Textures Analysis

Session delivered by:

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Session Outcomes

At the end of this session, student will be able to:

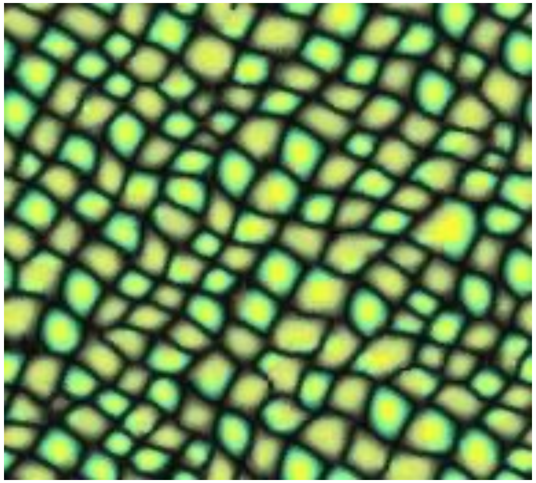
- Discuss Texture
- Analyse Image Texture
- Analyse Textures Features
- Discuss features extraction
- Discuss features extraction from varying textures
- Discuss Texture based matching
- Discuss Texture segmentation
  - Representing texture
- Discuss Texture synthesis
  - useful; also gives some insight into quality of representation
- Discuss Shape from texture

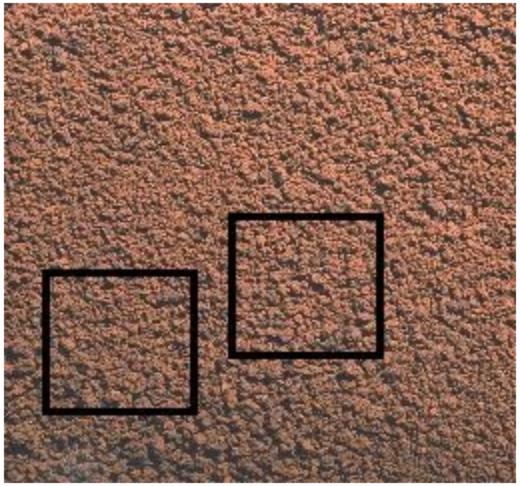
Session Topics

- Texture
- Image Texture
- Textures Features
- Texture features extraction
- Feature extraction from varying textures
- Texture based matching
- Texture segmentation

What is Texture?

- Texture is a feature that can help to segment images into regions of interest and to classify those regions.
- Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.
- Images containing repeating patterns
- Local & stationary



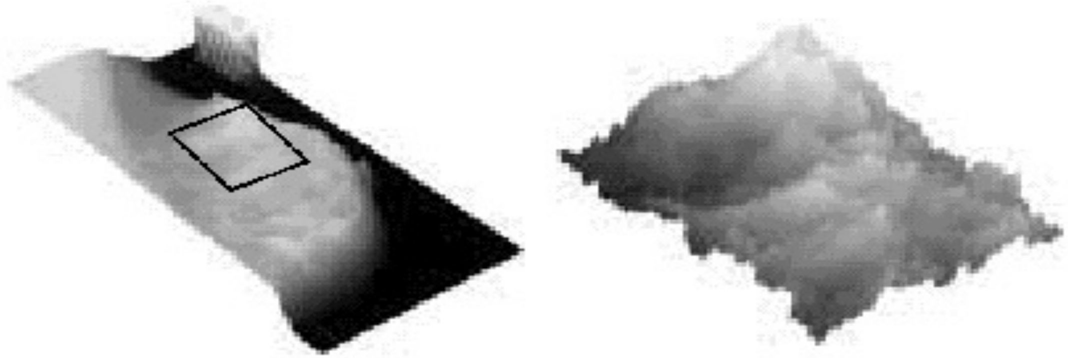


Cont..

- A feature is used to partition images into regions of interest and to classify those regions
- provides information in the spatial arrangement of colours or intensities in an image
- characterized by the spatial distribution of intensity levels in a neighbourhood
- repeating pattern of local variations in image intensity
- cannot be defined for a point

Cont..

- Texture is a repeating pattern of local variations in image intensity:



- For example, an image has a 50% black and 50% white distribution of pixels.

- 3 different images with the same intensity distribution, but with different textures.

Cont..

- Texture consists of texture primitives or texture elements, sometimes called ***texels***.
  - – Texture can be described as fine, coarse, grained, smooth, etc.
  - – Such features are found in the tone and structure of a texture.
  - – Tone is based on pixel intensity properties in the ***texel***, while structure represents the spatial relationship between ***texels***.
  - – If ***texels*** are **small** and tonal differences between texels are large a fine texture results.
  - – If ***texels*** are **large** and consist of several pixels, a coarse texture results.

Cont..

- The surface of any visible object is textured at certain scale.
- In general texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts .
- A texture is usually described as smooth or rough, soft or hard, coarse of fine, matt or glossy, and etc.
- Textures might be divided into 2 categories, ***tactile*** and ***visual textures***.
- **Tactile textures** refer to the immediate tangible feel of a surface. **Visual textures** refer to the visual impression that textures produce to human observer, which are related to local spatial variations of simple stimuli like colour, orientation and intensity in an image.

Cont..

- Def: The regular repetition of an element or pattern on a surface.
- Figures 1 and 2 show a few natural and man-made textures, respectively, which could be met in daily life.

Figure 1: Examples of natural textures

Figure 2: Examples of artificial regular textures

Definition

- An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image
- Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.
- Texture can be defined as an entity consisting of mutually related pixels and group of pixels.

Texture Analysis

- Because texture has so many different dimensions no single method of texture representation that is adequate for a variety of textures.

- **Texture analysis** refers to the characterization of regions in an **image** by their **texture** content. **It** attempts to quantify intuitive qualities described by terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities.

- Purpose of texture analysis is:
  - To identify different textured and non-textured regions in an image.
  - To classify/segment different texture regions in an image.
  - To extract boundaries between major texture regions.
  - To describe the texel unit.
  - 3-D shape from texture

Cont..

- Two primary issues in texture analysis:

  - ***texture classification***

  - ***texture segmentation***

- ***Texture classification*** is concerned with identifying a given textured region from a given set of texture classes.

  Each of these regions has unique texture characteristics.

  Statistical methods are extensively used.

  (*e.g. GLCM, contrast, entropy, homogeneity*)

- ***Texture segmentation*** is concerned with automatically determining the boundaries between various texture regions in an image.

Texture classification

- In texture classification the goal is to assign an unknown sample image to one of a set of known texture classes.
- Texture classification is one of the 4 problem domains in the field of texture analysis. The other 3 are
  - **texture segmentation** (partitioning of an image into regions which have homogeneous properties with respect to texture; supervised texture segmentation with a priori knowledge of textures to be separated simplifies to texture classification),
  - **texture synthesis** (the goal is to build a model of image texture, which can then be used for generating the texture) and
  - **shape from texture** (a 2D image is considered to be a projection of a 3D scene and apparent texture distortions in the 2D image are used to estimate surface orientations in the 3D scene).

Cont..

- Texture classification process involves 2 phases: 1. learning phase & 2. recognition phase.
- In the **learning phase**, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels.
- The texture content of the training images is captured with chosen texture analysis method, which yields a set of textural features for each image. These features can be scalar numbers or discrete histograms or empirical distributions, characterize given textural properties of the images, such as spatial structure, contrast, roughness, orientation, etc.
- In the **recognition phase**, texture content of the unknown sample is 1st described with the same texture analysis method. Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match.

Why we use texture ?

- Image textures can be artificially created or found in natural scenes captured in an image

- Used to help in segmentation
- Classification of image

Analyze texture in CG
- Structure approach
- Statistical approach

Defining Texture

- There are ***3 approaches*** to defining exactly what texture is:

  – ***Structural*** : texture is a set of primitive texels in some regular or repeated relationship.

  – ***Statistical*** : texture is a quantitative measure of the arrangement of intensities in a region.
  This set of measurements is called a *feature vector*.

  – ***Modeling*** : texture modeling techniques involve constructing models to specify textures.

Cont..

- Statistical methods are particularly useful when the texture primitives are small, resulting in ***<u>micro-textures</u>***.

- When the size of the texture primitive is large, first determine the shape and properties of the basic primitive and the rules which govern the placement of these primitives, forming ***<u>macro-textures</u>***.

Representing textures

- Textures are made up of quite stylized sub-elements, repeated in meaningful ways
- Representation:
  - find the sub-elements, and represent their statistics
- But what are the sub-elements, and how do we find them?
  - recall normalized correlation
  - find sub-elements by applying filters, looking at the magnitude of the response
- What filters?
  - experience suggests spots and oriented bars at a variety of different scales
  - details probably don't matter
- What statistics?
  - within reason, the more the merrier.
  - At least, mean and standard deviation
  - better, various conditional histograms.

❖ Texture segmentation:

- Unlike texture classification, texture segmentation is concerned with automatically determining the boundaries between various textured regions in an image.
- Both reign-based methods and boundary-based methods have been attempted to segments texture images.

❖ **Shape recovery from texture:**

- Image plane variation in the texture properties, such as density, size and orientation of texture primitives, are the cues exploited by shape –from-texture algorithms.

- Quantifying the changes in the shape of texture elements is also useful to determine surface orientation.

TECHNIQUES FOR TEXTURE EXTRACTION

- There are various techniques for texture extraction. Texture feature extraction algorithms can be grouped as follows:

- **Statistical**
- **Geometrical**
- **Model based**
- **Signal Processing**

Statistical method

A. Local features

i. Grey level of central pixels,
ii. Average of grey levels in window,
iii. Median,
iv. Standard deviation of grey levels,
v. Difference of maximum and minimum grey levels,
vi. Difference between average grey level in small and large windows,
vii. Kirsch feature,
viii. Combine features

Cont..

B. Galloway

i. run length matrix

C. Haralick

i. co-occurrence matrix

Geometrical method

- First threshold images into binary images of n grey levels.
- Then calculate statistical features of connected areas.

Model Based method

These involve building mathematical models to describe textures:

- Markov random fields
- Fractals 1
- Fractals 2

Signal processing method

These methods involve transforming original images using filters and calculating the energy of the transformed images.

- Law’s masks
- Laines – Daubechies wavelets
- Fourier transform
- Gabor filters

Texture Measures

- GLCM (Gray level Co-occurrence Matrices)
- Law's Texture Energy Measures
- Wavelets
- Steerable Pyramids

GLCMs

– The statistical measures described so far are easy to calculate, but do not provide any information about the repeating nature of texture.

– A gray level co-occurrence matrix (**GLCM**) contains information about the positions of pixels having similar gray level values.

Cont..

- A co-occurrence matrix is a two-dimensional array, *P*, in which both the rows and the columns represent a set of possible image values.

- A GLCM P_d [*i, j*] is defined by first specifying a displacement vector *d*=(d_x, d_y) and counting all pairs of pixels separated by *d* having gray levels *i* and *j*.

- 2D histogram of image intensities

- *P(i, j, d,* θ*)* : Count of occurrence of gray level *i* with j at distance d and in direction θ

Cont..

- The **GLCM** is defined by:

$$P_d[i, j] = n_{ij}$$

– where n_{ij} is the number of occurrences of the pixel values *(i, j)* lying at distance *d* in the image.

– The co-occurrence matrix P_d has dimension *n × n*, where n is the number of gray levels in the image.

Cont..

50	51	52	50
53	51	51	52
51	50	51	52
52	53	53	52

Intensity image patch

	50	51	52	53
50	0	2	0	0
51	1	1	3	0
52	1	0	0	1
53	0	1	1	1

$P(d,\theta)$, $d=1$, $\theta=0^o$
#(x,y)=(1,0)

	50	51	52	53
50	0	1	0	0
51	0	2	1	1
52	1	1	2	0
53	2	1	0	0

$P(d,\theta)$, $d=1$, $\theta=90^o$
#(x,y)=(0,1)

Cont..

50	51	52	50
53	51	51	52
51	50	51	52
52	53	53	52

Intensity image patch

	50	51	52	53
50	0	1	1	0
51	2	1	0	1
52	0	3	0	1
53	0	0	1	1

$P(d,\theta)$, d=1, $\theta=180^o$
#(x,y)=(-1,0)

	50	51	52	53
50	0	0	1	2
51	1	2	1	1
52	0	1	2	0
53	0	1	0	0

$P(d,\theta)$, d=1, $\theta=270^o$
#(x,y)=(0,-1)

Cont..

50	51	52	50
53	51	51	52
51	50	51	52
52	53	53	52

Intensity image patch

	50	51	52	53
50	0	1	0	0
51	1	1	2	0
52	1	0	0	0
53	0	2	1	0

P(d,θ), d=1, θ=45^{o}

	50	51	52	53
50	0	1	0	0
51	0	2	1	1
52	1	1	2	0
53	2	1	0	0

P(d,θ), d=1, θ=135^{o}

Cont..

50	51	52	50
53	51	51	52
51	50	51	52
52	53	53	52

Intensity image patch

	50	51	52	53
50	0	1	1	0
51	1	1	0	2
52	0	2	0	1
53	0	0	0	0

$P(d,\theta)$, $d=1$, $\theta=225^o$

	50	51	52	53
50	0	1	0	1
51	0	2	2	1
52	0	0	1	0
53	1	0	0	0

$P(d,\theta)$, $d=1$, $\theta=315^o$

Framework for the GLCM:

e.g. for glcm matrix for an image

image

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

glcm matrix

Spatial relationship between two pixels

GLCM texture considers the relation between two pixels at a time, called the **reference** and the **neighbor** pixel.

neighbor pixel value -> ref pixel value:	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

matrix framework

Cont..

- In the above illustration, the neighbor pixel is chosen to be the one to the east (right) of each reference pixel. This can also be expressed as a (1,0) relation: 1 pixel in the x direction, 0 pixels in the y direction.

Cont..

- Each pixel within the window becomes the reference pixel in turn, starting in the upper left corner and proceeding to the lower right. Pixels along the right edge have no right hand neighbor, so they are not used for this count.

How to read the matrix framework

The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many times within the image area a pixel with grey level 0 (neighbor pixel) falls to the right of another pixel with grey level 0 (reference pixel).

How to read the east matrix

Twice in the test image the reference pixel is 0 and its eastern neighbor is also 0. Twice the reference pixel is 0 and its eastern neighbor is 1. Three times the reference pixel is 2 and its neighbor is also 2.

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

east matrix framework

UNDERSTANDING GLCM

- GLCM represents the distance and angular spatial relationship over an image sub-region of specific region of specific size.

- The GLCM calculates, how often a pixel with gray-level (grayscale intensity or Tone) value i occurs either horizontally, vertically, or diagonally to adjacent pixels with the value j.

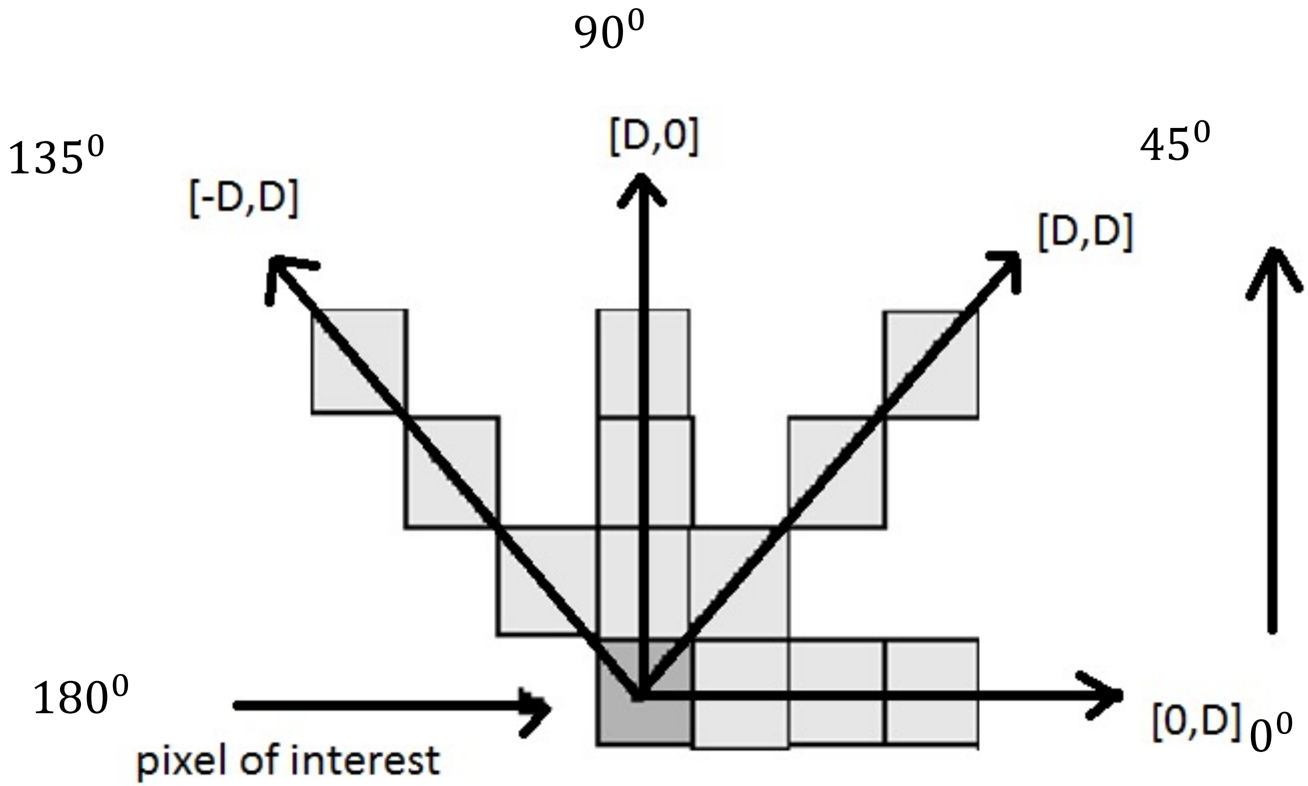
GLCM directions of Analysis

- *Horizontal (0^o) right*
- *Vertical (90^o) up*
- *Diagonal right(45^o):*
- *Bottom left to top right (-45^o=270+45=315)*
- *Top left to bottom right (-135^o)*

Denoted P_0, P_{45}, P_{90}, & P_{135} Respectively.

Ex. P_0 (i, j)

GLCM direction analysis:



Cont..

- GLCM of an image is computed using a displacement vector d, defined by its **radius δ** and **orientation θ**.

- Consider a 4x4 image represented by figure with four gray-tone values 0 through 3. A generalized GLCM for that image is shown in figure 1b where #(i,j) stands for number of times i and j have been neighbors satisfying the condition stated by displacement vector d.

Cont..

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

1a. Test image

Gray tone	0	1	2	3
0				
1				
2				
3				

1b. General form of GLCM

Cont..

- **The four GLCM for angles equal to 0°, 45°, 90° and 135° and radius equal to 1 are shown in figure 2 a-d**.

Cont..

4	**2**	**1**	**0**
2	4	0	0
1	0	6	1
0	0	1	2

GLCM for δ*=1 &* θ*=*0^0

6	**0**	**2**	**0**
0	4	2	0
2	2	2	2
0	0	2	0

GLCM for δ*=1 &* θ*=*90^0

Cont..

4	**1**	**0**	**0**
1	2	2	0
0	2	4	1
0	0	1	0

GLCM for δ=1 & θ=45^0

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

GLCM for δ=1 & θ=135^0

Choice of radius δ/d

- δ values ranging should be ranging from 1, 2 to 10, but the best result is for δ = 1 and 2.
- Applying large displacement value to a fine texture would yield a GLCM that does not capture detailed textural information.
- As a pixel is more likely to be correlated to other closely located pixel than the one located far away, the above consideration is correct.

Choice of angle θ

- Every pixel has eight neighboring pixels allowing eight choices for θ, which are 0°, 45°, 90°, 135°, 180°, 225°, 270° or 315°.

- According to the definition of GLCM, the co-occurring pairs obtained by choosing θ equal to 0° would be similar to those obtained by choosing θ equal to 180°. This concept extends to 0°,45°, 90°and 135° as well. Hence, one has four choices to select the value of θ.

GLCMs

- Too many parameters
- Computationally Expensive
- Not suitable for coarse texture
- Susceptible to noise

Common Statistics Derived From Co-occurrence Probabilities

ENERGY

- Also called **Uniformity or Angular second moment.**
- Measures **the textural uniformity that is pixel pair repetitions**.
- Detects disorders in textures.
- Energy reaches a maximum value equal to one.

$$Energy = \sum_i \sum_j {p_{ij}}^2$$

Entropy

- **Measures the disorder or complexity of an image**.
- The entropy is large when the image is not texturally uniform.
- Complex textures tend to have high entropy.
- Entropy is strongly, but inversely correlated to energy.
- $Entropy(ent) = -\sum_i \sum_j p_{ij} \log_2 p_{ij}$

Contrast

- **Measures the spatial frequency of an image and is difference moment of GLCM**.
- It is the difference between the highest and the lowest values of a contiguous set of pixels.
- It measures the amount of local variations present in the image.
- Contrast(con)=$\sum_i \sum_j (i-j)^2 p_{ij}$

Homogeneity

- Also called as **Inverse Difference Moment**.
- **Measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements**.
- It is more sensitive to the presence of near diagonal elements in the GLCM.
- It has maximum value when all elements in the image are same.
- Homogeneity decreases **if** contrast increases while energy is kept constant.
- Homogeneity(hom) = $\sum_i \sum_j \frac{1}{1+(i-j)^2} p_{ij}$

Variance

- **This statistic is a measure of heterogeneity and is strongly correlated to first order statistical variable such as standard deviation**.

- Variance increases when the gray level values differ from their mean.

- Variance(var)= $\sum_i \sum_j (i-\mu)^2 \, p_{ij}$

  where μ is the mean of p_{ij}

Cont..

Difference Variance

=variance of p_{x-y}

Difference Entropy

$$=\sum_{i=0}^{N-1} p_{x-y}(i) \log\{p_{x-y}(i)\}$$

Contd...

Proposed algorithm for μ-calcification detection of the segmented nodule :-

- *Step 1* :- Calculate the co-occurrence matrix H = $[h_{ij}]_{L \times L}$ of the segmented nodule .
- *Step 2* :- Calculate Haralick Texture Features of the co-occurrence matrix.
- *Step 3*:- Identify calcified mass from a set of benign and malignant mass (by applying Haralick Texture Features).

Contd..

- *Step 4* :- Calculate **Mean(*M_m*)** and **standard deviation(σ)** of the pixel values in the nodule and set the **threshold** value(***T***)

---------(19)

where, *k* = constant. $$T = M_m + k.\sigma$$

- *Step 5* :- As luminance of micro-calcifications is brighter than normal pixel, then micro-calcification can be distinguished from normal areas in the mass as - if the pixel value is greater than the threshold value(T) then that pixel is considered as micro-calcifications.

Contd..

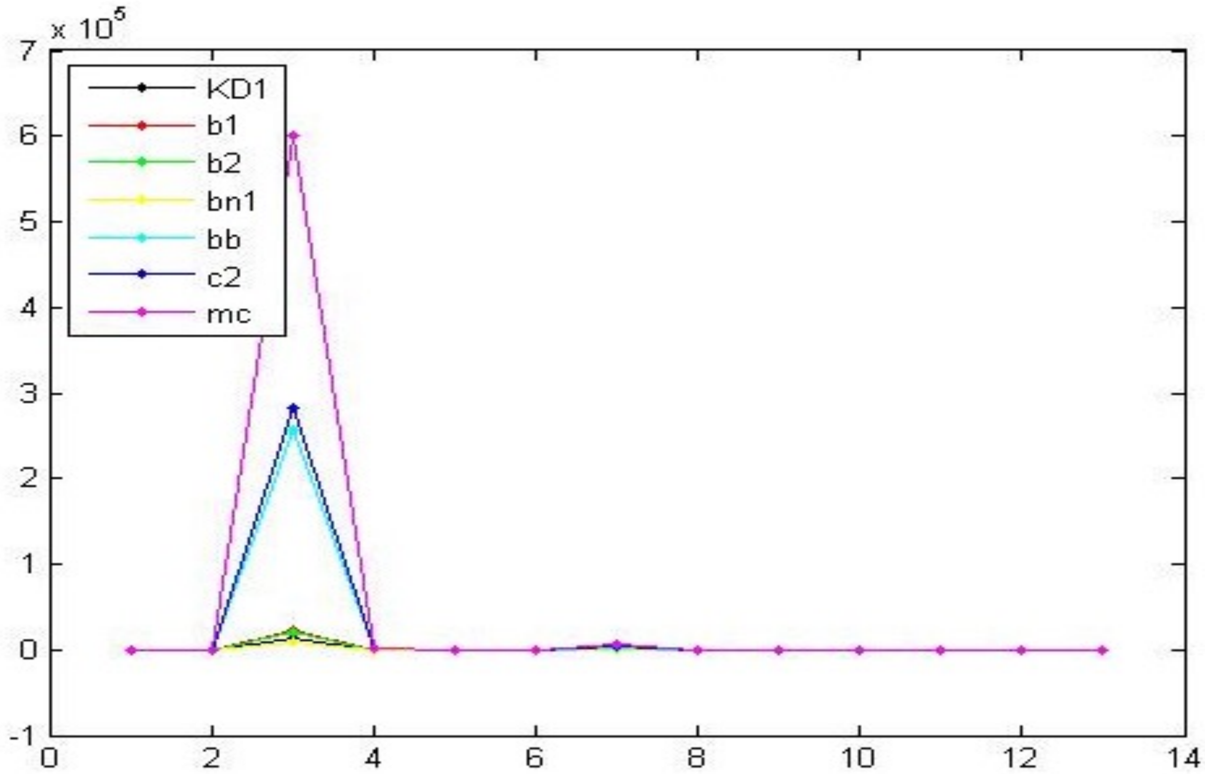


Fig. Plot of the Haralick texture features of Segmented mass

Results (Contd..)

- *Case Study I* :

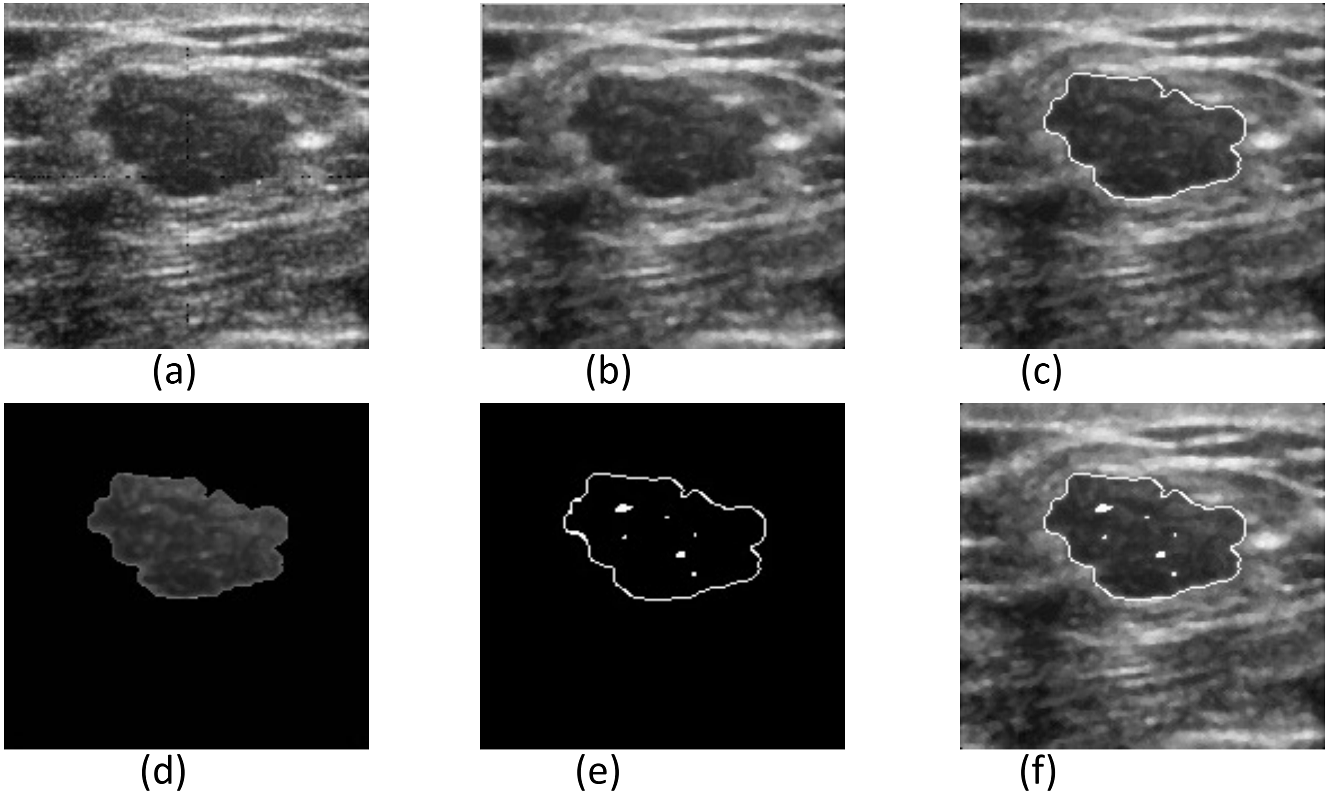
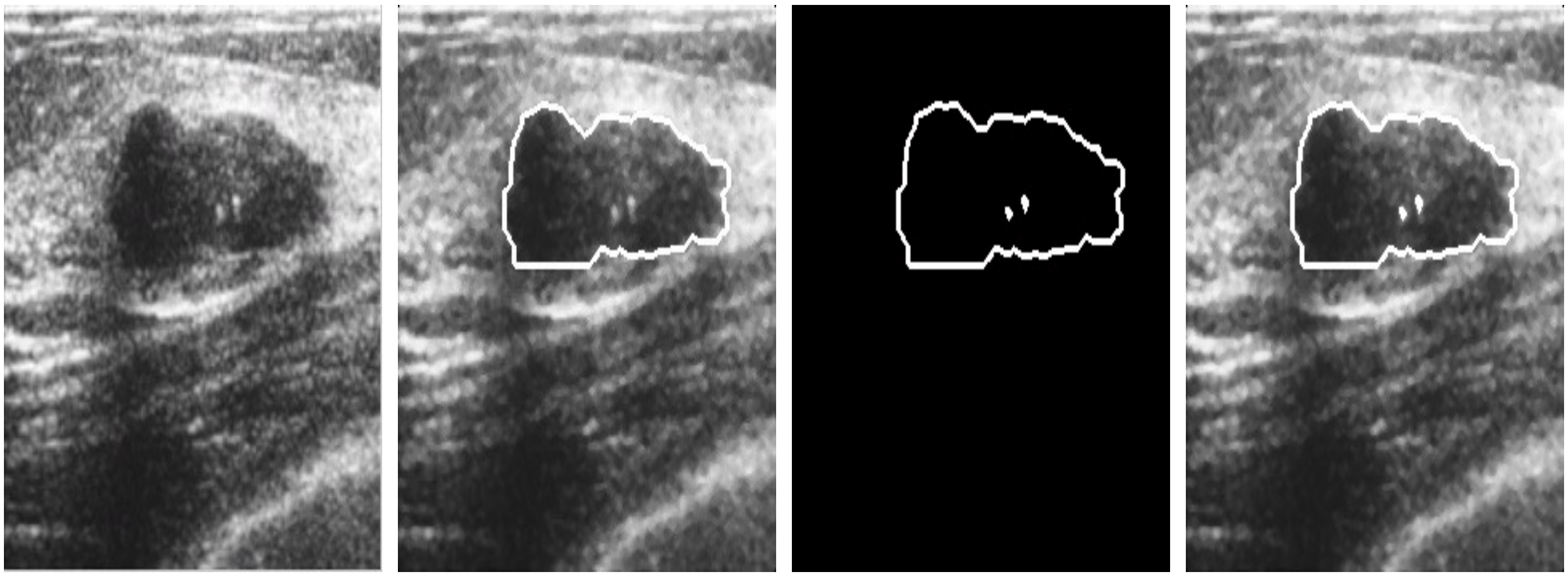


Fig. Example of nodule with
(a)Original Image captured by USG device, (b)Image after Unsharp Masking,
(c) Mass boundaries segmentation, (d) Segmented nodule, (e) Calcifications extracted from that nodule, (f) Detected Mass calcifications

Contd..

- *Case Study II* :

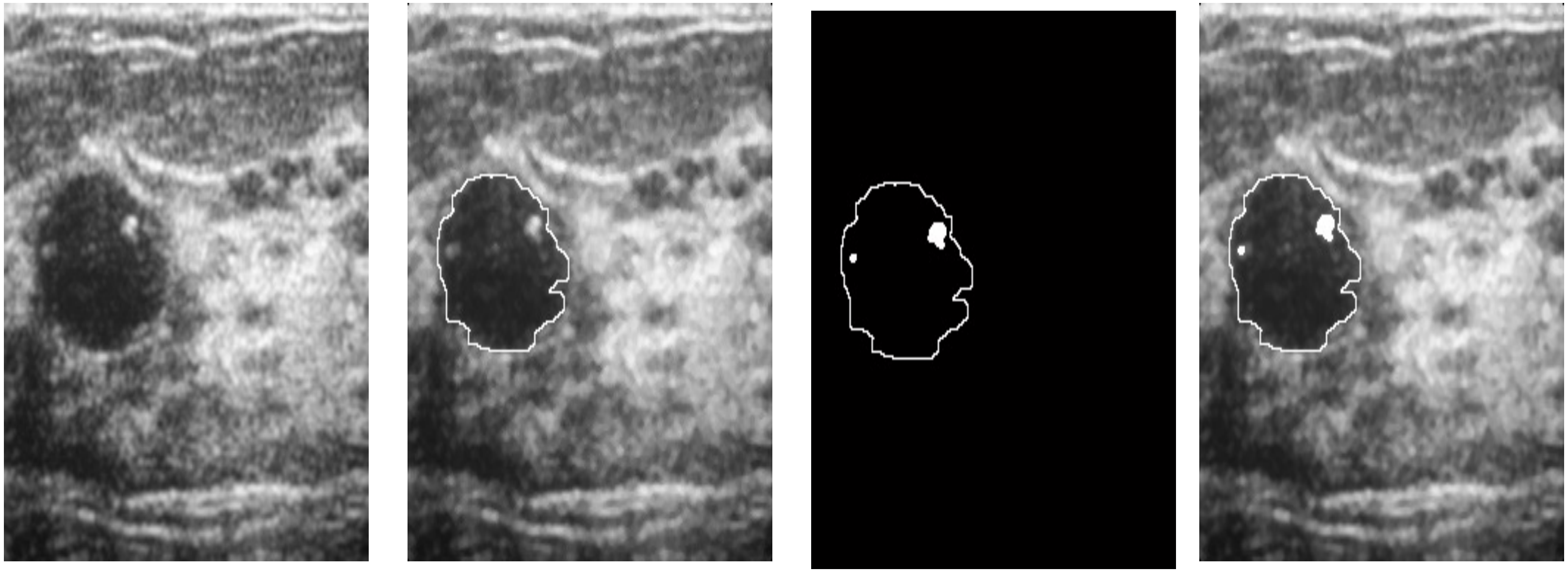


(a) (b) (c) (d)

Fig. Example of nodule with
(a) Original Image captured by USG device, (b)Mass boundary segmentation, (c) Calcifications extracted from that nodule, (d) Detected Mass calcifications

Contd..

- *Case Study III* :



(a) (b) (c) (d)

Fig Example of nodule with
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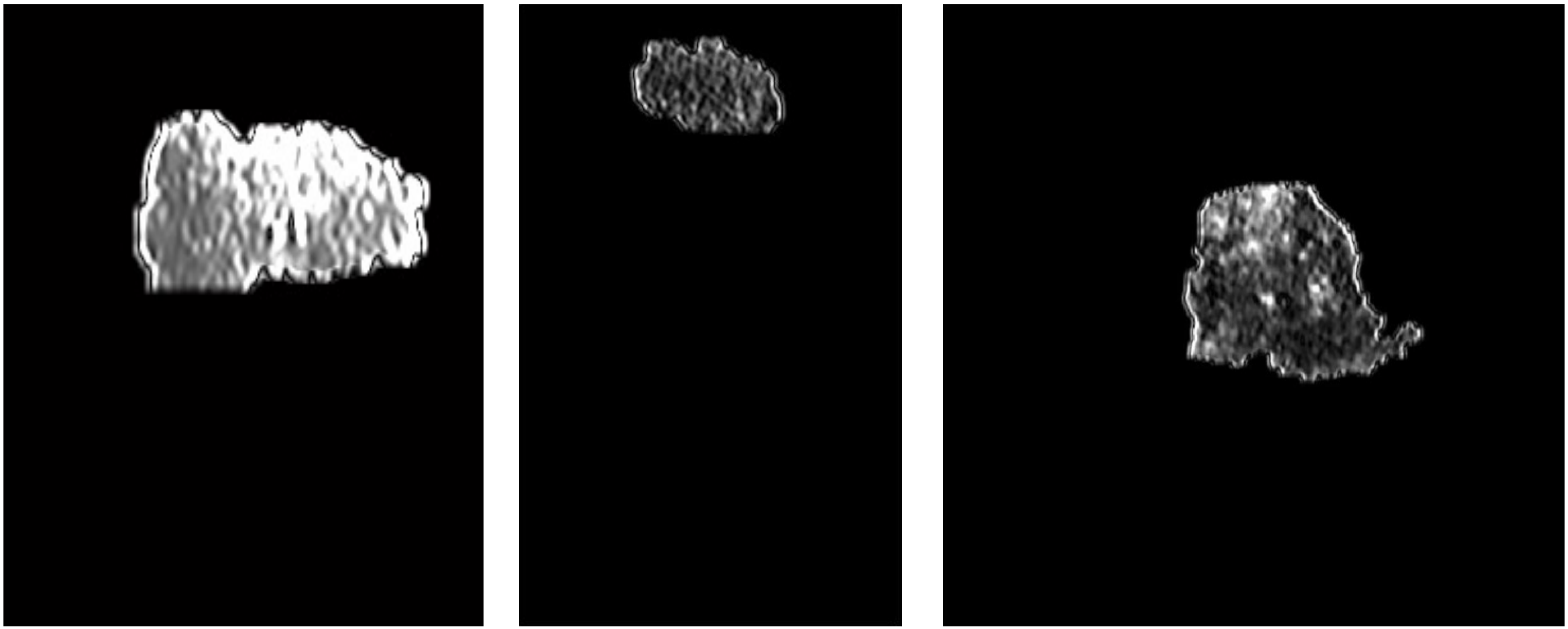
Contd..



(a) (b) (d)

Fig After applying Gabor filter on segmented nodule

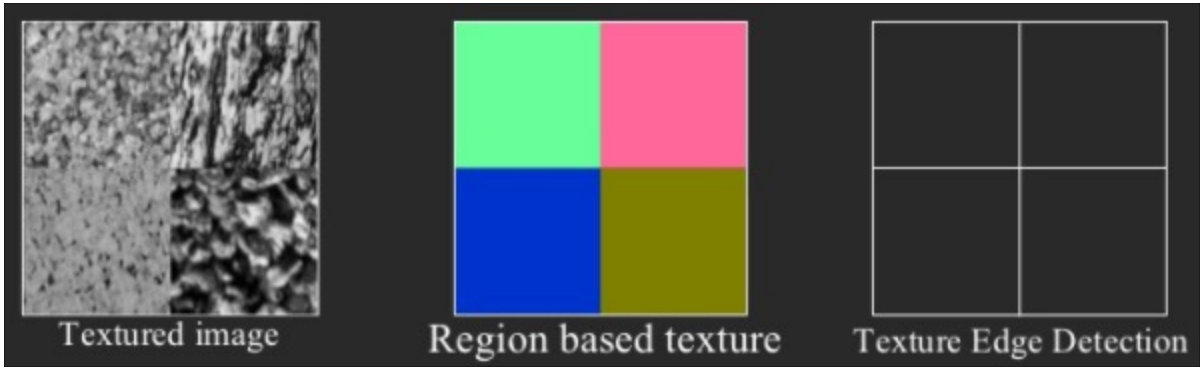
(a) and (c)Malignant nodule with detected Mass calcification, (b) Benign nodule

Final texture representation

- Form an oriented pyramid (or equivalent set of responses to filters at different scales and orientations).
- Square the output
- Take statistics of responses
  – e.g. mean of each filter output (are there lots of spots)
  – std of each filter output
  – mean of one scale conditioned on other scale having a particular range of values (e.g. are the spots in straight rows?)

Region Based Texture Segmentation

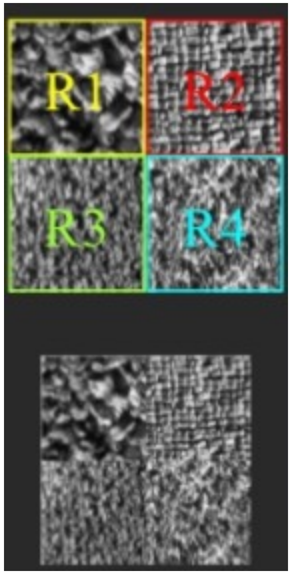
- In some images, it can be the defining characteristic of regions and critical in obtaining a correct analysis. The image of Figure 7.1 has three very distinct textures: the texture of the tiger, the texture of the jungle, and the texture of the water. These textures can be quantified and used to identify the object classes they represent.

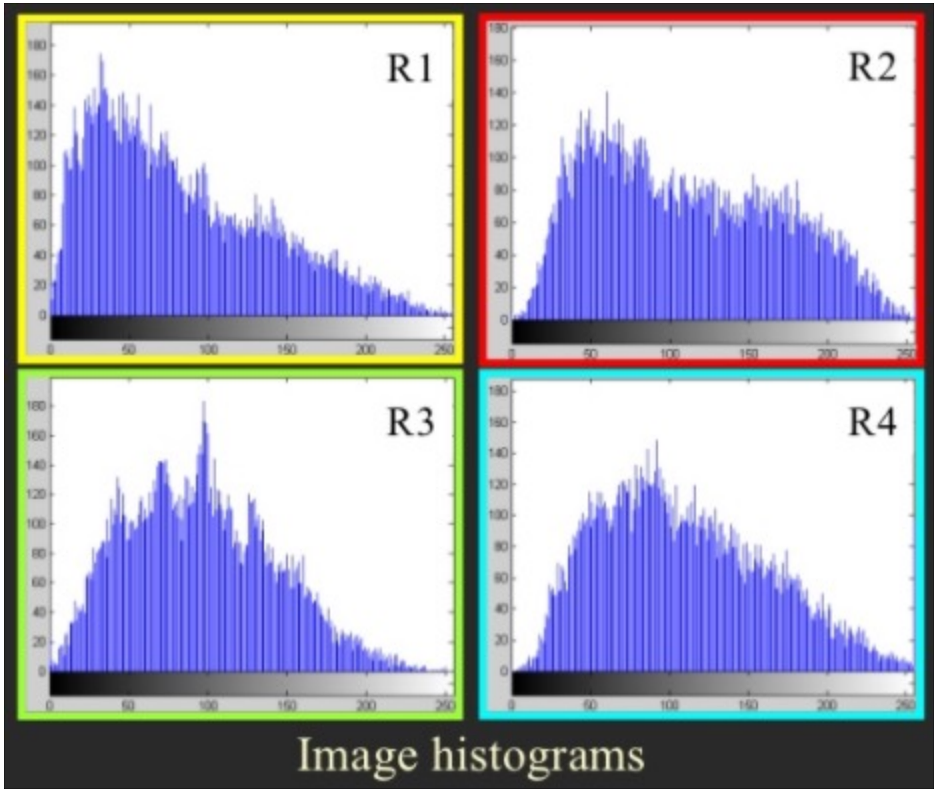


Cont..

- We usually operate on **digital** (**discrete**) images:
  - **Sample** the 2D space on a regular grid
  - **Quantize** each sample (round to nearest integer)
- If our samples are Δ apart, we can write this as:

  $f[i,j] = \text{Quantize}\{ f(i\,\Delta, j\,\Delta) \}$
- The image can now be represented as a matrix of integer values





Session Summary

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- Texture can be defined as an entity consisting of mutually related pixels and group of pixels.
- Texture consists of texture primitives or texture elements, sometimes called texels.
- Textures might be divided into 2 categories, tactile and visual textures.
- Texture analysis refers to the characterization of regions in an image by their texture content. It attempts to quantify intuitive qualities described by terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities.