Segmentation of brain MRI images

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Abstract— In this work we present a segmentation of brain magnetic resonance imaging (MRI) images based on the multi detector scales canny. The objective is to delineate the outline of a tumor in an magnetic resonance imaging (MRI) image of the brain reaches a frontal meningioma. Accurate and robust segmentation of brain tissue donated by MRI is a very important issue in many applications such as surgery and radiotherapy. The detector of multi-scale Canny is to use a wavelet transform, which is obtained by orthogonal projection of the image on the base affine space of wavelet multi-scale, we obtain an approximation space and retail space. From the latter we calculate the modulus images of details, which is used to extract the local maxima. These maxima are a decomposition multiscale edges, so we have a set of maxima at different scales, we membered to keep only the most significant contours.

Keywords: Segmentation, Canny detector, multi-scale wavelet, IRM, tumor.

I. INTRODUCTION

Segmentation is an image processing operation which aims to partition an image into homogeneous regions composed of pixels with the same characteristics according to predefined criteria. Most methods of image segmentation requires the adjustment of several control parameters to obtain good results but the multi sensor scales canny requires no fitting parameters.

The multi-scale analysis is to decompose the image on a wide range of scales, an operation that we can compare it to a mapping.

At each level, the image is replaced by the approximation most appropriate one can be drawn. Going the coarsest scale to the finer performances we access more and more accurate the image. The analysis is done by calculating what differs from one scale to another that is the details for a given resolution.

In one image a contour is an abrupt change in gray level, it is also defined as the boundary between two dissimilar regions. The contour extraction is to identify the significant features of the image.

II. PRESENTATION OF DATA

The data consist of magnetic resonance imaging (MRI) images of healthy brain and an magnetic resonance imaging (MRI) image of a brain with a tumor (frontal meningioma).

III. CONTINUOUS WAVELET TRANSFORM AND MULTI SCALE ANALYSIS

The continuous wavelet transform of a function f(x) is defined by the expression [1]:

\[ W[f(x)](a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(x) \psi^*(\frac{x-b}{a}) dx \]  

(1)

\( \Psi \): a wavelet
\( \Psi^* \): the complex conjugate of \( \Psi \).

« a » : scale and «b» : the position

A. Two dimension (2D) directional wavelet

For two dimension (2D) wavelet must vary the integration variable and the translation parameter x in \( R^2 \) and not in \( R \) [2] [3].
A wavelet is a function that checks the condition of eligibility following:

$$a_0 \int_{-\infty}^{\infty} \left| \frac{\partial^2 g}{\partial s^2} \right| ds < \infty$$  \hspace{1cm} (2)

In one image, the edges can be oriented in any direction along an edge, the image appears quite regular (unless it crosses another edge).

While two dimension (2D) for information in a given direction, it must involve a third parameter, an angle. This defines the directional wavelet transform.

Either a 2D Wavelet. The directional wavelet transform [4] of a function is defined for $$f \in L^2(\mathbb{R}^2)$$, for $$x \in \mathbb{R}^2, \alpha > 0, \theta \in [0,2\pi)$$ by:

$$Wf(x,\alpha,\theta) = \int_{\mathbb{R}^2} f(x,y) \frac{1}{\sqrt{\alpha}} \varphi(\frac{x-y}{\alpha}) e^{-i\theta y} dy$$ \hspace{1cm} (3)

Where $$\mathbb{R}^2$$: Denotes the rotation matrix

$$R^2 = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$$ \hspace{1cm} (4)

B. Discrétisation

The forms referred to above are continuous and can not be implemented as such, they must be discretised [5]. The principle is to take a discrete set of scales, and for each scale we take a discrete set of translation parameters covering the whole domain of definition of the image. We can discretise the wavelet transform by sampling the "a" scale and translation parameters "x" on a regular basis:

$$a = a_0^n$$ \hspace{1cm} (5)

With : $$n = 1 \ldots \alpha_{max}$$

The properties of the continuous wavelet transform are then preserved, especially the translation invariance. As we can discretise the wavelet transform is sampled scales are choosing :

$$a = a_0^\alpha$$ \hspace{1cm} (6)

With : $$\alpha_0 > 1$$

It runs well the frequencies of the signal much more quickly, while remaining accurate high frequencies (small scales). The most popular choice is to take $$a_0 = 2$$: the scales are discretized on dyadic values. This method is obtained by taking the formula for the continuous wavelet transform of a function $$f \in L^2(\mathbb{R})$$, and discretising the scale parameter depending on the values $$(2^j)_{j \in \mathbb{Z}}$$ is given by the equation:

$$\forall f \in L^2, \forall \alpha \in \mathbb{R}, Df(x,2^j) = \int_{\mathbb{R}} f(y) \frac{1}{\sqrt{\alpha}} \varphi(\frac{x-y}{\alpha 2^j}) dy$$ \hspace{1cm} (7)

IV. MULTI SCALE ANALYSIS

The multi-resolution analysis algorithm was proposed by S. Mallat. This algorithm is designed to extract the characteristics of a signal by analyzing at various scales. The decomposition is performed by a bank of filters (low pass and high pass) followed by a decimation along the lines and columns.

The drawback of the algorithm of Mallat is the decimation, we can not do a pixel by pixel correspondence between different resolutions.

A. Algorithm holes

In this type of transformation in the size of the detail band remains invariant regardless of the scale. The use of the algorithm creates a hole redundancy of information that keeps the translational invariance at every level of decomposition. In addition, it provides good spatial localization of lower frequencies [6] [7] [8]. But its drawback is the on échantonnage of the local maxima that diffuses through the scales.

To overcome the drawbacks of the algorithms mentioned above, we will adopt the algorithm by convolution cascade B-spline, which analyzes the image on scales small enough and are close to each other.

B. Convolution algorithm by cascade B-spline

The convolution algorithm by cascade B-spline can be interpreted as a filter bank with high-pass filter is a filter bypass $$Dx$$ and $$Dy$$, and low-pass filter is the mask B-spline $$\varphi$$ [9]. At each step, the low-frequency component is convoluted on the one hand by the low pass filter $$\varphi$$:

$$f \ast \varphi \ast \varphi \ast \ldots \ast \varphi$$ \hspace{1cm} (8)

On the other hand by a high-pass filter bypass horizontal $$Dx$$:

$$W^f(x,y) = f \ast \varphi \ast \varphi \ast \ldots \ast \varphi \ast Dx$$ \hspace{1cm} (9)

And finally by a vertical pass filter $$Dy$$:
To perform the decomposition in multi-scale gradient, Mallat and Zhong [9] we construct a wavelet belonging to the family of splines. This wavelet is associated with a discrete decomposition that approximates the first derivative of a Gaussian, which allows for some important properties:

- Compact: performs convolutions since the number of coefficients $h$ is necessarily finite, and the scaling function is compact.
- Regularity: this is an essential condition to avoid artifacts related to the irregularity of the scaling function

The mask is used:

$$\Theta = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$  \hspace{1cm} (11)

V. THE MULTI-SCALE DETECTOR CANNY

To work on two-dimensional functions, in particular images, the Canny detector is to use not one but two wavelet transforms oriented (the derivatives along x and y of a smoothing kernel).

whether $\psi$ a two-dimensional wavelet whose two components are derived according x and according to a function B-spline $\Theta(x, y)$

$$\psi^1 = \frac{\partial \Theta}{\partial x}$$ \hspace{1cm} (12)

$$\psi^2 = \frac{\partial \Theta}{\partial y}$$ \hspace{1cm} (13)

with $\psi = (\psi^1, \psi^2)$

with $\Theta$ a smoothing kernel that is positive and isotropic, with separate variables, it will check:

$$\int_{\mathbb{R}^2} \Theta = 1$$ \hspace{1cm} (14)

$\Theta(x, y)$ is isotropic where $\Theta(x, y) = \Theta_1(x).\Theta_2(y)$

We thus define two wavelet transforms, one detects the singularities vertical and horizontal the other singularities [10], whose values on the scale $a > 0$ and point $(x, y) \in \mathbb{R}^2$ are:

$$W^2f(x, y, a) = f \ast \frac{1}{a} \Theta(x/a, y/a) \hspace{1cm} (15)$$

$$W^1f(x, y, a) = \int_{xy} \frac{1}{a} f(x, y) \Theta^2(x/a, y/a) dx dy = f \ast \Theta^2(x, y) \hspace{1cm} (16)$$

with:

$$\Theta^2(x, y) = \frac{1}{a^2} \psi^2 \left( \frac{x}{a}, \frac{y}{a} \right)$$

$$\Theta^0(x, y) = \psi^0 \left( -\frac{x}{a}, -\frac{y}{a} \right) \text{ pour } a \in \mathbb{R}^+$$

Rather than representing $W^2f(x, y, a)$ its two components $W^1f(x, y, a)$ and $W^2f(x, y, a)$ it will be more convenient to use its module and direction [11][12].

$$Mf(x, y, a) = \sqrt{\left| W^1f(x, y, a) \right|^2 + \left| W^2f(x, y, a) \right|^2}$$ \hspace{1cm} (17)

and

$$Af(x, y, a) = \tan^{-1} \left( \frac{W^2f(x, y, a)}{W^1f(x, y, a)} \right) \hspace{1cm} (18)$$

A local maximum of $Mf(x, y, a)$ is the module $(x, y)$ the gradient of the image $f$ convolved with a smoothing kernel of scale $a$.

$Af(x, y, a)$ is the orientation $(x, y)$ the gradient of the smoothed image by the same kernel on the same scale.

A. local maximum

To decide if $Mf(x, y, a)$ is a local maximum, compared to the module in its two neighbors in the directions $Af(x, y, a)$ and $-Af(x, y, a)$ : called the $Mf(x_1, y_1, a)$ and $Mf(x_2, y_2, a)$.

A local maximum of $Mf(x, y, a)$ will in fact be a local maximum in the direction $Af(x, y, a)$ and will be defined in practice as follows :

whether $\varepsilon > 0$ a fixed threshold. $Mf(x, y, a)$ is a local maximum if:

$$Mf(x_1, y_1, a) - Mf(x, y, a) > \varepsilon \text{ at } Mf(x_2, y_2, a) \geq Mf(x, y, a) \hspace{1cm} (20)$$

or

$$Mf(x, y, a) - Mf(x_2, y_2, a) > \varepsilon \text{ at } Mf(x_1, y_1, a) \geq Mf(x, y, a) \hspace{1cm} (21)$$
Serve that small oscillations do not generate local maximum. These local maxima are detected at each scale: either \( \{a\} \) a scale set. If \( Mf(x, y, a) \) is not a local maximum, it is put to 0 as well as \( Af(x, y, a) \). Otherwise it retains its value.

**B. chaining**

Once the maximum modules are calculated on all scales, they must be chained across these scales [13]. We compare card to card to see if, for a pixel \((x, y, a)\) corresponding to a max module, there exists the lower scale, a pixel \((x, y, a-1)\) and its eight neighbors who could be linked to it. To do this, then we select among these 9 pixels one whose gradient direction is close to \( Af(x, y, a) \). The selected point characterizes a contour. Each of these comparisons two by two, until the finest scale.

**VI. RESULTS OBTAINED OF THE APPLICATION OF MULTI-SCALE SENSOR CANNY A PICTURE OF A HEALTHY BRAIN MAGNETIC RESONANCE IMAGING (MRI)**

**A. Application of the magnetic resonance imaging (MRI) image of healthy brain: axial plane**

1) **Vertical singularities**

![Vertical singularities at different scales](image)

(a) Vertical singularities in scale 1  
(b) Vertical singularities in scale 10  
(c) Vertical singularities in scale 15  
(d) Vertical singularities in scale 20

2) **Horizontal singularities**

![Horizontal singularities at different scales](image)

(a) Horizontal singularities in scale 1  
(b) Horizontal singularities in scale 10  
(c) Horizontal singularities in scale 15  
(d) Horizontal singularities in scale 20

3) **Maps of modules of gradient**

![Module of gradient at different scales](image)

(a) Module of the gradient in scale 1  
(b) Module of the gradient scale 10  
(c) Module of the gradient scale 15  
(d) Module of the gradient scale 20

4) **Local maxima of gradient**

![Local maxima of gradient at different scales](image)

(a) Local maxima in scale 1  
(b) Local maxima in scale 10  
(c) Local maxima in scale 15  
(d) Local maxima in scale 20
5) **Result obtained by chaining local maxima of gradient**

![Image](image1.png)

Figure 7. Result after chaining

**B. Application of the MRI image of healthy brain: sagittal plane**

1) **Vertical singularities**

![Image](image2.png)

(a) Vertical singularities in scale 1  
(b) Vertical singularities in scale 10  
(c) Vertical singularities in scale 15  
(d) Vertical singularities in scale 20

![Image](image3.png)

Figure 8. Vertical singularities at different scales  
(a) Vertical singularities in scale 1  
(b) Vertical singularities in scale 10  
(c) Vertical singularities in scale 15  
(d) Vertical singularities in scale 20

2) **Horizontal singularities**

![Image](image4.png)

(a) Horizontal singularities in scale 1  
(b) Horizontal singularities in scale 10  
(c) Horizontal singularities in scale 15  
(d) Horizontal singularities in scale 20

![Image](image5.png)

Figure 9. Horizontal singularities at different scales  
(a) Horizontal singularities in scale 1  
(b) Horizontal singularities in scale 10  
(c) Horizontal singularities in scale 15  
(d) Horizontal singularities in scale 20

3) **Maps of modules of gradient**

![Image](image6.png)

(a) Module of the gradient in scale 1  
(b) Module of the gradient in scale 10  
(c) Module of the gradient in scale 15  
(d) Module of the gradient in scale 20

![Image](image7.png)

Figure 10. Module of the gradient at different scales  
(a) Module of the gradient in scale 1  
(b) Module of the gradient in scale 10  
(c) Module of the gradient in scale 15  
(d) Module of the gradient in scale 20

4) **Local maxima of gradient**

![Image](image8.png)

(a) Local maxima in scale 1  
(b) Local maxima in scale 10  
(c) Local maxima in scale 15  
(d) Local maxima in scale 20

![Image](image9.png)

Figure 11. Local maxima of gradient at different scales  
(a) Local maxima in scale 1  
(b) Local maxima in scale 10  
(c) Local maxima in scale 15  
(d) Local maxima in scale 20
5) Result obtained by chaining local maxima of gradient

![Figure 12. Result after chaining](image)

VII. RESULTS OBTAINED OF THE APPLICATION OF MULTI-SCALE SENSOR CANNY A PICTURE OF A MRI BRAIN WITH A FRONTAL MENINGIOMA

1) Vertical singularities

![Figure 13. vertical singularities at different scales](image)

- (a) Vertical singularities in scale 1
- (b) Vertical singularities in scale 10
- (c) Vertical singularities in scale 15
- (d) Vertical singularities in scale 20

2) Horizontal singularities

![Figure 14. horizontal singularities at different scales](image)

- (a) Horizontal singularities in scale 1
- (b) Horizontal singularities in scale 10
- (c) Horizontal singularities in scale 15
- (d) Horizontal singularities in scale 20

3) Maps of modules of gradient

![Figure 15. module of gradient at different scales](image)

- (a) Module of the gradient in scale 1
- (b) Module of the gradient in scale 10
- (c) Module of the gradient in scale 15
- (d) Module of the gradient in scale 20

4) Local maxima of gradient

![Figure 16. Local maxima of gradient at different scales](image)

- (a) Local maxima in scale 1
- (b) Local maxima in scale 10
- (c) Local maxima in scale 15
- (d) Local maxima in scale 20
5) Result obtained by chaining local maxima of gradient

![Figure 17. Result after chaining](image)

VIII. INTERPRETATION OF RESULTS

Figures (3, 4, 8, 9, 13, 14) of the different magnetic resonance imaging (MRI) images show that the horizontal and vertical singularities are detected. When we go to finer scales coarse scales we see that the image quality decreases which is due to blur induced by the smoothing operation. From the horizontal and vertical singularities, we obtain maps of modules of the gradient (Figure "5, 10, 15"). Analysis of these shows and small scale we can detect the finest details, and going to the coarse scales, only the important details are present.

Maps of local-maxima (Figures "6, 11, 16") are obtained by combining the cards guidance modules and those of the gradient. We note that while the fine scale local maxima we see all the details, even the insignificant and that due to the detection of noise peaks. On intermediate scales we find that only significant contours and boundaries between the structures of the image are detected. From the coarse scales the details disappear. After chaining (Figures "7, 12, 17") we find the contours of the most common among the scales, so the most significant contours.

IX. CONCLUSION

The application of this method to magnetic resonance imaging (MRI) images of a healthy brain and one with a tumor has led to very significant results. Indeed, the different brain structures have been well localized in both types of images and the tumor was well circumscribed in the image reaches the brain. These results show that the method developed is suitable for this type of treatment and could be used advantageously in surgery and radiotherapy.

REFERENCES


