# RESEARCH ON THE IMAGE SEGMENTATION BY WATERSHED TRANSFORMS

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***ABSTRACT***

*Segmentation is a very important step in medical image processing. The mathematical morphology is very suitable for the pretreatment and segmentation of medical images, which present rich information content. In this work we presented a segmentation paradigm by Watershed preceded by a filtering to eliminate insignificant minima, a marking to remove unmarked minima, and finally we implemented a hierarchical segmentation using the mosaic image of the original image. In principle, watershed segmentation depends on ridges to perform a proper segmentation, a property that is often fulfilled in contour detection where the boundaries of the objects are expressed as ridges. Watershed is normally implemented by region growing, based on a set of markers to avoid over segmentation. The diversity of segmentation offers us several ways to segment the image, always we must look for the right method to get good results.*

***KEYWORDS***

*Image, Filtering, Mathematical Morphology, Watershed, Segmentation.*

## 1. INTRODUCTION

The segmentation is the process which consists to partition an image of homogeneous related areas. Obliged stage of any system of intelligent analysis of scenes (modules of assistance to control, of assistance to diagnostic medical, remote monitoring… to quote only some examples), the segmentation is also used in less obvious fields a priori such as the coding of image (coding directed object), the material analysis. Just like there are many ways of interpreting an image, there exists many possible approaches to solve the problem of the segmentation [1-2]. To date, there are several methods of segmentation, which one can gather in four principal classes [3-6]: Region based segmentation, edge-based segmentation, classification or thresholding and the segmentation based on co-operation between the first three segmentations. Gustavo et al [7] is used the split and merge method for colour image segmentation. This method combines the advantages of the approaches based on split and merge and region growing, and use of RGB and HSV colour representation model. In [8], using a combination of three algorithms namely, WAVELET, OTSU and CURVELET. Wavelet and curvelet transforms are incorporated for sub band decomposition of frequency coefficients. Otsu algorithm has a novel approach for segmentation where thresholding is done using histogram analysis. In addition, [9] is used wavelet transform and Gabor filter technique. Wavelet transforms are used for increasing accuracy. Resolution reduction by wavelet is dependent on amount of noise in the document image and also the desired target size. This has been efficiently exploited by using a Gabor Filter.

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They is various approaches have in common that they are generally specific to a well defined type of image and they thus test a difficulty of segmenting images of the different type. One will obtain, thus, in certain cases, under segmentation or on the contrary one on-segmentation of the image thus requiring the intervention of a human expert to carry out a correction.

Our method is based on the algorithm of the watershed to the original image.In image processing, the segmentation by watershed designates a family of methods the segmentation image exits of mathematical morphology which regard an image on levels of gray as a topographic relief, which one simulates the flood.

The watershed, introduced by H. Digabel and C Lantuéjoul [10] for the analysis of image, is one of the most powerful methods and rapids to carry out the stages of segmentation of image.Within this framework, the watershed allows partitioning the pixels of an image in a whole of related areas separated by a closed contour. It thus constitutes, by nature, a tool adapted well to the segmentation. However, the watershed algorithm called upon the morphology operators (erosion-dilation), and the combination between the two last will give the closing (or opening). Also, this algorithm uses an adequate pretreatment made up by the gradient, the alternate filter sequential, the markers, and the segmentation by watershed [11-12].The fuzzy watershed algorithm Raswan et al, [13] is modified to handle the problem of over segmentation by initially partioning the image. The segmentation by the watershed with markers avoids the on-segmentation. It is necessary to fix where to locate the markers in the gradient to begin the rise of water. One cannot apply the watershed without regulating in first where will start the areas (i.e. where will be the minimums), to avoid the on-segmentation. A mask thus should be created where there are only the markers and to superimpose it on the image of the gradient, while imposing that the absolute minima of the image resulting from this superposition are the points of the image of the markers. In this way, one avoids the on-segmentation about which one already spoke previously.

## 2. ASPECT THEORY OF THE WATERSHED

In mathematical morphology, the watershed is a very significant concept to solve the problems of segmentation. Intuitively, it is definite by analogy geographical like complementary to basins slopes, a catchment area being the zone associated with a regional minimum such as a water drop falling into this zone and following the line of greater slope will stop in this minimum. To obtain it, it is necessary to imagine the immersion of a relief in water, by specifying that water can penetrate in the valleys only by its minima (figure.1).The watershed is represented by the points where two disjoined lakes meet during the immersion. This approach "immersion" which consists in filling the basins slopes gradually (starting from the regional minima) to determine their limits [14-15].

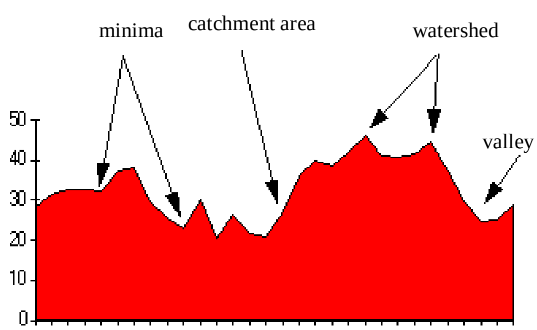



Figure 1. Principle of the watershed

## A) Mathematic morphology

Mathematical morphology is a nonlinear theory of treatment of information very much used in the analysis of images. The morphology operators whom one will use in our work are: erosion, dilation, opening, closing, Top Hat transform, morphological filter, sequential filter. We limit ourselves here to the operations defined starting from a structuring element [16-19].

### 1) Erosion

One moves the structuring element *B* in all the image *X* and one replaces the value of the pixel p which is in the center of the structuring element by the minimal value of the pixels of the structuring element. As the following equation shows, in the result of erosion, related components more small that *B* will have to be eliminated.

`

$$\delta_B(X) = \{B_p \backslash p \complement X\} \qquad (1)$$

Erosion is useful to reduce the clear objects of the image, as one can see it on the Fig. 2. i.e., the goal of erosion is to eliminate the narrow courses, to widen channels and holes and to transform an almost-island into island.

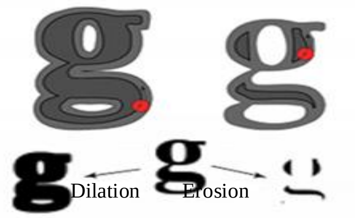



Figure 2. Dilation and erosion of an image.

### 2) Dilation

This operator is dual erosion. The structuring element *B* is moved successively to occupy all the positions of space *X* and one replaces the value of the central pixel *p* by the maximum value of the pixels of *Bp*. For each position, if *B* intersects with *p* the pixels are dilated.

$$\boldsymbol{\varepsilon_B(X)} = \cup \{\boldsymbol{B_p \backslash p \in X}\} \qquad (2)$$

Dilation is used to increase the clearest objects of the images, as one can observe it on the figure 2.More precisely, the objective of this operation is of stopping the holes smaller than *B*, widening the courses, to fill the narrow channels and to weld two close forms.

### 3) Opening

It is about an erosion of the image followed by dilation. In a binary image, an opening enables us to eliminate the smaller related objects (with the sense from the inclusion), that the tructuring element B (white components).Compared to erosion, the opening does not eliminate that the objects smaller than the structuring element and does not affect the objects larger than the structuring element. One can see in the Fig. 3 like the image result has forms more smooth and it preserved the size and the form.

$$Open_B = (\delta \; o \; \varepsilon)_B \qquad (3)$$

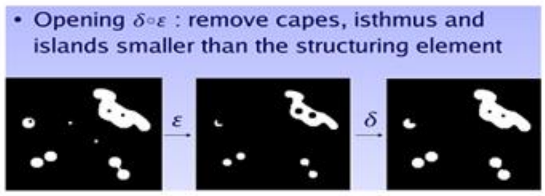



Figure 3. Opening of a binary image

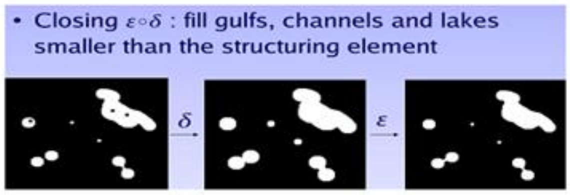



Figure 4. Closing of a binary image

**4) Closing**

This operation is dual opening and defined like a dilation followed by an erosion.

In a binary image, a closing fills the black holes smaller than the structuring element $B$ in the white objects (Figure 4). In other words closing welds the close forms and, like the opening, the result will have the same size and form.

$$Clos_B = (\varepsilon \; o \; \delta)_B \qquad (4)$$

## B) Other tools [20-21]

**1) Morphological filter**

Closing and the opening are increasing operations and idempotent, two properties which define the morphological filter. Closing is extensive, and the opening is anti-extensive.

The morphological filters constitute an invaluable help in a process of segmentation. In particular, leveling make it possible to filter the images while preserving significant contours, which to simplify the operation of segmentation itself. In certain cases, a significant filtering can itself produce a relevant partition. But the morphological tool most known in segmentation of image is the watershed.

**2) Sequential alternate filters (SAF)**

We saw that the openings and closings were morphological filters. Without going into the theory of the morphological filters, we will describe here only the sequential alternate filters, which are used much in practice, and which are built starting from continuations of openings and closings of increasing sizes. In the discrete case, such a filter applied to a function $F$ is expressed like:

$$\left(\ldots\ldots\left(\left(\left(\left(f_{B_1}\right)^{B1}\right)_{B_2}\right)^{B_2}\right)\ldots\ldots B_n\right)^{B_n} \qquad (5)$$

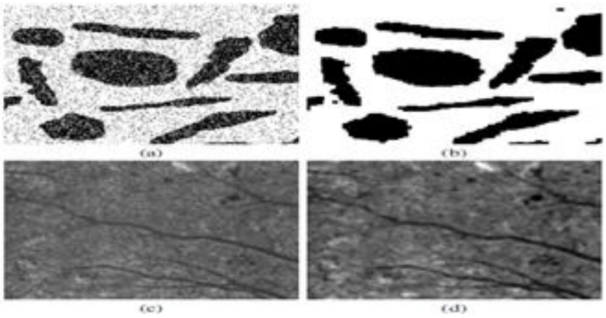


Figure 5. Applications of the SAF a) Binary image, b) SAF white cuts 2
c) Melts of eye d) SAF black cuts 1.

They are used in practice to gradually filter the positive noise (narrow peaks) and the negative noise (narrow valleys).The last structuring element used (of size N) is given according to the minimal size of the objects of the image which one wants to preserve after filtering.

### 3) Top hat transform

One calls top hat transformation the difference between the original image and the open one of this image, or between closed image and the original image. The first type of top hat transform is called white top hat transform because it makes it possible to detect what the opening made disappear, i.e. peaks or clears parts of the original image. The second type of top hat transform, dual of the first, is called black top hat transform, because it detects the valleys, or left dark an image.

### 4) Morphological gradient

The morphological gradient of a function $F$ is defined in the continuous case by the following function $g$:

$$g(x) = \lim_{\alpha\to 0} \frac{\varepsilon(f,B_\alpha)(x)-\delta(f,B_\alpha)(x)}{2\propto} \qquad (6)$$

And in the discrete case by

$$g(x) = \varepsilon(f,B)(x) - \delta(f,B)(x) \qquad (7)$$

This transformation finds its applications in the contours detection.

## C) The proposed method

The method used follows the stages which one can see in the diagram of Fig. 6.

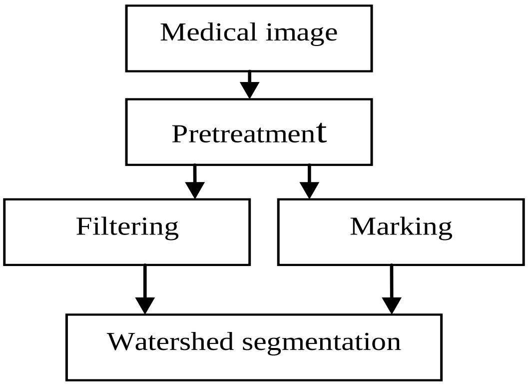



Figure 6. Synoptic diagram of the watershed transform.

We saw that the determination of the watershed is a tool largely studied for the segmentation of images in the field of mathematical morphology. Following one principle, each minimum produces an area or a zone, called catchment area. The difficulty comes owing to the fact that the real images are generally disturbed, when one calculates the watershed while basing oneself on gradients that leads to a strong on-segmentation due to the presence of many minima generated by the noise. In order to overcome this on-segmentation, one proposed several approaches. The first approach is filtering. The idea consists in filtering the original image in order to remove all the not-significant minima. The second approach consists in choosing the number of local minima as well as the number of zones to be highlighted grace with the watershed. Here it is supposed that the characteristics of the interested objects are known.

The useless minima are unobtrusive. The choice is carried out by selecting automatic or manual markers. It is the approach markers. Third approach consists in improving an initial segmentation by amalgamating pairs repeatedly of close areas: It is the method of fusion of areas basing itself on the calculation of a hierarchy. The calculation of the hierarchy, based on values of extinction, occurs with one level different for each fusion from areas. This is useful for the approaches of interactive segmentation because this method offers a great flexibility. The values of extinction can be the result of measurement.

The data base with which one worked is obtained "Center of Imagery Medical algria CIMM ". This base includes a unit real medical images of examination MRI of three examinations of the brain:

**Cranium normal**: constituted of two Sequences and it contains 26 images for each method, and these sequences.

**Cranium tumoral**: constituted of eight (08) sequences. The pathological examinations are always carried with injection of product of contrast "GADOLINIUM".

Each examination is composed of a whole of sequences of methods, each sequence constitutes of the whole of the images, and the number of sequence is different according to the examination. The format of each image is format DICOM (DIGITAL Imaging and Communication in Medical). A file DICOM consists of several different data (various images, data on the patient, the medical examination, and the services associate).

One also implemented our procedure on a whole of images "CT scan" of format "JPG" and which contains various examinations such as: the teletorax, lumbar, cranial, UIV.

## 3. RESULTS AND DISCUSSIONS

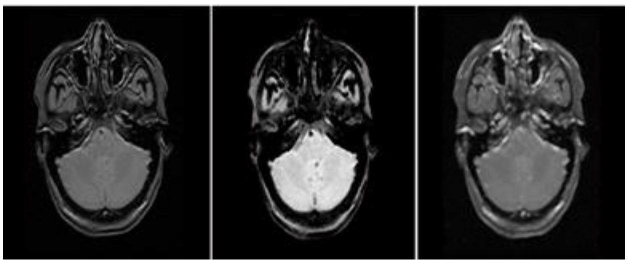
In this part, one will show the effectiveness of the basic operators of mathematical morphology. They are the basic transformations of the analysis of image by morphology, one calculates erosion and the dilation of the image by using a structuring element defines by the connexity (either 4 or 8) and cuts it connexity which is expressed in a number of odd pixels. One applies it to images in level of gray (8 bit), for images DICOM one them converted of 16 bit with 8 bit before applying the treatment.

The Fig (7-9) illustrates the results of erosion and dilation, such as: The forms eroded and dilated in the objects strongly depend on the shape of the structuring element. Erosion in levels of gray reduces the light intensity of the pixels which are surrounded by neighbors of less intensity (visible on the reversed images). This vicinity is defined by the structuring element. The whole of the pixels of the image is swept by applying the structuring element. The value of a pixel after erosion is then defined as being the minimal value of all the pixels of its vicinity.

Dilation in levels of gray increases the light intensity of a pixel surrounded by more luminous neighbors (visible on the reversed images).The whole of the pixels of the image is swept by applying the structuring element.

The value of a pixel after dilation is then defined as being the maximum value of all the pixels included in the vicinity.

The Fig. 10 presents the result of opening and closing which is applied to the tumoral cranium.



**(a)** **(b)** **(c)**

Figure 7. a) Normal cranium (MRI) b) erosion c) dilation.

**(a)** **(b)** **(c)**

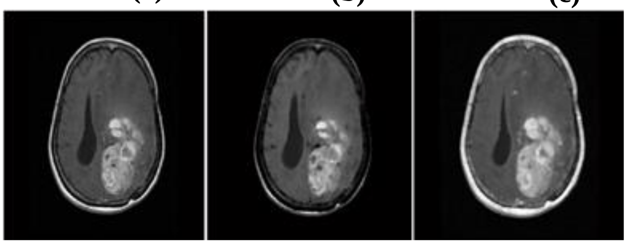


Figure 8. a)Tumoral cranium (MRI), b) erosion, c) dilation.

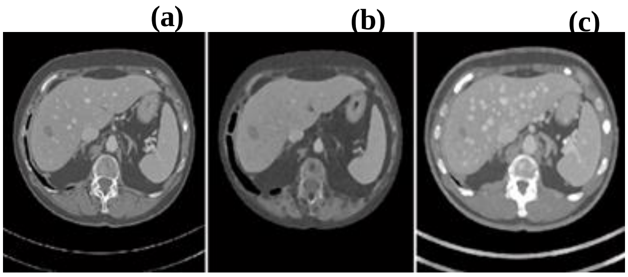



Figure 9. a) Tumoral cranium, b) opening, c) closing.

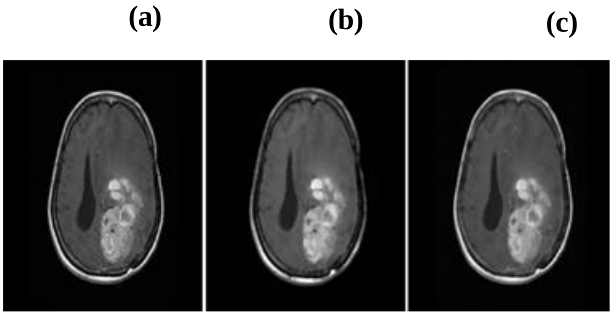



Figure 10. a) Tumoral cranium, b) opening, c) closing.

The result of erosion followed by dilation which made up an opening to tumoral cranium image is presented in the figure 10.b.Here, the opening eliminates the clear point's isolated and smooth contours. One also observes a segmentation of the various forms of the image. In addition, closing in levels of gray is a dilation followed by erosion in levels of gray. It removes the dark points isolated and smooth contours.

## A) Segmentation of images by the watershed

### 1) Application Of the watershed algorithm on images filtered

In this part one seeks to eliminate all the minima not-significant for the image gradient. In this direction one thus seeks certain manner to realize the image locally.

Whereas with the approach marker one seeks to replace the minima of the gradient by images of markings, here one rather will seek to remove the not-significant minima in the image itself.

### a) Morphological gradient

The morphological gradient is a residual operation by using a combination of the erosion and/or the dilation of the image of origin. Like other gradients, it makes it possible to highlight variations of intensity of the image and is used to carry out the detection of contour (see Fig. 12).

**(a)** **(b)** **(c)**

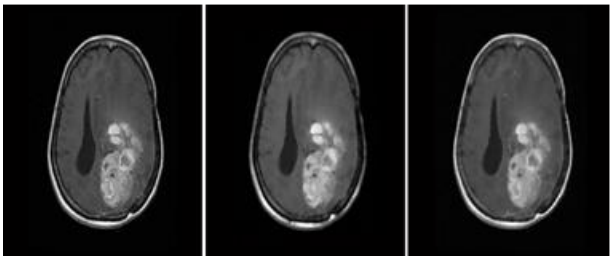


Figure 11. a) Tumoral cranium, b) morphological gradient.

**(a)** **(b)** **(c)**

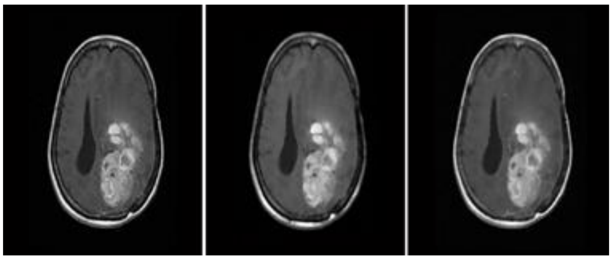


Fig. 12. a) A cut Ct of the liver, b) morphological gradient.

**b) Smoothing by a Gaussian filter (linear)**

We saw that one of the principal sources of the phenomenon of on-segmentation is the noise present in the natural images. In order to mitigate this noise one operates a space average using a Gaussian filter [22].

Are *U(x)* the level of gray in an item *X* of the image to treat and Gaussian $G_\sigma$ standard deviation $\sigma$ given by the following formula:

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma}} exp\left(-\frac{|x|^2}{2\sigma^2}\right) \quad (8)$$

The Gaussian filtering of the image results from the convolution of this function with the Gaussian ones in each point of the image:

$$U(x,\sigma) = (G * U_0)(x) = \int_{R^2}^{\infty} G_\sigma(x-y)U_0(y)dy \quad (9)$$

This convolution is a regularizing operation. In practice, this regularization of $U$ makes it possible to smooth in a coarse way, by weakening the information which presents space variations on scales lower than $\sigma$.

An obvious disadvantage of Gaussian filtering is that it does not smooth only the noise, but it gums also contours, making them not easily identifiable.

Let us observe the influence of such a filtering on images MRI and CT. The images are smoothed with Gaussian dimension 10 pixels and standard deviation of 10 (Fig. 13).

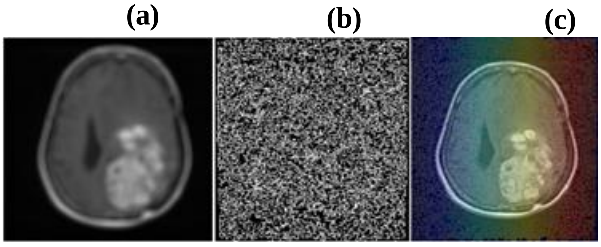



Figure 13. a) Image filtred by a Gaussian filter, b) Watershed of the image filtred c) watershed on the image filtred by a gaussian filter.

The detection of contours obtained remains very on segmented, even if there is an improvement when the gradient is calculated on the smoothed image. The gradient is always better if it is calculated on an image smoothed by linear diffusion.

**c) Sequential alternate filter (SAF)**

This filter is a morphological filter which consists in making a succession of openings and closings by spheres of increasing rays. It will be noticed that the first operation is a closing in order to privilege the suppression of the supernumerary minima. The parameters are: size of the structuring element with which one carries out the morphological operations but also the iteration count (iter-ct) . This filtering reduces the original on-segmentation appreciably but there remains less powerful remain to go up a on-segmentation (Fig. 14-15).

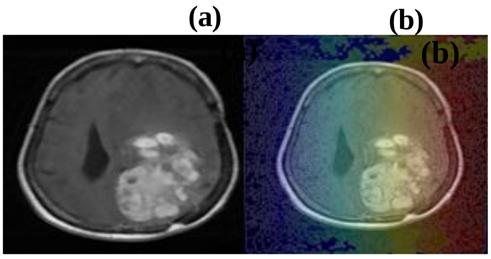



Figure 14. a) Image smoothed by SAF (5 iter-ct), b) Watershed on image smoothed by SAF

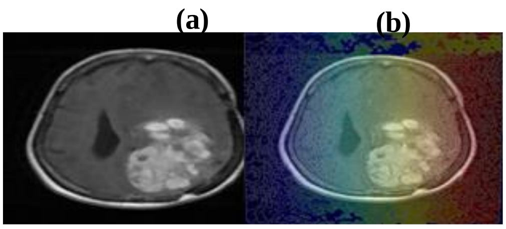



Figure 15. Image smoothed by SAF (50 iter-ct), b) Watershed on image smoothed by SAF

This filtering reduces the original on-segmentation appreciably but there remains less powerful remain to go up a on-segmentation.

**d) anisotropic diffusion (nonlinear filter)**

Major problem of the operators of smoothing (low-pass filter) linear: it removes the noise but also many relevant information such as contours of the objects, by moving them and making them fuzzy. The non-linear filters correct that partly but do not allow a fine control of smoothing. They do not take into account the amplitude of contours to be preserved.

To solve the problems resulting from an isotropic diffusion, the first anisotropic idea of diffusion was proposed by *Malik and Perona* [19], the idea is to create a filter which preserves and raises contours and which floute the zones with weak gradient.

The equations of diffusion allow this control.

$$\begin{cases} \frac{dU}{dt} = div(g(|\nabla U|)\nabla U) \\ U(x,y,t=0) = U_0(x,y) \end{cases} \tag{10}$$

To show the influence of smoothing by diffusion on the segmentation, one adds a Gaussian noise (level 0.3) to the image then one calculates his gradient and finally one applies the watershed to his gradient (Fig. 16).

Now one will leave the noising image by a filter of diffusion (degree of smoothing is 50) then one calculates his gradient then to apply the watershed (Fig. 17). This type of filtering is particularly interesting when the images to be analyzed are noising. Indeed induced noise of multiple basins not-significant slopes. A means easy to remove them is to carry out a low-pass filtering. This filter, as we saw previously, has the disadvantage of attenuating contours. This is why one uses a non-linear filter. Concerning the filtered image, one observes that various contours were indeed preserved, except for the contours located in zones at weak gradient and who were thus diffused. The image gradient makes it possible to check that the amplitude of the gradient did not decrease whereas the effect of the noise was removed. What can be checked on the watershed calculated with the gradient of the image smoothed by non-linear diffusion the watershed remains despite everything very on-segmented.

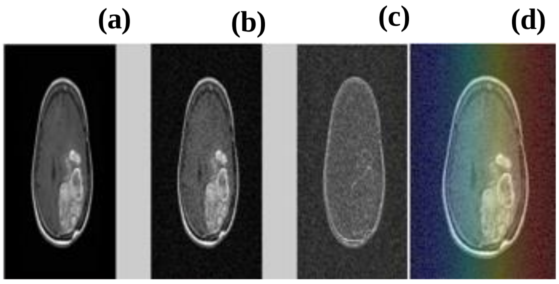



Figure 16.a) Original image, b) noised image, c) gradient of the noising image, d) watershed on the gradient of the noising image.

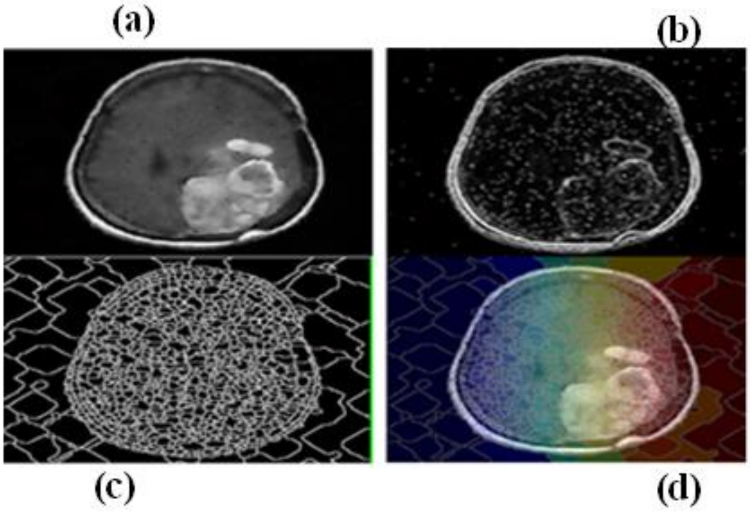



Figure 17. a) noising image smoothed by diffusion, b) gradient of the smoothed image, c) gradient of smoothed image and watershed calculated with the gradient

## 2) Application of the watershed algorithm with markers

In an image the objects placed seem areas on level of homogeneous gray. These areas are highlighted by the morphological gradient, whose minima define in fact of the markers. Nevertheless the morphological gradient comprises well too many not-significant minima which one thus will seek to remove. The idea of the approach by markers is to force the LPE to consider a judiciously selected whole of markers beforehand and. The realization of this idea requires two things: initially, to build the markers and then to integrate this information in the original image.

### a) Interior markers "Top hat transform"

The Top hat transformation is defined like the difference between the image and its open of size L. This method consists in extracting the elements smaller than the structuring element. I.e. the markers in this case are the elements which are inside the top hat(Fig.18).

One chooses the value of L according to the size of the elements to be highlighted. For example for the lipome image, the size of the top hat is regulated to 80 so that the tumor can return inside the hat. In addition, the segmentation is of good quality. But it does not make it possible to separate the badly contrasted areas or of low intensity thus it considers these areas by holding with the bottom of the image as much of contours of the image are not taken into account. This segmentation is much practical to detect and characterize the tumors of which they appear more contrasts that the remainder of the image (Fig. 19).

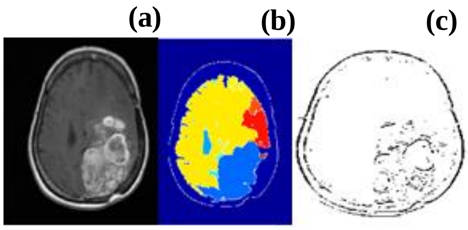



Figure 18. Interior marking by top hat, a) initial image, b) interior marker of the image by top hat l=50, c) LPE on the rebuilt image

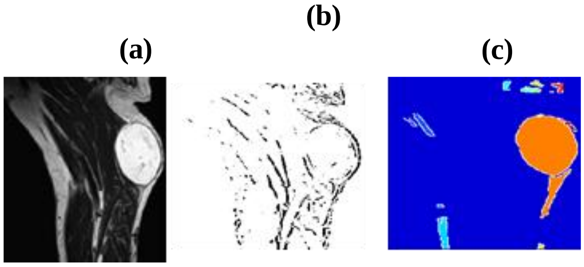



Figure 19. Interior marking by top hat, a) initial image, b) interior marker of the lipome image by top hat l=80, c) watershed on the rebuilt image

One chooses the value of L according to the size of the elements to be highlighted. For example for the lipome image, the size of the top hat is regulated to 80 so that the tumor can return inside the hat. In addition, the segmentation is of good quality. But it does not make it possible to separate the badly contrasted areas or of low intensity thus it considers these areas by holding with the bottom of the image as much of contours of the image are not taken into account. This segmentation is much practical to detect and characterize the tumors of which they appear more contrasts that the remainder of the image.

**b) Interior markers:H minimum method**

This method consists in determining the minimal areas of the image obtained by geodetic rebuilding by erosion of the image source I by J, relocated of I of a level H. This geodetic rebuilding causes "to fill" the non-significant areas catchment (a good choice of H entrain a raising of level of gray) to preserve only the interesting minima. One changes the value of translation according to minima's which one wants to make appear according to the nature of the image and his diagnosis. For the tumor image cranium (Fig. 20) the segmentation is not powerful considering it confuses the tumor with the grey matter which surrounds it. For the angiographic image arterio the various areas are well detected nevertheless it exists always contours which are not put in account what thus leads to one on segmentation the problem is not solved yet(Fig. 21).

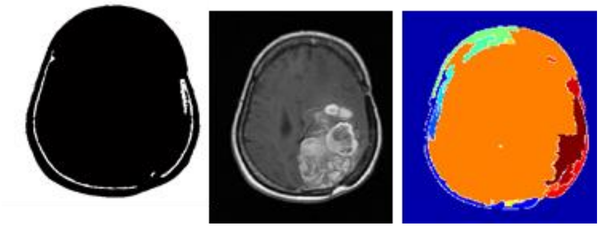



Figure 20. Interior marking by the H minimum method, a) initial image, b) marker of the bottom H = 5, c) watershed on the rebuilt image.

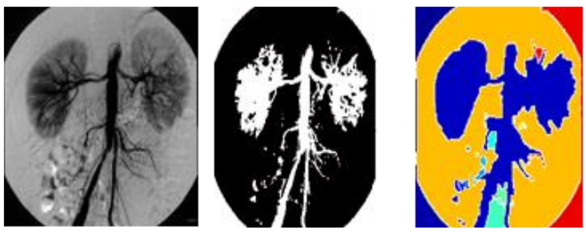



Figure 21. Interior marking by the H minimum method, a) arterio image, b) marker of the bottom H = 5, c) watershed on the rebuilt image.

**c) Constraint by contrast: Thresholding of dynamic of basins**

The idea is to remove the minima with weak contrast. One creates an element structuring disk of size 15. One makes the top hat transform and bottom hat transform. The top hat transform finds the objects, which place themselves in the structuring element and the bottom hat transform of form calculates the gaps between the objects. In order to maximize contrast between the objects one adds the image of the top hat to the original image and one withdraws the result from the image of the bottom hat of form. One makes in continuation the complement of the image found to stress the En valleys using the function imextendmin one removes the local minimax by thresholding the image obtained previously with a favorable threshold according to the histogram of the image and one imposes the total minima on the image (Fig. 22). Thus while applying the watershed all the areas containing minima imposed will be detected. There is one on considerable segmentation what leaves the non powerful constraint by contrast for the segmentation of the medical images. The problem of on segmentation is not solved yet, we then seek to decrease it the maximum while making use of the mosaic image of the original image it is the hierarchical segmentation (Fig. 23).

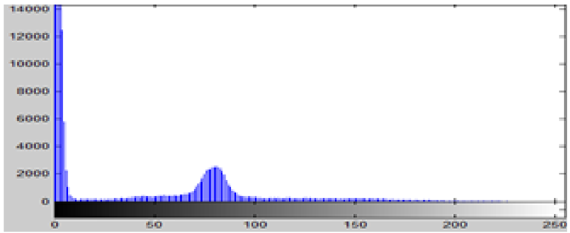



Figure 22. Histogram of the image in level of gray.

(b)

(a)

(c)

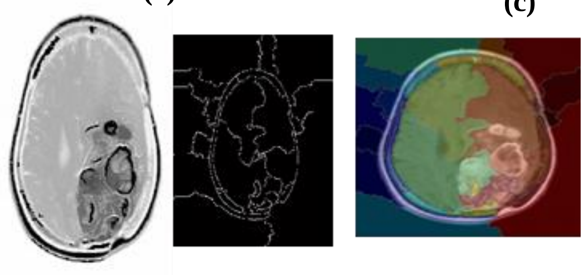


Figure 23. Segmentation by constraint of contrast, a) marked image, b) watershed of the image marked, c) superposition of the watershed on the marked image.

## d) The Hierarchical Segmentation

One builds a mosaic image in the following way. One applies initially the watershed to the image gradient of an image. Then for each minimum of the gradient and thus for each catchment area one determines the level of gray in the initial image (value corresponding at least of the gradient) and one fills the area catchment with this value. One applies the watershed this time to the mosaic image of the original image, although the watershed of an image is completely illegible, it gives a mosaic image good structured. Considering the gradient of the mosaic image, formed of thin vertical walls whose value is the value of the mosaic gradient, one removes the walls lower than all those which surround it. This operation is interpreted like a watershed on a planar graph [24-25]. The segmentation becomes increasingly simple with the wire of the iterations, until going until the disparition of certain essential elements of the image.

The parameters are, the iteration count one changes it according to areas' into interest, the height H which one decreases the gradient in these two cases one always fixes it at 9, and of course the structuring element used in the form of a disc of size equal to 4 for the calculation of the morphological gradient. We add that this type of segmentation allows that one modifies the mosaic image obtained with each iteration by applying to him one of the methods of pretreatment already seen previously (in particular filtering which makes it possible to attenuate discontinuities of the mosaic).

The results would be only better; the following figures show the result.

One sees obviously that it on segmentation a decrease considerably by applying the filters alternate sequential and Gaussian to the mosaic image of the rough image, then applies the algorithm of watershed.

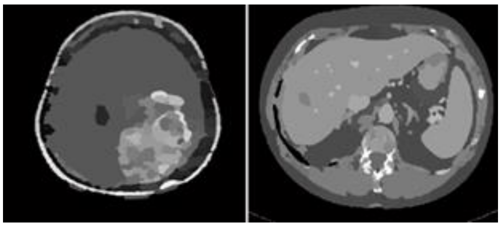


Figure 24. Mosaic image of cranium tumoral and the liver.(1 era iterations).

First iteration two iteration five iteration

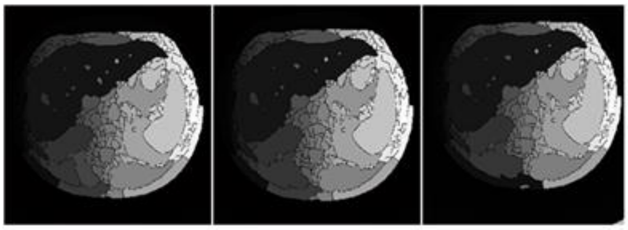


Figure 25. Mosaic hierarchical segmentation of cranium tumoral (MRI)

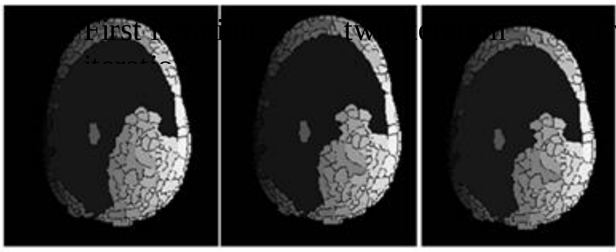


Figure 26. Hierarchical segmentation of liver (CT scan)

## 4. CONCLUSION

In this article we presented a hybrid approach for the segmentation of the medical images by the watersheds based on an approach of filtering then an approach of marking and finally by a process of hiearchisation.

This segmentation is strongly related to the type of image which one seeks to segment, not only because one will be able to seek various types of objects in the same image but also because the characteristics of the image (luminosity-contrast-size -…) influence notably the result of the segmentation. To extract the objects from the image, it is necessary in this approach to have a clear idea of what one seeks to extract, which means that one must have a certain comprehension and medical context on the image to be segmented. The diversity of the methods of segmentation offers several manners to us to segment the image. Indeed there is nota method precise and general to segment an image the good method always should be sought.

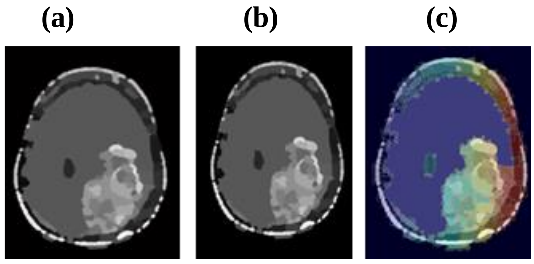



Figure 27. Watershed on the mosaic image filtered by a Gaussian filter, a)mosaic of the original image, b) mosaic smoothed by Gaussian filter, c)watershed on the mosaic image smoothed by Gaussian.

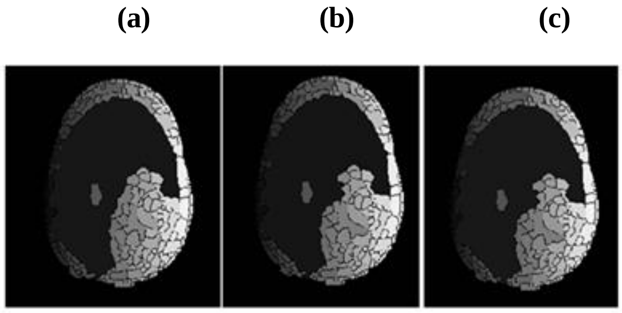



Figure 28. Watershed on the mosaic image filtered by an AFS, a) mosaic of the original image, b) mosaic smoothed by AFS, c)watershed on the mosaic image smoothed by AFS.

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