Segmentation of Cerebrospinal Fluid through Orthogonal Polynomial Transform

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***Abstract*— We present a novel approach for accurate, robust and automated cerebrospinal fluid (CSF) segmentation of MRI brain data of a single as well as multiple magnetic resonance sequences. The proposed methodology performs intensity based thresholding to get boundaries between skull, brain and others. Combined with preprocessing techniques we use simple morphological operators like dilation, erosion, opening and closing to the binarized MRI brain image to extract the brain cortex by stripping the skull. Subsequently, the cerebrospinal fluid is segmented by using orthogonal polynomial transform. We applied our proposed method to several MR images and observed that our method is capable of producing skull stripped brain suitable for further analysis.**

***Keywords*— Image segmentation, skull stripping, Morphological operator, brain segmentation, MR image, Morphology, Cerebrospinal fluid**

I. INTRODUCTION

Magnetic resonance imaging (MRI) is an advanced medical imaging technique providing rich information about the anatomy of human soft tissue. Magnetic Resonance (MR) has become the main modality for brain imaging that facilitates safe, non-invasive assessment and monitoring of patients with neurodegenerative diseases such as Parkinson's disease, Alzheimer's disease (AD), epilepsy, schizophrenia and multiple sclerosis (MS) [1] – [6]. The MRI of the normal brain can be divided into 3 regions other than the background as white matter (WM), Grey matter (GM) and cerebrospinal fluid. 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. Most of these techniques require medical expert to actively control the segmentation process and interactively correct the results. Therefore, the accuracy of the process depends upon the accuracy and repeatability of the necessary operator intervention. Neural networks [7] are also used to learn in order to segment. In this case, it is necessary to train a group of pairs of images (sample in/ideal out) to ensure a good accuracy.

The major problems that affect the quality of MRI segmentation are noise, inhomogeneous pixel, intensity distribution and blunt boundaries in the medical MR images caused by MR data acquisition process. These problems do make manual quantative analysis of brain imaging data a tedious and time consuming procedure, prone to observer variability [8]. 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.

Therefore our present approach consists of two stages, preprocessing and segmentation. In the first stage, the skull from the sample image is stripped and in the second stage, the cerebrospinal fluid (CSF) region is segmented from the skull stripped image using orthogonal polynomial transform. Thus the main goal of this paper is to introduce an automatic method for robust cerebrospinal fluid segmentation to facilitate accurate measurement of brain tissues.

The next section presents some basics on morphological operations. Section 3 describes our methodology. Finally we show some results in section 4 and draw some conclusions and future work perspectives in section 5.

II. MATHEMATICAL MORPHOLOGY CONCEPTS

Binary mathematical morphology is an algebraic system based on set theory that provides two basic operations: dilation and erosion. Combination of these operations enables underlying object shapes to be identified and reconstructed from their noisy distorted forms. A combination of dilation and erosion gives rise to two additional operations, opening and closing which forms the basis for most morphological processing.

Mathematical morphology has been largely used in several practical image processing and analysis problems. 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 [9]. 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 operations of and erosion are fundamental to morphological image processing.

Dilation is an operation that ‘grows’ or ‘thickens’ objects in a binary image. The specific manner and the extent of this thickening are controlled by the structuring element [10]. Computationally, structuring elements are represented by a matrix of 0’s and 1’s. Suppose the original image, I and the structuring element, S are represented as sets in 2-dimensional Euclidean space. Let S_x denote the translation of S so that its origin is located at x. Then the dilation of I by S is defined as the set of all points of ‘x’ such that S hits I, i.e., they have a non-empty intersection [10].

$$\text{Dilation: } I \oplus S \triangleq \{x: S_x \cap I \neq \Phi \} \qquad (1)$$

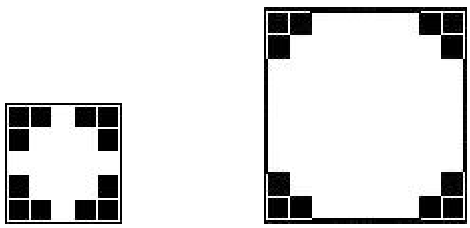
Therefore dilation allows objects to expand then potentially filling in small holes and connecting disjoint objects. The performance of dilation is laying the structuring element on the image and sliding it across the image. If the origin of the structuring element coincides with a ‘0’ in the image then there is no change, now move to the next pixel. But if the origin of the structuring element coincides with a ‘1’ in the images then perform the OR logic operation on all pixels within the structuring element.

Similarly, erosion of I by S is defined as the set of all points x such that S_x is included in I [10], i.e.,

$$\text{Erosion: } I \ominus S \triangleq \{x: S_x \subset I\} \qquad (2)$$

Erosion shrinks objects by etching away (eroding) their boundaries. The performance of erosion is laying the structuring element on the image and sliding it across the image. 1. If the origin of the structuring element coincides with a ‘0’ in the image, there is no change; move to the next pixel. 2. If the origin of the structuring element coincides with a ‘1’ in the image and any of the ‘1’ pixels in the structuring element extend beyond the object in the image, then change the ‘1’ pixel in the image to a ‘0’.

In image processing applications, dilation and erosion are always used in combination. In our method we used opening and closing operator. Even though many structuring element are available we used disk shaped structuring element of various radius as shown in Fig. 1 in our method.



(a) (b)

Fig. 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.

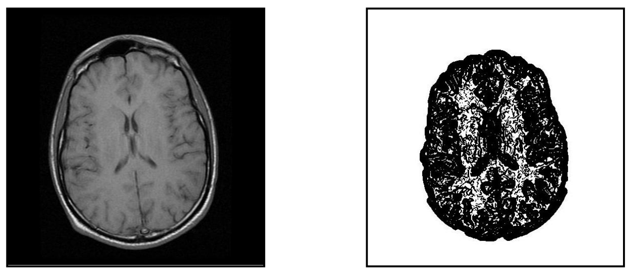
In the proposed method for skull stripping, we see the brain surface as a smooth manifold with relatively low curvature that separates brain from non-brain regions. Also, the brain cortex can be visualized as a distinct dark ring surrounding the brain tissues in the T1-weighted axial MR images.

The steps involved in the proposed methodology for skull stripping and cerebrospinal fluid segmentation consists of four steps.

1. Binarization of every image.
2. Opening operation and closing operation on every image in the sequence using the structuring element.
3. Applying the binary mask to the received MRI input image.
4. Cerebrospinal fluid segmentation by applying orthogonal polynomial transform on skull stripped 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)

Fig. 2. (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. 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].

$$IoS = (I \ominus S) \oplus S \quad (3)$$

The Fig. 3 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.

Fig. 3 Binarized image after applying opening operator

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],

$$I \bullet S = (I \oplus S) \ominus S \quad (4)$$

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. 4 shows the image after applying the closing operator.

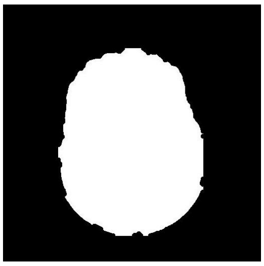


Fig. 4 Binarized image after applying closing operator

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

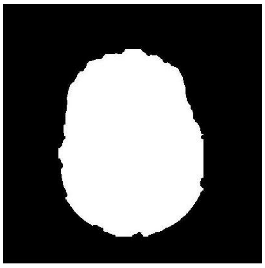


Fig. 5. Brain Mask

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.5 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. 6.

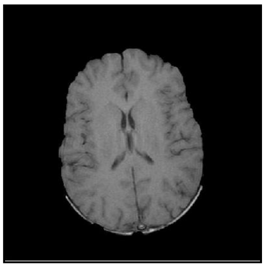


Fig. 6 Skull Stripped Brain Image

C. Region-based binary mask extraction

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,

$$S' = Sin\left(\frac{S_{(i)}^{\ 3}}{100}\right)^2 + \left(0.05 * rand(|S|)\right) \quad (5)$$

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]:

$$\sum_{0 \leq l < m} \frac{1}{\mu_l} p_l(x) p_l(y) = \begin{cases} c_m \dfrac{p_{m-1}(y) p_m(x) - p_m(y) p_{m-1}(x)}{x-y}, & x \neq y \\ c_m \left(p_{m-1}(x) p'_m(x) - p_m(x) p'_{m-1}(x)\right), & x = y \end{cases} \quad (6)$$

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. 7.

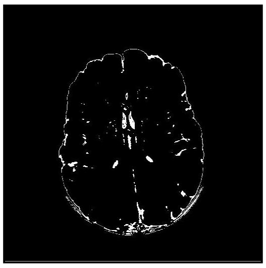
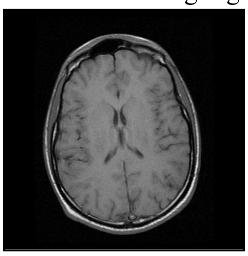


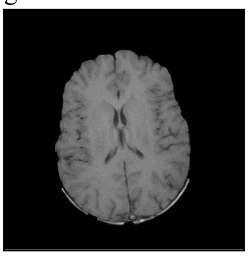
Fig. 7 Segmented cerebrospinal Fluid

IV. EXPERIMENTAL RESULTS

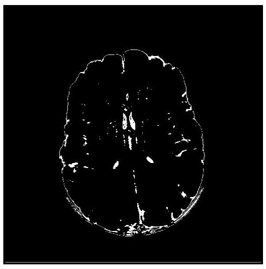
The experimental results of the proposed methodology for segmenting cerebrospinal fluid of MRI brain images are presented in this section. The proposed methodology is implemented in Matlab (7.4). The input to the proposed methodology is T1-weighted brain MRI images collected from publicly available databases. Regarding T1-weighting, every tissue in the human body has its own T1 and T2 value. This term is used to indicate an image where most of the contrast between tissues is due to differences in the T1 value. 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 Fig.8 to Fig. 10.



(a)

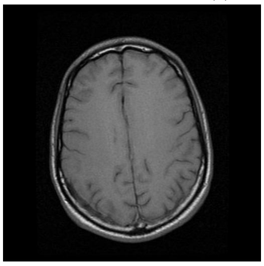


(b)

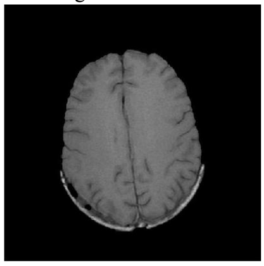


(c)

Fig. 8 (a) Input Image, (b) Segmented Brain Image (c) CSF Segmented Image



(a)

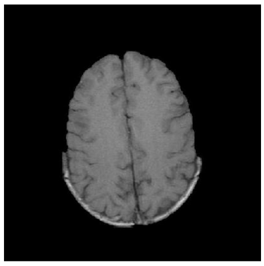


(b)

(c)

Fig. 9 (a) Input Image, (b) Segmented Brain Image (c) CSF Segmented Image

(a)



(b)

(c)

Fig. 10 (a) Input Image, (b) Segmented Brain Image (c) CSF Segmented Image

V. 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 and verify whether it is segmenting the CSF region. Also we can segment grey matter and White matter from the skull stripped brain image produced by this method.

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