An Experimental segmentation study techniques and Analysis of Medical images

HADJI SALAH
Laboratory of nano-materials and Energy (LANSER)
CRTEn Borj- Hamm-lif Tunis 2050, TUNISIA

Abstract: Research field in Image processing have many topics such as medical image segmentation to make it we must extract relevant feature of desired image into regions of pixels having same characteristics which provide invaluable information about shape, size, and localization of object (tumors cancer for example) , without exposing the patient to a high ionization radiation. There are different types of segmentation techniques denoted: 1- Edge based segmentation. 2-Threshold Based Segmentation 3-Region Based Segmentation 4- Clustering 5- Matching. In this paper we have implement most segmentation techniques for medical image in Matlab environment and compare them.

Keywords: Image Segmentation, Segmentation Methods, Clustering, Image processing, Thresholding Methods, Edge based Methods

1. Introduction

Segmentation is the first basic step of many analysis procedures in medical image processing field. It is the important way to identify regions or objects of interest (ROI) and discern it from others organs of the human body. When we have the ability to precise exactly edges of object or region (image segmentation) we can easily decide of the status of human organ. There are many approaches to do medical image segmentation by applying specific techniques and approaches depending on imaging modality such as CT, MRI. In our work we have implemented many image segmentation methods: threshold based, region based segmentation and edge based segmentation method (Sobel, Prewiett and Canny) are performed are experimented in Matlab environment and MRI images are extracted from private medical imaging and analysis laboratory..

This paper includes also an application allowing integrating under a graphical interface tools and

2. Segmentation techniques

Segmentation is the partition of an image into a finite number of regions R1..... Rs such as:

$$R = \bigcup_{i=1}^{s} R_i , R_i \bigcap R_j \neq \phi, i \neq j \qquad \text{(II.1)}$$

An object in the image must correspond to each of these regions because, in this image analysis process, the ultimate objective is to be able to decompose an image into a group of distinct objects composing it. In general, these objects have properties of their own in relation to the image itself. Thus, it is possible to distinguish such objects by different measures such as: [3]

- Their related aspect
- Their consistent color
- Their contours
- Their texture

Although there is a multitude of segmentation algorithms according to the field and the constraints studied, we can group this technique into 3 large families:

• region segmentation

• edge segmentation

• cluster segmentation

There are several types of segmentation techniques that are developed to process the medical image.

2.1. region segmentation

The purpose of segmenting images into regions is to partition an image into areas of interest corresponding to objects in the scene from which it originated. It can be situated in the more general framework of data segmentation. [3] The result of the segmentation into regions is an image in which a label is assigned to each pixel. The label of a pixel corresponds to the number of the region to which it belongs. Let us now deal closely with the strategies of segmentation into regions, strategies which are grouped into two large sub-families: The first offers a separation of the image into regions of points, not necessarily connected without allowing, in itself, to define "threshold" objects

The second brings together the methods which consider a region as a set of connected pixels whose colors are close to each other or which meet certain similarity criteria: methods which fall within the framework of "Segmentation by analysis of properties spatial "since they proceed by scanning the image in order to construct the regions and involve colorimetric information for decision-making.

2.1.1 Thresholding

Thresholding aims to segment an image into several classes using only the histogram. It is therefore assumed that the information associated with the image alone allows segmentation, (i.e. that a class is characterized by its distribution of gray levels). A class is associated with each peak of the histogram. [3] There are many different methods for thresholding a histogram (Manually, by hysteresis, Automatically…). Binary image contains information's such as position and shape of candidate. Threshold technique can be expressed as: $T = T[x, y, p(x, y), f(x, y)]$, T is the value of threshold having (x, y) coordinates of point and p(x,y) ,f(x,y) are points the grey level image pixels. [7]

We can define threshold image g(x, y) as:

$$\begin{cases} g(x,y) = 1, if\ ,\ f(x,y) \succ T \\ \quad 0, if\ ,\ f(x,y) \leq T \end{cases} \qquad (II.2)$$

2.2. Segmentation by region growth

This method is based on a set a starting point in the image (the germ) verifying homogeneity criteria for the region (generally intensity between two values), like the thresholding method. By a recursive procedure, we include in this region, the related points which satisfy the criteria. In this way, we grow the region as long as the criterion is met and we end up with a new related region. [2] This recursive method is called: the labyrinth algorithm:

• we start from a random point on the image.

• mark this point as part of the current region.

• we check for each neighbor whether it fulfills the criterion of homogeneity and whether it has not already been verified if so, we apply the same procedure to the neighbor. If not, we stop the procedure. This algorithm has several advantages.

• It ensures to touch all the points of a related field which check the criterion.

• It is a powerful and simple 'brute force' method. But it also has a big drawback:

• It is a heavy method in machine resources and is therefore not suitable for real-time oriented applications. Like the thresholding method, the difficulty of the region growth method lies essentially in determining the stopping criterion. This may be an a priori value, derived from physiological data or may be more sophisticated. This type of segmentation is often used for the semi-automatic segmentation of tumors or the segmentation of brain regions on MRI.

2.3 Segmentation by Continental Divide (LPE)

Consider the topographic representation of a grayscale image and a stream of water flowing over that surface. The water will flow down the steepest slope until it comes to a minimum. The set of points on the surface whose slope leads to a minimum constitutes a catchment basin associated with this minimum. The watersheds are the lines separating the adjacent watersheds. The LPE transformation is a very powerful segmentation tool, it is usually partitions the image into meaningful regions. [20]

2.4. Segmentation by clustering

Consists of assigning each pixel in the image a class (label). This assignment can be carried out on the basis of regions whose classes of membership are known a priori, this is referred to as supervised classification, or not, in this case we speak of unsupervised classification. Segmentation and classification issues are closely related and can be used to mean the same thing. A classification implicitly segments an image: all the pixels having the same class form a region of the image, segmentation implies a classification (regions are labeled according to their membership) [12]

2.4.1 K-Means segmentation

The K-mean method can be used to segment an image which has areas of relatively uniform color. We represent all the pixels of the image in a three-dimensional space based on their components of intensities, in other way **K- mean** clustering aims to minimize an objective function **J** named squared error function : $J = \sum_{j=1}^{k}\sum_{i=1}^{N}\left\|x_i^{(j)} - c_j\right\|^2$,

where $\left\|x_i^{(j)} - c_j\right\|^2$ is the distance measure between data point $x_i^{(j)}$, but cluster center c_j indicates respectively distance for each point data from their cluster centers [9]

Algorithm:

1- we have chosen (at random) a number k of groups to constitute.

2- We choose k records, that is to say k points of space called “centers”.

3- one then constitutes the k initial groups by affecting each of the records in the group corresponding to the closest center for each group formed one calculates its new center (of gravity) by affecting the average of the points of the group and one reiterates the criterion process d 'stop: if no point has changed group, the groups are stable.

2.4.2 FCM segmentation (Fuzzy C-Means)

The fuzzy c-means method is a fuzzy classification method based on the optimization of a quadratic classification criterion where each class is represented by its center of gravity. The method requires knowing the number of classes beforehand and generates the classes in such a way that the sums of the interclass and intra-class quadratic deviations are maximum and minimum respectively. The fuzzy classification allows overlap of regions. A fuzzy segmentation can be obtained by assigning each pixel to the class for which its degree of membership is maximum. This property is exploited in image processing and more precisely in classification where the classes, also called regions, are represented by fuzzy sets. This is very useful when regions cannot be defined neatly and precisely, this method is used in pattern recognition and it is based on the minimization of the objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{\ m}\left\|x_i - c_j\right\|^2 , \quad 1 \leq m \prec \infty \qquad \text{(II.3)}$$

where m is a real number greater than 1, u_{ij}: degree‘s membership of x_i in cluster j. Fuzzy classification is an iterative optimization of following objective function based on update membership u_{ij} and cluster center c_j:

$$u_{ij} = \frac{1}{\sum_{K=1}^{c}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \qquad \text{(II.5)}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij} . x_i}{\sum_{i=1}^{N} u_{ij}^{\ m}} \qquad \text{(II.6)}$$

Iteration stop when $\max_{ij}\left\{\left|u_{ij}^{(k+1)}-u_{ij}^{(k)}\right|\right\}\prec\varepsilon$,
k is the iteration step and $0\le\varepsilon\le1$ termination criterion [9]

Algorithm: there are four steps mentioned as follows:

1) Initialize $U=[u_{ij}]$ matrix, $U^{(0)}$
2) Calculate centres vectors $C^{(k)}=[c_j]$ with $U^{(k)}$ for k-step

$$c_j=\frac{\sum_{i=1}^{N}u_{ij}.x_i}{\sum_{i=1}^{N}u_{ij}^{m}}$$

3) Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij}=\frac{1}{\sum_{K=1}^{c}\left(\frac{\left\|x_i-c_j\right\|}{\left\|x_i-c_k\right\|}\right)^{\frac{2}{m-1}}}$$

4) Iteration stops when $\left\|U^{(k+1)}-U^{k}\right\|\prec\varepsilon$, otherwise return to second step

2.5. Segmentation by contours (edge-detection)

The principle of segmentation by contours and of detecting the contours contained in the images in order to eventually be able to separate them and thus segment them. There are several methods of finding outlines in an image, here are some of them[2]

• Places where the pixel intensity jumps suddenly.
• Places where the intensity profile presents a variation (first derivative is maximum and second derivative goes through zero).

In our work we have implemented three operators to detect edges: Sobel, Perwitt and Canny operators that are first-order derivatives in an image

- *Sobel operator,* is a filter calculating the approximate absolute gradient magnitude of any pixel by using the convolution for gray scale input image with a pair of 3x3 filter (mask) used to estimate the gradients and gradient in both directions (horizontal (x) and vertical (y)) , the next figure shows the masks for Sobel operator.

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

X- direction

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

Y- direction

Fig.2.Sobel operator mask

- *Perwitt gradient edge detector*

It is similar to the Sobel operator using different kernel having a small separable and integer valued filter in both horizontal and vertical directions (x,y), fig.3 shows masks for Perwitt gradient edge detector.

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

X- direction

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

Y- direction

Fig.3. Perwitt operator masks

- *Canny edge detector* :

The methods based on the computation of the first derivative following a very precise direction come essentially from the work of Canny which stipulates that the optimal operator for detection of noisy edges is the first directional derivative (i.e. in the direction of the gradient) of a Gaussian function Gσ with standard deviation σ. Such an edge is then defined as the local maximum, in the direction of the gradient, of the operator G_n convoluted with the reference image I.

$$G_n=\frac{\partial}{\partial_n}G_\sigma \qquad \text{(II.3)}$$

Convolution and the derivation are both linear:

$$I*G_n=I*\frac{\partial}{\partial_n}G_\sigma=\frac{\partial}{\partial_n}(I*G_\sigma) \qquad \text{(II.4)}$$

Pixel is considered active (indicates the presence of an edge) if its gradient amplitude is maximum in the direction of the gradient. After each pixel has been processed, an image of the edges is then obtained on which a thresholding can be applied in order to eliminate variations considered too slight. Unfortunately, this threshold is still so difficult to determine and can lead to destructive results if it is wrongly chosen.

2.5. Wavelet contour detection

Multiresolution edge detection algorithm and wavelet transform was introduced by Mallat and Zhong

Let be $f(x,y) \in L^2(R^2)$ an image and $\psi(x,y)$ a wavelet. The bidimensional wavelet transform of f(x, y) is defined as:

$$w_s f(u,v) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)\frac{1}{s}\psi\left(\frac{x-u}{s},\frac{y-v}{s}\right) \quad \text{(II.5)}$$

Thus, dilation of ''s'' factor can be defined as :

$$\psi_s(x,y) = \frac{1}{s}\psi\left(\frac{x}{s},\frac{y}{s}\right) \quad \text{(II.6)}$$

And $\widetilde{\psi}(x,y)$, we can rewrite as a convolution:

$$w_S f(u,v) = f * \widetilde{\psi}(u,v) \quad \text{(II.7)}$$

From equation in (II.7), wavelet transform was a filter of f(x, y) by the function $\Psi(x,y)$, having a variable width band pass filter (Mallat1989).hence we can extract N directional wavelet $\Psi(x,y)(1 \le i \le N)$, satisfying the properties of energy conservation, then we can define the directional wavelet transform as :

$$w_s^i f(u,v) f * \Psi_s^{-i}(u,v) \quad \text{(II.8)}$$

Which represents filtering of $f(x,y)$ by bidimensional, directional band pass filter $\Psi_s^{-i}(x,y)$

Discrete Wavelet Transform (DWT) can be made as follows:

We select scales inside a dyadic grid and scale is chosen as $s = 2j$, $j \in Z$, in this case 2-D wavelet transform is the filtering of 2-D discrete signal (original image) by band pass directional filter(FIR)

The detection of edges in image proposed a special no orthogonal wavelet (Mallat $\wp$ zhong1992) satisfying the condition: $\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\Psi(u,v)dudv = 0$, we can define two functions $\Psi^1(x,y), \Psi^2(x,y)$ as :

$$\Psi^1(x,y) = \frac{\partial\theta(x,y)}{\partial x}, \quad \Psi^2(x,y) = \frac{\partial\theta(x,y)}{\partial y}$$

$\theta(x,y)$ is a smoothing function having the same integral over x and y and converging to zero at infinity

3. Tests and Results

3.1. Active snake segmentation

It is a semi-interactive method whose principle consists in placing in the image in the vicinity of the shape to be detected an initial contour which will then be deformed under the action of several forces:

• An internal energy E allowing to regulating the contour.

• E image potential energy linked to the image.

• An external connects to the particular constraints that it can add.

These energies will allow the active contour to evolve for the minimum energy position which will thus be a compromise between the various constraints of the problem

• Results in pictures

.The following figures shows the results.

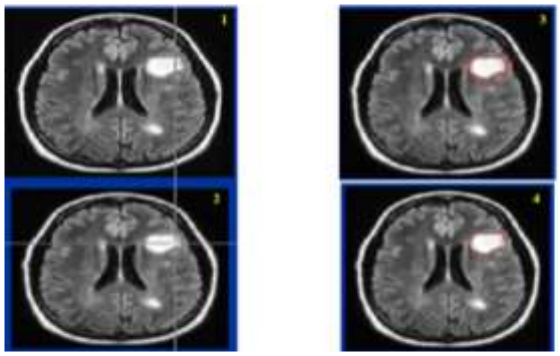

Figure 22: snake segmentation

1) Image processed.

2) Image filtered and ready for processing.

3): image to illustrate the segmented area.

4): image shows the result of this segmentation.

3.2. Hysteresis segmentation

We choose the threshold then by pressing the hysteresis button the figure below presents the result (the processed image and a transverse shot of the human body):

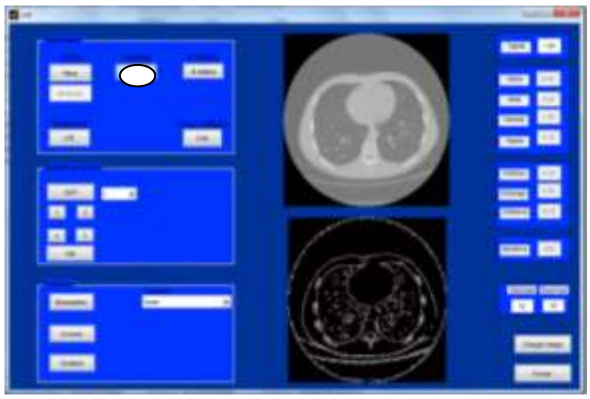

Figure 23: Hysteresis segmentation

3.3. K-means segmentation

This is a semi-interactive method, the principle of which consists in placing in the image near the shape to be detected an initial contour which will then be deformed under the action of several forces:

• An internal energy $E_{internal}$ making it possible to regularize the contour.

• A potential energy E_{image} linked to the image.

• An external $E_{xternal}$ relates to the particular constraints that may be added. These energies will allow the active contour to evolve for the minimum energy position which will thus be a compromise between the various constraints of the problem.

is the result of this segmentation we can see the localized tumor.

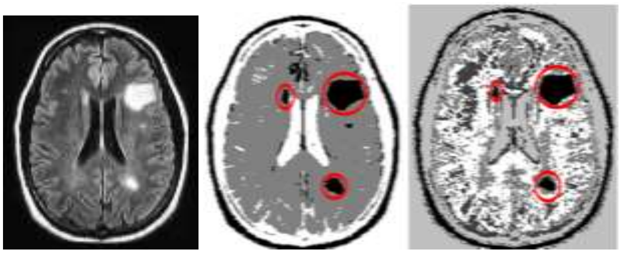

Figure 24: original Image, Figure 25: segmentation

k = 3   Figure 26: segmentation k =

3.4. "Fuzzy c-means" FCM segmentation

The principle of this segmentation and the decomposition of the image according to the gray level the figure below, presents the result of this segmentation by pressing the FCM button**.**

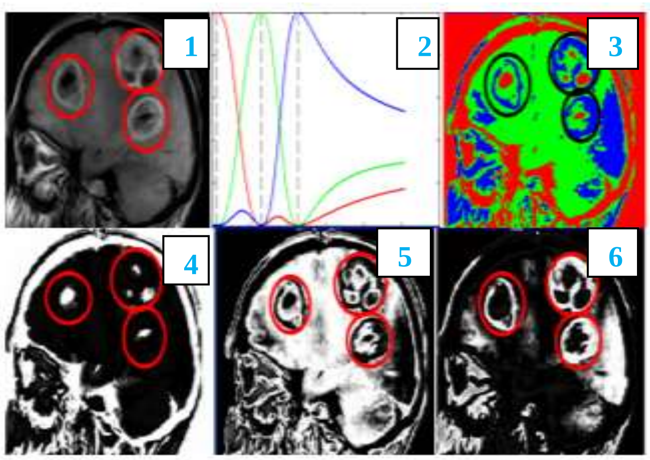

Figure 27: FCM segmentation

1- Image processed.

2- Three curves which give us the 3 colors of the image black, gray and white.

3- We change the color black by red, gray by green and white by blue. Now we do the decomposition we apply white to the first color and black or two other colors

4- White is applied to the red zone and black or two other zones.

5- Same principle as (4) (6): same principle as (4) and (5)

3.5 Watershed Segmentation results

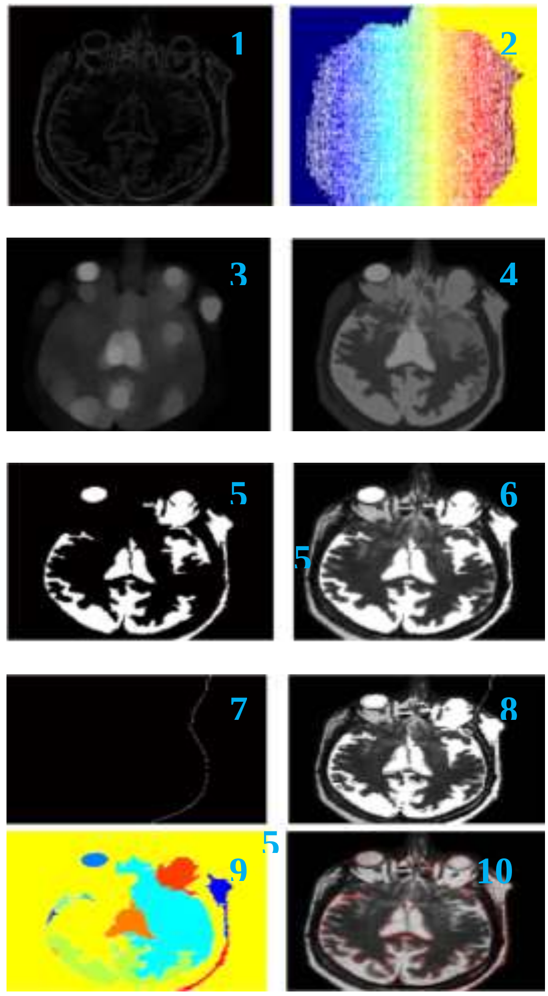

Fig.28. LPE segmentation stages

1- "Gradient modulus": We start by generating the image of the gradient modulus

2- "Regions detected by the LPE: over-segmentation": Then an evaluation of the contour detection by the LPE is carried out by detecting the closed contours and doing over-segmentation

3- 'Regional maxima'

4- 'superimposition of maxima with the original image 'the application of dilation and erosion serves to detect regional maxima in the image.

5- Dilation

6- ’expansion. These different operations allow us to detect regions in the image and separate them using lines called watersheds

7- "Watershed lines".

8- Superposition of markers and dividing lines on the image " We are now interested in what we call markers that exist in the objects sought in the image which are in our case the edges of the image

9- 'Colored matrix of regions applied to the original image', we finally obtain the matrix corresponding to the application of these contours and markers and which defines the different regions of the image as if they were a topographic map

10-‘colored matrix outline overlay on the main image’

3.5.1. Wavelet edge-detection

Fig.29.DWT edge detection

You can modify the color intensity of the given result as indicate below:

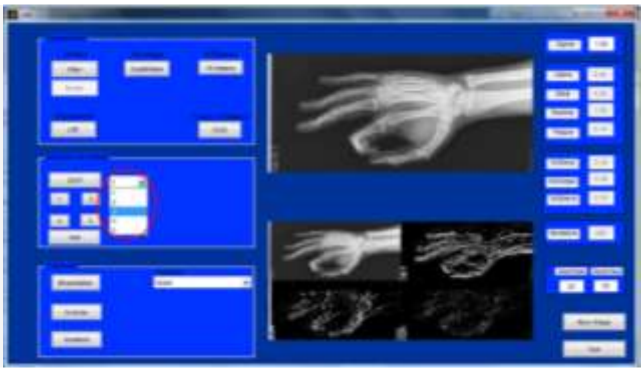

Fig.30. Intensity factor variation

Fig.31. horizontal detection

Fig.33: Vertical detection Fig.34: Diagonal detection

The display of the histogram of the image the figure below shows the result of this action

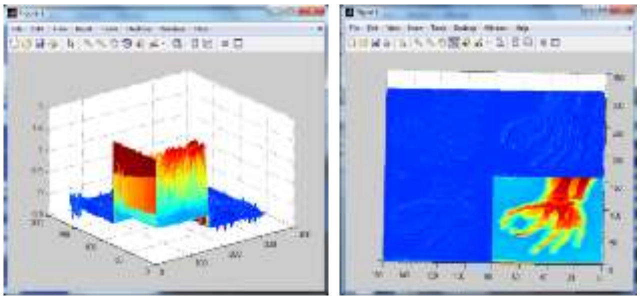

Fig.35: The histogram

Edge-detection results:

In first step we present simple gradient edge detection for color edge, then we present the results of contour detection by filtering, namely the filters: Sobel, canny, Perwitt..... tec.

Fig.36. (a) binary image (b) Color outline

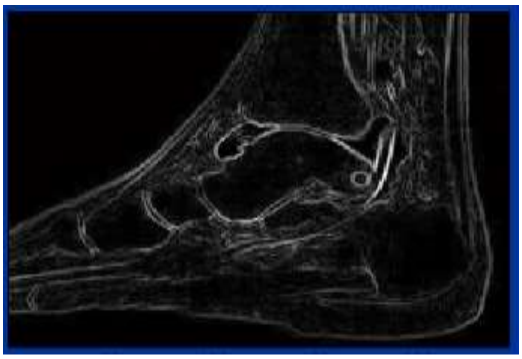

Fig.37. Gradient

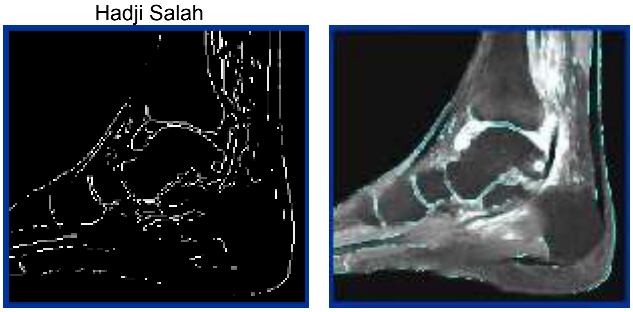

Fig.37(a)Sobel outlines (b) superimposition + image.

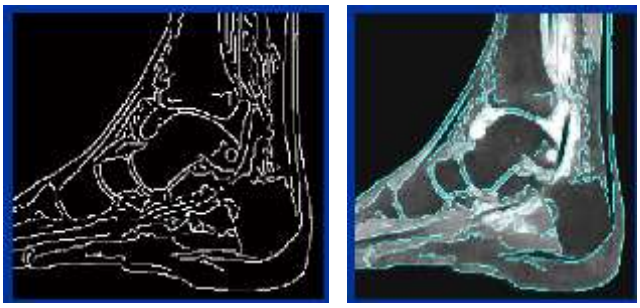

Fig.38 (a) Canny outlines (b) superposition + image

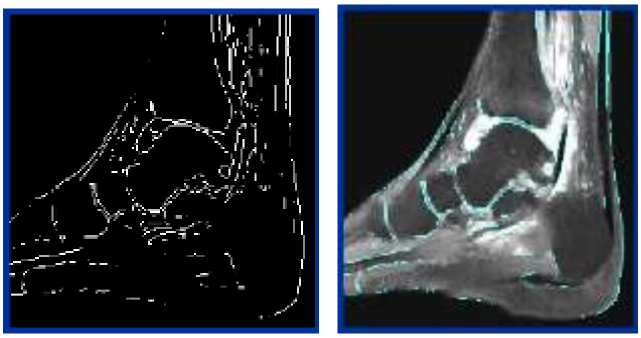

Fig. 38 (a) Perwitt outlines (b) superposition + image

Experimental Comparison for implemented segmentation techniques

Segmentation by active snake contour

Advantages and disadvantages

Problems related to configuration: The definition of energy depends on how you set up the snake. In addition, the initial outline must be close enough to the object to be able to converge, otherwise it risks collapsing on itself.

Topology issues: The snake thus defined will be incapable of distinctly detecting two objects on an image: at best, the contours of the two objects will be linked. The object to be detected must also be convex, as the snakes have difficulty in entering the concavities.

- Hysteresis segmentation

The choice of thresholds is important. Low thresholds will give an image with a lot of outlines. On the contrary, too high thresholds will give an image with few outlines. We have to find the right balance in relation to the expected result.

- K-means segmentation

Advantages and disadvantages: The number of classes is a parameter supplied as an input.⌉ The final distribution of classes depends on the first centers chosen.⌉ The method is especially well suited to spherical classes.⌉

- FCM “Fuzzy c-means” segmentation

Benefits: gives the best result for the overlapped dataset and relatively better then the k-means algorithm. Unlike k-means where the data-point must exclusively belong to one cluster center here data-point is assigned membership to each cluster center as a result of which data-point can belong to more than one cluster of the cluster.⌉ Disadvantages: a priori specification of the number of classes.⌉

-Segmentation by the "Watershed" shared water line method

Benefits: The Continental Divide method provides regions delimited by closed contours forming a partition of the image.

Disadvantages: Despite the good separation of the various partially covered particles, we can observe an over-segmentation of the image, showing crest lines outside the objects, as well as inside convex objects. The main conclusion of our comparative study on segmentation is that there is no universal method for segmenting images and that one technique or another must be used, and even several simultaneously, depending on the case and on the image area.

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