Medical Image Processing

12 Object Features

Prof. Dr. Marcin Grzegorzek

Research Group for Pattern Recognition
Institute for Vision and Graphics
University of Siegen, Germany

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Overview

Introduction to Image Feature Generation (1)

- The major goal can be summarised as follows: *Given an image, or a region within an image, generate the features that will subsequently be fed to a classifier in order to classify the image in one of the possible classes.*

- A digital image results from sampling of a continuous image function $I(x, y)$ to a two-dimensional array $I(m, n)$ with $m = 0, \ldots, N_x - 1$ and $n = 0, \ldots, N_y - 1$.

- The intensity of gray level image pixels $I(m, n)$ is quantised in N_g levels and N_g is known as the depth of the image. Then, a pixel $I(m, n)$ can take one of the values $0, 1, \ldots, N_g - 1$.

Introduction to Image Feature Generation (2)

- Features are generated from images, because using row image data is highly inefficient. Already for a small 64×64 image the number of pixels 4096 is too large for many classification techniques.

- The goal is to generate features that exhibit high information packing properties. Features should encode efficiently the relevant information residing in the original data.

Types of Image Features

- Colour Features
- Texture Features
- Shape Features

Overview

MPEG-7 Colour Descriptors

- Dominant Colour
- Scalable Colour
- Colour Layout
- Colour Structure

MPEG-7 Texture Descriptors

- Edge Histogram
- Homogeneous Texture
- Texture Browsing

MPEG-7 Shape Descriptors

- Region Shape
- Contour Shape

http://www.chiariglione.org/mpeg/

Overview

Texture Features

- Although there is no clear definition of “texture”, we describe an image by the look of it as fine or coarse, smooth or irregular, homogeneous or inhomogeneous...
- Our goal here is to generate features that somehow quantify this kind of properties of an image region.
- These features will emerge by exploiting space relations underlying the gray level distribution.

Texture - First Order Statistics Features (1)

- Let I be the random variable representing the gray levels in the region of interest. The first order histogram $P(I)$ is defined as

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

- The following quantities can be now defined:

$$\text{Moments:} \quad m_i = E[I^i] = \sum_{I=0}^{N_g-1} I^i P(I), \quad i = 1, 2, \dots$$

$$\text{Central moments:} \quad \mu_i = E[(I - E[I])^i] = \sum_{I=0}^{N_g-1} (I - m_1)^i P(I)$$

Texture - First Order Statistics Features (2)

- The most frequently used central moments are μ_2, μ_3, and μ_4. $\mu_2 = \sigma^2$ is the variance, μ_3 is known as the skewness, and μ_4 as the kurtosis of the histogram.

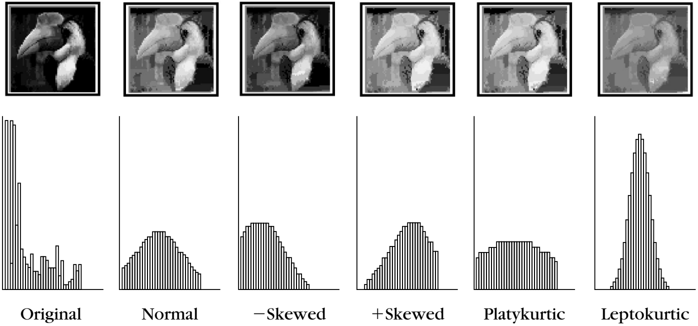
- Other quantities that result from the first order histogram are:

$$\text{Absolute Moments:} \quad \widehat{\mu}_i = E[\|I - E[I]\|^i] = \sum_{I=0}^{N_g - 1} \|I - E[I]\|^i P(I)$$

$$\text{Entropy:} \quad H = -E[\log_2 P(I)] = -\sum_{I=0}^{N_g - 1} P(I) \log_2 P(I)$$

- Entropy is a measure of histogram uniformity. The closer to the uniform distribution $P(I) = \mathrm{constant}$, the higher the H.

Texture - First Order Statistics Features (3)



$\mu_3 \rightarrow$	587	0	-169	169	0	0
$\mu_4 \rightarrow$	16609	7365	7450	7450	9774	1007
$H \rightarrow$	4.61	4.89	4.81	4.81	4.96	4.12

Texture - Second Order Statistics Features (1)

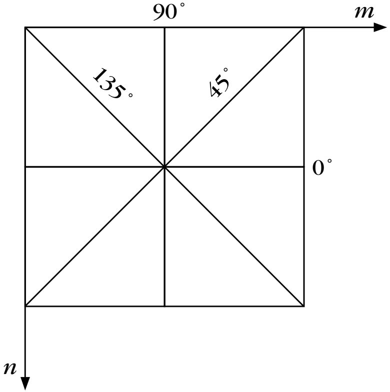
- The first order statistics features provide information related to the distribution of gray levels, however, they don't provide any information about the relative positions of the various gray levels in the image.

- This type of information can be extracted from the second order histograms, where the pixels are considered in pairs.

- Two more parameters are used in this case, namely the relative distance among the pixels and their relative orientation.

Texture - Second Order Statistics Features (2)

- Let d be the relative distance measured in pixel numbers. The orientation ϕ is quantised in four directions: horizontal, diagonal, vertical, and anti-diagonal (0°, 45°, 90°, 135°):



Texture - Second Order Statistics Features (3)

- For each combination of d and ϕ a two-dimensional histogram is defined:

$$0^\circ: \; P(I(m,n) = I_1, I(m \pm d, n) = I_2)$$

$$= \frac{\text{no. of pixel pairs at distance } d \text{ with values } I_1, I_2}{\text{total number of possible pairs}}$$

- In a similar way

$$45^\circ: \; P(I(m,n) = I_1, I(m \pm d, n \mp d) = I_2)$$

$$90^\circ: \; P(I(m,n) = I_1, I(m, n \mp d) = I_2)$$

$$135^\circ: \; P(I(m,n) = I_1, I(m \pm d, n \pm d) = I_2)$$

Texture - Second Order Statistics Features (4)

- For each of these histograms an array is defined, known as the co-occurrence or spatial dependence matrix.

$$\mathbf{A} = \frac{1}{R}\begin{bmatrix} \eta(0,0) & \eta(0,1) & \eta(0,2) & \eta(0,3) \\ \eta(1,0) & \eta(1,1) & \eta(1,2) & \eta(1,3) \\ \eta(2,0) & \eta(2,1) & \eta(2,2) & \eta(2,3) \\ \eta(3,0) & \eta(3,1) & \eta(3,2) & \eta(3,3) \end{bmatrix}$$

- $\eta(I_1, I_2)$ is the number of pixel pairs, at a relative position (d, ϕ), which have gray level values I_1 and I_2 respectively. R is the total number of possible pixel pairs. Thus,

$$\frac{1}{R}\eta(I_1, I_2) = P(I_1, I_2)$$

Local Linear Transforms (1)

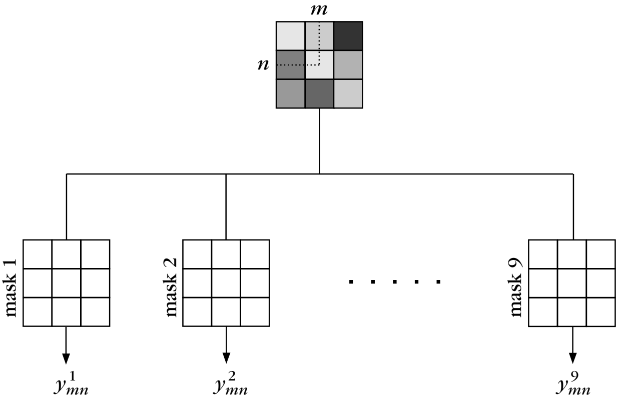
- Let us consider a neighbourhood of size $N \times N$ cantered at pixel location (m, n). Let $\mathbf{x}_{mn}$ be the vector with elements being the N^2 points within the area, arranged in a row-by-row mode.

- A local linear transform or local feature extractor is defined as

$$\mathbf{y}_{mn} = \mathbf{A}^{\mathrm{T}}\mathbf{x}_{mn} \equiv \begin{bmatrix} \mathbf{a}_1{}^{\mathrm{T}} \\ \mathbf{a}_2{}^{\mathrm{T}} \\ \vdots \\ \mathbf{a}_{N^2}{}^{\mathrm{T}} \end{bmatrix} \mathbf{x}_{mn}$$

Local Linear Transforms (2)

- The problem of local linear transform can be interpreted as a series of N^2 filtering operations



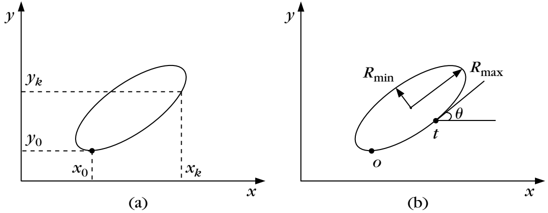
Overview

Introduction

- While texture features describe whole images or image regions, shape and size features are related to objects.
- Some objects have exactly the same shape and can be distinguished by the texture, other have exactly the same texture, but different shapes.
- Extraction methods for shape features depend on segmentation algorithms and, therefore, their performance is limited for images with heterogeneous backgrounds.

Fourier Features (1)

- Let (x_k, y_k) with $k = 0, \ldots, N-1$ be the coordinates on the boundary of an object.



- For each pair (x_k, y_k) we define the complex variable $u_k = x_k + jy_k$ and obtain the DFT f_l

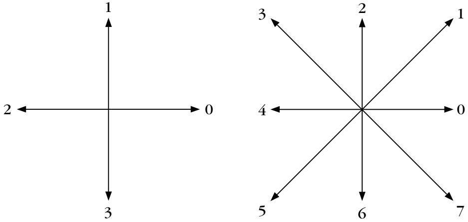
$$f_l = \sum_{k=0}^{N-1} u_k \exp\left(-j\frac{2\pi}{N}lk\right), \quad l = 0, 1, \ldots, N-1$$

Fourier Features (2)

- The coefficients f_l are known as Fourier descriptors of the boundary.
- Once f_l are available, the u_k can be recovered and the boundary can be reconstructed.
- However, the goal of pattern recognition is not to reconstruct the boundary. Thus, a smaller number of coefficients is usually used.

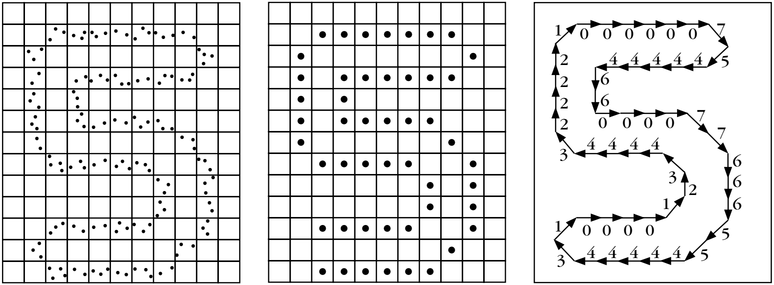
Chain Codes - Introduction

- Chain coding is the most widely used technique for shape description.
- Directions for a four-directional (a) and an eight-directional (b) chain code are defined as follows:



(a) (b)

Chain Codes - Example



(a) (b) (c)

(a) - original sample image
(b) - its resampled version
(c) - the resulting chain code.

CBIR Example using Shape Features

Content-Based Image Retrieval using Shape Features

Online YouTube Video