VIDÉO ET
TRAITEMENT D'IMAGES MÉDICALES

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Département Informatique

Procédure du cours

- **Présence**
- Prises de notes de cours
- Diffusion de l'information:
  - **Responsable** de la section
  - facebook : **Dept Info FSA**
  - Contact: lahmyed.redouan@gmail.com

References

- "Medical Imaging: Principles and Practices" by Albert Macovski.
- "Computer Vision: Algorithms and Applications" by Richard Szeliski.
- "Deep Learning for Medical Image Analysis" by Gustavo Carneiro, Ian Reid, and Andrew P. Bradley.
- "Handbook of Medical Image Processing and Analysis" by Isaac Bankman.
- "Introduction to Medical Imaging: Physics, Engineering, and Clinical Applications" by Nadine Barrie Smith and Andrew Webb.

- Radiopaedia (https://radiopaedia.org/).
- DICOM Standard (https://www.dicomstandard.org/).

Objectifs

- Research Article Understanding and Analysis
- English Language Development for Research
- Online Course Proficiency
- Python Coding with TensorFlow or PyTorch

Objectifs

- Research Article Understanding and Analysis
  - ➢ Develop the ability to comprehend and analyze research articles in the medical imaging field.

Objectifs

- English Language Development for Research

  - Improve proficiency in the English language, especially in the context of medical imaging research.

Objectifs

- Online Course Proficiency

➢ Learn to navigate and utilize the Coursera platform effectively.

➢ Successfully complete an online course on Coursera.

Objectifs

- Python Coding with TensorFlow or PyTorch
  - ➢ Develop coding skills in Python.
  - ➢ Gain proficiency in using TensorFlow or PyTorch for medical imaging applications.

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Plan du cours

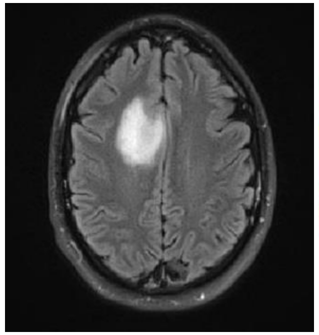
Overview of Medical Imaging Modalities

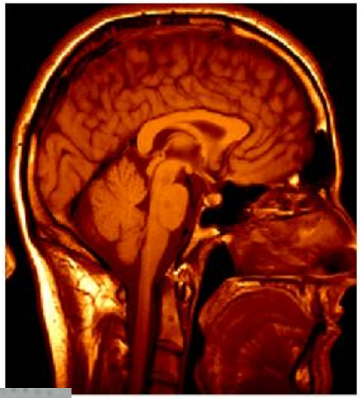
1. Introduction to Medical Imaging
2. Basic Principles of Image Formation
3. Common Medical Imaging Techniques

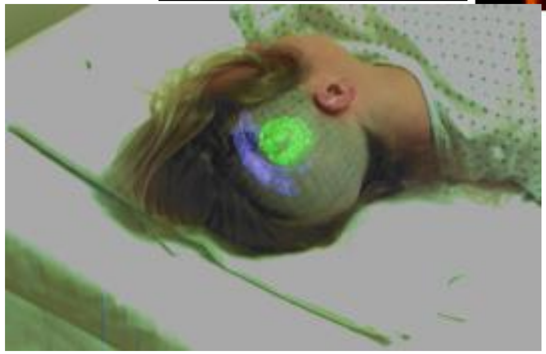
DEFINITION OF MEDICAL IMAGING

- Medical imaging refers to the methodologies and procedures employed for the purpose of generating visual representations of the internal structures of the human body, with the aim of facilitating clinical scrutiny and medical intervention.

- It involves different imaging modalities that produce images (organs, tissues, bones, and physiological processes), aiding in the diagnosis, observation, and treatment of medical conditions.







SIGNIFICANCE OF MEDICAL IMAGING IN HEALTHCARE

1. Diagnostic Tool:

- Medical imaging plays a crucial role in identifying diseases and conditions by providing detailed visual information about the body's anatomy and pathology.

- It helps clinicians identify abnormalities, lesions, tumors, fractures, and other structural changes that may not be apparent through physical examination alone.

Significance of Medical Imaging in Healthcare

2. Treatment Planning:

- Imaging techniques are essential for planning and guiding medical interventions, surgeries, and treatments.

- They enable healthcare professionals to precisely localize and target areas of interest, improving the accuracy and effectiveness of procedures while minimizing risks to patients.

SIGNIFICANCE OF MEDICAL IMAGING IN HEALTHCARE

3. Disease Monitoring:

- Medical imaging allows for the monitoring of disease progression, response to treatment, and post-treatment outcomes over time.

- Sequential imaging studies provide valuable insights into changes in disease status, treatment efficacy, and potential complications, guiding adjustments in patient management plans.

SIGNIFICANCE OF MEDICAL IMAGING IN HEALTHCARE

4. Preventive Screening:

- Imaging modalities such as mammography, CT colonography, and lung cancer screening enable early detection of diseases in asymptomatic individuals, facilitating timely intervention and improving long-term outcomes

- Screening programs based on medical imaging contribute to the prevention and early management of diseases, reducing morbidity and mortality rates.

Significance of Medical Imaging in Healthcare

5. Research and Innovation:

- Medical imaging serves as a cornerstone of medical research, enabling scientists and researchers to investigate disease mechanisms, develop new diagnostic tools, and evaluate novel therapeutic interventions.

- Advances in imaging technology, such as functional MRI and molecular imaging, drive innovation and pave the way for personalized medicine approaches.

TYPES OF IMAGES UTILIZED IN MEDICAL IMAGING FIELD

1. X-ray Images:

- *Overview:* X-rays use ionizing radiation to create images of the internal structures of the body.

- *Applications:* Skeletal imaging, chest radiography, fluoroscopy.

TYPES OF IMAGES UTILIZED IN MEDICAL IMAGING FIELD

2. Computed Tomography (CT) Images:

- *Overview:* CT scans use X-rays to create detailed cross-sectional images of the body.

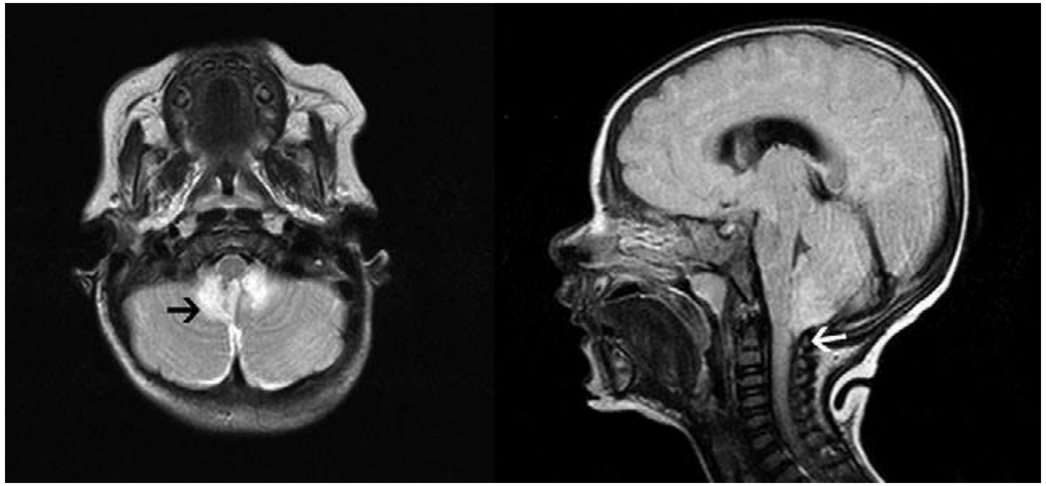
- *Applications:* Soft tissue and bone imaging, cancer detection, trauma assessment.

TYPES OF IMAGES UTILIZED IN MEDICAL IMAGING FIELD

3. Magnetic Resonance Imaging (MRI) Images:

- *Overview:* MRI uses strong magnetic fields and radio waves to generate detailed images.

- *Applications:* Soft tissue imaging, brain and spinal cord studies, musculoskeletal imaging.



TYPES OF IMAGES UTILIZED IN MEDICAL IMAGING FIELD

4. Ultrasound Images:

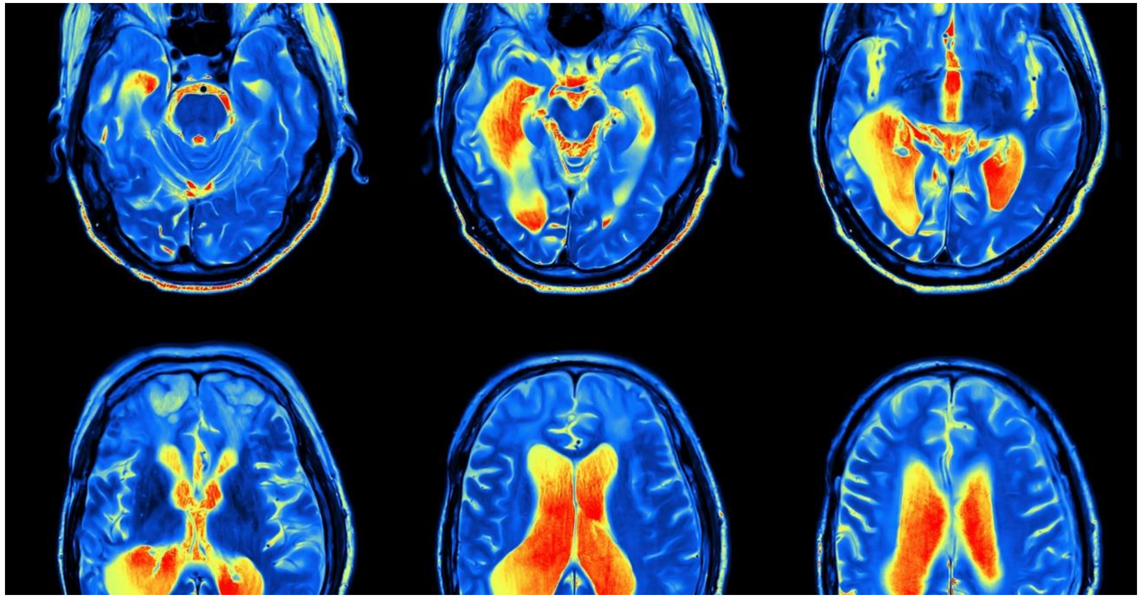
- *Overview:* Ultrasound uses high-frequency sound waves to create real-time images.

- *Applications:* Obstetric imaging, abdominal imaging, cardiovascular imaging.

TYPES OF IMAGES UTILIZED IN MEDICAL IMAGING FIELD

5. Nuclear Medicine Images:

- *Overview:* Nuclear medicine involves the use of radioactive tracers to create images.



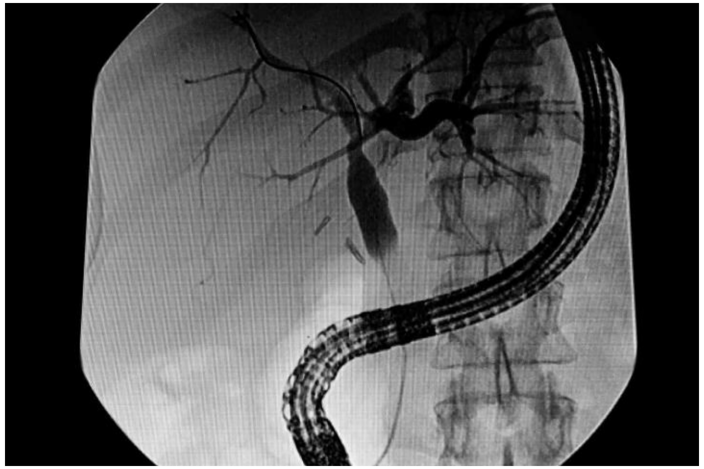
- *Applications:* SPECT (Single Photon Emission Computed Tomography), PET (Positron Emission Tomography), functional imaging

TYPES OF IMAGES UTILIZED IN MEDICAL IMAGING FIELD

6. Fluoroscopy Images:

- *Overview:* Continuous X-ray imaging used for real-time visualization.

- *Applications:* Barium studies, cardiac catheterization, gastrointestinal procedures.



Types of images utilized in medical imaging field

7. Mammography Images:

- *Overview:* X-ray imaging specifically for breast examination.

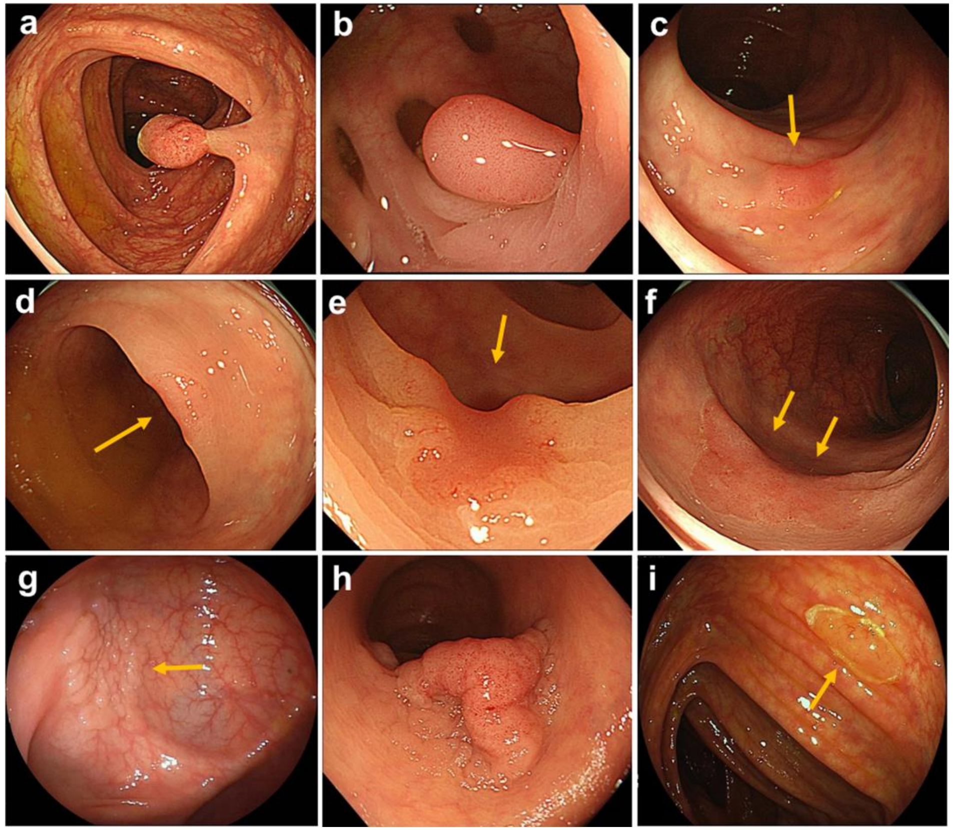
- *Applications:* Breast cancer screening and diagnosis.

Types of images utilized in medical imaging field

8. Endoscopy and Laparoscopy Images:

- *Overview:* Direct visualization of internal organs using a flexible or rigid scope

- *Applications:* Gastrointestinal examination, minimally invasive surgery.

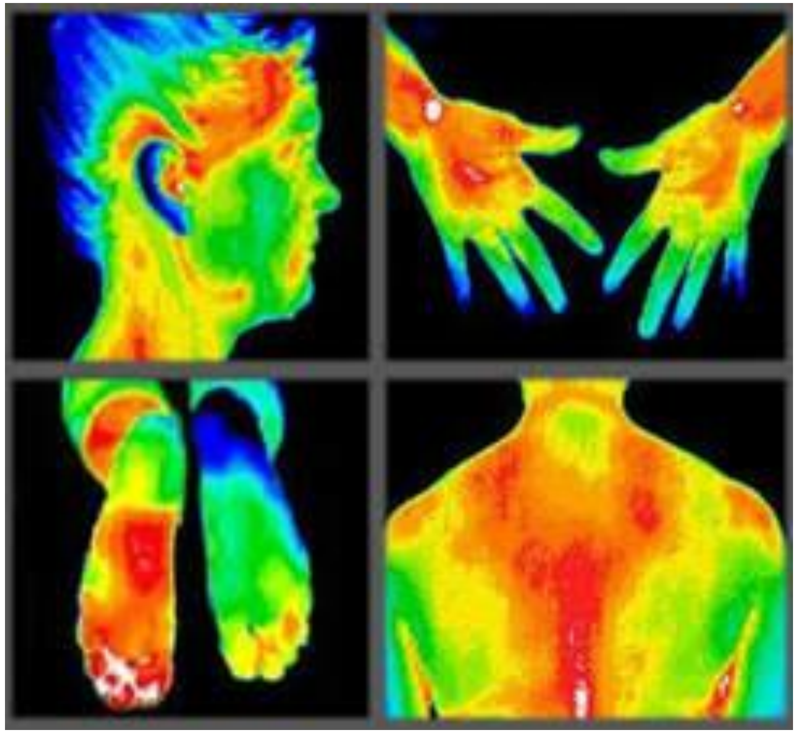


TYPES OF IMAGES UTILIZED IN MEDICAL IMAGING FIELD

9. Thermography Images:

- *Overview:* Infrared imaging to capture temperature variations on the body's surface.

- *Applications:* Detection of inflammation, vascular disorders.



THE HISTORICAL EVOLUTION OF MEDICAL IMAGING TECHNIQUES

1. X-ray Imaging (Late 19th Century)
2. Fluoroscopy (Early 20th Century)
3. Ultrasound Imaging (20th Century)
4. Computed Tomography (CT) (1970s)
5. Magnetic Resonance Imaging (MRI) (1970s)
6. Nuclear Medicine Imaging (20th Century)
7. Digital Imaging and PACS (Late 20th Century)
8. Advancements in 21st Century:
    - 3D and 4D Imaging (2000s)
    - Emergence of Artificial Intelligence (2010s)

Fundamentals of Computer Vision for Medical Image

Image Acquisition and Preprocessing

Image definition:

A digital image is a visual representation stored in a computer as a collection of pixels, forming a two-dimensional grid. Each pixel holds color or grayscale information, enabling easy storage, manipulation, and transmission through electronic devices. Digital images are widely used in fields like photography, computer vision, and medical imaging.

Sensors type used to capture an image:

Sensors type

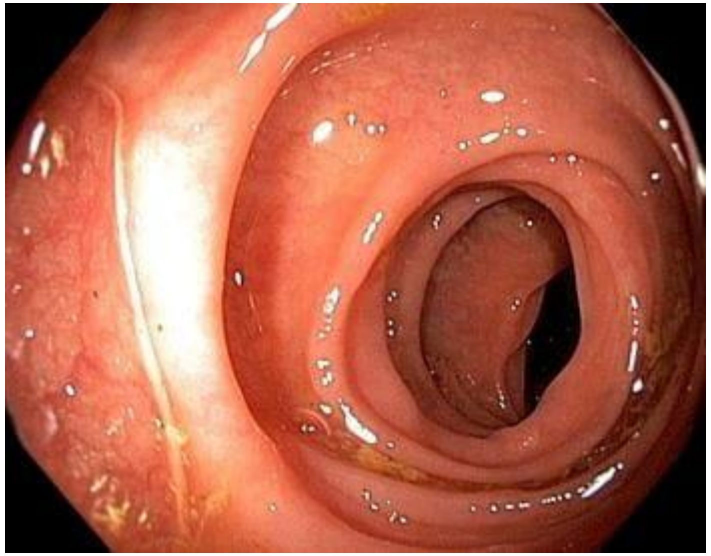
Passive Sensors

Active Sensor

Types of images:

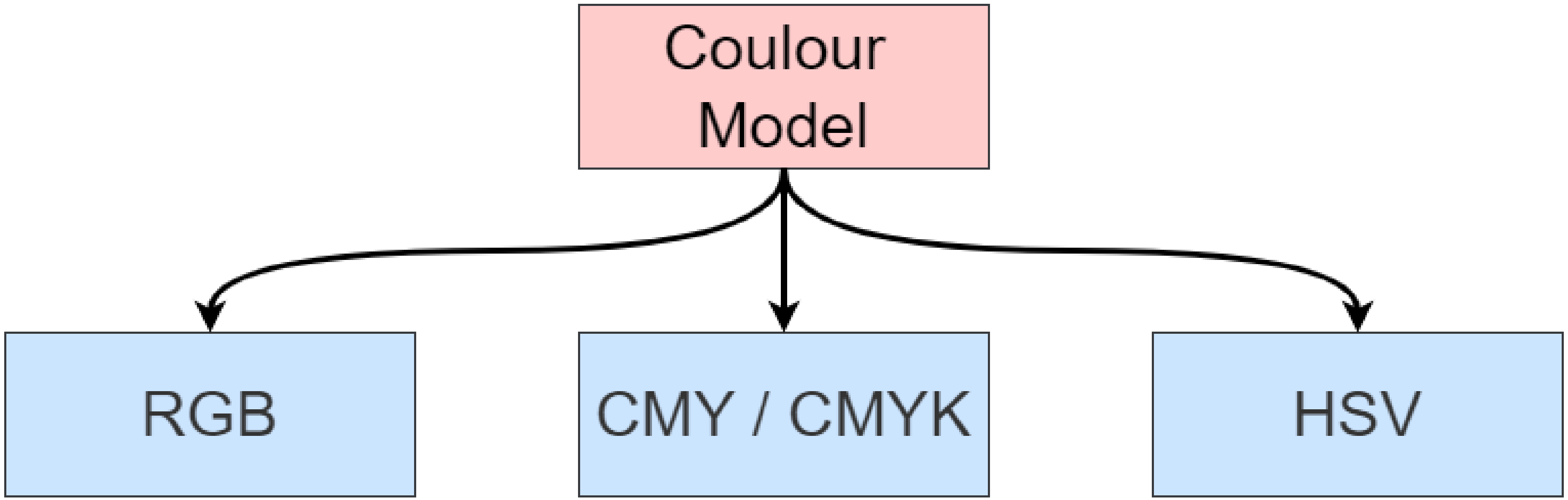
1. Colour image

A color image is a digital image that contains multiple channels of information, typically representing the three primary colors (red, green, and blue) or other color models. Each pixel in a color image has color information, allowing the representation of a wide spectrum of hues.



Types of images:

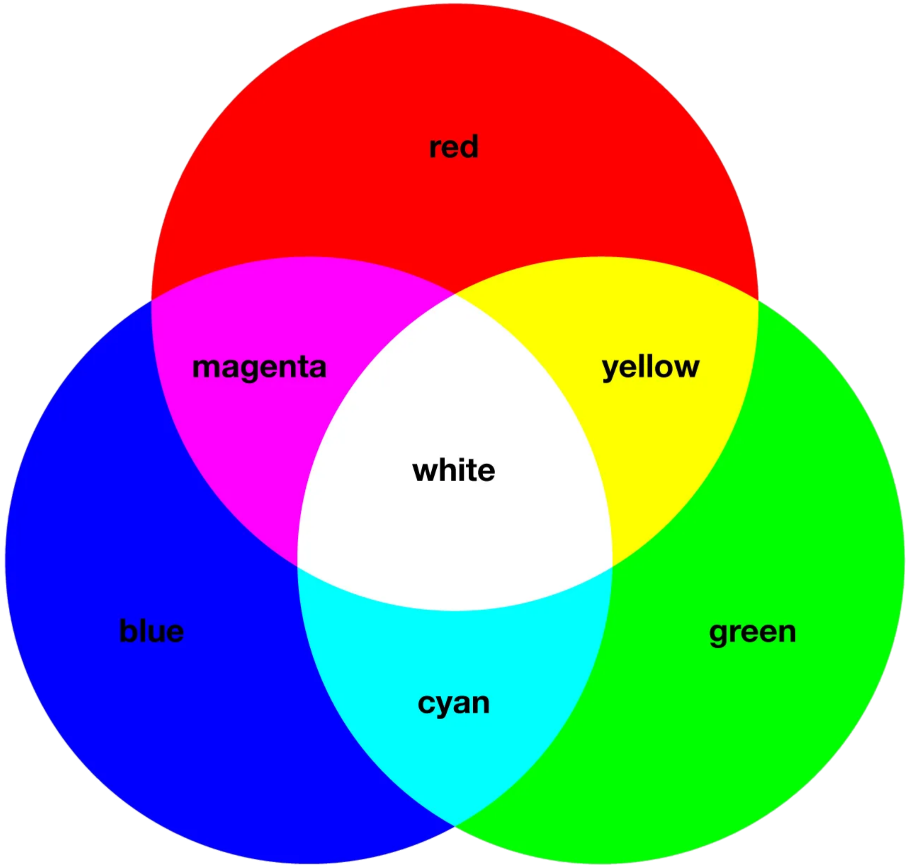
1. Colour image



Types of images:

1. Colour image

RGB Color Model

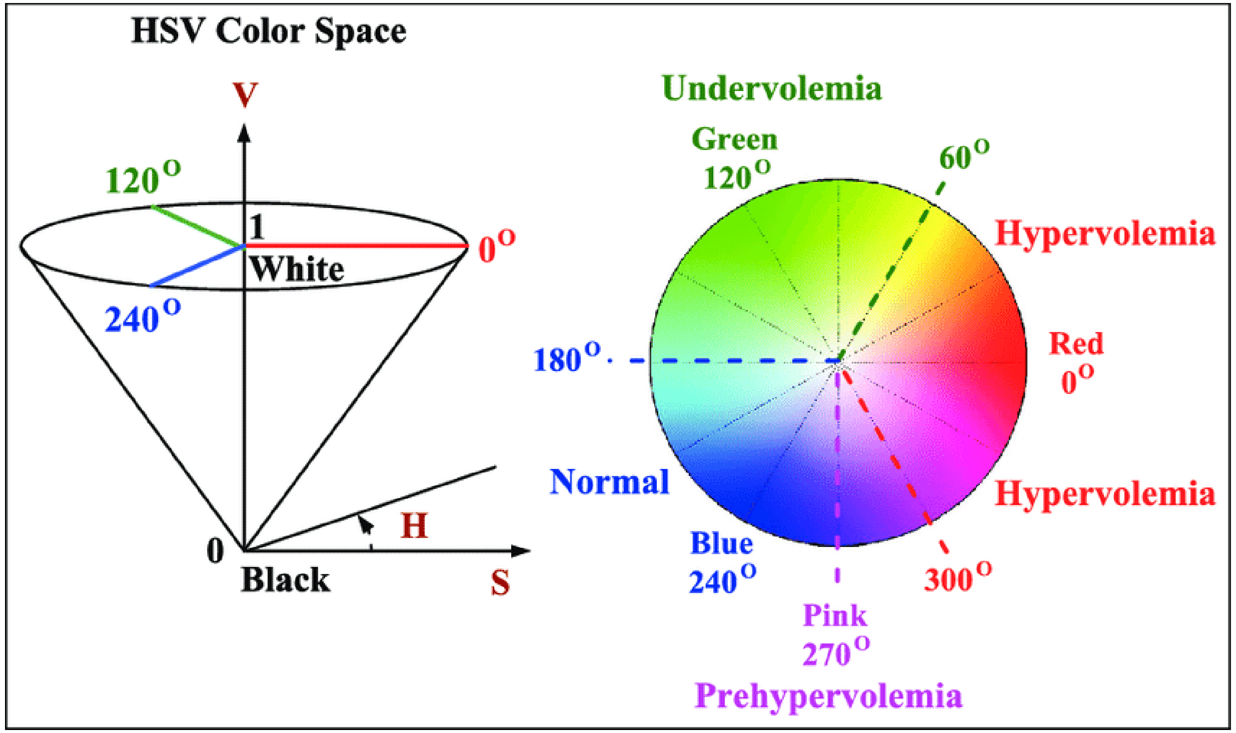


CMYK Color Model

Primary Colors & Secondary Colors

Types of images:

1. Colour image

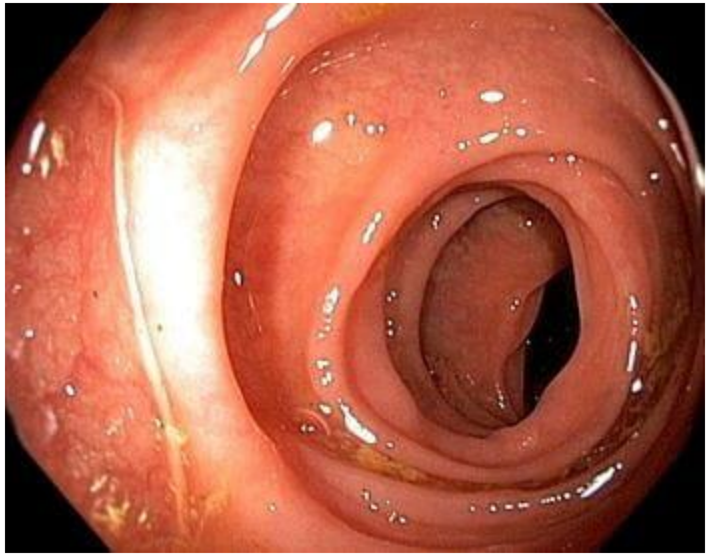


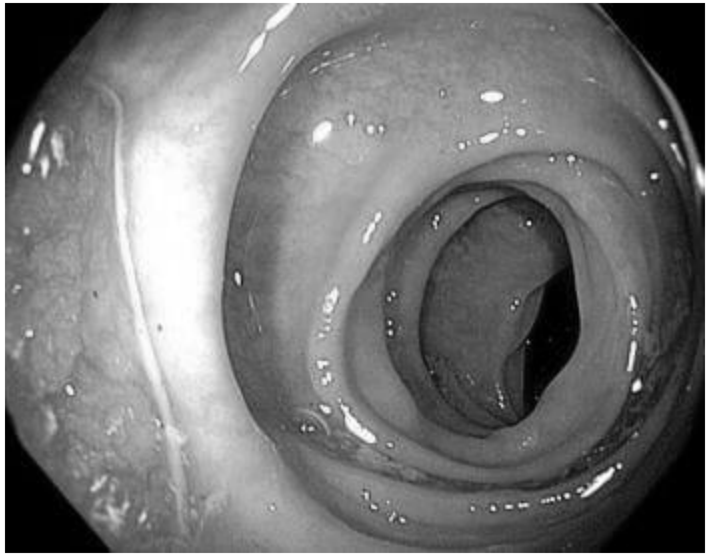
HSV Color Model

Types of images:

2. Grayscale image

A grayscale image is a digital image in which each pixel represents varying shades of gray, without color information. It uses a single channel to convey the intensity or brightness of each pixel, often ranging from black to white. Grayscale images are commonly employed in applications where color is unnecessary, simplifying image representation and processing





Types of images:

3. Binary image

A binary image is a digital image consisting of pixels with only two possible values, typically black and white. It represents the presence or absence of an object or feature, commonly used in image processing and computer vision applications.

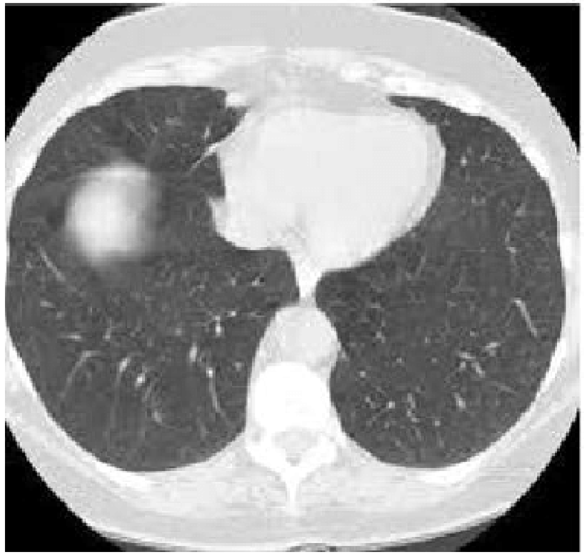


Image pre-processing:

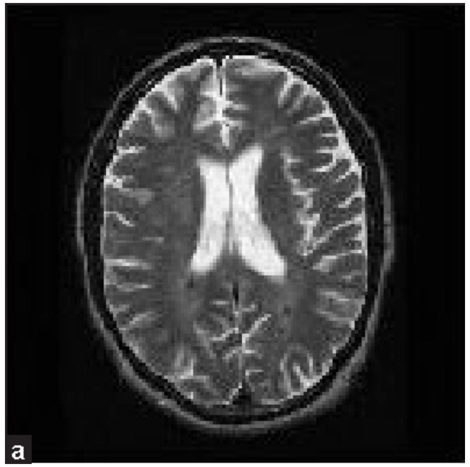
What’s noise ?

Definition: In the context of image processing, "noise" refers to random variations or unwanted interference in pixel values, which can degrade the quality of an image.

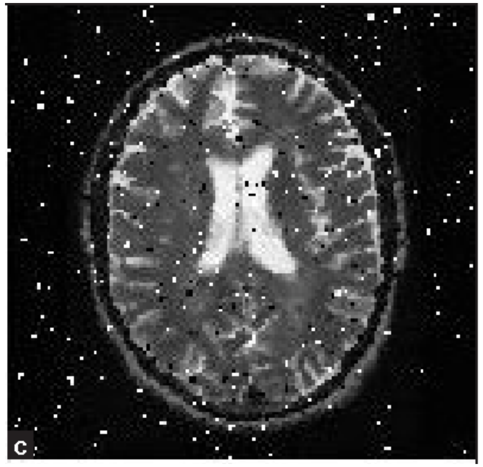
Common types of noise

- **Salt and pepper**: random occurrences of black and white pixels.
- **Impulse noise**: random occurrences of white pixels.
- **Gaussian noise**: variations in intensity drawn from a Gaussian normal distribution.

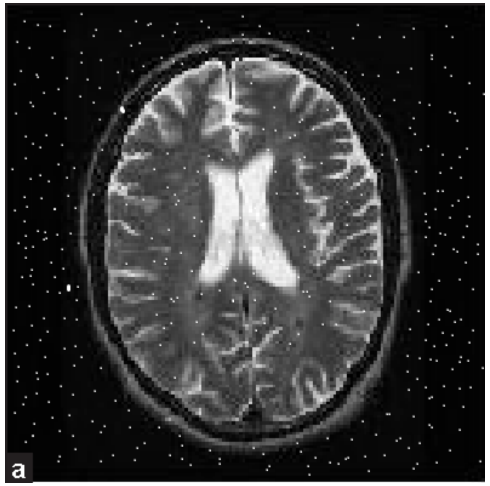
Image pre-processing:



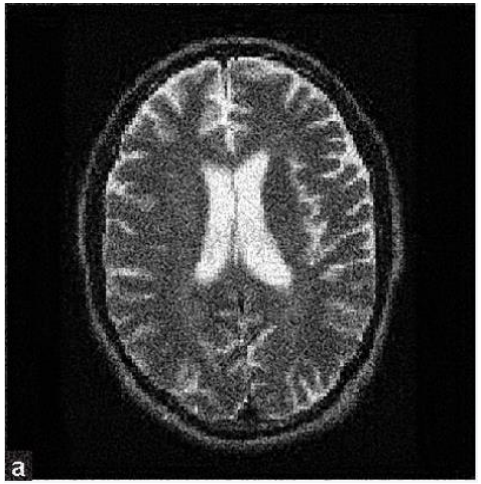
Original image



Salt and pepper noise



Impulse noise



Gaussian noise

Image pre-processing:

Smoothing Spatial Filters

- Smoothing filters are use for blurring and noise reduction.
- Blurring is used in preprocessing tasks, such as removal of small details from an image prior to (large) object extraction.
- Noise reduction can be accomplished by blurring with a linear filter and also by non-linear filtering

Image pre-processing:

Smoothing Spatial Filters

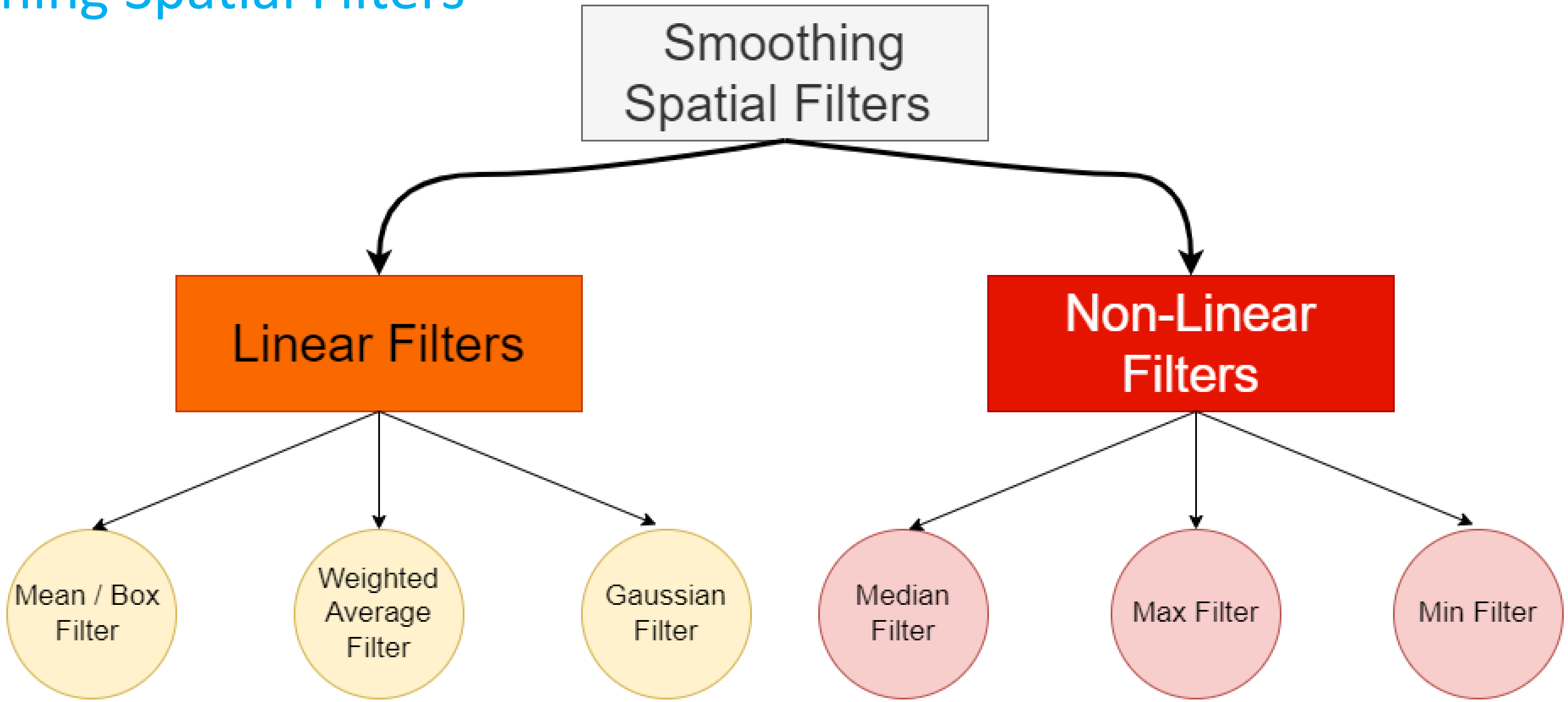


Image pre-processing:

Smoothing Spatial Filters

- **Box filter** : All coefficiants are equals

$$\frac{1}{9} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \longrightarrow \text{Mask}$$

- **Weighted average** : Give more (less) weight to pixels near (away from) the output location.

$$\frac{1}{16} \times \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \longrightarrow \text{Mask}$$

Image pre-processing:

Smoothing Spatial Filters

- **Gaussian filter** : The weight are samples of the 2D Gaussian function.

$$\frac{1}{16} \times \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \longrightarrow \text{Mask}$$

> ➢ It is used to blur edges and reduce contrast.

Fundamentals of Computer Vision for Medical Image

Feature Extraction and Image Enhancement

Feature Extraction :

Definition :

- Feature extraction in computer vision refers to the process of identifying and extracting relevant information or distinctive patterns from images to represent specific visual characteristics.

- Image features :
  - ✓ Edges
  - ✓ Corners
  - ✓ Textures
  - ✓ keypoints
  - ✓ shapes
  - ✓ Colors
  - ✓ ……

Feature Extraction :

Feature extraction importance :

- Feature extraction is essential in computer vision for several reasons :

✓ Dimensionality Reduction: It reduces this high-dimensional data into a more compact and meaningful representation, making it more manageable for subsequent analysis and processing.

✓ Information Compression: we can compress the visual information into a more concise and informative form. This compression allows for efficient storage, transmission, and processing of image data

✓ Robustness to Variability : Robust features enable computer vision systems to perform reliably across diverse conditions and environments.

✓ Efficient Processing : This efficiency improves the speed and scalability of computer vision algorithms, making them suitable for real-time applications and large-scale datasets.

Feature Extraction :

Feature detection and feature description :

- There are two principal aspects of image feature extraction : Feature detection, and feature description.

- That is, when we refer to feature extraction, we are referring to both detecting the features and then describing them.

Feature detection

↓

Feature description

Feature Extraction :

Feature Extraction :

Features extraction techniques for images :

- Histogram of gradient (HOG)
- Maximally stable extremal regions (MSER)
- Scale Invariant feature Transform (SIFT)
- Speed Up Robust Pattern (SURF)
- Local binary pattern (LBP)
- Edge detection techniques (Canny ...etc)

Feature Extraction :

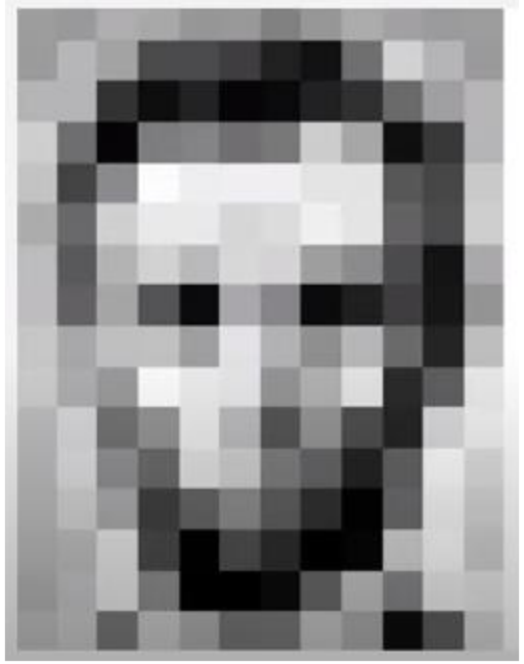
Where Local Binary Patterns is used? :

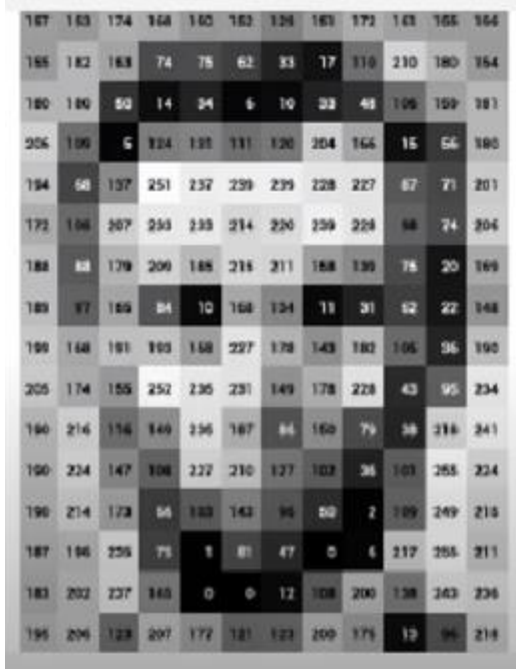
- Local Binary Pattern (LBP) is a popular technique used for image/face representation and classification.

- Local Binary Patterns (LBPs) have been used for wide range of applications :
  - Face detection
  - Face detection
  - Face recognition
  - Facial expression recognition
  - Texture classification
  - Object detection systems

Feature Extraction :

How LBP works? :





157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Feature Extraction :

How LBP works? :

$$\text{LBP} = \sum_{n=0}^{7} s(i_n - i_c)2^n$$

Here, i_c = Center Pixel Value

i_n = Neighbor Pixel Values

$$S(z) = \begin{cases} 1, & z >= 0 \\ 0, & \text{Otherwise} \end{cases}$$

Feature Extraction :

Example:

5	9	1
4	4	6
7	2	3

i_0	i_1	i_2
i_7	i_c	i_3
i_6	i_5	i_4

1	1	0
1		1
1	0	0

Binary Number Generated

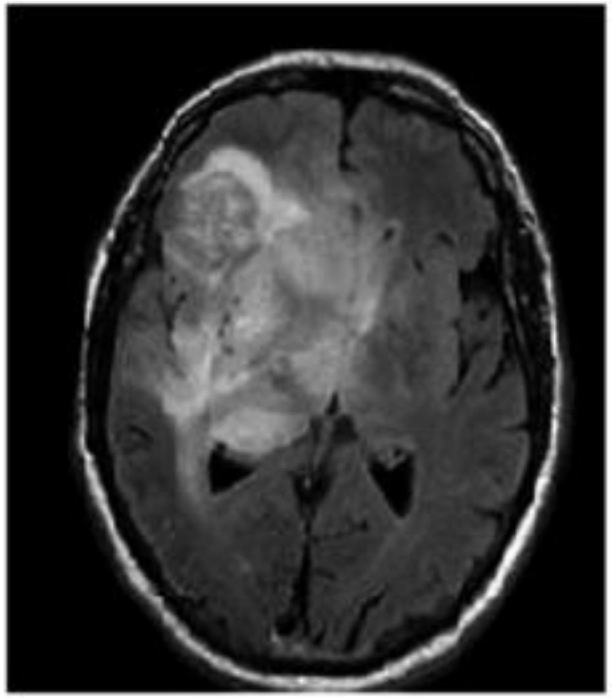
1	1	0	1	0	0	1	1

= (1 x 128) + (1 x 64) + (1 x 16) + (1 x 2) + (1 x 1)

= 211 (LBP code generated)

Feature Extraction :

How LBP works? :

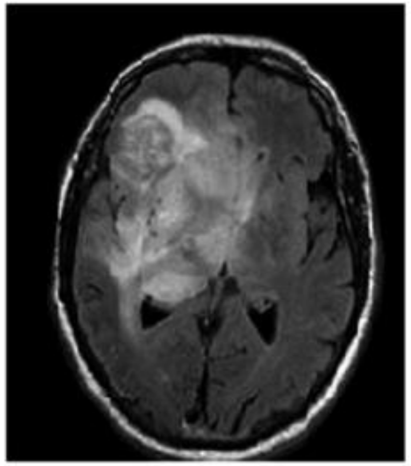


(a) Input MR Image

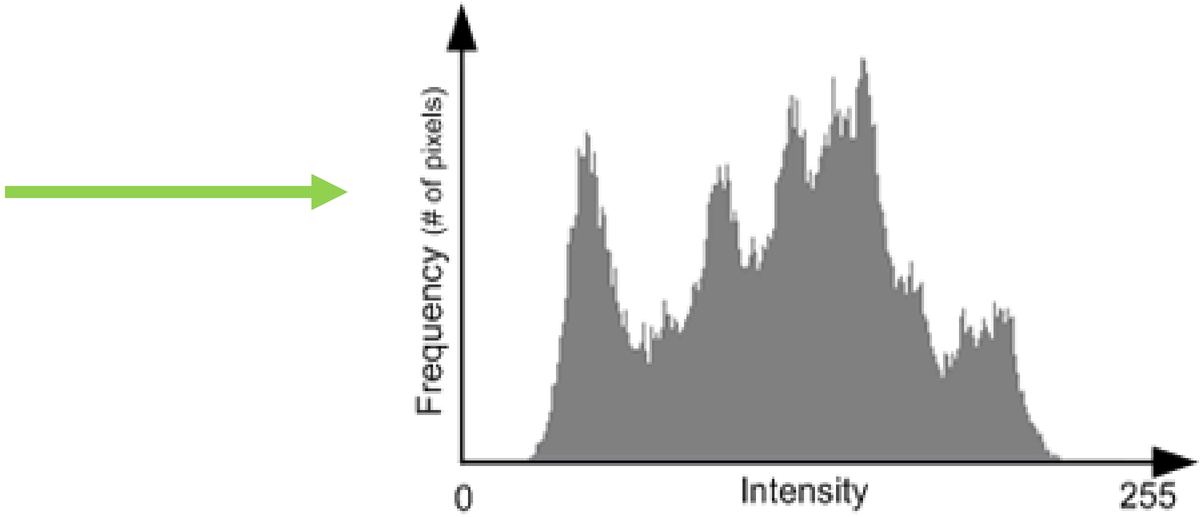
(b) LBP representation of MR Image

Feature Extraction :

How LBP works? :


(a) Input MR Image


(b) LBP representation of MR Image



Feature Extraction :

Disadvantages of LBP :

- Ineffective in case of noisy regions (i.e. complex background).
- Overfitting in case of low-resolution images.

As a solution :

- ➢ The idea to handle this is to remove the LBP resulting from the noisy background.
- ➢ This kind of LBP is called non-uniform LBP pattern.

Feature Extraction :

Uniform LBP (uLBP) :

- Non-Uniform LBP generally results from the noisy region.
- In general, the point in noisy background has significant intensity variation.
- Uniformity measure U ("pattern") is the number of bitwise transitions from 0 to 1 and vice versa.
- A local binary pattern is called uniform if its uniformity measure is at most 2.

Feature Extraction :

Uniform LBP (uLBP) :

- *Example*

Bit Sequence	# Transition	Uniform ?
0000 0000	0	**Yes**
0000 0001	1	**Yes**
0000 0101	3	**No**

Feature Extraction :

Uniform LBP (uLBP) :

- 59-Level Encoding :
  - 58 uniform LBP : Assign each with an unique index (from 0 to 57).
  - 198 non-uniform LBP: Assign all with index 58

LBP	Uniform?	Bin Index
0000 0000	Yes	0
0000 0001	Yes	1
0000 0010	Yes	2
0000 0011	Yes	3
0000 0100	Yes	4
0000 0101	No	
0000 0110	Yes	5
0000 0111	Yes	6

LBP	Uniform?	Bin Index
0000 1000	Yes	7
0000 1001	No	
0000 1010	No	
0000 1011	No	
0000 1100	Yes	8
0000 1101	No	
0000 1110	Yes	9
0000 1111	Yes	10

LBP	Uniform?	Bin Index
1111 1000	Yes	51
1111 1001	Yes	52
1111 1010	No	
1111 1011	Yes	53
1111 1100	Yes	54
1111 1101	Yes	55
1111 1110	Yes	56
1111 1111	Yes	57

Feature Extraction :

Uniform LBP (uLBP) :

- 59-Level Encoding :
  - 58 uniform LBP : Assign each with an unique index (from 0 to 57).
  - 198 non-uniform LBP: Assign all with index 58

LBP	Uniform?	Bin Index
0000 0000	Yes	0
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0000 0010	Yes	2
0000 0011	Yes	3
0000 0100	Yes	4
0000 0101	No	58
0000 0110	Yes	5
0000 0111	Yes	6

LBP	Uniform?	Bin Index
0000 1000	Yes	7
0000 1001	No	58
0000 1010	No	58
0000 1011	No	58
0000 1100	Yes	8
0000 1101	No	58
0000 1110	Yes	9
0000 1111	Yes	10

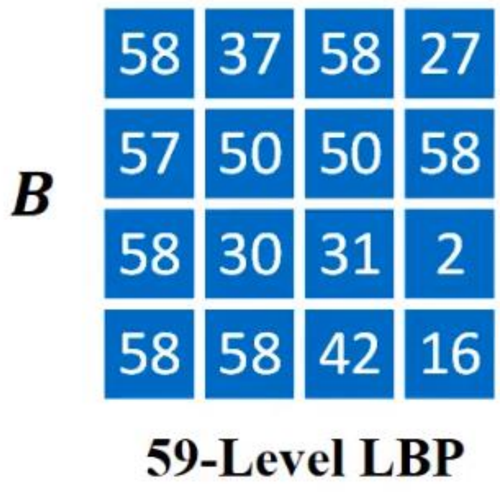
LBP	Uniform?	Bin Index
1111 1000	Yes	51
1111 1001	Yes	52
1111 1010	No	58
1111 1011	Yes	53
1111 1100	Yes	54
1111 1101	Yes	55
1111 1110	Yes	56
1111 1111	Yes	57

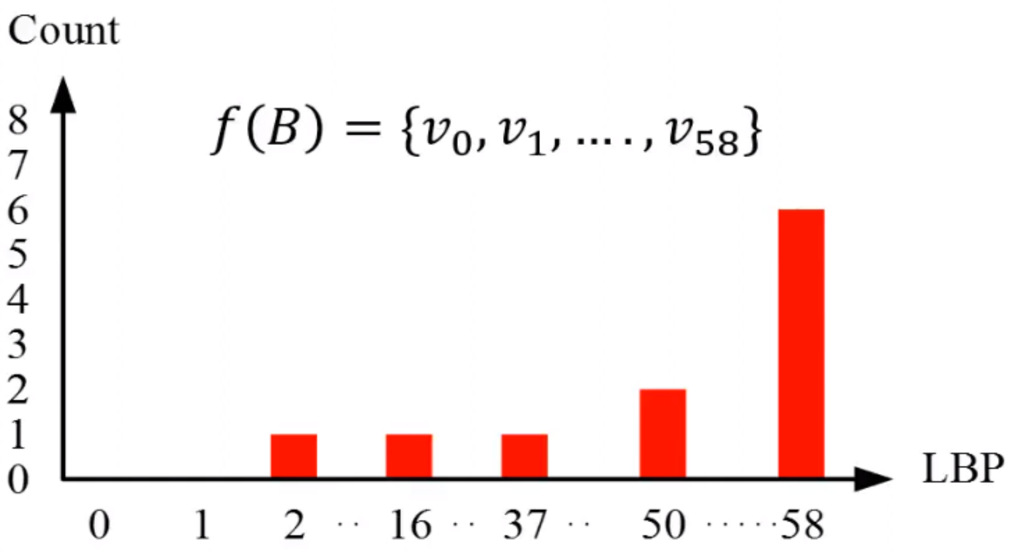
Feature Extraction :

Uniform LBP (uLBP) :

❑ LBP Histogram Formation :

- gather statistics of LBP occurrence in a form of histogram.





Feature Extraction :

HOG (Histogram of Oriented Gradients) :

- HOG or Histogram of Oriented Gradients is used for object detection.
- It is useful in different applications such as human detection, pedestrian detection.
- Its main idea is to compute the gradient magnitude et orientation for each block.
- It is first invented by Dalal and triggs at 2005.
- Paper: N. Dalal et B. Triggs, « Histograms of Oriented Gradients for Human Detection », 2005 IEEE Computer Society Conference on Computer Vision and Pattern.

Feature Extraction :

HOG (Histogram of Oriented Gradients) :

- HOG steps :

Resize to 64 x 128	Create cells and blocks	Calculate the gradients
Calculate the magnitude, and the orientation	Create Histogram of 9 bin	Normalization

Feature Extraction :

HOG (Histogram of Oriented Gradients) :

❑ HOG step 01 :

Resize to 64 x 128

❖ The size of the image should be with aspect ratio 1 : 2.
i.e 64 : 128 or 100 : 200.

❖ The size used by authors in the original paper is 64 : 128

Feature Extraction :

HOG (Histogram of Oriented Gradients) :

- HOG step 02 :

Create cells and blocks

- Split the resized image into cells :
  - ✓ Each cell has 8 x 8 pixels.
  - ✓ Total cells are 8 x 16 cells

- Combine each 2 x 2 cells into one block with 50% overlap.
- Total blocks are 7 x 15.

Feature Extraction :

HOG (Histogram of Oriented Gradients) :

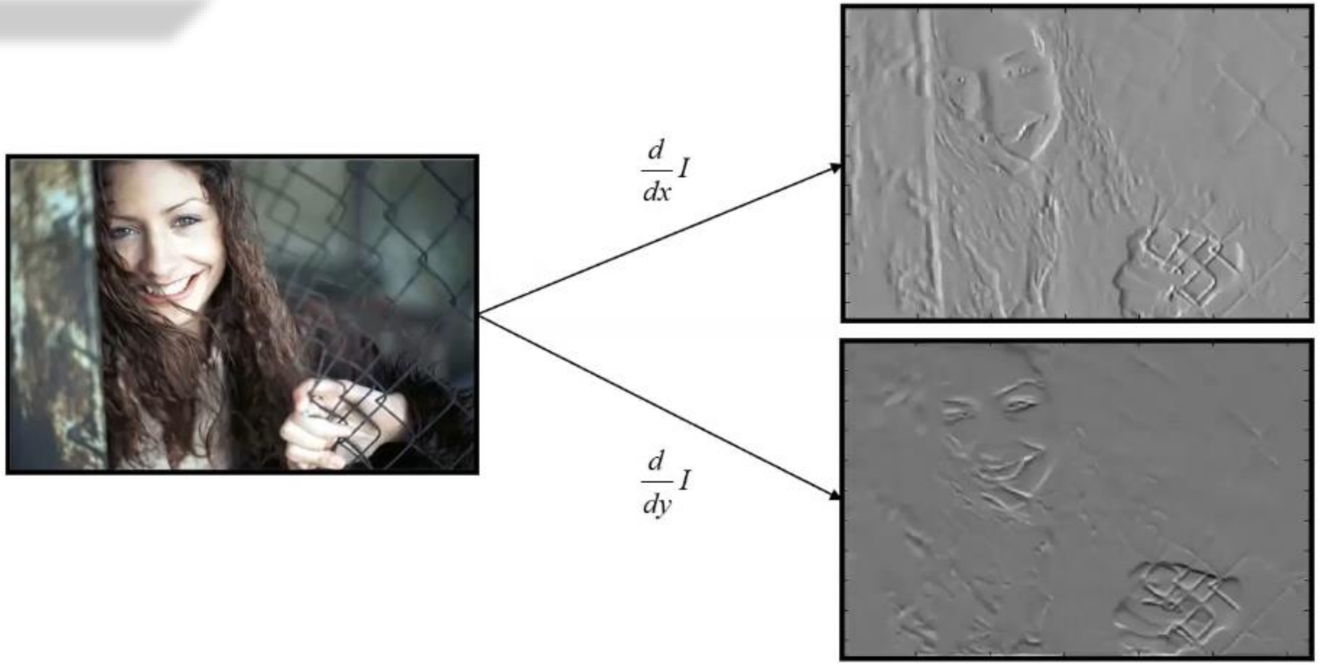
❑ HOG step 03 :

Calculate the gradients

❖ Compute the gradient for the (X) and (Y) directions using the masks:

1
0
-1

-1	0	1



Feature Extraction :

HOG (Histogram of Oriented Gradients) :

❑ HOG step 04 :

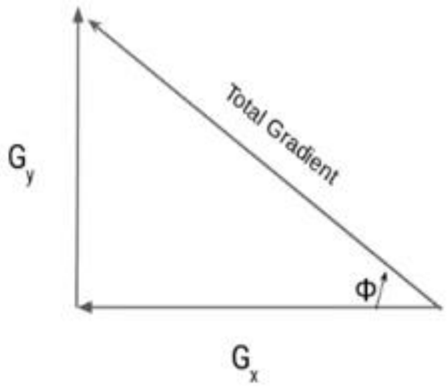
Calculate the magnitude, and the orientation

❖ By applying the Pythagoras theorem, we calculate the total gradient Magnitude:

$$\text{Total Gradient Magnitude} = \sqrt{[(G_x)^2+(G_y)^2]}$$

$$\tan(\Phi) = Gy / Gx$$

$$\Phi = \text{atan}(Gy / Gx)$$



Feature Extraction :

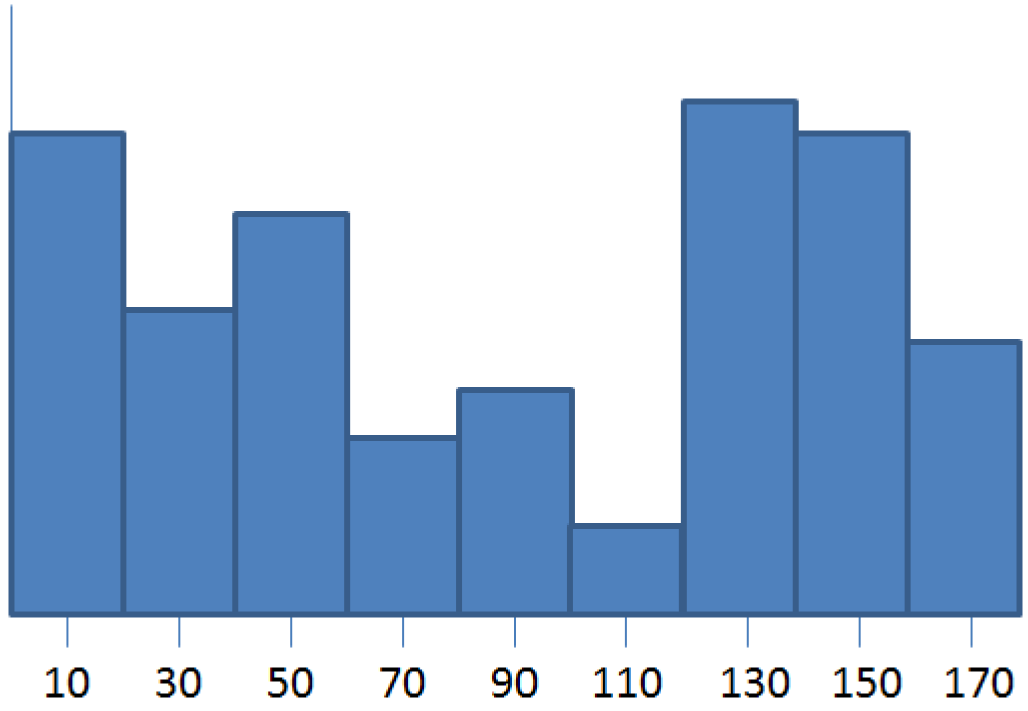
HOG (Histogram of Oriented Gradients) :

❑ HOG step 05 :

Create Histogram of 9 bin

❖ For each pixel's orientation, add its corresponding magnitude in the frequency table.

❖ The magnitude values are added in the bin 0, if its corresponding orientation is in the range 0 - 19.



Feature Extraction :

HOG (Histogram of Oriented Gradients) :

❑ HOG step 06 :

Normalization

❖ The normalization factor can be one of the following:

L2-norm: $f = \dfrac{v}{\sqrt{\|v\|_2^2 + e^2}}$

L1-norm: $f = \dfrac{v}{(\|v\|_1 + e)}$

L1-sqrt: $f = \sqrt{\dfrac{v}{(\|v\|_1 + e)}}$

Fundamentals of Computer Vision for Medical Image

Image Segmentation in Medical Images

Image Segmentation :

Definition :

- Image segmentation in medical imaging refers to the process of partitioning or dividing a medical image into multiple meaningful and homogeneous regions or segments based on certain criteria, such as pixel intensity, texture, or spatial relationships.

- The goal of image segmentation in medical images is to identify and delineate distinct anatomical structures, organs, tissues, or abnormalities present within the image for further analysis, visualization, or diagnosis.

Image Segmentation :

Algorithms are based on one of the 2 properties :

1. Discontinuity : Partition an image based on the abrupt changes in intensity, such edges in an image.

2. Similarity : partitioning an image into regions that are similar according to a set of predefined criteria. Thresholding, region splitting and merging.

Image Segmentation :

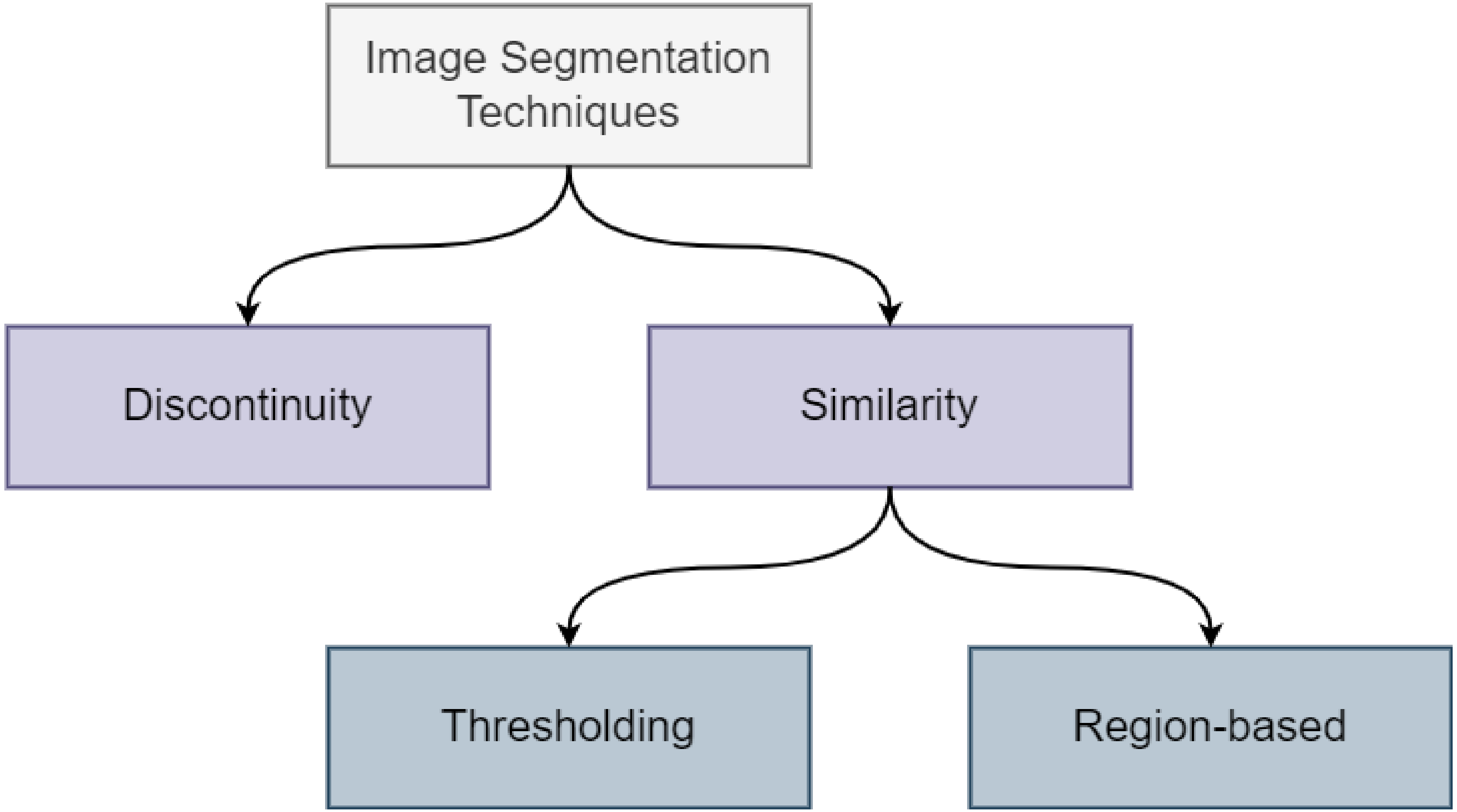
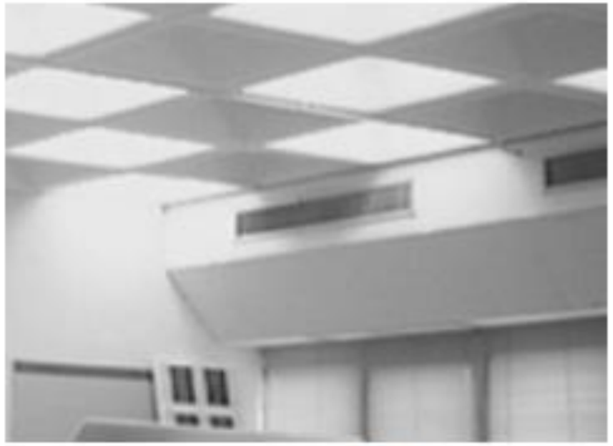


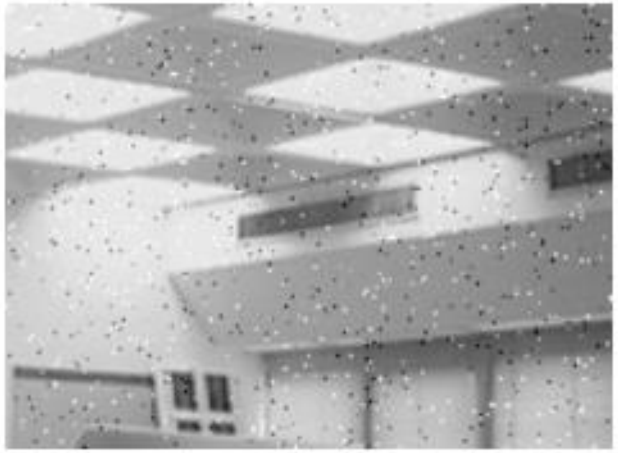
Image Segmentation :

Discontinuity: Point detection :

Point detection can be achieved simply using the mask below:

-1	-1	-1
-1	8	-1
-1	-1	-1





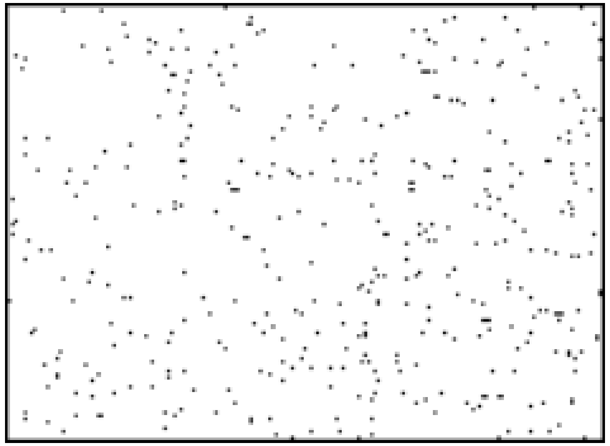


Image Segmentation :

Discontinuity: Line detection :

- Line masks:

-1	-1	-1
2	2	2
-1	-1	-1

Horizontal Line

-1	2	-1
-1	2	-1
-1	2	-1

Vertical Line

2	-1	-1
-1	2	-1
-1	-1	2

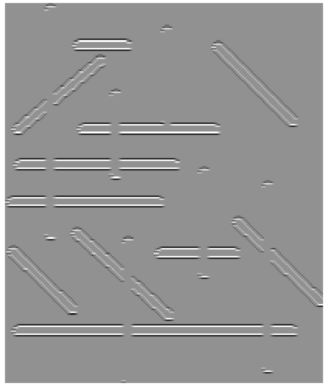
-45° Line

-1	-1	2
-1	2	-1
2	-1	-1

45° Line

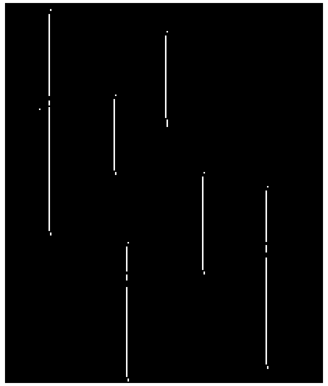
Image Segmentation :

Discontinuity: Line detection :



Input Image

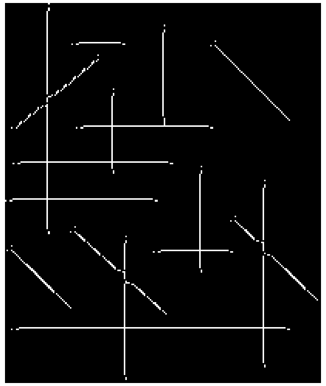
Horizontal Line



Vertical Line

-45° Line

45° Line



The resulting Image

Image Segmentation :

Discontinuity: Edge detection :

- It is an approach used frequently for segmenting images based on abrupt (local) changes in intensity.

- First order derivatives such as Robert-Cross, Prewitt and Sobel operators are preferred for thicker lines.

- Second Order derivatives (Laplacian) are used for detecting thinner lines.

Image Segmentation :

Discontinuity: Edge detection :

1. Roberts cross-gradient operators

-1	0
0	1

0	-1
1	0

2. Prewitt operators

-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

3. Sobel operators (have better noise suppression)

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

4. Prewitt maks for diagonal edges

-1	-1	-1
0	0	0
1	1	1

+45°

-1	0	1
-1	0	1
-1	0	1

-45°

Image Segmentation :

Thresholding :

- It is carried out with the assumption that the range of intensity levels covered by objects of interest different from the background.
- The quality of thresholding algorithm depends on the selection of a suitable threshold.
- Tool that helps to find the threshold is histogram

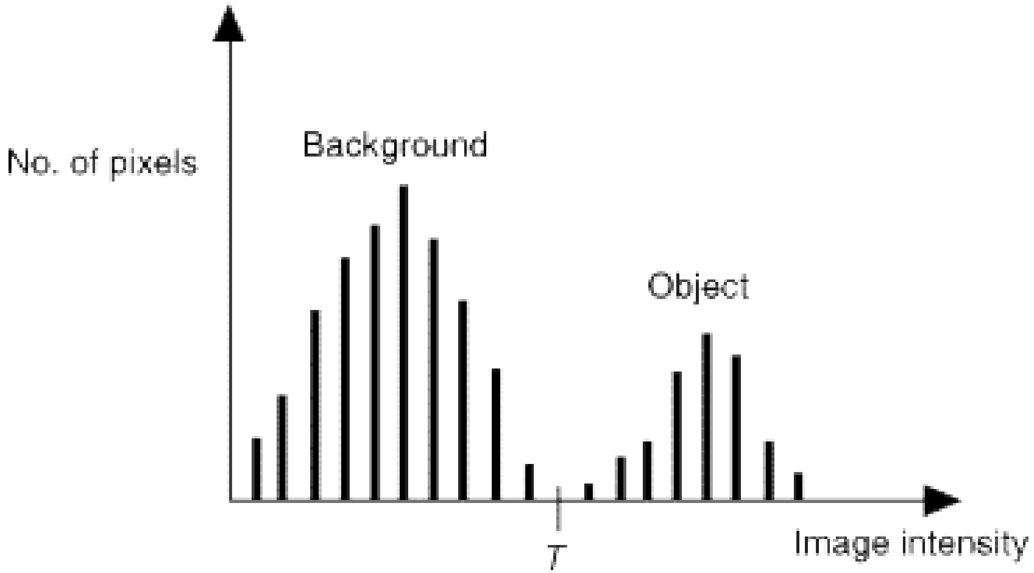
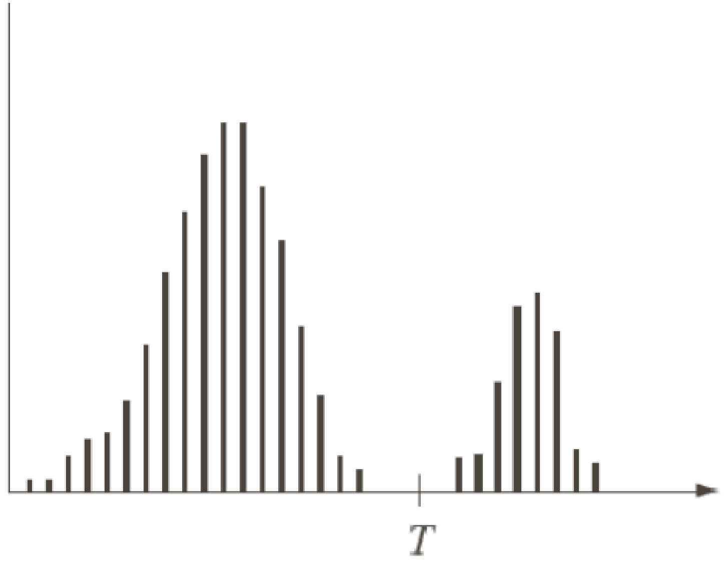


Image Segmentation :

Thresholding :

- Single Level Thresholding :The objects can be extracted by comparing pixel values with a threshold T.
- Single Level Thresholding : It is also possible to extract objects that have a specific intensity range using multiple thresholds.



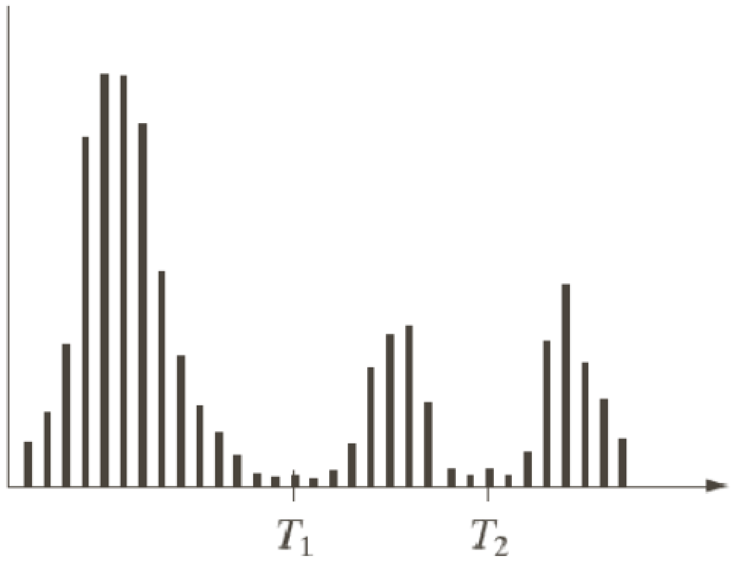


Image Segmentation :

Thresholding :

The basic global threshold (T) is calculated as :

1) Randomly select an intial threshold T
2) Segment the image using two group G1 and G2
3) Determine mean (m1) of pixels (in G1 group) that lie below T in histogram
4) Determine mean (m1) of pixels (in G1 group) that lie above T in histogram

5) New threshold is:

$$T_{new} = (m1 + m2\ ) /2$$

6) Repeat the steps no. 2-5 until the difference in T in successive iterations is less than a predefined limit.

Image Segmentation :

Otsu's method algorithm :

❖ It searches for the threshold intensity I_t which maximizes the between class variance σ_B^2

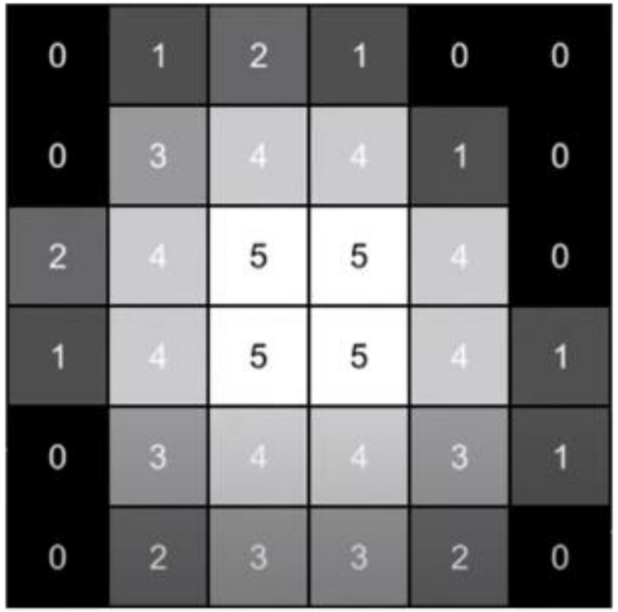
$$\sigma_B^2 = W_b W_f (\mu_b - \mu_f)^2$$

$W_{b,f}$: Number of pixels in background (forground) / Total number of pixels

$\mu_{b,f}$: Mean intensity of background (foreground)

Image Segmentation :

Otsu's method algorithm Example :



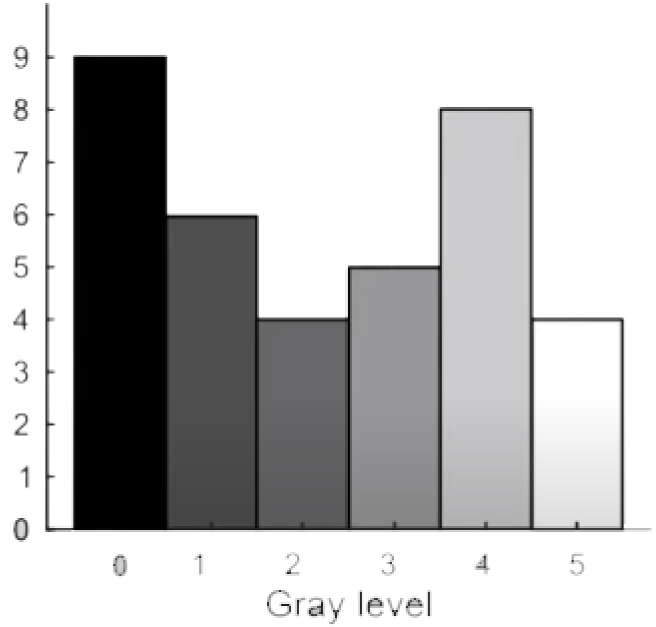
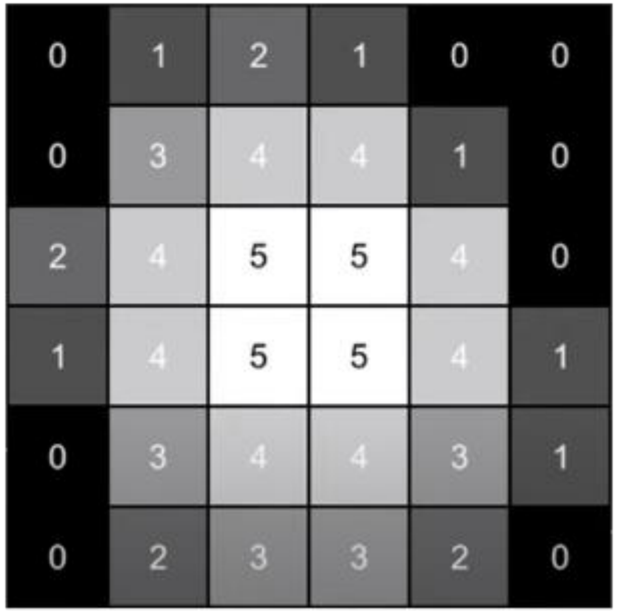


Image Segmentation :

Otsu's method algorithm Example :



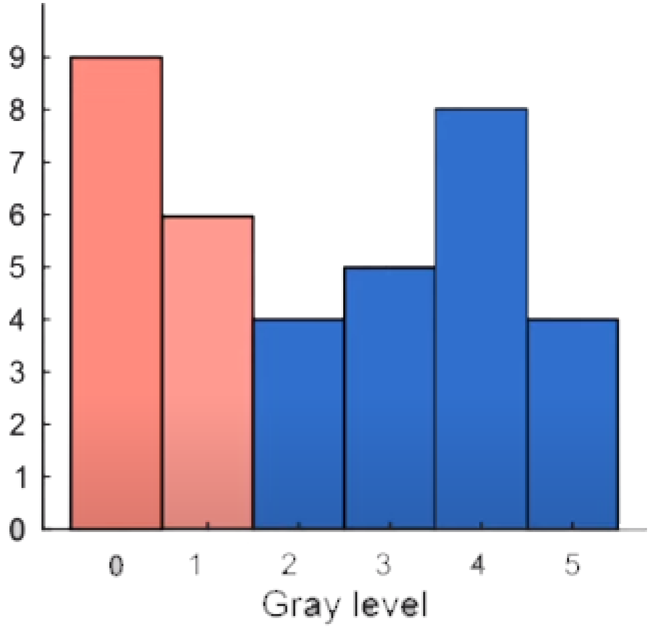


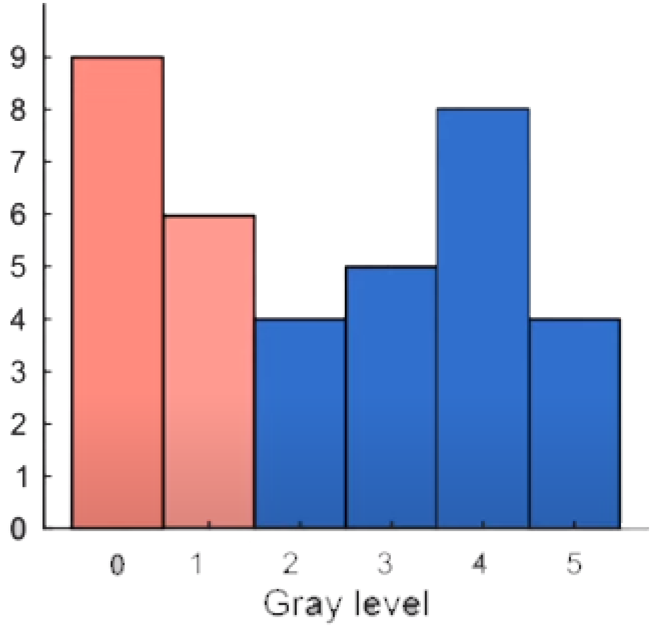
Image Segmentation :

Otsu's method algorithm Example :

Background

$$W_b = \frac{9 + 6}{36} = 0.42$$

$$Mean_b = \frac{(9 \times 0) + (6 \times 1)}{9 + 6} = 0.4$$



Foreground

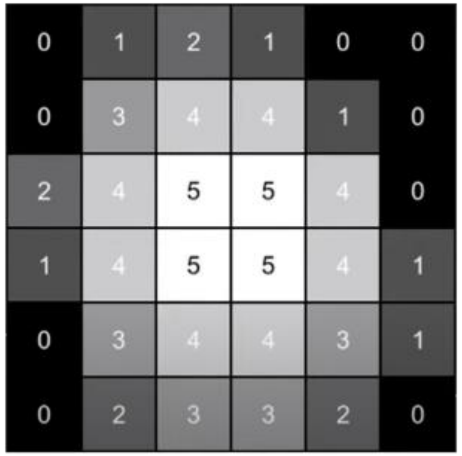
$$W_f = \frac{4 + 5 + 8 + 4}{36} = 0.58$$

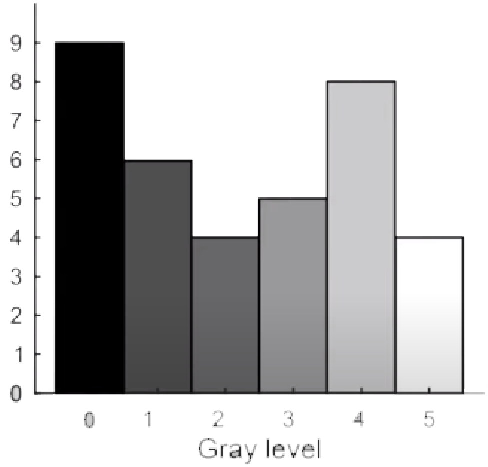
$$Mean_f = \frac{(4 \times 2) + (5 \times 3) + (8 \times 4) + (4 \times 5)}{4 + 5 + 8 + 4} = 3.57$$

$$\sigma_B^2 = W_b W_f (\mu_b - \mu_f)^2 = 2.44$$

Image Segmentation :

Otsu's method algorithm Example :

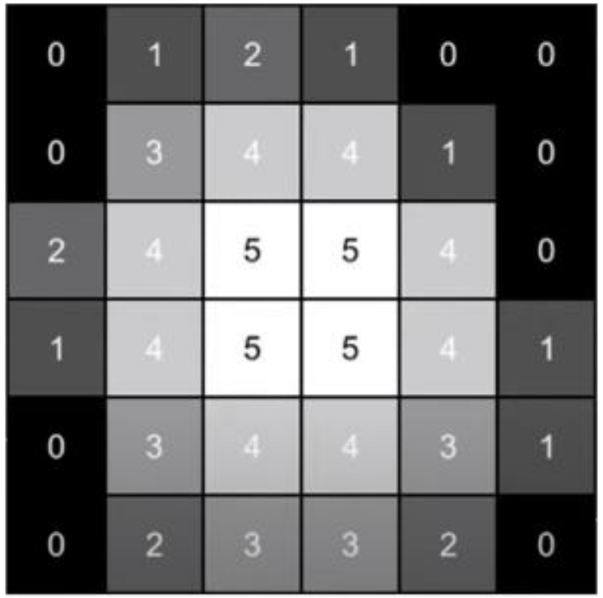


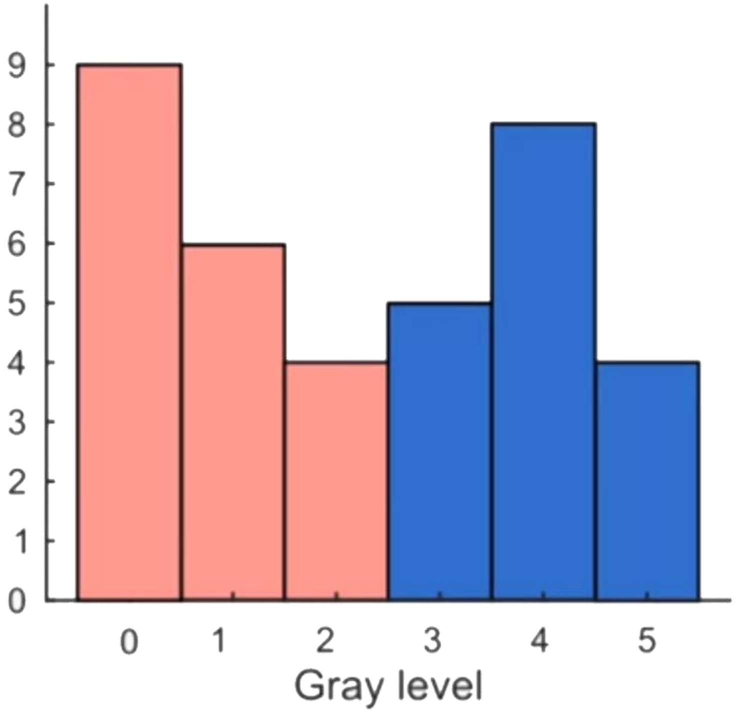


I_t	0	1	2	3	4	5
W_f	1	0.75	0.58	0.47	0.33	0.11
$Mean_f$	2.25	3.00	3.57	3.94	4.33	5.00
W_b	0	0.25	0.42	0.53	0.67	0.89
$Mean_b$	0	0	0.40	0.74	1.21	1.91
σ_B^2	0	1.69	2.44	2.56	2.17	0.95

Image Segmentation :

Otsu's method algorithm Example :





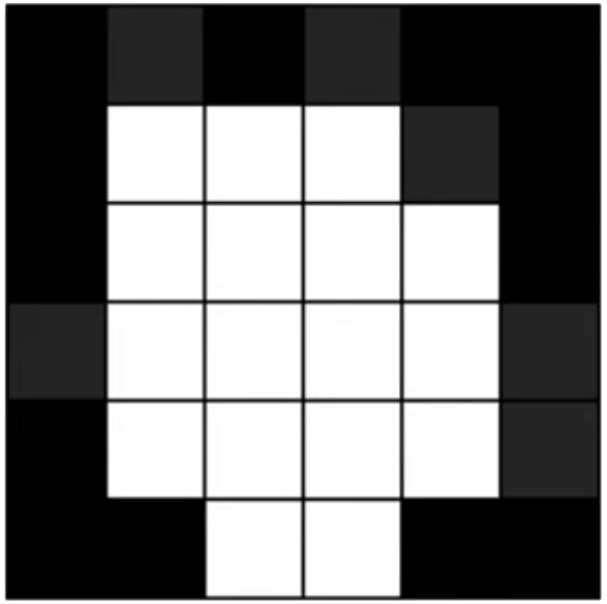


Image Segmentation :

Region Spelitting and Merging :

- ❖ It is an alternative method of image segmentation.
- ❖ An image is subdivided into arbitrary disjoined region.
- ❖ Arbitrary regions can be split and merged in order to satisfy the condition

The algorithm is stated in two phases :

➢ Phase I :

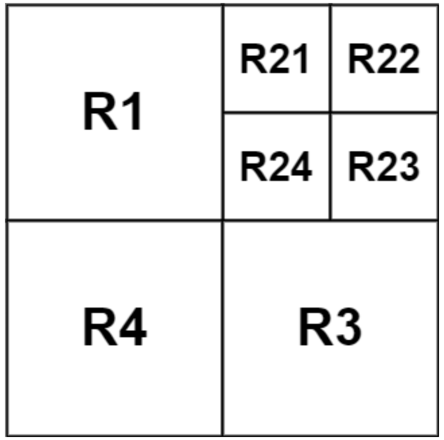
- Split and continue subdivision process until some stopping criteria is fulfilled.
- Often it is stopped when no further splitting is possible.

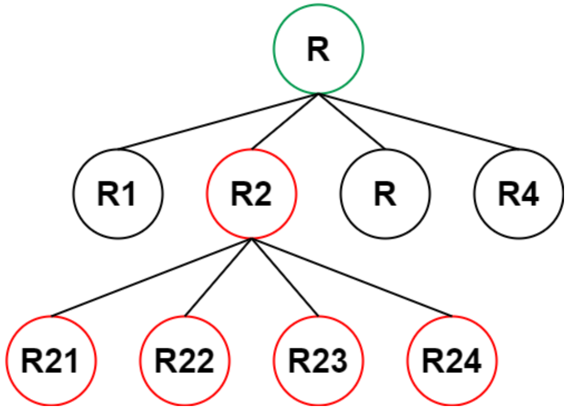
➢ Phase II :

- Merge adjacent regions if the regions share any common criteria.
- Stop the process when no further merging is possible.

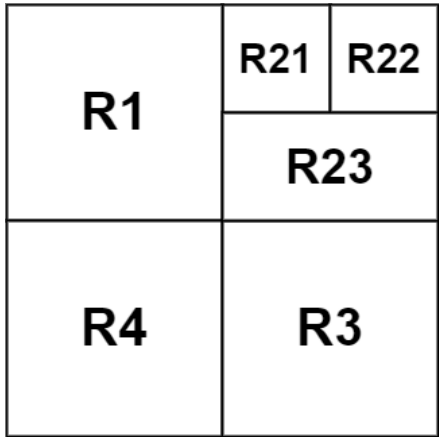
Image Segmentation :

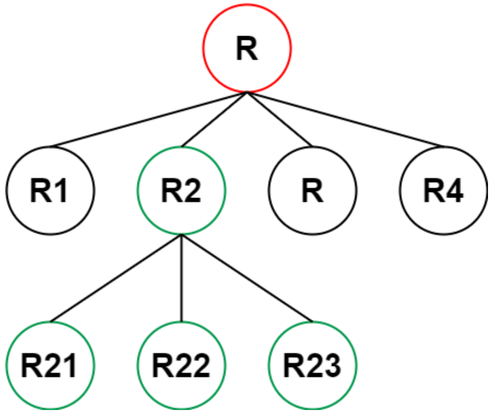
Region Spelitting and Merging :





Quadtree Of splitting





Quadtree Of splitting and merging

Image Segmentation :

Region Spelitting and Merging :

Example: For a given image, apply split and merge algorithm (T <= 3)

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

Image Segmentation :

Otsu's method algorithm Example :

Example: For a given image, apply split and merge algorithm (T <= 3)

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

Image Segmentation :

Otsu's method algorithm Example :

Example: For a given image, apply split and merge algorithm (T <= 3)

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

Image Segmentation :

Otsu's method algorithm Example :

Example: For a given image, apply split and merge algorithm (T <= 3)

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

Image Segmentation :

Otsu's method algorithm Example :

Example: For a given image, apply split and merge algorithm (T <= 3)

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

Image Segmentation :

Otsu's method algorithm Example :

Example: For a given image, apply split and merge algorithm (T <= 3)

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

6	5	6	6	7	7	6	6
6	7	6	7	5	5	4	7
6	6	4	4	3	2	5	6
5	4	5	4	2	3	4	6
0	3	2	3	3	2	4	7
0	0	0	0	2	2	5	6
1	1	0	1	0	3	4	4
1	0	1	0	2	3	5	4

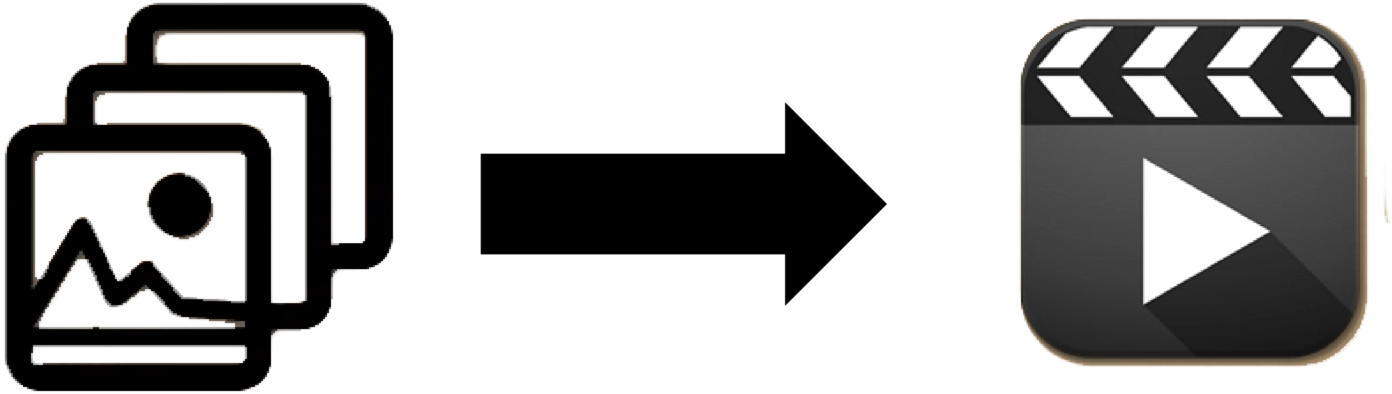
Fundamentals of Computer Vision for Medical Image

Video Processing in Medical Applications

Video Processing :

Definition :

▪ A video is a sequence of visual images or frames displayed in rapid succession to create the illusion of motion. Each frame consists of a two-dimensional array of pixels, where each pixel represents a specific color or intensity value. When these frames are played back sequentially at a consistent frame rate, the human eye perceives them as continuous motion.



Video Processing (Pre-Processing) :

Video preprocessing can be approached in two primary ways :

- Frame-Level Preprocessing
  - In this approach, the video is treated as a sequence of individual frames. Each frame is processed independently using traditional 2D image processing techniques, such as noise reduction, color correction, and edge detection.
- Volume-Level Preprocessing
  - In this approach, the video is treated as a 3D volume, where each voxel represents a pixel in a specific frame and slice of the video. Temporal filtering techniques, such as those mentioned earlier (e.g., Gaussian filtering, temporal median filtering), are applied across the temporal dimension to smooth or enhance the entire video sequence simultaneously.

Video Processing (Feature Extraction) :

Video preprocessing can be approached in two primary ways :

- Feature extraction from 2D to 3D involves transitioning from analyzing features in two-dimensional (2D) images to extracting features from three-dimensional (3D) volumetric data. This transition often occurs in fields such as medical imaging, computer vision, and 3D object recognition, where data is represented in 3D space rather than on a 2D plane.

  - Spatial Features to Volumetric Features
  - Temporal Features
  - Sapatio-Temporal Features

Video Processing (Feature Extraction) :

2D LBP Descriptor

$$\text{LBP} = \sum_{n=0}^{7} s(i_n - i_c)2^n$$

5	9	1
4	4	6
7	2	3

i_0	i_1	i_2
i_7	i_c	i_3
i_6	i_5	i_4

1	1	0
1		1
1	0	0

Binary Number Generated

1	1	0	1	0	0	1	1

= (1 x 128) + (1 x 64) + (1 x 16) + (1 x 2) + (1 x 1)

= 211 (LBP code generated)

Video Processing (Feature Extraction) :

3D LBP Descriptor :

f_n

10	12	41
12	12	02
144	07	17

10	12	41
12	12	02
144	07	17

→

0	1	1
1		0
1	0	1

f_{n+1}

23	16	0
20	23	48
160	23	68

23	16	0
20	23	48
160	23	68

→

1	0	0
0		1
1	1	1

0	1	1	0	1	0	1	1	1	0	0	1	1	1	1	0

(LBP code generated)

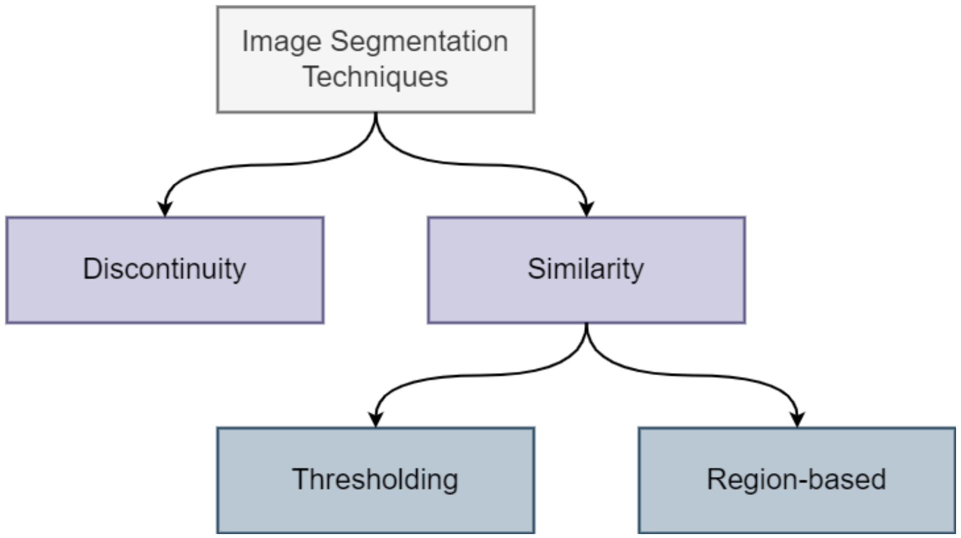
= 27550

Video Processing (Segmentation) :

Video segmentation can also be approached in two primary ways :

- Frame-Level segmentation

  - In frame-level segmentation, each frame of the video is segmented independently using traditional image segmentation techniques. Each frame is treated as a separate image, and segmentation algorithms are applied to identify and delineate objects or regions of interest within each frame.



Video Processing (Segmentation) :

Video segmentation can also be approached in two primary ways :

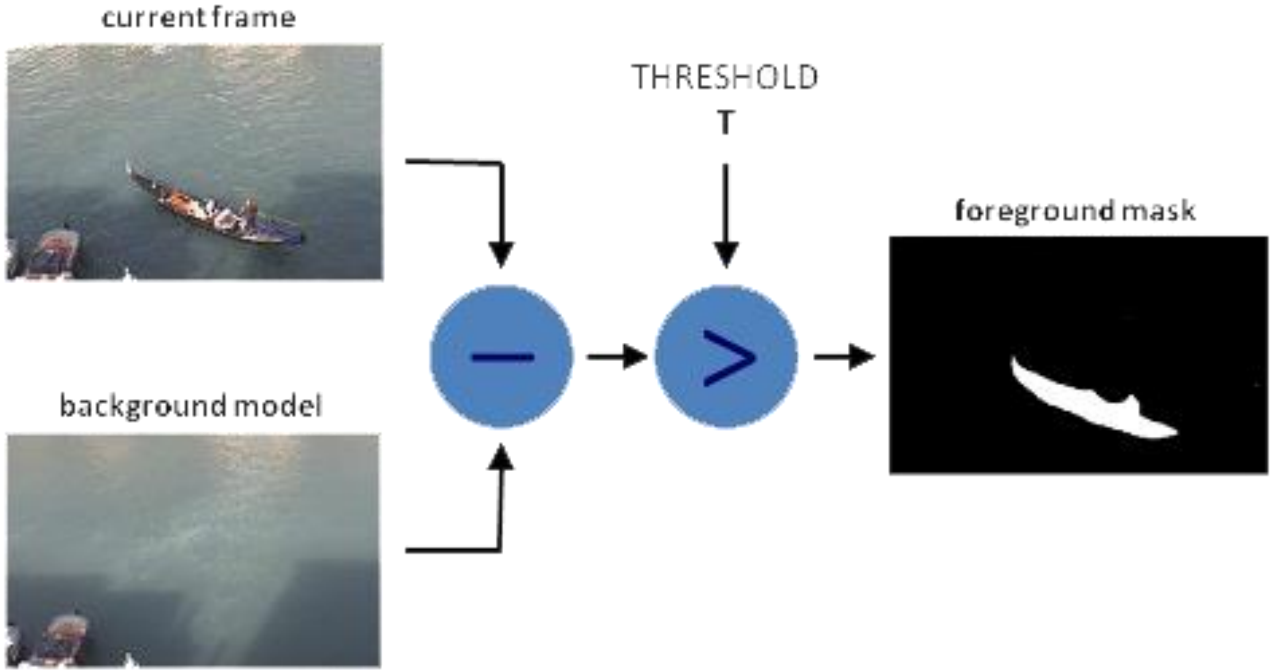
- Frame-Level segmentation
  - In frame-level segmentation, each frame of the video is segmented independently using traditional image segmentation techniques. Each frame is treated as a separate image, and segmentation algorithms are applied to identify and delineate objects or regions of interest within each frame.
- Volume-Level segmentation
  - In volume-level segmentation, the entire video sequence is treated as a 3D volume, and segmentation algorithms are applied to segment objects or regions of interest across multiple frames or slices simultaneously.

Video Processing (Segmentation) :

Video segmentation can also be approached in two primary ways :

- Volume-Level segmentation

Example: Background Subtraction Method



Video Processing (Segmentation) :

Video segmentation can also be approached in two primary ways :

- Volume-Level segmentation

Example: Back.Sub (T >= 42)

Current image

30	20	16	11	30
28	27	125	130	14
10	20	200	220	20
10	30	22	08	30

Video Processing (Segmentation) :

Video segmentation can also be approached in two primary ways :

- Volume-Level segmentation

Example: Back.Sub (T >= 42)

Current image

30	20	16	11	30
28	27	125	130	14
10	20	200	220	20
10	30	22	08	30

Bg model

25	18	07	09	18
20	21	34	34	14
02	14	54	44	10
04	11	18	10	25

Substraction op. result

05	02	09	02	12
08	06	91	96	00
08	06	146	176	10
06	19	04	02	05

Video Processing (Segmentation) :

Video segmentation can also be approached in two primary ways :

- Volume-Level segmentation

Example: Back.Sub (T >= 42)

Current image

30	20	16	11	30
28	27	125	130	14
10	20	200	220	20
10	30	22	08	30

Thresholding result

0	0	0	0	0
0	0	1	1	0
0	0	1	1	0
0	0	0	0	0

Back.Sub Method reslt

30	20	16	11	30
28	27	125	130	14
10	20	200	220	20
10	30	22	08	30

Fin du cours