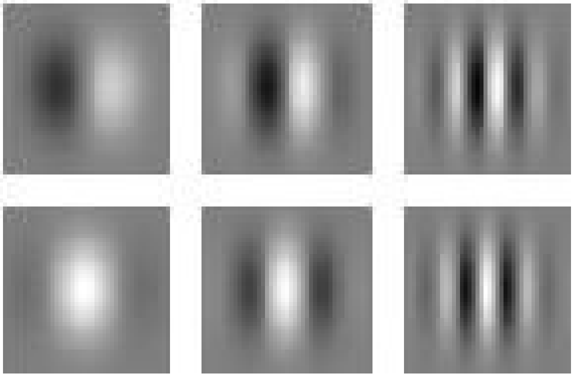
Response for different filters



Gabor filter



Gabor filters (ctd.)



Non-linear transformations

You can try several non-linear transformations, e.g.

- Squaring, polynomials
- Absolute value
- Thresholding (in particular taking the positive and negative parts of a signal).

Spatial Aggregation: Mean value filtering or Max pooling

After non-linear transformation, often it is a good idea to form the mean over a region, e.g. using mean value filtering.
Similar to what we did with the orientation tensor.
Alternatively one could take the maximal value over a region.

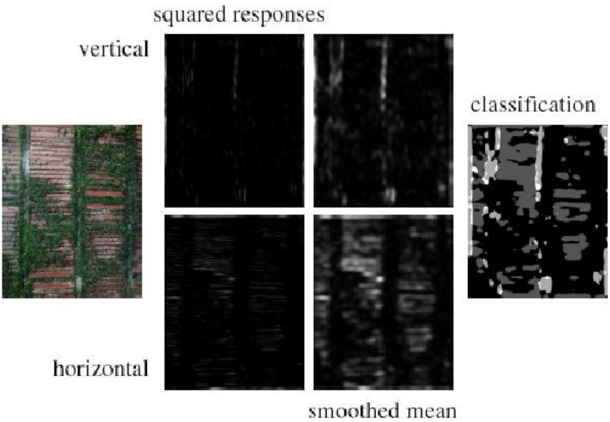
Filterbank + Non-linear + Spatial Aggregation

The result is a number of values (channels, features) for every pixel.
The goal is now to classify pixels in different classes (textures).
Use Machine learning techniques.

Other popular features

One possibility is to take the mean and variance of the channel within a region.
Co-occurance matrices.

Example of texture classification



What is segmentation?

Goal: Segment the image into pieces/segments, i.e. regions that belong to the same object or that has the same properties.
Can also be seen as a problem of 'grouping' of pieces (pixels, regions) together.
Edges, Ridges, Blobs, Interest Points, Textures - already a step towards segmentation.
More generally - segmentation is about cutting out the interestings regions/parts.

Examples of segmentation

Some typical segmentation problems are:

- Cut an image sequence into shots
- Find manufactured parts in an industrial environment
- Find humans in images and video
- Find houses in satellite images
- Find faces in images

Example: OCR.
Example: Image interpretation
Example: Road user analysis
Example: Medical Image Analysis, e.g. Cell analysis

Segmentation using clustering

Using clustering:

- Segment images into pieces
- Fit lines to a set of points
- Fit a fundamental matrix to image pairs

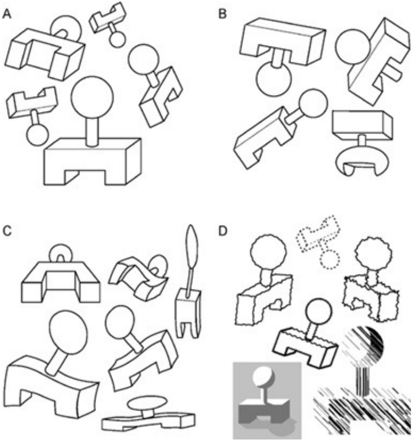
In some cases it is easier to view segmentation as the problem of putting pieces together. This is usually called **grouping** (less precise) or **clustering** (which has a precise meaning in the field of pattern recognition).

Gestalt laws

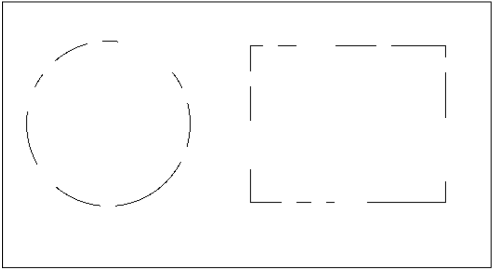
Around 1900 the 'Gestalt' theory was developed by psychologists in Germany, the Berlin school. They developed a descriptive theory of mind and brain. Some principles that they discovered for human grouping of features are:

- Proximity
- Similarity
- Same fate
- Same region
- Closedness
- Symmetry
- Parallelism

Invariance



Closure



Mathematical Morphology

Operations on binary images. Can be regarded as non-linear filtering.
$A = \{ (x, y) \in \mathbb{Z}^2 \mid f(x, y) = 1 \}$ is considered as a subset of the image.

Definition

Let A and $B \subset \mathbb{Z}^2$.
The **translation** of A with $x = (x_1, x_2) \in \mathbb{Z}^2$ is defined as

$$(A)_x = \{ c \mid c = a + x,\ a \in A \} \ .$$

The **reflection** of A is defined as

$$\hat{A} = \{ c \mid c = -a,\ a \in A \} \ .$$

Definitions

Definition

The **complement** of A is defined as

$$A^c = \{ c \mid c \notin A \} \ .$$

The **difference** of A and B is defined as

$$A - B = \{ c \mid c \in A, \ c \notin B \} = A \cap B^c \ .$$

Dilation

Let $B \subset \mathbb{Z}^2$ denote a **structure element**. (Usually B=”a circle” with centre at the origin is chosen.)

Definition

The **dilatation** of A with B is defined by

$$A \oplus B = \{\, x \mid (\hat{B})_x \cap A \neq \emptyset \,\} \ .$$

∎

This can also be written

$$A \oplus B = \{\, x \mid ((\hat{B})_x \cap A) \subseteq A \,\} \ .$$

The dilation of A with B can be seen as extending A with B.

Erosion

Definition

The **erosion** of A with B is defined by

$$A \ominus B = \{\, x \mid (\hat{B})_x \subseteq A \,\} \quad .$$

■

The erosion of A with B can be seen as diminishing (eroding) A with B.

Opening

Definition

The **opening** of A with B is defined by

$$A \circ B = (A \ominus B) \oplus B \quad .$$

Opening = first erosion, then dilation.

- Gives smoother contours.
- Removes narrow passages.
- Eliminates thin parts.

Closing

Definition

The **Closing** of A with B is defined by

$$A \cdot B = (A \oplus B) \ominus B \quad .$$

Closing = first dilation, then erosion.

- Gives smoother contours.
- Fills up small parts.
- Fills up holes.

The distance transform

Definition

Start with a binary image $A \subset \mathbb{Z}^2$ and a metric $d(x, y)$ that defines the distance between x and y and fulfils

- $d(x, y) \geq 0$ with equality iff $x = y$.
- $d(x, y) = d(y, x)$.
- $d(x, z) \leq d(x, y) + d(y, z)$ (the triangle inequality)

Try to for each pixel calculate the shortest distance to A.

Different metrics

Different metrics gives different distances!

- $d^E(x, y) = \sqrt{x^2 + y^2}$ (Euclidean metric)
- $d^4(x, y) = |x| + |y|$ (Manhattan)
- $d^8(x, y) = \max(|x|, |y|)$ (Chess-board)
- d^{oct} = compromise between d^4 and d^8 (Octagonal)
- d^{ch} = Chamfer 3-4 given by the mask

$$\begin{bmatrix} 4 & 3 & 4 \\ 3 & 0 & 3 \\ 4 & 3 & 4 \end{bmatrix}$$

Calculating the distance transform

The distance transform can be calculated by

- Forward propagation
- Backward propagation

A "mask" is propagated through the image row-wise from the upper left corner to the lower right corner and another "mask" is propagated in the reverse direction. This procedure is repeated until convergence.

Skeleton

The **Skeleton** to a binary image, A, is defined by

- For each point, x, in A find the closest boundary point.
- If there are more than one closest boundary point, then x belongs to the skeleton of A.

The skeleton is dependent on the chosen metric!

Given the skeleton and the actual distance to the boundary for each skeleton point, the binary image A can be recovered.

Skeleton calculation

Calculating the skeleton:

- Using a distance map
- Using morphological operations (thinning).

Masters thesis suggestion of the day: Analysis of road user behaviour

There are several interesting and useful applications of algorithms for automatic detection and tracking of road users (cars, bicycles, pedestrians). Two such uses are (i) to increase safety in traffic and (ii) decrease the environmental load of traffic.

Recommended reading

- Forsyth & Ponce: **9. Texture**, **14. Segmentation.**
- Szeliski: **5. Segmentation.**

Summary - Lecture 6

- Texture recognition
  - Filter bank
  - Nonlinear transformations
  - Spatial Aggregation
    - Mean value filtering
    - Max Pooling
    - Histograms
  - Classification
- Segmentation
  - Gestalt laws
  - Clustering
  - Graph theoretical clustering
- Morphology