Texture-based recognition and segmentation in biomedical images and human-computer interaction domain

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Texture

• a very important property of the surfaces of the objects

• refers to an image area, characterized through a regular arrangement of the intensities of pixels
• this arrangement could be characterized through a statistic

• no accepted definition

• A. K. Jain, *Fundamentals of image processing*:

  “*texture refers to the repetition of some basic cells called texels; the cell is made by a number of pixels, whose placement can be periodic, quasi-periodic or random*”
Texture recognition

1. Texture analysis – characterize the texture through first or second order statistics, through a model (Markov Random Field Model, Fractals), through the spatial relations between pixels or through a transform (Fourier, Gabor, Wavelet)

2. Texture recognition – use a recognition method for the features previously extracted, like
   - a distance (e.g. the Euclidean distance)
   - the k-nn classifier
   - neural networks
   - support vector machine method (SVM)
Road quality analysis and road material recognition

• Analyze the road texture from the point of view of its specific microstructures: ridges, edges, spots, waves, ripples, grooves
• Use the Laws convolution filters in order to detect these microstructures
• Also use the Image Shape Spectrum (ISS) and the Laplacian of Gaussian (LoG)
Laws convolution filters:

- Level
  \[ L_5 = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix} \]

- Edge
  \[ E_5 = \begin{bmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & -2 & 0 & 0 \\ -1 & -2 & 0 & 2 & 1 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \]

- Spot
  \[ S_5 = \begin{bmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 4 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \end{bmatrix} \]
Waves

Test

\[ W_5 = \begin{bmatrix}
0 & 0 & -1 & 0 & 0 \\
0 & 0 & 2 & 0 & 0 \\
-1 & 2 & 0 & -2 & 1 \\
0 & 0 & -2 & 0 & 0 \\
0 & 0 & 1 & 0 & 0
\end{bmatrix} \]

original image  waves detection
The image shape spectrum (ISS)

- characterize the 3D shape of the surface

- use the image shape spectrum in a point \( p \) of the surface

\[
S(p) = \frac{1}{2} - \frac{1}{\pi} \cdot \arctan \frac{k_1(p) + k_2(p)}{k_1(p) - k_2(p)}
\]

- evaluate the difference between the main principal curvatures of the image surface[12], based on the spatial derivatives of the image intensity \( I \)
• **Road quality analysis**
  - compute the frequency of microstructures:
    - ridges – rough surfaces
    - spots – pitches
    - edges – cracks

• **Road material recognition**
  - use a recognition method which is invariant to changes in orientation and illumination
  - the texton-based method
The texton-based method

- **textons**: correspond to the microstructures in the texture
- **extract texture features** using the Laws convolution filters, the Image Shape Spectrum and the Laplacian of Gaussian => feature vectors
- **texton formation**: group the feature vectors in classes using the k-means clustering method; the centers of classes: “appearance vectors”, characteristic for a texton
- mark each pixel with the label of the corresponding texton
- build the histogram of textons
- use the chi-squared distance in order to compare two histograms

\[
\chi^2 (h_1, h_2) = \frac{1}{2} \sum_{n=1}^{\# \text{bins}} \frac{(h_1(n) - h_2(n))^2}{h_1(n) + h_2(n)}
\]
Invariant recognition

3D textons

• *different microstructures generate the same appearance* in certain orientation or illumination conditions (shadows, grooves)

• *2D structures algorithm will integrate them in the same class*

• use multiple *images*, representing the same thing under different illumination and orientation conditions

• each pixel will be characterized by an $N_{fil}N_{img}$ vector (resulted from the chaining of the feature vectors) [1]
The main steps

• **Learning**
  - build the textons histograms for a number of images representing instances of some known materials, taken under different orientation and illumination conditions
  - store the histograms in the database

• **Unknown material recognition**
  - use a single image, under arbitrary orientation and illumination conditions
  - use a Markov-Chain-Monte-Carlo method in order to decide the most probable configuration of textons and the most probable class
The Markov-Chain-Monte-Carlo Method

Repeat

• randomly assign to each pixel in the image the label of a texton, to which it probably correspond
• compute the probabilities of belonging to the classes

Until convergence
Experimental results

- 3 different illumination conditions for each image

<table>
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<th>At noon</th>
<th>In the evening</th>
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<td><strong>Class 6</strong></td>
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<table>
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<tr>
<th>Test image</th>
<th>Class</th>
<th>Distance between histograms</th>
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<tr>
<td></td>
<td>5</td>
<td>D5 = 0.096</td>
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<tr>
<td></td>
<td>1, 4</td>
<td>D1 = 0.180</td>
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<tr>
<td></td>
<td></td>
<td>D4 = 0.173</td>
</tr>
<tr>
<td></td>
<td>1,4,5</td>
<td>D1 = 0.183</td>
</tr>
<tr>
<td></td>
<td></td>
<td>D4 = 0.141</td>
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<tr>
<td></td>
<td></td>
<td>D5 = 0.123</td>
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<tr>
<td></td>
<td>1</td>
<td>D1 = 0.375</td>
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<tr>
<td></td>
<td>2</td>
<td>D2 = 0.187</td>
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Biomedical image recognition

- recognition in ultrasonic liver images (echographies)
- **purpose:** elaborate non-invasive, image-based methods in order to differentiate diffuse liver diseases – steatosis, cirrhosis, hepatitis, normal state
- these affections imply tissue modifications – texture characterization
- differences are almost no visible; the textons maps are apparently the same

- Normal
- Steatosis
- Hepatitis
- Cirrhosis
• use statistical texture characterization
• compute the gray level average on small rectangles, taken from the surface to deepness, on the median line
• gray level average decreases slowly in the case of normal liver and drastically in the case of steatosis

Ultrasonic image with selected ROI – hepatic steatosis

Gray level average plot for the selected ROI; Slope= -0.0271; negative; average=71
Ultrasonic image with selected ROI – normal liver

Gray level average plot for the selected ROI; Slope = 0.0017; **positive**; average = 69
• also use the gray level co occurrence matrix (GLCM) and the second order statistics plots taken towards the deepness of the image

**The Gray Level Cooccurrence Matrix (GLCM)**

- **f** - the digital image
- **D**={((dx, dy))} - a set of displacement vectors, for a certain value i:
- **C_D** (g_1, g_2)= #{((x,y), (x’,y’))):

  
  \[
  \begin{align*}
  f(x,y)&=g1, f(x’,y’)=g2 \\
  x&=x’+dx_i, y=y’+dy_i
  \end{align*}
  \]

#S = the size of set S

Normalized GLCM:

\[
p(g_1, g_2) = C_D (g_1, g_2) / \sum C_D (g_1, g_2)
\]

- the probability that 2 pixels are situated at the distance (dx, dy) and have the intensities (g_1, g_2)
The Gray Level Cooccurrence Matrix (GLCM)

The original image

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<tr>
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<tbody>
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<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
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<td>2</td>
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<tr>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
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</tbody>
</table>

The cooccurrence matrix for dx=1, dy=0

<table>
<thead>
<tr>
<th>V/R</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
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<tbody>
<tr>
<td>0</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>0</td>
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<tr>
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<td>2</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>1</td>
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<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
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Second order statistics

Contrast = \sum \sum (i-j)^2 p(i, j)
Entropy = - \sum \sum p(i, j) \log p(i, j)
Variance = \sum \sum (i - \mu)^2 p(i, j)

\begin{align*}
\text{Correlation} &= \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu_x)(j - \mu_y) p(i, j)}{\sigma_x \sigma_y} \\
\text{Angular second moment} &= \sum \sum (p(i, j))^2 \text{ (total energy)} \\
\text{Cluster shade} &= \sum \sum (i+j - \mu_x - \mu_y)^3 p(i, j) \\
\text{Cluster proemminence} &= \sum \sum (i+j - \mu_x - \mu_y)^4 p(i, j)
\end{align*}
Biomedical Image Recognition

- Compute GLCM and the second order statistics
- Plot the evolution of the second order statistics towards the deepness of the image
- Store these plots in a database – features vectors
- Apply the k-nn classification method and decide between steatosis, hepatitis, cirrhosis
• Image preprocessing – *elimination of artifacts* (e.g. blood vessels, muscles), using an averaging filter
Texture-based segmentation

Problems:
- textured surfaces of objects in real-life scenes
- textured areas with vague contours in biomedical images

Usual methods:
- extract texture features and use some supervised or unsupervised classification methods in order to segment different texture regions
- compare neighboring regions and decide if they belong to different textures or not
Defect detection in road surface

• Find textons in the given image and mark each pixel with the corresponding texton label
• Split the image in small enough blocks and compute the textons histogram for each block
• Compare the histogram of the current block with the histograms of the neighboring blocks (chi-square distance)
• Localize the center of the region with defect (corresponding to the maximum distance between histograms)
• Extend the region as much as necessary
Texture-based hand detection

• Find textons in the given image and mark each pixel with the corresponding texton label
• Split the image in small enough blocks and compute the textons histogram for each block
• Compare the histograms of the neighboring blocks, in the horizontal direction (chi-square distance)
• Decide a texture border if the chi-squared distance between the histograms overpasses the threshold:

\[
\text{Threshold} = \frac{\chi_{\min}^2 + \chi_{\max}^2}{2} + \sigma^2 \chi \quad (3)
\]

• \( \chi_{\min}^2 \) and \( \chi_{\max}^2 \) represent the minimum and maximum values of the distances computed, from left to right, between the neighboring blocks of the image
• \( \sigma^2 \) is the squared variance of these distances.
• Compare the textons histogram with some histograms previously stored in the training set, corresponding to the texture of the hand skin

• Use other features like size and shape in order to distinguish the hand from other parts of body

• Results:
Contours detection in biomedical images

• Use active contour models and the GLCM based texture features

• Active contour models (Snakes): an arbitrarily initialized contour evolves in order to fit the real contour, based on energy minimization principles

• Energies: elastic energy, bending energy, image energy (usually the intensity gradient)

• For image energy: use the texture energy, based on the GLCM computation and differences between the second order statistics of the neighboring blocks
Conclusions

• texture is a very important feature in images with real-life scenes, as well as in biomedical images, in recognition and segmentation problems.

• the texton-based method is suitable for recognition and segmentation in images containing real objects (asphalt or human hands).

• in ultrasonic images of liver, the second order statistics of GLCM are more suitable, in order to differentiate between the diffuse liver diseases.
References

[1] Larry S. Davis, Department of Computer Sciences, University of Texas at Austin, Austin, Texas 78712: "Image Texture Analysis Techniques – A Survey"


[7] M. Heikkila, M. Pietikainen and J. Heikkila, Machine Vision Group, Infotech Oulu and Department of Electrical and Information Engineering, P.O. Box 4500 FIN-90014 University of Oulu, Finland, A Texture-based Method for Detecting Moving Objects, 2004

THANK YOU!