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

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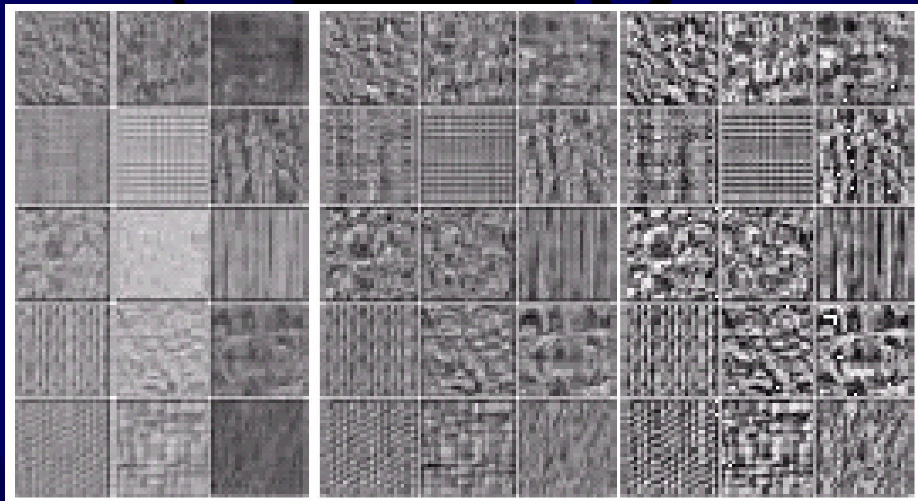
Texture



• 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

$$E_5 = \begin{bmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & -2 & 0 & 0 \\ -1 & -2 & 0 & 2 & 1 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

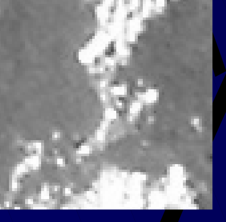
- Spot

$$S_5 = \begin{bmatrix} 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 4 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \end{bmatrix}$$

- Wave

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

- Test



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

$$c^{2}(h_1, h_2) = \frac{1}{2} \sum_{n=1}^{\#bins} \frac{(h_1(n) - h_2(n))^{2}}{h_1(n) + h_2(n)}$$

Invariant recognition

3D textons

• ***different microstructures gererate the same apearance*** 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 diferent 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

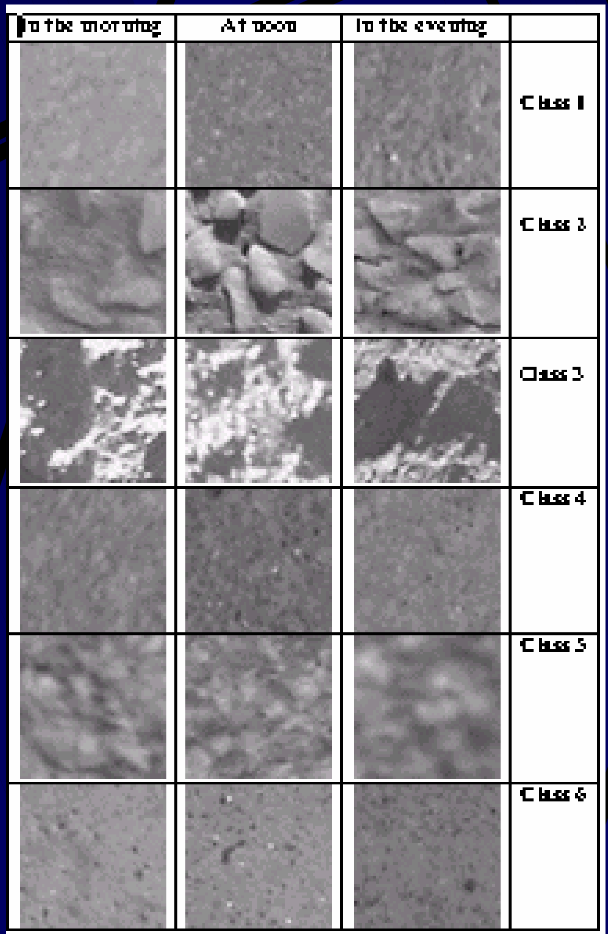
Repeat

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

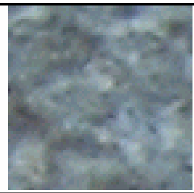
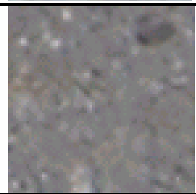
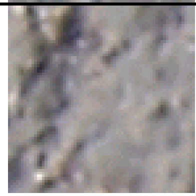
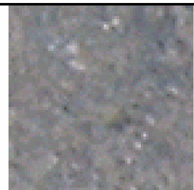
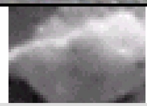
Until convergence

Experimental results

- 3 different illumination conditions for each image



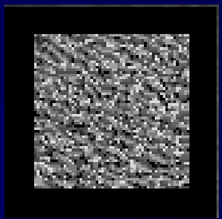
Training set

Test image	Class	Distance between histograms
	5	D5=0.096
	1, 4	D1= 0.180 D4 = 0.173
	1,4,5	D1= 0.183 D4 = 0.141 D5 = 0.123
	1	D1 = 0.375
	2	D2 = 0.187

Result set

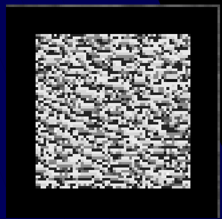
Biomedical image recognition

- 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

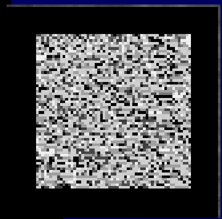


Normal

Steatosis



Hepatitis

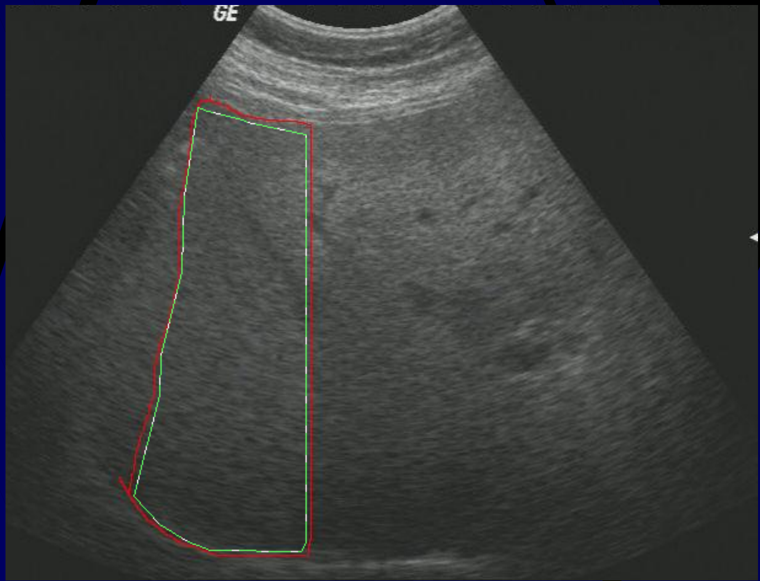


Cirrhosis

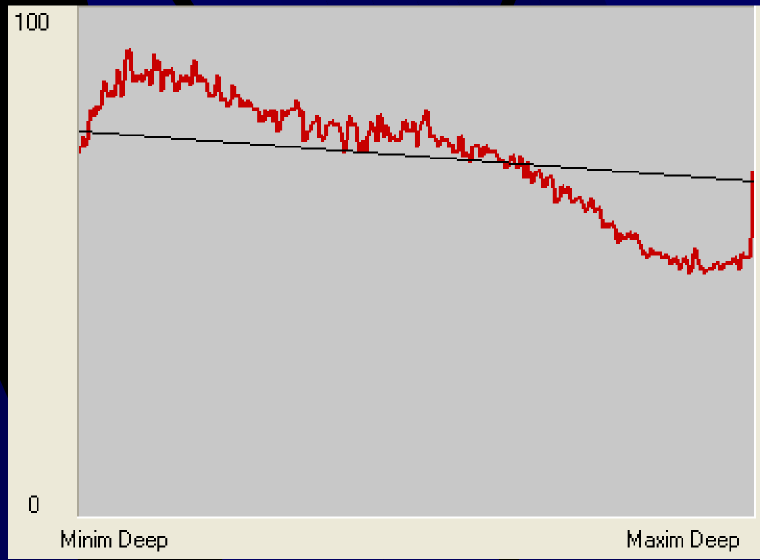
• use statistical texture characterization

• compute the gray level average on small rectangles, taken from the surface to deepness, on the median line

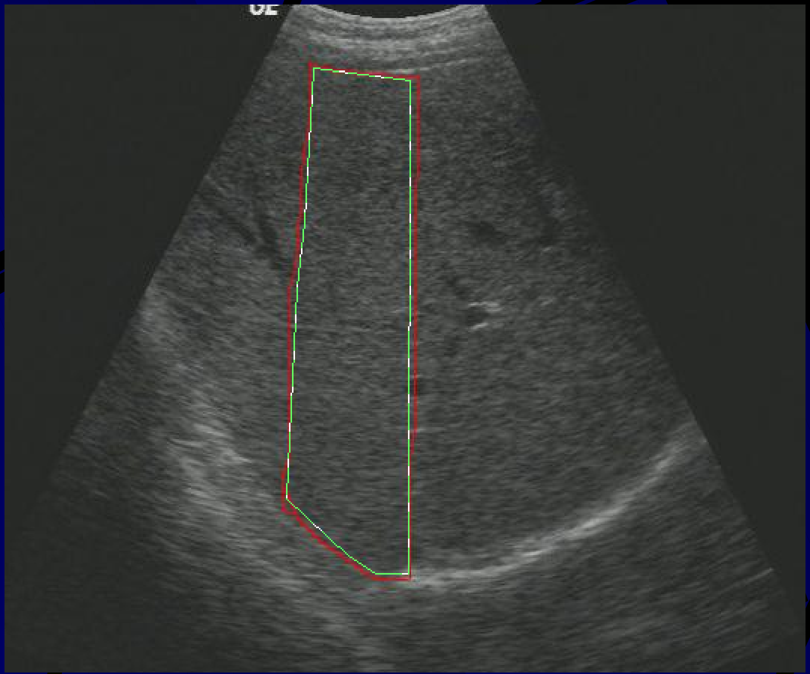
• gray level average decreases slowly in the case of normal liver and drastically in the case of steatosis



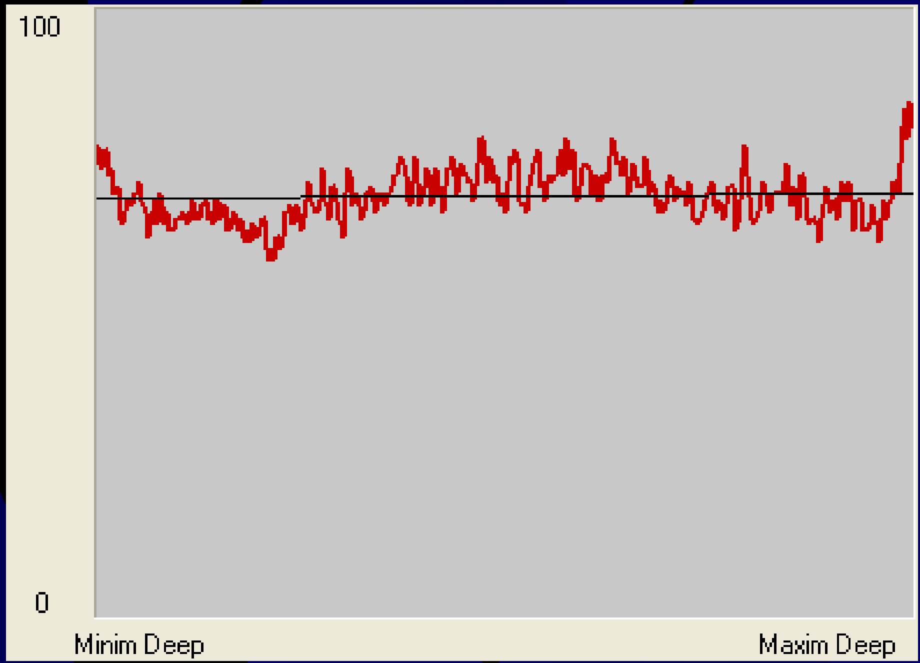
Ultrasonic image with selected ROI – hepatic stheatosis



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 Cooccurence Matrix (GLCM)

f - the digital image

$D=\{(dx_i, dy_i)\}$ - a set of displacement vectors, for a certain value i:

$C_D(g_1, g_2) = \#\{((x,y), (x',y')):$

$f(x,y)=g1,\ f(x',y')=g2$

$x=x'+dx_i\ \ y=y'+dy_i\}$

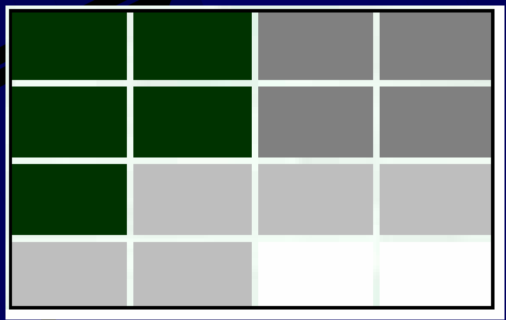
#S = the size of set S

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 Cooccurence Matrix (GLCM)



The original image

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

V/R	0	1	2	3
0	**2**	**2**	**1**	**0**
1	**0**	**2**	**0**	**0**
2	**0**	**0**	**3**	**1**
3	**0**	**0**	**0**	**1**

The cooccurrence matrix
for dx=1, dy=0

Second order statistics

Contrast **= å å (i-j)^2 p(i, j)**

Entropy **= - å å p(i, j)log p(i, j)**

Variance **= å å (i - •)^2 p(i, j)**

Correlation **=**

$$\frac{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(\mathrm{i}-\mathrm{m}_x)(j-\mathrm{m}_y)\,\mathrm{p}(\mathrm{i},\ \mathrm{j})}{\mathrm{s}_x\mathrm{s}_y}$$

Angular second moment **= å å (p(i, j))^2 (total energy)**

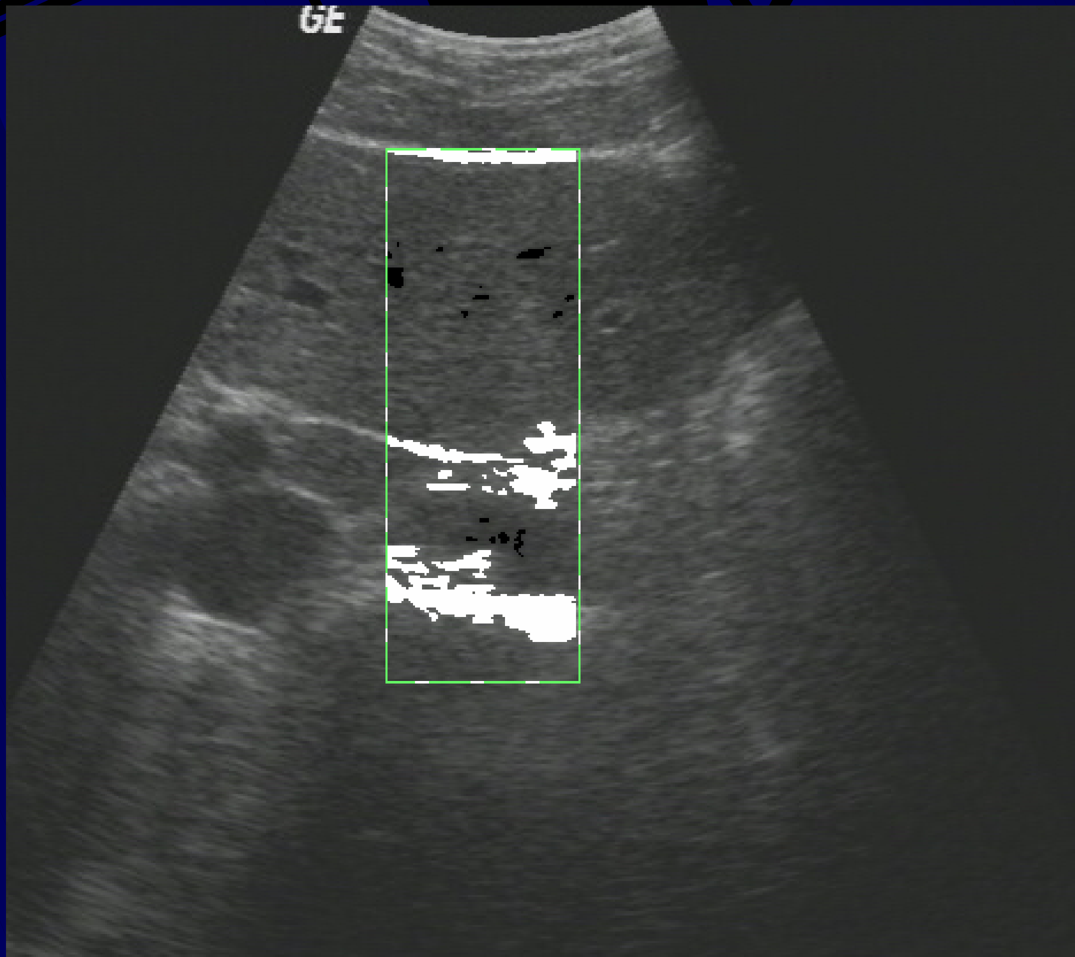
Cluster shade **= å å (i+j- •$_x$- •$_y$) ^{3} p(i, j)**

Cluster proemminence **= å å (i+j- •$_x$- •$_y$)^4 p(i, j)**

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:

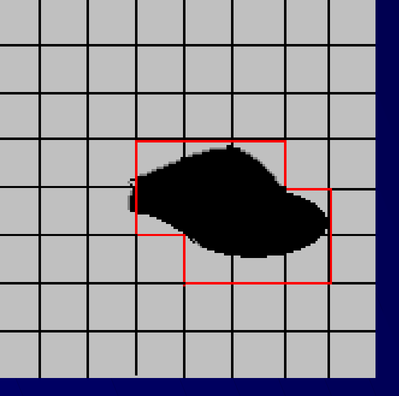
- textured surfaces of objects in real-life scenes
- textured areas with vague contours in biomedical images

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-sqare 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:

$$Threshold = \frac{\chi^2_{min} + \chi^2_{max}}{2} + \sigma^2_c \quad (3)$$

- χ^2_{min} and χ^2_{max} represent the minimum and maximum values of the distances computed, from left to right, between the neighboring blocks of the image
- σ^2_c 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

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THANK YOU !