Medical Image Segmentation by Multilevel Thresholding Based on Histogram Difference

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Abstract— This paper presents an automatic method of medical image segmentation used inthe study of the Central Nervous System (CNS) by multilevel thresholding based on histogram difference. Our method produced a performance of an 88.6%, for the considered testing images, when the results where compared with those provided by a human expert.

Keywords- medical image, Magnetic Resonance Imaging (MRI), image segmentation, automatic thresholding

I. INTRODUCTION

The increase and the specificity of the new neuroimaging techniques permit us to obtain a new vision of pathological substrate, enabling a better comprehension of the causes and underlying processes of the different neurological diseases. The medical images segmentation is an open question, considering the variety of individual pathologies and the related clinical requirements for accuracy. The automatic (or semi-automatic, with minimal operator interaction) segmentation methods for specific applications are still current topics of research. This is due to the large variability of anatomical structures and challenging needs of reliable, accurate and diagnostically useful segmentation, as shown in [1] and [2].

Image segmentation is an essential process for most image analysis subsequent tasks. In particular, many of the existing techniques for image description and recognition depend highly on the segmentation results [3], [4], [5] and [6].

Thresholding is an important approach for image segmentation. The purpose of thresholding is to distinguish different classes of interest from the determination of thresholds which separate the relevant objects. The simplest methods of thresholding employ only a threshold to isolate the objects of interest, which in many situations don't result to be a good segmentation of the image. The multilevel thresholding is an extension of the segmentation method in two levels that allows segmentation of the image in multiple classes [7]and [8].

Several multi-level thresholding methods have been proposed for image segmentation. W. Tsai [9] suggests a method based on the conservation of moments of the histogram. J. Cocquerez et al. [10] present a thresholding method based on histograms of distribution in gray levels, which employs the criterion of minimization of the sum of inertia to determine the thresholds among the different classes. G.X. Ritter and J. Wilson [7] describe an approach for multilevel segmentation that extends the bimodal approach proposed by N. Otsu [11]. M. Cheriet et al. [12] propose a general recursive solution, that also is an extension of the method of N.Otsu. H. Yan [13] proposes three approaches: Thresholding of Yan-Otsu, Thresholding of Yan-Kittler, Thresholding of Yan-Huang, named Unified Method of thresholding of Yan. P.R. Martins and J. Facon [14] present a method of multimodal histogram thresholding based on the notion Watershed by immersion and a multimodal thresholding method by simulating of immersion in the presence of markers, both based on the notion of relief adapted to the context of the histogram. S. R. Aboud Neta et al. [15] present a method, based on the division of the histogram into sub-regions, where a threshold is determined for each of these sub-regions.

In general, these methods have good results, however, approaches that employ exhaustive research, demand a high processing time, making use of these methods impractical when the number of thresholds exceed three [16]. Other approaches are not fully automatic, requiring a prior knowledge of the number of thresholds or classes in the histogram. Others are sensitive to the uniformity of the histogram, a factor extremely important for the success of segmentation.

II. THEORETICAL BASIS

A. *Medical Image Modalities and their Applications*

Nowadays, the techniques of magnetic resonance (MRI) are increasingly used to delimit and enter into the etiologic analysis of Central Nervous System diseases. The Central Nervous System (CNS), is composed by the brain and the spinal cord, which is submerged in cerebrospinal fluid (CSF).

The human brain is made up of three parts: the forebrain, the brainstem and the hindbrain. Each of the structures is made of smaller substructures. CSF is a clear bodily fluid that occupies the subarachnoid space in the brain (the space between the skull and the cerebral cortex). The striatum is a structure of the midbrain that is further composed of two substructures, the caudate striatum and the Putamen.

The most advanced techniques in the field of neuroimaging may be classified as functional MRI, diffusion MRI or structural MRI. These acquisition and postprocessing technologies are made up to be effective in more specific subprocesses (these are: sequences and acquisition parameters, filters and statistical analysis) that are critical in the moment of getting robust and consistently results of the patients's examinations.

Thus such essential tasks as the delimitation and selection by the segmentation of the study areas or the correct disposal of the artifacts and disturbances present in the images (filtering) are still difficult questions to resolve, yet, in an optimal and general way, as there is still no common scientific criterion.

Accordingly, analyzing these images for computer aided diagnosis and therapy planning is becoming a more challenging research task. Nevertheless the segmentation of non easy images is one of the most difficult tasks in image processing. Segmentation accuracy determines the success or failure of computerized analysis procedures [1] and [17].

Despite the advances in novel analytical imaging techniques MRI, MRI Morphometry, functional MRI, Diffusion Tensor Imaging (DTI), CT, Positron Emission Tomography (PET), help physicians to diagnose in a qualitative sense. However, new challenges in patient – specific treatment, targeted delivery of drugs to the brain and image-guided treatment call for a quantification of the imaging data. The current lack of basic understanding of the intracranial dynamics also prevents the implementation of effective invasive drug delivery into the brain [18].

B. Thresholding

Thresholding is a method of segmentation based on the similarity to be able to choose one or more thresholds to find the best separation among groups of pixels with similar features [19].

A histogram of intensity of an image composed of bright objects on a dark background, known as bimodal histogram, will have two dominant regions of intensity, one formed by the pixels of the objects and the other by pixels of the background.

An alternative to extract the objects of the background is selecting a threshold T somewhere among these regions in order to separate them. Therefore, any image pixel whose intensity is greater than or equal to T is called a point object, otherwise it is called the background point.

Formally, Thresholding converts an input image f (x, y) of N levels of gray in an image g (x, y) with a number of gray levels smaller than N, defined as:

$$g(x,y)=\begin{cases} 1\ (object), & if\ \ f\ (x,y)\geq T \\ 0\ (background), & if\ \ f\ (x,y)<T \end{cases} \quad (1)$$

where pixels labeled as 1 correspond to objects, whereas pixels labeled as 0 correspond to the background.

Several methods have been proposed to find the maximum points (corresponding to the peaks) and then to select the threshold value as the minimum point among them (located somewhere in the valley) in order to obtain a better separation among regions .

So, the main problem of Thresholding is to select a T value that gives the best segmentation. However, due to the possibility of many points to be maximum and minimum in an image, even the determination of peaks and valleys is already a non-trivial problem [20].

When just one threshold is used to segment the image, the process is called Global Thresholding. However, rarely the histogram of real images shows two distinct peaks associated to the background and the objects [21]. The non-uniform lighting or the presence of noise, for example, can generate changes on gray levels of the objects and of the background making the use of a single threshold inappropriate for the image segmentation. In this case, better results can be obtained by analyzing the intensities of the pixels in an image region to determine local thresholds, method known as Local Thresholding.

Global Thresholding can be generalized to consider an arbitrary number of levels. In a multilevel Thresholding, the purpose is to determine the various T values that effectively isolate the regions of interest, as illustrated in Figure 1.

In a multilevel Thresholding, the image g (x, y) can be segmented:

$$g(x,y)=\begin{cases} L_1, & if\ \ \ \ \ \ \ \ f\ (x,y)\leq T_1 \\ L_2, & if\ \ T_1<f\ (x,y)\leqslant T_2 \\ L_3, & if\ \ T_2<f\ (x,y)\leqslant T_3 \\ L_4, & if\ \ \ \ \ \ \ \ f\ (x,y)>T_3 \end{cases} \quad (2)$$

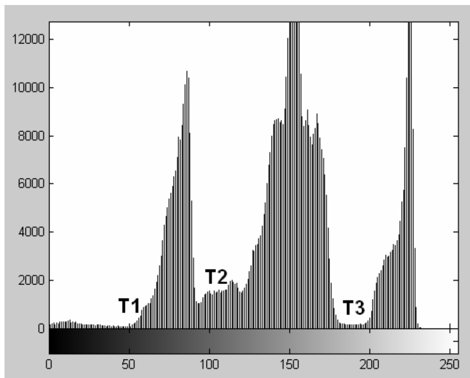

Figure 1. Threshold value multiples

III. Proposed Method

The proposed multi-level thresholding automatic method consists of three phases: preprocessing, processing and postprocessing.

In the preprocessing phase, the image is filtered with a Gaussian filter to eliminate noises. Then, the image histogram is calculated and smoothed with a filter pyramid *1 x n*, where *n* is defined by the user. The filter type pyramid has the edges increased symmetrically in one unid until the central pixel, which will possess the greatest value. This filter is applied in the image histogram to minimize the presence of shallow valleys and short peaks that could cause the excessive location of thresholds.

An array (z) is constructed in the processing phase, of the differentiation of the histogram (h):

$$z(i)=\begin{cases}1, & if \quad h(i+1)-h(i)<0 \\ 0, & if \quad h(i+1)-h(i)>0\end{cases} \qquad (3)$$

After further, new differentiation of the array z is performed:

$$z(i)=z(i)-z(i+1) \qquad (4)$$

A list of the intensities in the histogram corresponding to peaks (5) and thresholds (6) is determined:

$$Peaks \quad list=h(find(z=-1)+1) \qquad (5)$$

$$Thresholds \quad list=h(find(z=1)+1) \qquad (6)$$

The number of possible classes is equal to the number of thresholds increased by one. Then, a test is performed on each class, through an input parameter defined by the user, to see if the class contains a minimum percentage of pixels related to the total of pixels in the image. The threshold whose class to attend this parameter is accepted, otherwise, is rejected and the class is grouped to the next, so that all classes have a minimum percentage of pixels required.

In the postprocessing, colors are assigned to the pixels according to the list of threshods produced. As a final result, a color image representing the segmentation is returned.

IV. EXPERIMENTS

To evaluate the proposed method, a collection of 30 color and gray scale images, without loss of information, in BMP format and with spatial resolutions from 512x512 pixels were used. For each image it was determined manually the ideal thresholds.

The quality of the results was obtained by a performance indicator for the thresholds. The performance indicator proposed by P.R. Martins and J. Facon [14] is based on simultaneous evaluation of the amount and accuracy of the thresholds found. The value of performance indicator for the histogram *H* of the base *B*, denoted *PM [B, H]* is given in (3) and (4):

$$P_M[B,H]=\frac{h}{k.(1+D)} \quad para\, k\geqslant h \qquad (3)$$

$$P_M[B,H]=\frac{k}{h.(1+D)} \quad para\, 0\leqslant k<h \qquad (4)$$

Where *h* is the amount of thresholds expected , *k* is the amount of thresholds found and *D* represents the sum of the module of the difference between the thresholds values expected and the thresholds values found.

The calculation for *D* is made by a set *Z* of pairs of thresholds (t_i, w_i) corresponding to the combination of closed elements of *T* and *W*, where each value t_i and w_i can only appear in a single pair of *Z*, (5) and (6).

$$Z=[(t_1,w_1),(t_2,w_2),\ldots,(t_h,w_h)] \quad para \quad k\geqslant h \qquad (5)$$

$$Z=[(t_1,w_1),(t_2,w_2),\ldots,(t_k,w_k)] \quad para \quad 0\leqslant k<h \qquad (6)$$

Having defined the set Z, the value of D will be as:

$$D=\sum_{i=1}^{h}\frac{[t_i-w_i]}{256} \quad para \quad k\geq h \qquad (7)$$

$$D=\sum_{i=1}^{k}\frac{[t_i-w_i]}{256} \quad para \quad 0\leq k<h \qquad (8)$$

The denominator 256 in the calculation of *D* is necessary to provide a differentiation between a threshold found, although inaccurate, and a threshold not detected. Thus, failure to detect a threshold will be more severely penalized than an inaccurate threshold .

V. RESULTS

Table I and figure 2 show the minimum, average and the maximum results for the performance indicator found for the collection of images. Each image resulted in a thresholds list ranging from 1 to 10.

TABLE I. PERFORMANCE INDICATOR

Thresholds Number	Parameters		
	Min	*Average*	*Max*
1	100,00	100,00	100,00
2	50,00	75,00	100,00
3	66,67	86,11	100,00
4	66,67	87,78	100,00
5	100,00	100,00	100,00
6	75,00	87,05	100,00
8	88,89	94,44	100,00
9	90,00	90,00	90,00
10	76,92	76,92	76,92
Average	79,35	88,59	96,32

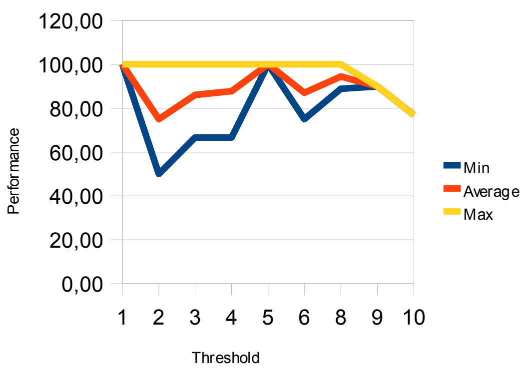

Figure 2. Performance indicator for the thresholds found

Figure 3 shows the segmentation of a medical image with proposed method for three thresholds or four classes.

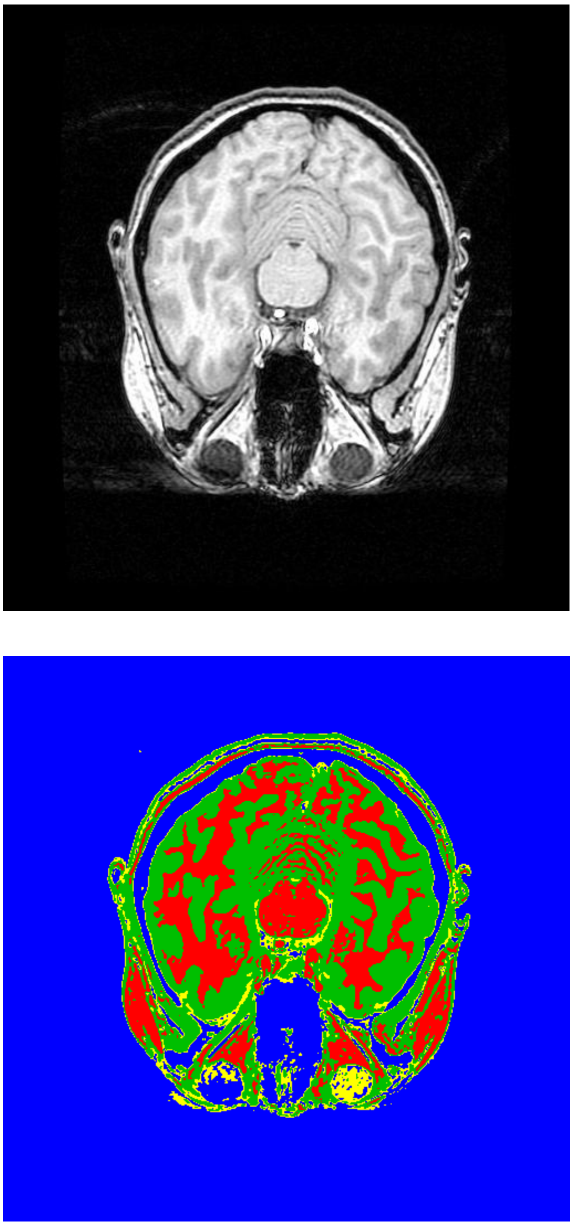

Figure 3. (above) Original test image. (bellow) automatic method with segmentation in four classes

VI. Conclusion

We presented a multilevel thresholding segmentation method to medical images. The detection of peaks and valleys through the differentiation of the smoothed histogram was fast and flexible allowing the effective location of the ideal thresholds. Our method produced a performance of an 88.6% for the test images considered. A future work is the extension of this approach to different types of images.

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