Novel approach for segmentation of brain magnetic resonance imaging using intensity based thresholding

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***Abstract*—Magnetic resonance imaging (MRI) is an advanced medical imaging technique providing rich information about the human soft tissue anatomy. The goal of brain MRI segmentation is to accurately identify the principal tissue structures in these image volumes. There are many methods that exist to segment the brain. One of these, conventional methods that use pure image processing techniques are not preferred because they need human interaction for accurate and reliable segmentation. Unsupervised methods, on the other hand, do not require any human interference and can segment the brain with high precision. In the light to this fact, A novel approach is developed. Our approach is based on intensity based thresholding to get boundaries between cerebrospinal fluid (CSF), Gray Matter (GM), White Matter (WM) and others. After the brain extraction by mathematical morphology algorithm, we proceed to brain segmentation. The CSF is segmented by using orthogonal polynomial transform. Finally the gray matter and white matter regions in the MRI are segmented based up on the intensity values. Experimental results show that the proposed method achieves reasonable good segmentation.**

Keywords- Brain segmentation, Magnetic resonance imaging, skull stripping, Morphological operator, White Matter (WM), Cerebrospinal fluid(CSF), Thresholding, Gray matter (GM)

I. INTRODUCTION

Magnetic resonance imaging (MRI) is an important diagnostic imaging technique to obtain high quality brain images in both clinical and research areas because it is virtually non invasive and it possesses a high spatial resolution and an excellent contrast of soft tissues [1], [2]. MR images are widely used not only for detecting tissue deformities such as cancers and injuries, but also for monitoring patients with neurodegenerative diseases such as Parkinson's disease, Alzheimer's disease (AD), epilepsy, schizophrenia and multiple sclerosis (MS) [1] – [6]. MRI is also used for studying brain pathology. In order to offer useful and accurate clinical information, the segmentation and recognition algorithms of MR images are becoming important subject of the study on medical image processing. Brain tissue segmentation typically classifies voxels into grey matter (GM), white matter (WM), and Cerebrospinal fluid (CSF). Segmentation of MR brain images into different classes of tissue is an important task for improving the understanding of many neurological disorders.

Most MRI segmentation techniques can be categorized into automatic and semi-automatic methods [7], [15]. Segmentation of MRI is performed manually by trained radiologists, but now there are many recent developments are employing to segment the MRI, since manual segmentation of images is a time consuming process and is susceptible to human errors. So there is a need for computer analysis of MRI such as precise delineation of tumours and reliable reproducible segmentation of images.

In segmenting MRI data, we have mainly three considerable difficulties: noise, partial volume effects (where more than one tissue is inside a pixel volume) and intensity in-homogeneity [1]. The majority of intensity in-homogeneities are caused by the irregularities of the scanner magnetic fields–static (B0), radio-frequency (B1) and gradient fields, which produce spatial changes in tissue static. Partial volume effects occur where multiple tissues contribute to a single voxel, making the distinction between tissues along boundaries more difficult. Noise in MR images can induce segmentation regions to become disconnection. Two main reasons lead to the problem of partial volume effects. On the one hand, due to the imaging resolution, the complexity of tissue boundaries causes many voxels to be composed of at least two or more tissues. On the other hand, the constitution of a brain cannot be restricted to only three pure tissues (GM, WM, and CSF). Therefore, due to the characteristics of brain MRI, development of automated segmentation algorithms require preprocessing which includes denoising, striping of skull.

This paper presents a new segmentation method for denoising and skull striping using a sequence of mathematical morphological operations: erosion and dilation and their compositions i.e., opening and closing. The operators of morphological processing are particularly useful for the analysis of binary images so that MRI images needed to be previously binarized. After the skull striping process, the cerebrospinal fluid is segmented by using orthogonal polynomial transform [12].

Therefore our present approach consists of two stages, one is preprocessing and the second is segmentation. In the first stage, the skull from the sample image is stripped and in the second stage, the cerebrospinal fluid (CSF) region is

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segmented from the skull stripped image using orthogonal polynomial transform. Finally the gray matter and white matter regions are segmented from the skull stripped image based on intensity values.

The next section presents some basics on morphological operations. Section 3 describes our methodology for stripping skull. Section 4 describes the segmentation of grey matter (GM), white matter (WM), and Cerebrospinal fluid (CSF). The experimental results for the proposed method are demonstrated in section 5 and finally drawn some conclusions and future work perspectives in section 6.

II. MATHEMATICAL MORPHOLOGY CONCEPTS

Mathematical morphology is a non-linear image analysis technique that extracts image objects information by describing its geometrical structure in a formal way [7]. Mathematical morphology has been largely used in several practical image processing and analysis problems [9]. Here we briefly review some mathematical morphology operators and the corresponding operations used in this work.

Mathematical operators take two data as an input: an image to be processed and a structuring element, which is a matrix used for defining a neighbourhood shape and size [1]. By choosing the shape and size of the element, we can influence the morphological operations sensitivity to specific shapes appearing in the processed image. The elementary shapes of symmetrical structuring elements [10] used in the following processing are shown in Fig. 1.

The erosion of binary image I by structuring element S is defined by the formula [1]:

$$I \otimes \Sigma = \{\xi,\psi : \Sigma_{\xi\psi} \subseteq I\} \qquad (1)$$

The dilation of binary image I by structuring element S is defined by the formula [1]:

$$I \oplus \Sigma = \{\xi,\psi : \Sigma_{\xi\psi} \cap I \neq \emptyset\} \qquad (2)$$

Let $f : D \subset R^n \rightarrow R$ be an image function and $g : G \subset R^n \rightarrow R$ be a structuring function. The two fundamental operations of gray-scale morphology, erosion and dilation are defined as:

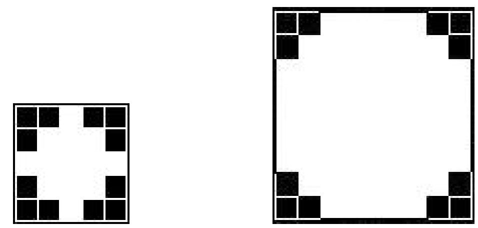
Definition 1: [8] (Dilation) The dilation of the function f(x) by the structuring function g(x), $(f \oplus g)(x)$, is given by:

$$(f \oplus g)(x) = \max\{f(z) + (g_x)(z) : z \in D[g_x]\} \qquad (3)$$

Definition 2: [8] (Erosion) The erosion of the function f(x) by the structuring function g(x), $(f \ominus g)(x)$, is given by:

$$(f \ominus g)(x) = \min\{f(z) - (g_x)(z) : z \in D[g_x]\} \qquad (4)$$

where gx indicates the translation by x $(g_x)(z) = g(z - x)$, and D[gx] denotes the domain of the translated structuring function. The operations of closing and opening are the combinations of erosion and dilation, both using the same structuring element. Morphological opening is erosion followed by dilation and morphological closing is dilation followed by erosion. The Fig.3 shows that in a binarized image there are some remaining pixels that represent the noise. To remove the left-over pixels the opening operation was used.



(a) (b)

Figure 1. Disk shape structuring elements: (a) 2-pixel radius, (b) 5-pixel radius

III. PROPOSED METHODOLOGY FOR STRIPPING SKULL TO SEGMENT BRAIN

This section presents the proposed methodology for segmenting brain MRI images. The fundamental task in brain MRI segmentation is the classification of volumetric data into grey matter, white matter and cerebrospinal fluid but it is not easy as there are some inherent difficulties associated with image segmentation; among them are RF coil in homogeneity, brain tissue susceptibility and other systematic artifacts. Various preprocessing steps have been proposed to deal with some or all of these difficulties. Skull stripping is the first processing step in the segmentation of brain tissue as shown in Fig. 2.

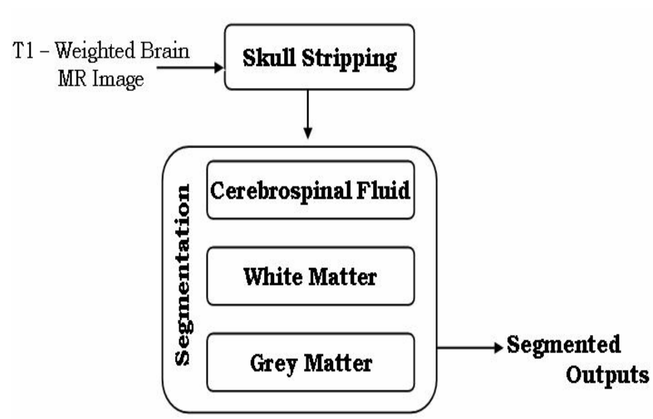


Figure 2. Overview of proposed methodology

In the proposed method for skull stripping, we see the brain surface as a smooth manifold with relatively low curvature that separates brain from non-brain regions. Also, the brain cortex can be visualized as a distinct dark ring surrounding the brain tissues in the T1-weighted axial MR images.

The steps involved in the proposed methodology for skull stripping consists of three steps.

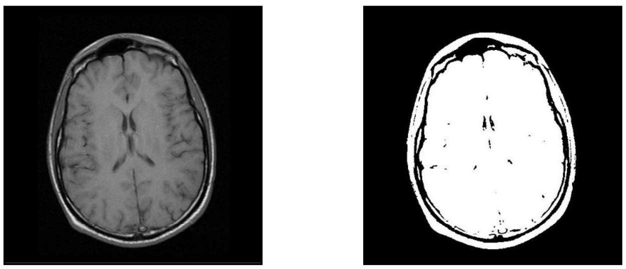
step1: Binarization of every image.

step2: Opening operation and closing operation on every image in the sequence using the structuring element.

step3: Applying the binary mask to the received MRI input image.

A. *Binarization*

Binarization is the process that converts a grey level image into a binary image. The binarization process involves examining the grey-level value of each pixel in the enhanced image, and if the value is greater than the global threshold, then the pixel value is set to a binary value one; otherwise it is set to zero.



(a) (b)

Figure 3. (a) Input Image, (b) Binarized Image

B. *Morphological Operation*

The binary morphological operators are then applied on the binarized image. Elimination of any obstacles and noise from the image is the primary function of the morphological operators [9]. The morphological operators namely, opening and closing are being employed in the proposed method.

1) Opening: An opening operation consists of erosion followed by dilation with the same structuring element. Opening operator consists of an erosion followed by a dilation and can be used to eliminate all pixels in regions that are too small to contain the structuring element. In this case the structuring element is often called a probe, because it is probing the image looking for small objects to filter out the image [11].

The morphological opening of I by S, denoted as IoS is simply erosion of I by S, followed by dilation of the result by S [11].

$$IoS = (I \ominus S) \oplus S \quad (5)$$

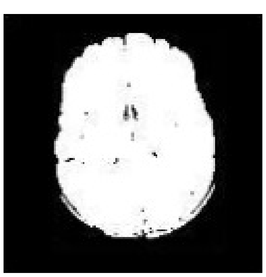


Figure 4. Binarized image after applying opening operator

The Fig. 4 shows the image after applying the opening operator. Morphological opening removes completely regions of an object that cannot contain the structuring element, smoothens object contours, breaks thin connections and removes this protrusion.

2) Closing: A closing operation consists of a dilation followed by erosion with the same structuring element. The morphological closing of I by S, denoted as I•S [11],

$$I \bullet S = (I \oplus S) \ominus S \quad (6)$$

Like opening, morphological closing operator tends to smooth the contours of objects, it joins narrow breaks, fills holes smaller than the structuring element. The Fig. 5 shows the image after applying the closing operator.

Figure 5. Binarized image after applying closing operator

3) Erosion: Erosion operation on an image I containing labels 0 and 1, with a structuring element S, changes the value of pixel i in I from 1 to 0, if the result of convolving S with I, centered at i, is less than some predetermined value. We have set this value to be the area of S, which is basically the number of pixels that are 1 in the structuring element itself. The structuring element (also known as the erosion kernel) determines the details of how particular erosion thins boundaries.

4) Dilation: Dual to erosion, a dilation operation on an image I containing labels 0 and 1, with a structuring element S, changes the value of pixel i in I from 0 to 1, if the result of convolving S with I , centered at i , is more than some predetermined value. We have set this value to be zero. The structuring element (also known as the dilation kernel) determines the details of how a particular dilation grows boundaries in an image

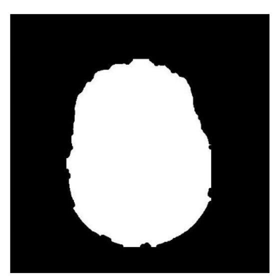


Figure 6. Brain Mask

C. *Region-based binary mask extraction*

Region-based extraction is done by examining the properties of each block that satisfy some criteria. We have used one of two criteria. One criterion is to look at the max-min difference and the other is to determine the mean values of the blocks. The process results with a brain mask as shown in Fig.6 is then applied to the original MRI image as shown in Fig. 1. Consequently, we attain a brain MRI image with its brain cortex stripped as shown in Fig. 7.

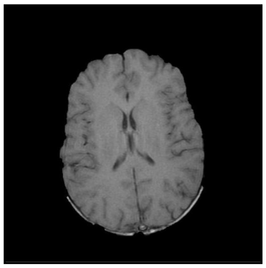


Figure 7. Skull Stripped Brain Image

IV. SEGMENTATION OF CSF, GM AND WM

A. *Segmentation of cerebrospinal fluid*

Regarding CSF segmentation, we assume that there exists some contrast between brain tissue (gray matter and white matter) and cerebrospinal fluid, which separates the brain from the extra-cranial tissue. The segmentation methods we have seen so far can be roughly grouped into 2 categories: intensity based or surface based. Our method is an intensity based method and it does simple thresholding.

In order to segment the cerebrospinal fluid from the brain MRI image, we apply the orthogonal polynomial transform to the skull stripped image. Prior to transformation, the image S is blended using the formula,

$$S' = Sin\left(\frac{S_{(i)}^{\ 3}}{100}\right)^2 + \left(0.05 * rand(|S|)\right) \qquad (7)$$

1) Orthogonal polynomial transform: Let $(p_l \mid l \geq 0)$ be a sequence of orthogonal polynomials on I with respect to some weight function $w(x)$, and let μ_l be defined [12, 13]. Let β_l be the leading coefficient of p_l. We choose a value $m \geq 0$, and define $c_m = \beta_{m-1} / (\beta_m \mu_{m-1})$. Then the following equation holds [14]

$$\sum_{0 \leq l < m} \frac{1}{\mu_l} p_l(x) p_l(y) = \begin{cases} c_m \dfrac{p_{m-1}(y) p_m(x) - p_m(y) p_{m-1}(x)}{x - y}, & x \neq y \\ c_m \left(p_{m-1}(x) p'_m(x) - p_m(x) p'_{m-1}(x)\right), & x = y \end{cases} \qquad (8)$$

Where p'_l denotes the derivative of p_l .After applying the polynomial transform, the region corresponding to the CSF are segmented as in the Fig. 8.

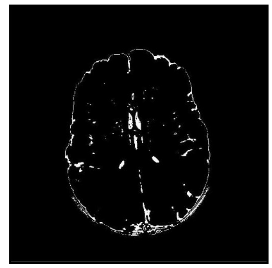


Figure 8. Segmented cerebrospinal Fluid

B. *White matter and Gray matter segmentation*

Following CSF segmentation, the next step is the segmentation of white matter and grey matter present in the brain MRI. The input to the process is the skull stripped image. The major steps used to segment the gray matter and white matter is as shown in Fig 9 below.

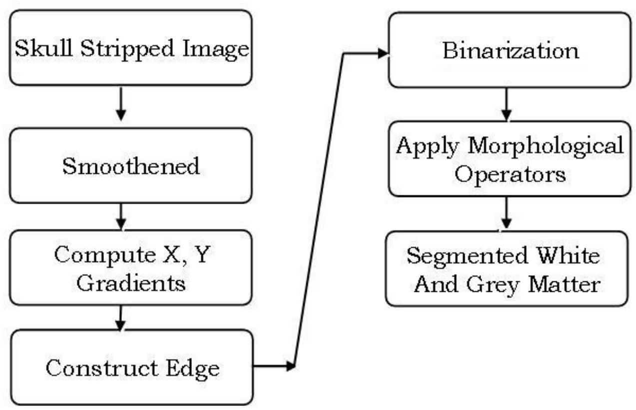


Figure 9. Steps to segment GM and WM

The skull stripped input image S is smoothened by applying the 2-d Gaussian convolution filter to obtain another image as shown in Fig.10.

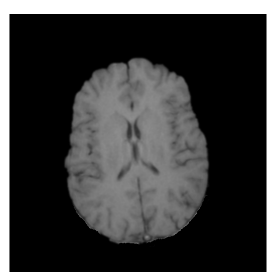


Figure 10. Smoothening Results

Then, the x, y gradients of the smoothened image is computed (Fig 4). The gradient of two variables x and y is defined by,

$$\nabla f(x, y) = \frac{\partial f}{\partial x}\hat{i} + \frac{\partial f}{\partial y}\hat{j} \tag{9}$$

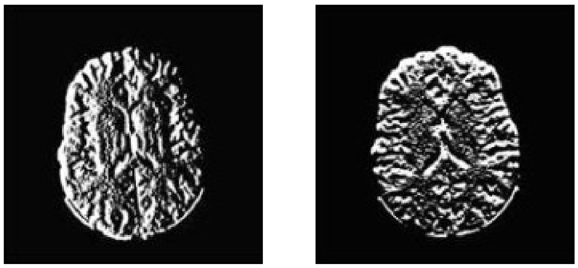


Figure 11. (a) Gradient w.r.to x (b) Gradient w.r.to y

Using the gradient values, the edges present in the image are marked using the following equations,

$$F = x_{(i)}^{\,2} + y_{(i)}^{\,2} \tag{10}$$

$$E_I = \frac{1}{1+F} \tag{11}$$

The image E_I with the edges marked, is then subjected to binarization. The binarization process involves examining the grey-level value of each pixel in the enhanced image by means of global threshold T. The global threshold T is determined by means of the function,

$$T = G_{Th}(E_I) \tag{12}$$

Then the binarized image BI is subjected to binary morphological operators *opening* and *closing*. The morphological operators are applied mainly for the purpose of removing any of the obstacles and noise from the image.

The white matter WM and the gray matter GM tissues in the brain MRI are finally segmented (thresholding) based on their intensity values

$$R_{out} = \begin{Bmatrix} WM; & BI_i = 1 \\ GM; & BI_i = 0 \end{Bmatrix} \tag{13}$$

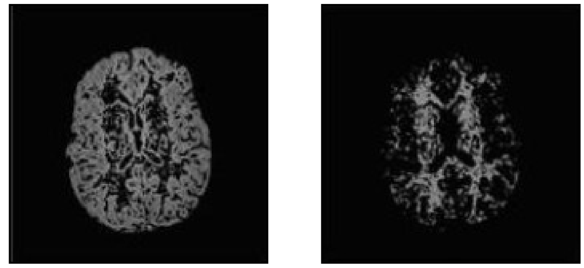
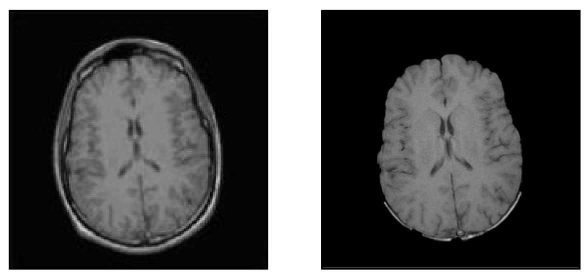


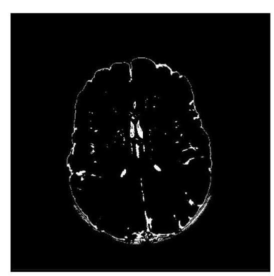
Figure 12. (a) segmented GM (b) segmented WM

V. EXPERIMENTAL RESULTS

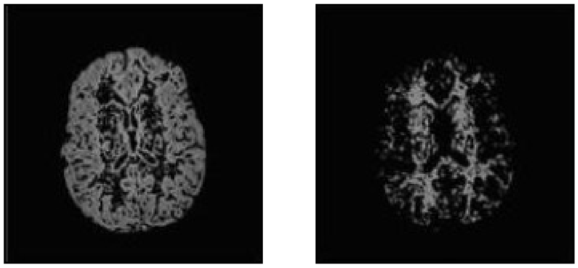
The experimental results of the proposed methodology for segmenting cerebrospinal fluid (CSF), gray matter (GM), white matter (WM) of MRI brain images are presented in this section. The proposed methodology is implemented in Matlab (7.4). The input to the proposed methodology is T1-weighted brain MRI images collected from publicly available databases (http://www.bic.mni.mcgill.ca/brainweb) The proposed methodology is based on Intensity Thresholding (IT), which is the easiest and fastest segmentation method, often adopted for preprocessing of medical images and preregistration problems. The sample results of brain MRI segmentation obtained using the proposed methodology is shown in the following figures.



(a) (b)

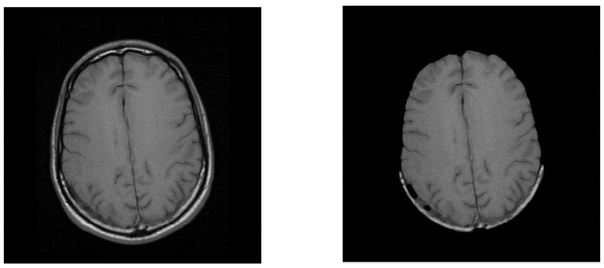


(c)



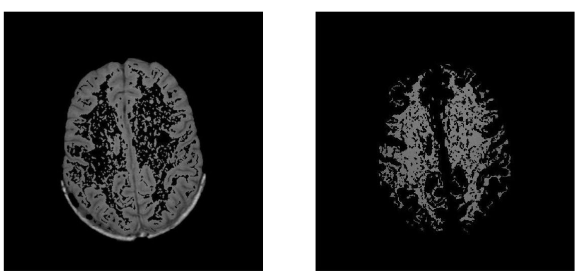
(d) (e)

Figure 13. (a) Input Image, (b) Segmented Brain Image (c) CSF Segmented Image (d) segmented GM (e) segmented WM



(a) (b)

(c)



(d) (e)

Figure 14. (a) Input Image, (b) Segmented Brain Image (c) CSF Segmented Image (d) segmented GM (e) segmented WM

VI. CONCLUSION

In this paper, an automated, simple and efficient brain MRI segmentation method for segmenting cerebrospinal fluid (CSF) has been presented. Initially, the cortex present in the brain MRI images is extracted by combining preprocessing techniques and incorporating mathematical morphological operators and later cerebrospinal fluid is segmented using orthogonal polynomial transform (OPT). Experimental results have showed that the proposed method does a reasonably good job in terms of segmenting skull and CSF. In this present paper normal images were used. So, in future, the method can be implemented on the abnormal images.

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