A SEGMENTATION'S TECHNIQUE FOR VOLUMETRIC CALCULATION OF MULTIPLE SCLEROSES IN NUCLEAR MAGNETIC RESONANCE IMAGING.

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SUMMARY

We are suggesting a new approach to NMR image segmentation for multiple scleroses volume quantification. The choice of a segmentation technique is conditioned by whatis known in NMR acquisition artefacts. This research has been conducted in collaboration with the Lille Neuroradiology Laboratory leading to the implementation of a disease development index.

SEGMENTATION.

1.1. Introduction.

Calculating the volume of tumors from NMR X-rays is a mean that enables to quantify developments in diseases or positive results in treatments. Its clinical implementation is going to depend on the development of automatic or semi--automatic segmentation techniques. Developping such methods is also important in investigations on degeneration diseases like Alzheimer, multiple scleroses, etc ... In research departments, studies are carried out on: white matter volumes, grey matter volumes, cerebrospinal fluids and lesions found in the white matter. Two reasons are restricting the use of manual outlining:

- outlining for grey matter, white matter, and white matter lesions on quite a few NMR X-rays is a time consuming, tedious, indeed even impossible operation.
- manual outlining for one and the same organ carried out by two different persons gives, in most cases, other results.

A great many automatic methods have been implemented. Amongst the most recent ones, we find methods inspired by supervised and non supervised pattern recognition techniques giving results ratified by experts[2]. However, as acquisition conditions are not taken into consideration in these methods, they cannot be reliable, precise nor be reproduced[3]. Other approaches of more classical semi-automatic segmentations have been used for the volumetric study of brain elements. Such methods require human surgery needed to initialize and guide segmentation (pixels classification in homogeneous areas[4], area growths[5], outline sensors[6]).Our approach to segmentation is strongly influenced by edge detector segmentation technique . This segmentation technique goes through different stage :

- Extraction of transition .
- Edge detection from transition modélisation.
- Segmented image reconstruction from the fusion of edge detected in the xand y direction.

We are about to explain in this article the three stages wich goes through the edge detection in the image and in the last stage we will present the results.

1.2. Detection of transitions.

Image pre-treatment.

Pre-treatment consists for the entire image in defining transitions in the x and y image direction. It is treated one line at a time, each line representing a density profile (Fig.01).

Transition dynamics.

For each line out of the density profile , transition dynamics and transition width are extracted. Dynamic extractions are split into three stages.

Extraction of gradients in x direction of the density profile: r(x)

Consider f(x) the density profile and r(x) the gradient extracted in the x direction..

$\forall x \in [0,T]$ x varying from 0 to T

if $\frac{\delta f(x)}{\delta x}$ has the sign of $\frac{\delta f(x-1)}{\delta x}$ then r(x)=r(x-1)

else r(x)=f(x)

Extraction of gradients in '- x' direction of the density profile:i(x)

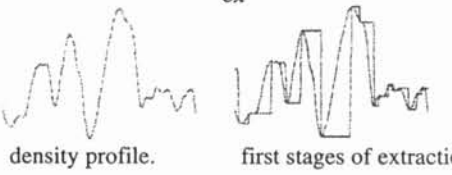
Same treatment for x varying from T to 0 from f(x) to i(x) .

Extraction of transition dynamics:dt(x)

We have then $\forall x \in [0,T]$ for x varying from 0 to T : dt(x)=r(x) - i(x)

We remark dt(x)>0 $\forall \frac{\delta f(x)}{\delta x} > 0$

and dt(x)<0 $\forall \frac{\delta f(x)}{\delta x} < 0$



density profile. first stages of extraction.

second stages of extraction transition dynamics and transition width.

Fig.01 Extraction of transition dynamics.

Density profile treatments.

Two types of noise are found on density profiles: quantification noise and acquisition noise brought in by the sensor. Quantification noise is expressed by the presence of levels in transitions. The acquisition noise often refered to as a white noise is expressed by weak variations in grey layers.

Treatment of quantification noise.

First of all it is important to point out that for transition dynamics extractions, the information to be shown, after treatment is transition dynamics and the beginning or the end of the transition. Indeed the beginning and the end of the transition are reversable by working on the initial density profile or its complementary aspect in relation to the maximum colour.

$\forall x \in [0,T]$

If f(x)=f(x+1) and f(x)>f(x-1) or f(x)=f(x-1) and f(x)>f(x+1)

$$\text{then} \quad f(x) = \frac{f(x-1)+f(x+1)}{2}$$

It can be seen that this treatment does not modify transition dynamics, the beginning of up-going transitions and the end of down-going transitions.

Let dt(x) be the transition dynamics extracted after quantification noise treatment.

Let f(x) be the profile of the initial density and f(x) its complement.

Let ext( ) be the extraction operation of dynamics.

Let tbq( ) be the quantification noise treatment.

We have: $dt(x) = ext(tbq(f(x)) \cap ext(tbq(\overline{f(x)}))$

Please note that the greater the quantification noise, the more will the noise treatment stage need be repeated.

Acquisition noise treatment.

Acquisition noise is expressed by weak amplitude oscillations not visible with the naked eye. Such oscillations correspond to dynamics of weak transition. A threshold is carried out on the transition histogram (Fig.02). The threshold is defined as being the average in transition dynamics.

when the quotient $\frac{S}{B}\uparrow$, threshold $\uparrow$ noise transition <signal transition

when the quotient $\frac{S}{B}\downarrow$, threshold $\downarrow$ noise transition $\rightarrow$ signal transition signal

The threshold defined as such makes it possible to become adapted to acquisition conditions.

Colour histogram for transition endings.

The image histogram is constructed from the frequency of visible transitions towards a colour after. The noise brought by the scanner and the modification of acquisition parameters are about to distort the histogram in the abscissa (colour) direction without altering its amplitude.

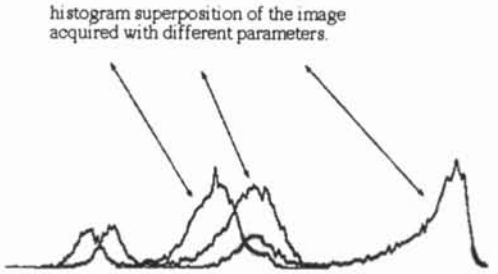


Fig.02 Transitions histogram stability.

The shape stability of transition histogram let us suppose that the treatement using transition information will be stable. This fact will increase the stability and the reproductibility of the segmentation.

1.3. Edge detection from transition modelization.

Edges are characteristic of a sudden and large variation in image grey layers. In practise, segmentation of biomedical images is broken down into two stages. At first, the image is partitioned into areas visually perceptible from statistical and geometrical properties of the image. Subsequently, this initial segmentation is refined and corrected from what is known about the objects present in the image. The gradient methods that at first use a filter to smooth the image and then an edge detector are standard methods that give satisfactory results in cases of images with weak noises (Gradient, Laplacien, Sobel Prewitt).

The problem of images with loud noise led scientists to developping various optimal operators associated a low-pass filter to edge detectors themselves[7].

We are suggesting an edge detection method based on transition modelization through an exponential starting from the real image and from a pre-treatment that makes it possible to define the grey layer transitions in the x and y directions of the image. Treatment and localization of density curves in the x and y direction were dealt with in the previous chapter.

In the first part, we are going to describe transition modelization and edge detection.

In the second part, we will present an image reconstruction from segmented edges in the x and y direction of the image and we shall bring in the notion of minimum edge and maximum edge associated to interpoled edge.

Finally, in the last part, we will make comments on the results obtained.

Transition modelization and edge detection.

The acquisition of a MRI image involves the presence of blurred images in transitions. Indeed, a

blurred image can be due to the partial volume, to dielectrical discontinuities amongst the organs, to scanner resolution, patients moving etc ... It is generally acknowledged that this blurred image caused by the average is correctly modelized by an image gaussian filtering. When it comes to transitions, the result is an ' erf ' type law for which modelization is difficult. We suggest that a transition is modelized using the following function:

$$S_1(x) = A_1 e^{k_1 t} \qquad t \le 0 \ (1) \quad \text{with} \quad t = x - x_i$$

$$S_2(x) = y_i - A_2 e^{-k_2 t} \qquad t \ge 0 \ (2)$$

To improve the modelization, we suppose in a first time there is no discontinuities at t=0 between $S_1(x)$ and $S_2(x)$.Consider $S_1(0) = S_2(0)$, we have then

$$A_1 = y_i - A_2 \quad (3)$$

In a second time, we suppose there is a continuity of the first derivation at t=0.

We have $\frac{\delta S_1(x)}{\delta x} = \frac{\delta S_2(x)}{\delta x}$ in $x = x_I$

then $A_2 = \frac{y_i}{1 + \frac{k_2}{k_1}}$ (4)

We can express (1) et (2) like:

$$S_1(x) = \frac{y_i k_2}{k_1 + k_2} e^{k_1 (x - x_i)} \quad (5)$$

$$S_2(x) = y_i - \frac{k_1 y_i}{k_1 + k_2} e^{-k_2 (x - x_i)} \quad (6)$$

We defined $S(x) = S_1(x) \cup S_2(x)$ the transitions modelisation. We can infer the edge x position in the maximum gradient meaning $\frac{\delta S(x)}{\delta x}$ on [0,T] as $x = x_I$.

Looking for k1,k2 and x_I of S(x) for the best transitions modelizations will give us the best edge position x_I.

Looking for k1, k2, xl parameters for the best modelization possible.

we defined f_i , $i = \{0,1,...,T\}$ the transitions points. we have $S(x) = S_1(x) \cup S_2(x)$ and c $\{x_I, y_i\}$ the edge point in the transition defined with the following formule(Fig.03):

$$d(x_i, y_i) = \sum_{i=1}^{T} abs(f_i - S(i)) \quad \text{minimum.}$$

The criterion for optimum modelization used is the minimum distance between the contours points and their modelization. The minimum distance is calculated from the x_I variation in [0,T] and the y_i variation in [0,y1].We defined the S(x) parameters k1, k2 with the variations of x_I from 0 to T and y_i from 0 to y1 and the following restraints :

$S_1(x_I) = y_i$ then $y_i = \frac{y_i k_2}{k_1 + k_2}$.

$S_1(0) = 1$ then $k_1 = \frac{\log(y_i)}{x_i}$.

$S_2(x_I) = y_i$ then $k_2 = \frac{y_i k_1}{y_1 - y_i}$.

$S_2(T) = y_1$ then $y_i - S_2(T) \le 1$.

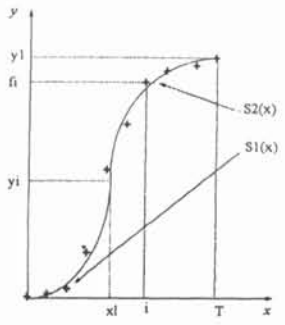


Fig.03 Transitions modelizations.

1.4 Constructing the segmented image.

Segmentation through modelization enables us to define edges from detected transitions in the x and y direction of the image. Fusion in partial segmentations enables us to associate a maximum and minimum edge to edges respectively deducted from the beginning and the end of each grey layer transition. We are going to describe image fusion with an example and define the maximum and minimum edges as well as the reconstructed edges.

Determination of a maximum edge and of a minimum edge.

We define f(x,y)the image and $t_\phi(x,y)$ the transition image in the ø direction.

$$t_\phi(x,y) = \begin{cases} 1 \Rightarrow \frac{\partial f}{\partial x}\sin(\theta) + \frac{\partial f}{\partial x}\cos(\theta) > 0 \\ -1 \Rightarrow \frac{\partial f}{\partial x}\sin(\theta) + \frac{\partial f}{\partial x}\cos(\theta) < 0 \\ 0 \Rightarrow \frac{\partial f}{\partial x}\sin(\theta) + \frac{\partial f}{\partial x}\cos(\theta) = 0 \end{cases}$$

We define mi(x,y) the image of minimum edge .

$$mi(x,y) = 1 \forall \theta \in \{\theta_1, \theta_2\} \forall a \in \{1, \tan(\theta)\}$$

$$\Rightarrow t_\phi(x,y) \neq 0, t_\phi(x+a, y+a) = 0$$

with

$$\forall \theta' \in \{\theta_1, \theta_2\} \forall a \in \{1, \tan(\theta)\}$$

$$\Rightarrow t_\phi(x,y) \neq 0, t_\phi(x+a, y+a) = 0$$

the angles limitation of transition images introduce undesirable points

Elimination of the undesirable points.

mi(x,y) is a minimum edge point if :

$$\forall \theta \frac{\partial f}{\partial x}\sin(\theta) + \frac{\partial f}{\partial y}\cos(\theta) = 0 .$$

we will make the same reasoning for the determination of the maximum edge.

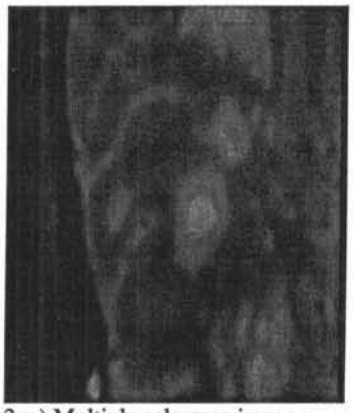
Determination of a reconstructed edge .

The edge points are recorded, if the transition beginning and ending to which they are associated fulfill the following conditions:

The transition beginning and ending in a given direction must not be found on a transition going in the other direction.

The transition beginnings and endings associated to the edge point must be placed on a transition.

1.5. Results.



2.a) Multiple scleroses image.

2.d) Minimum and maximum edges.

2.e) Edge modelization.

CONCLUSION.

We developped in a first stage a segmentation technique in homogeneous area through transition histogram thresold.

However this segmentation method was depending on homogeneous surface area, and most of the time the surface we want to segment are very small and inhomogeneous. Such a consideration induced us to develop an edge detector segmentation technique based on transition modelisation. We can determine with this segmentation technique the maximum edge and the minimum edge. The maximum contour will be , for example in the segmentation of the multiple scleroses disease, the lesion part that can evolute, and the minimum contour will be the stable part of the lesion. In another context we will use the minimum and maximum contour to define a precision indice on the surface calculation from the contour modelisation.The research work carried out in medical scanning enabled us to create a volumic quantification tool for multiple scleroses in MRI. The restraints for such a tool in clinical application are as follow: automatic segmentation, segmentation reproduction capability, volume calculations and precision assessment.

The MRI research work enabled us to place restraints for segmentation and to determine the advantages and drawbacks for the original solutions we propose. However, a certain amount of problems, like organ reconstruction for volume calculations, are only partly solved.

The research work we are contemplating now regard edge chaining for organ reconstruction, extension of transition detection to all the 3D space directions.

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