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Characterization Of The Topography Of Hemorrhagic Stroke By Segmentation Of Hematomas

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ABSTRACT:- The hemorrhagic stroke is caused by the rupture of the cerebral blood vessels. The blood clot formed is called hematoma. The diagnosis of hemorrhagic stroke is the diagnosis of the hematoma. One of the essential parameters for diagnosis is the topography. The knowledge of the topography of the hematoma is crucial information to the care because it is decisive on the type of rehabilitation to adapt to the victim. In this article, we have researched the methods for efficiently detecting the contours of cerebral CT images of hemorrhagic stroke. Four methods were used, namely the gradient methods of Prewitt, Sobel, and Roberts, and Canny's method. The results obtained have shown that the four methods allow the overall detection of contours, but that Sobel and Prewitt have thick contours and are therefore not suitable for CT scan images. Roberts has fine contours but does not accurately detect all forms of the hematoma. Only Canny's method gives an almost perfect detection of the contours of the hematoma and is therefore the most suitable method for detecting contours of cerebral CT images.

Key words: Hemorrhagic stroke, Hematoma, topography, contour detection

I. INTRODUCTION

Medical imaging is one of the technological breakthroughs that has contributed the most to improving the diagnosis of stroke. Indeed the observation of the brain by autopsy was imprecise and incomplete, especially because of the post mortem observation of a frozen organ, which could not account for the displacement of brain tumors causing cognitive disorders. Since 1972, the year in which Godfrey Newbold Hounsfield presented the first CT scan (Bhattacharyya, 2016, Vega et al., 2017), brain imaging techniques have constantly evolved, competing in performance and analytical techniques and in 2d and 3d image reconstruction. From the CT scan with two (02) detectors in 1994 we had already in 2009 CT scan with 310 detectors (Muller et al., 2016, Kerrien, 2018). But despite these remarkable technological advances, it should be noted that the detection of certain parameters is still manual, While, given the urgency of stroke, accuracy and promptness in diagnosis are crucial for outcome. The knowledge of the topography of the hematoma is crucial information to the care because it is decisive on the type of rehabilitation to adapt to the victim. Topography is then a predominant factor of vital and functional prognosis of haemorrhagic stroke. That is why the present work aims to provide tools and methods for automatic treatment of the detection of hematoma contours. More specifically, it aims to "propose mathematical and algorithmic methods for segmenting the brain CT scan image in order to determine the most suitable method for haemorrhagic stroke scan images.

II. MATERIAL AND METHODS

The material consists essentially of brain CT scan images collected at the CT scan unit of Hubert MAGA University Hospital Center (CNHU-HKM) located at the Faculty of Health Sciences (FSS) of Cotonou. This image database was processed in a Matlab version 8.5 environment (R2015a).

1. The characteristic noises of cerebral images: "Pepper and salt" noise and Gaussian noise

2. Known as impulse noise, salt and pepper noise is a noise that assigns a number of pixels in the image a value of 0 or 255 randomly. This noise is due either to data transmission errors, or to sensor element failure, or to the presence of fine particles on the image sensor. A "pepper and salt" noise of order 2 is obtained by adding white pixels and black pixels randomly in an image. It is often characterized by the percentage of pixels replaced.

Impulse noise is defined by the probability density:

$$f(a) = C.e^{-K|a|^{\alpha}} \quad (1)$$

For α =1, it is an exponential noise and for α =2 it is a Gaussian noise.

2. Filtering adapted to brain images

2.1 Gaussian filter

The principle of this filtering is a convolution with a Gaussian. The expression of a Gaussian in dimension 2 of zero mean is:

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

To converse with a Gaussian, we use a convolution mask obtained by discretizing a Gaussian on a nucleus generally of size (2p + 1) x (2p + 1). Some masks are integer coefficients to allow faster calculations.

Gaussian smoothing makes it possible to correct the noise in the homogeneous parts of the images but is less effective than the averaging smoothing. However, it degrades the averaging smoothing less.

The Gaussian filter is coupled to a median filter to effectively smooth the brain CT scan images.

2.2 Median filter

The median of a set of numbers $\{a_1, a_2, \dots, a_n\}$ is the value a_k such that there are as many $\boldsymbol{a_i \leq a_k}$ as $\boldsymbol{a_i \geq a_k}$. It is easily found by sorting the a_i in ascending order and taking the value of the medium. In image denoising, the median filter is used to attenuate isolated pixels, a value very different from their surroundings. This filter makes it possible to obtain good results on pepper and salt noise but remains inefficient for Gaussian noise.

3. Contour detection of the hematoma by gradient methods.

In general, for contour detection of cerebral scanner images, methods based on the first order gradient are quite effective. To achieve this, it is sufficient to perform a good binarization of the image from the thresholding. But the question is: « *which conventional gradient methods is most suitable for segmenting the contours of a hemorrhagic stoke hematoma from CT scan images ?* »

3.1 The first order gradient

The gradient of the image **f** in a pixel M (x, y), if it exists is equal to:

$$\nabla f(x,y) = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right)$$

In practice, we bring these gradients closer together with discrete gradients, which corresponds to rates of variation. This makes it possible to calculate them using convolution with very simple nuclei. The approximation of ∂f / ∂x is done by convolution with [0 -1 1] in this case the discrete convolution formula gives:

$$g(x,y) = \sum_{i=-1}^{1} \sum_{j=0} f(x+i, y+j)k(i,j) = -f(x,y) + f(x+1,y) \simeq \frac{\partial f}{\partial x}(x,y) \quad (3)$$

In the same way, the approximation of ∂f / ∂y is done by convolution with $\begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$:

$$g(x,y) = -f(x,y) + f(x,y+1) \simeq \frac{\partial f}{\partial y}(x,y) \quad (4)$$

This method generally makes it possible to obtain convolution masks in the horizontal direction and the vertical direction.

We will apply here some classical methods of contour detection based on the first order gradient including Prewitt, Sobel, and Roberts whose convolution masks are:

- **Sobel Convolution Mask ((Sobel, 1978, Capelle-Laizé, 2003)**

$h_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}$ $h_y = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}$

➢ **Prewitt Convolution Mask,(Prewitt 1970)**

$P_h = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$ $P_v = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$

➢ **Roberts Convolution Mask (Roberts, 1965)**

$h1 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$ $h2 = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$

3.2 Segmentation by optimization approach.

Two methods of contour detection using the optimization approach are most often cited in the literature. This is the method of Hueckel (1971) (Haton, 1987**)** and the method of Canny (1986). Canny's method is the most used because of its robustness and the simplicity of its implementation.

➢ **Canny Contour Detection**

Let I (x) be a one-dimensional signal representing a jump of amplitude A, embedded in a Gaussian noise n (x) of zero mean and of variance n_o:

$$I(x) = A_{u-1}(x) + n(x) \qquad (5)$$

Where $u - 1$denotes the function of Heaviside.

Let $\theta(x_0)$ be the output at the point x_0 of the convolution of the signal I (x) with a detection operator f (x):

$$\theta(x_0) = \int_{-\infty}^{+\infty} I(x) f(x_0 - x) dx \qquad (6)$$

The problem is to find f (x) such that $\theta(x_0)$ is maximum under the following 3 constraints:

1) **Good detection**: this criterion amounts to looking f (x) antisymmetric and such that The signal-to-noise ratio S/N is maximum:

$$S/N = \frac{A \int_{-\infty}^{0} f(x) dx}{n_0 \sqrt{\int_{-\infty}^{+\infty} f^2(x) dx}} \qquad (7)$$

2) **Good localization**: This criterion corresponds to the minimization of the variance σ^2 of the position of the zero crossings and amounts to maximizing the localization $\wedge$ defined as the inverse of σ^2:

$$\wedge = \frac{A\left|f'(0)\right|}{n_0 \sqrt{\int_{-\infty}^{+\infty} f'^2(x) dx}} \qquad (8)$$

3) **Uniqueness of the answer**: this criterion corresponds to the limitation of the number of local maxima detected in response to a single contour. The average distance between the local maxima, denoted x_{max} is then constrained to the following equality:

$$x_{max} = 2\pi \left(\sqrt{\frac{\int_{-\infty}^{+\infty} f'^2(x) dx}{\int_{-\infty}^{+\infty} f''^2(x) dx}} \right) \qquad (9)$$

Finding f (x) which maximizes the product S/N * $\wedge$ under the constraint that the third criterion is fixed to a constant k then amounts to finding the solution of the following differential equation:

$$2f(x) - 2\lambda_1 f''(x) + 2\lambda_2 f'''n(x) + \lambda_3 = 0 \qquad (10)$$

Who admits as a general solution:

$$f(x) = a_1 e^{\alpha.x} \sin(\omega.x) + a_2 e^{\alpha.x} \cos(\omega.x) + a_3 e^{-\alpha.x} \sin(\omega.x) + a_4 e^{-\alpha x} \cos(\omega.x) \qquad (11)$$

Looking for the operator f (x) as a finite impulse response filter defined over the interval [-W, + W] and having a slope S at the origin, Canny has set the following boundary conditions:

$$f(0) = 0, \quad f(W) = 0, \quad f'(0) = S \ et\ f''(W) = 0$$

These 4 boundary conditions make it possible to determine the coefficients a_1, a_2, a_3 and a_4

f (x) being odd, the solution is extended to x negative with f (x), -f (-x).

Using constrained optimization, Canny found that the best performer was an S/N performance index of $\wedge$ = 1.12.

Since the operator has no simplicity in its implementation, he approximates it in view of its shape by the first operator derived from a Gaussian that has a performance index S/N * $\wedge$ = 0.92 and k = 0.51 gradient of 20%.

III. RESULTS AND DISCUSSIONS

1. Topography of the hematoma.

1.1 Filtering brain scanner images

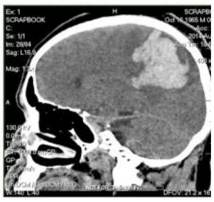
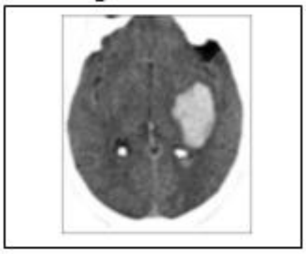


Image N° 1

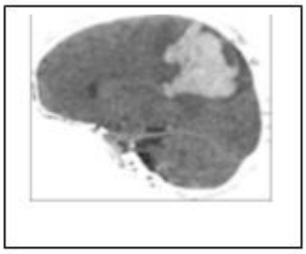
Image N°1 filtered

Fig. 1: Result of filtering brain CT scan images

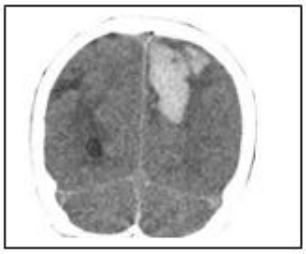
1.2 Segmentation



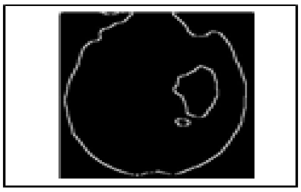
Filtered Image N°1



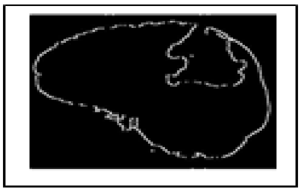
Filtered Image N°2



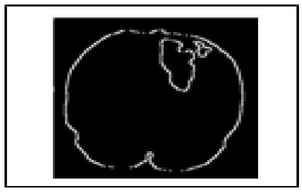
Filtered Image N°3



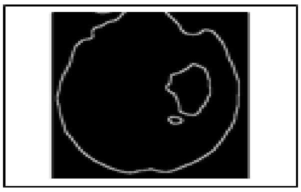
Sobel Contour detection N°1



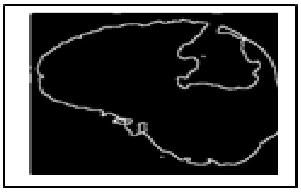
Sobel Contour detection N°2



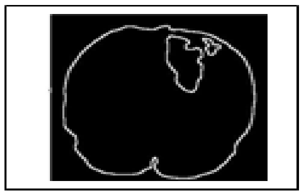
Sobel Contour detection N°3



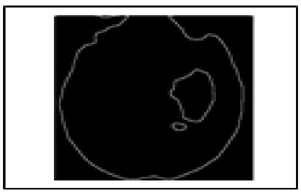
Prewitt Contour detection N°1



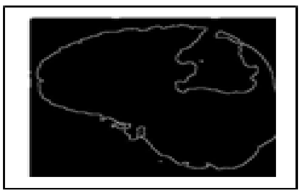
Prewitt Contour detection N°2



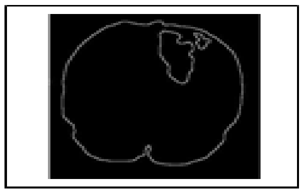
Prewitt Contour detection N°3



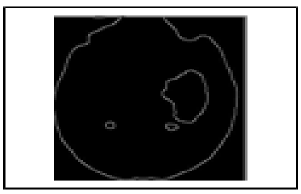
Roberts Contour detection N°1



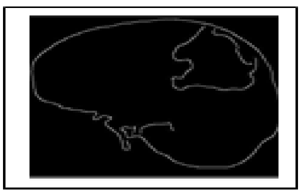
Roberts Contour detection N°2



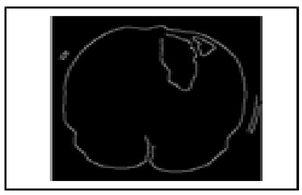
Roberts Contour detection N°3



Canny contour detection N°1



Canny contour detection N°2



Canny contour detection N°3

Fig. 1: Image segmentation result according to Sobel, Prewitt, Roberts and Canny

1.3 Discussions

Overall we can say that the three methods based on the gradient and the method of Canny allow to make a contour detection of brain CT scan images. It should be noted that the Prewitt and Sobel methods have abnormally high edge thicknesses. Consequently, they are not sufficiently adapted to the detection of the contours of the hematoma in the case of brain CT scan images.

Roberts Vs Canny

We realize a manual delineation of the contours of the hematoma and we will try to superimpose the results obtained by each method Roberts and Canny to the non-segmented images.

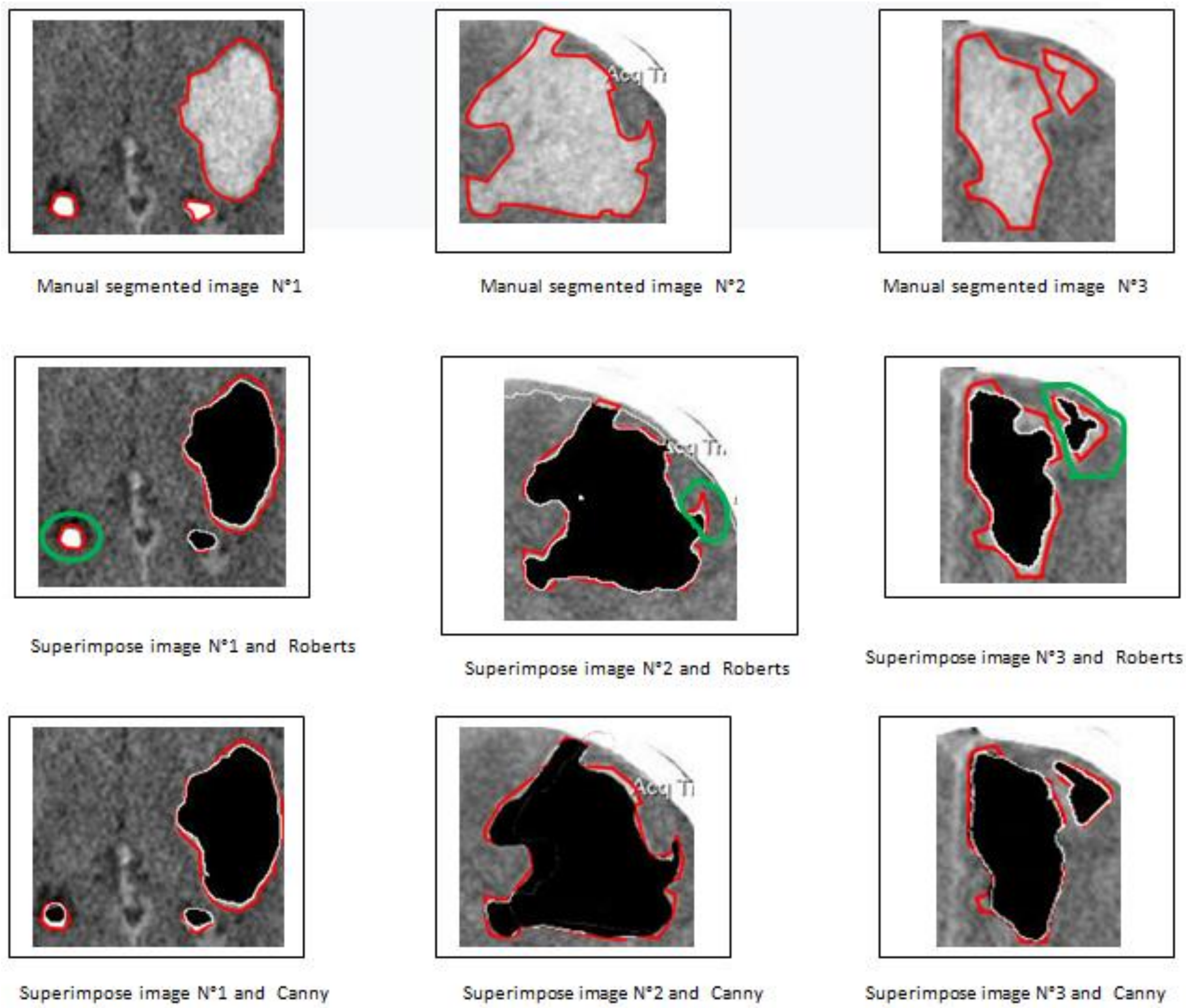


Fig. 3: Overlay of original images and segmented images by Roberts and Canny methods

In these images, the segmented contours are in black and the manual contours are in red. These images overlays make it possible to observe globally that Roberts's and Canny's two methods are effective in detecting contours of CT scan images.Because segmented images are relatively superimposable to real images and have fine outlines. But a careful analysis reveals that Roberts' detection method has flaws:

• At image N°1, even if the segmented image seems to be perfectly superimposable to the original image, the portion highlighted in green in the image was not segmented by Roberts contrary to the method from Canny.

• At image N°2, Roberts' segmented image appears to be as close as possible to the original image but has a major flaw. This is the tail shape highlighted in green in superimposed image N°2. This defect is all the more remarkable as we are in the micro vascularization zone. This zone in the form of that could precisely be an artery or vein fissure therefore a probable cause of the hemorrhage that was not detected by the method of Roberts. As it can be seen in the Canny overlaying image, Canny's method allowed to segment this above indicated portion of the image.

• At the level of the image N° 3 we see that the image segmented by the method of Roberts is rather small compared to the original image. This is a defect that could reduce the estimate of hematoma volume. We also note that the segmentation of the area highlighted in green in the image (butterfly-shaped area) gives a shape completely different from the shape of the original image. This defect can cause an erroneous diagnosis and therefore distort the parameters of the support. Which is not the case with the segmented image by Canny's method.

IV. CONCLUSION

We can say that the four methods studied here make it possible to segment cerebral scanner images globally. Gradient methods are quite sensitive to noise, but a good filtering method allows them to be used for edge detection. The Roberts detection method provides finer contours than those of Prewitt and Sobel, but has some defects related to the non-detection of certain areas of the image and the non-compliance of the detected dorms. Canny's method which is less sensitive to noise, has fine contours and allows segmenting the brain CT image. It respects the shapes of the original image and detects all parts of the image. The contours detected by Canny may not be totally closed, but we can conclude that the Canny edge detection method is the most suitable for the detection of contours of brain CT scan images.

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