An Improved Method for Cortical Surface Identification based on Local Information

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Abstract

Skull stripping head magnetic resonance (MR) images is a classification problem, which is a difficult task due to the convoluted brain surface. This paper presents an automated, robust, and accurate brain volume extraction method (BVE)based on a combined image segmentation and bias estimation method (ISBEM) and a 3D mathematical morphology method. The ISBEM segments brain tissues efficiently and accurately, while estimating the bias field. The new 3D mathematical morphology method can remove the noncerebral tissues efficiently. The results show that our method can obtain more accurate results.

Keywords*: Brain MRI, Skull stripping, Bias field*

1 Introduction

Brain extraction, commonly referred to as skull stripping, is essential for a variety of neuro imaging applications [1]. Numerous automated skull-stripping methods have been proposed and are widely used. Recent studies indicated that accurate skull stripping can improve the validity of voxel-based morphometry (VBM) results due to better tissue segmentation and brain registration [2].

Skull stripping in general can be categorized into the following three methods: intensity based,morphology based, and deformable model based. Intensity based methods [2] use intensity distribution functions to identify major brain tissues. Each brain tissue is modeled as a modified normal distribution function. However, they are sensitive to the bias field, sequence variations, scanner drift and random noise [3].

Morphology-based methods [4] frequently combine connectivity-based morphological operations with thresholding or edge detection to extract image features and identify brain surfaces. Shattuck *et al.*, developed a tool called the brain surface extractor (BSE) [5], which uses a combination of edge detectors and morphological operators to skull strip the brain images. Brain extraction tool (BET) is another automated brain segmentation algorithm for MR head scans, which was developed by Smith [6]. All these methods are sensitive to intensity bias, weak edges and noise.

We developed a new, automatic algorithm called the brain volume extraction (BVE) to remove the skull and intracranial tissues surrounding the brain in MR images. The proposed method contains three steps: 1) Segment the image; 2) Obtain the coarse brain tissues; 3) Refine the results for improves accuracy. In this paper, we present an automated, robust, and accurate brain volume extraction method (BVE) based on a combined image segmentation and bias estimation method (ISBEM) and a 3D mathematical morphology method. The ISBEM can segment the brain images and meanwhile estimate the bias field. However, in the segmented images, some non-brain tissues have the same intensities as those of brain tissues.

In order to deal with this drawback, we propose a new 3D mathematical morphology method to strip the non-brain tissues efficiently and accurately.

2. Methods

2.1. Image Segmentation and Bias Estimation Method (ISBEM)

The observed MRI signal Y is the product of the true signal I generated by the underlying anatomy and the spatially varying field factor B, and an additive noise N:

$$Y = I \cdot B + N \tag{1}$$

Given the observed signal Y, the problem is to estimate the true image I. To simplify the computation, one often ignores the noise and takes the logarithmic transform of both sides.

$$\log(Y) = \log(I \cdot B) = \log(I) + \log(B) \tag{2}$$

If we approximate $\log(Y)$ with Y, $\log(I)$ with I and $\log(B)$ with B respectively. Eq. 2can be written as $Y = I + B$. The generally accepted assumption on the bias field B is that it is smooth or slowly varying. Ideally, the intensity I of each tissue should take a specific value c_i of the physical property being measured. In this section, we present our method based on Eq .2. We assume that the true image I and the bias field B have the following properties: (1) The bias field B is slowly varying across the entire image domain.(2) The true image intensities I are approximately a constant within each class of tissue.

As mentioned previously, the measured data Y in the whole image are not separable based on their intensity values. Our method introduced in this section is based on an observation that intensities in a relatively small region are separable.We consider a circular neighborhood with a relatively small radius r centered at each point y in the image domain Ω, defined by $\Lambda_y = \{X :| \|x - y\| \le r\}$. The partition $\Omega_{ii=1}^{N}$ induces a partition of the neighborhood Λ_y. For a slowly varying function B, the values $B(x)$ for all x in the circular neighborhood Λ_y can be well approximated by its value $B(y)$ at the center of Λ_y. As a result, the image $B(x) + I(x)$ is approximately the constant $B(y) + c_i$ in each subregion $\Lambda_y \bigcap \Omega_i$ of the neighborhood Λ_y, for $i = 1, \ldots, N$. Therefore, we have the following approximation:

$$B(x) + I(x) \approx B(y) + c_i, x \in \Lambda_y \bigcap \Omega_i \tag{3}$$

The constants $B(y) + c_i$ can be considered as the approximations of the cluster centers of the clusters within the neighborhood Λ_y. Therefore, the intensities in the neighborhood Λ_y are around N cluster ave values $m_i \approx B(y) + c_i$ However, these cluster centers are unknown.

Consider a task of classifying the data $Y(x)$ in the neighborhood Λ_y into N clusters using a K-means type clustering method. By introducing a weighting function into the objective function to be minimized in standard K-means clustering method and the following objective function is defined as:

$$\varepsilon_y = \sum_{i=1}^{N} \int_{\Lambda_y \cap \Omega_i} \omega(x-y) \left| Y(x) - B(y) - c_i \right|^2 dx \tag{4}$$

where $B(y) - c_i$ are the cluster ave values to be optimized, and $\omega(x-y)$ is a non-negative weighting function such that $\omega(x-y) = 0$ for $|x-y| > r$ and $\int_{\Lambda_y} \omega(x-y)dx = 1$.

Therefore, we define an energy:

$$\varepsilon = \int_{\Omega} (\sum_{i=1}^{N} \int_{\Omega_i} \omega(x-y) \left| Y(x) - B(y) - c_i \right|^2 dx) dy \tag{5}$$

Directly minimizing the energy with the partition $\Omega_{i\,i=1}^{\;N}$ as a variable is not convenient. We will use one or multiple level set functions to represent a partition $\Omega_{i\,i=1}^{\;N}$ .The energy minimization can thus be performed by solving a level set evolution equation[7].

The segmentation method segments images meanwhile estimates the bias field. However, some non-brain tissues, which are connected with brain tissues, have similar intensities with brain tissues, which makes the proposed hard to obtain satisfied results. In order to obtain accurate results we use a 3D mathematical morphology method to separate brain tissues from others.

2.2. 3D Mathematical Morphology Method

The 3D mathematical morphology method consists of four major steps:

Step 1: Segment the image

We use the ISBEM to segment the brain images into four classes: background and regions with similar intensities, CSF and regions with similar intensities, GM, WM and some regions with similar intensities. It is well known that the intensities of CSF, GM, WM and some other tissues change from low to high. We define a Table M with the same size as the image data. The skull stripping is realized by adapting the Table M . The elements belong to the background class in the table M are set to zeros. The adapted M is marked as M_1. Figure 1 shows the segment result result on a real brain MR image data. Figure 1(a) shows the initial image. The segmentation result of the ISBEM is shown in Figure 1(b). Figure 1(c) is the background and regions with similar intensities removed image and the table M_1 is shown in Figure 1(d).

Step 2: Obtain the coarse brain tissues

In this step, the brain tissues are obtained by adapting the table M_1 in four steps.

Step. (1) A morphological binary erosion is applied to M_1 using a 3D spherical structuring element with a radius of three voxels. M_1 is adapted to be M_2. The result of M_2 in this step on Figure 1(d) is shown in Figure 1(f) and the corresponding image is shown in Figure 1(e). It can be seen from the result that the non-brain tissues have been separated from brain tissues;

Step. (2) The table method, which is can be found in [8], is used to find the brain tissues. The elements that belong to the other non-brain tissues in M_2 are set to zero and the adapted M_2 is marked as M_3. The result of M_3 in this step on Figure 1(f) is shown in

Figure 1(h) and the corresponding image is shown in Figure 1.(g). It can be seen from the result that the non-brain regions have been deleted;

Step. (3) A morphological binary dilation is applied to M_3 using a 3D spherical structuring element with a radius of three voxels. The adapted M_3 is marked as M_4. The result of M_4 in this step on Figure 1(h) is shown in Figure 1(j) and the corresponding image is shown in Figure 1 (i). It can be seen from the result that there are some holes in the M_4;

Step. (4) A morphological binary closing is applied to M_4 using a 3D spherical structuring element with a radius of three voxels in a similar manner. The adapted M_4 is marked as M_5. The result of M_5 in this step on Figure 1(j) is shown in Figure 1(l) and the corresponding image is shown in Figure 1.(k). It can be seen from the result that the holes have been filled up;

Remark: The radius of the 3D spherical structuring element is set as three, which is a experiential parameter from more than forty brain images segmentation.

The erosion in Step. (1) separates the brain tissues from other tissues. The table method in Step. (2) distinguishes which region belongs to the brain tissues. The dilation in Step. (3) find the brain tissues. However, with the effect of noise, there are some holes in M_4. Step. (4) can fill up those holes. The segmented images I_1 are generated by voxel-to-voxel multiplication between the initial image I_0 and the Table M_5.

$$I_1 = I_0 \cdot M_5 \tag{6}$$

In the image I_1, the skull and subhead tissues have been removed. However, due to weak edges and the characters of brain organization, some small fragments of non-brain tissues with similar intensities are connected to the brain tissues. These fragments need to be removed afterwards.

Step 3: Obtain the accurate brain tissues

The image has been classified into four classes by using the ISBEM. Voxels in Class1 belong to low-intensity components such as the CSF, sinus, and dura. Class 2 includes higher intensity components such as the GM. Class 3 includes voxels of the WM. Finally, voxels in Class4 belong to the tissues with the highest intensities. After Step 2, voxels in Class 1 and Class 4 are deleted. However, due to the effect of the skull, the ISBEM cannot obtain accurate results. In order to obtain more accurate results, we segment I_1 repeat the procedure from Step. 1 to Step. 2. In Step. 1, we use the final ϕ_1, ϕ_2 as the initial curves of the ISBEM. The adapted M_5 is marked as M_6. The result can be seen in Figure 1(m). It can be seen that the result is more accurate than the coarse result.

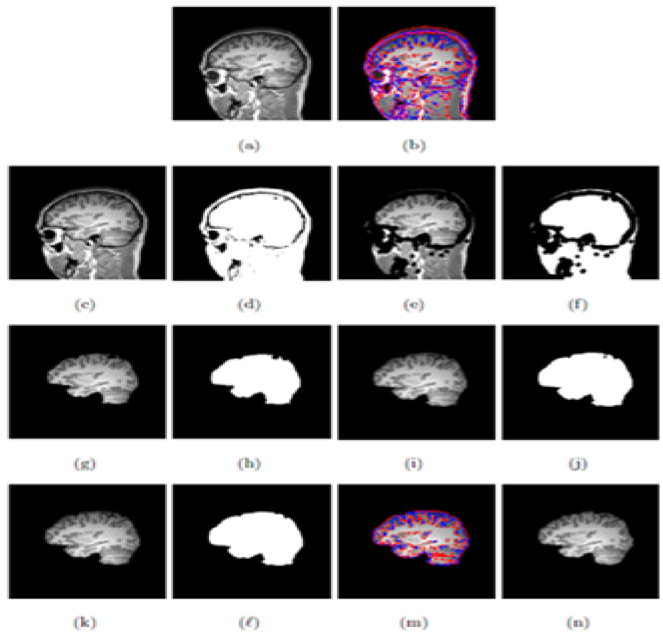


Figure 1. An Example of the Skull Stripping Procedure of A Brain MR Image. (A) Is One of the Initial Image. (B) Is the Result of the ISBEM. (C) Is the Background Removed and Tissues with the Lower Intensity Removed Image. (D) Is M1. (E) Is the Result after Applying a Morphological Binary Erosion. (F) Is M2. (G) Is the Corresponding Result of M3. (H) Is M3. (I) Is the Corresponding Result of M4. (J) Is M4. (K) Is the Coarse Result of the Brain. (L) Is M5. (M) is the Segmentation Result of I1 by using the ISBEM. (N) Is the Final Result

With the effect of the weak edges and the characters of brain organization, some of the voxels belonging to the GM have been deleted by using the morphological operations. In order to find these voxels, We use Eq.(7) to judge whether the elements, which were connected with the GM, belonging to the GM.

$$M_7(x) = \begin{cases} 0, & if \quad J(x) < T, \\ 1, & \quad else \end{cases} \tag{7}$$

where T is a threshold based on the images, $J(x) = \exp(-(\|\mu_x - \mu\| + \|\sigma_x - \sigma\|))$, μ, μ_x, σ, σ_x denote the mean intensity of the GM and the local mean intensity of the point x, the variance of the GM, the local variance of the point x, respectively. If the element x belongs to the GM, J(x) is close to 1, otherwise, J(x) is close to 0. Therefore, the table M_6 is adapted as final Table M_7.

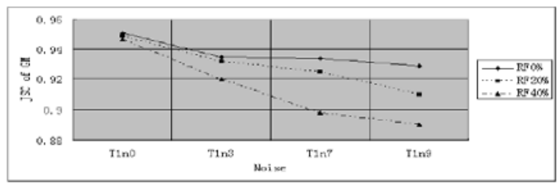
And then we apply a morphological binary closing to M_7 using a 3D spherical structuring element with a radius of three voxels. The adapted M_7 is marked as M_{end}.

Afterwards, the segmented brain image I_{end} is generated by voxel-to-voxel multiplication of the initial image I_0 and the table M_{end} and the final result of Figure 1(a) is shown in Figure 1(n).

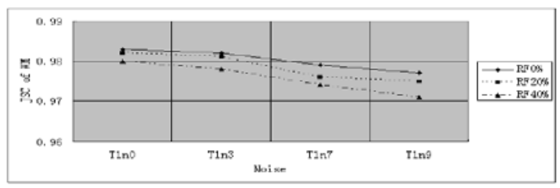
$$I_{end} = I_0 \cdot M_{end} \tag{8}$$

3. Results

SBMR images with different noise and heterogeneity levels were segmented using our method. Figure 2 depicts the average brain tissue segmentation accuracy using our method on SBMR images with different noise levels and heterogeneities. Figure 2(a)-(b) shows the accuracy of segmenting GM and WM. The accuracy decreased for GM and WM when the images combined with noise levels increased form 0% to 9% and the RF levels increased form 0% to 40%. From the results, we can found that our method can obtain more accurate results.



(a)



(b)

Figure 2. Accuracy Rates of Tissues Segmentation using our Method on Simulated Brain MR Images. (A) Accuracy Rates of GM Segmentation. (B) Accuracy Rates of WM Segmentation

Illustrations of skull-stripping results of the sagittal section slices, the axial section slices and the coronal section slices are shown in Figure 3. The skull stripping results of the BET, BSE and our method are shown from the second column to the 4th column. The ground truths are shown in the right column. It can be seen from these figures that BET and BSE fail to extract the brain tissues, while our method obtains good results similar to the ground truth

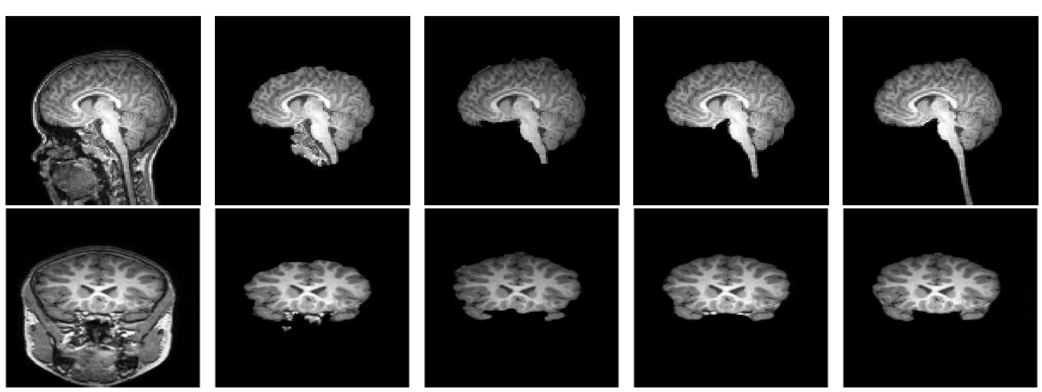


Figure 4. Illustrations of Skull-Stripping Results. The First Row and Second Row Show the Results in Sagittal Section Slices, The 3rd Row and 4th Row Show the Results in the Axial Section Slices and the 5th Row and 6th Row Show the Results in the Coronal Section Slices. The Left Column is the Initial Image. The Second Column is the Results of BET. The Third Column Illustrates Results of the BSE. The Right Column is the Results of our Method. The Right Column Show the Ground Truth

4. Discussion

Brain segmentation is widely used as a preliminary step in many MR imageprocessing methods. Different MRI data sets may be collected under various conditions, such as different people and different machines. It is necessary to develop a simple algorithm applied to images collected under various conditions. For this reason, we developed the BVE algorithm, which can be easily adopted and programmed. As a preliminary step in complex image-processing procedures, the segmentation algorithm should be accelerated in computational speed. To accomplish these goals, the BVE algorithm was developed based on the intensity information and some simple morphological operations. When the accuracy of a method is evaluated, a “gold standard” is usually used as a reference to judge the performance of the method. To evaluate the accuracy of BVE, we segmented 20 computer-simulated MRI data sets and 40 normal MRI brain volumes. BVE achieved 0.95% average error. For an accurate separation in BVE, mean values of GM and WM are found and non-brain tissues are stripped more accurately step by step. The excess non-brain tissues may greatly affect the extraction accuracy of BET and BSE. Neck or shoulder region in the image volume largely biases the estimation of the brain centroid and the brain size. Therefore, the methods may locate the initial surface far from a reasonable position and thus fail to drive it toward the target. On the contrary, the BVE is more robust so that the excess non-brain regions do not obviously affect the segmentation results.

The degree of reproducibility is another important aspect of an algorithm’s performance. Variations in the volume measurements are assessed among separate data sets in the same session and different sessions. Due to various noise, bias field factors and the head motion of the subject being scanned, the voxel dimension may fluctuate among different imaging trials in the same session or in different sessions. We tested BVE for segmenting image data sets with 10% noise level and 40% RF. All data sets could be segmented accurately in about two minutes.

5. Conclusions

In this work we developed and implemented a skull stripping algorithm which is basically designed for T1 weighted anatomic images. This brain segmentation technique named BVE, is based on ISBEM and 3D morphological operations such as opening, dilation and connectivity judgment. The experiment results show that the proposed method out performs the conventional tools and can accurately skull strip the brain MR images to delineate the brain volume with high reproducibility.

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