

An Improved Cortical Surface Identification Method

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Abstract. Skull stripping head magnetic resonance (MR) images is a classification problem. Accurate segmentation is a difficult task due to the convoluted brain surface and the inapparent brain/non-brain boundaries in images. This paper presents an automated, robust, and accurate brain volume extraction method. The results show that our method can obtain more accurate results.

Key words: Brain MRI, Skull stripping, Bias field

1 Introduction

Skull-stripping is concerned with the predominant tissues of the brain: gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). The measured signal intensities of these tissues overlap with others, such as skin, bone, muscle, fat, and dura. Skull stripping in general can be categorized into the following three methods: intensity based, morphology based, and deformable model based. Intensity based methods [1] use intensity distribution functions to identify major brain tissues (e.g. CSF, GM and WM). 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 [2].

Morphology-based methods [3] frequently combine connectivity-based morphological operations with thresholding or edge detection to extract image features and identify brain surfaces. Dark pixels are separated from bright pixels by thresholding and brain regions are identified by using a connectivity-based algorithm. Shattuck et al. developed a tool called the brain surface extractor (BSE) [4]. The main disadvantage of these methods is that the final results depend on many parameters, which are often empirically generated and sensitive to small variations in the data. Brain extraction tool (BET) is an automated brain segmentation algorithm for MR head scans, which was developed by Smith [5]. All these methods are sensitive to intensity bias, weak edges and noise.

The performance of these methods, which rely on intensity and contrast, can be influenced by numerous factors such as MR signal inhomogeneities, type of MR image set, gradient performance, stability of system electronics.

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. The accuracy of the segmentation affect the accuracy of the model. Unfortunately, most tissue segmentation methods are hindered by various imaging artifacts such as noise and intensity inhomogeneities. The intensity inhomogeneities usually refer to the slow, nonanatomic intensity variations of the same tissues over the image domain. It can be due to imaging instrumentation (such as radio-frequency nonuniformity, static field inhomogeneity, etc.) or subject motion artifacts. This artifact is particularly severe in MR images captured by surface coils. With the effect of the bias field, brain tissues are connected with other tissues. 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)

Many clinical and research applications of MR imaging rely on segmentation in order to delineate different intensity classes in each image. Unfortunately, most tissue classification methods are hindered by various imaging artifacts such as noise and intensity inhomogeneities. Segmentation experiments presented by Jungke et al.[6] illustrate that the major problem for brain MR image segmentation is not noise but rather, intensity inhomogeneities. A widely used model for intensity inhomogeneities is to lump all sources of intensity inhomogeneities in one multiplicative factor: the bias field.

Level set methods have been extensively used for image segmentation. We use a variational level set approach to bias correction and segmentation for images corrupted with intensity inhomogeneities[7]. A unique advantage of our method is that the smoothness of the computed bias field is intrinsically ensured by the data term in the variational formulation. Furthermore, the method is not sensitive to initialization, thereby allowing fully automated applications.

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:

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

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, the final energy can be defined as:

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

Directly minimizing the energy with the partition $\Omega_{i=1}^N$ as a variable is not convenient. The energy minimization can thus be performed by solving a level set evolution equation.

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 . Fig. 1 shows the segment result result on a real brain MR image data. Fig. 1(a) shows the initial image. The segmentation result of the ISBEM is shown in Fig.1(b). Fig. 1(c) is the background and regions with similar intensities removed image and the table M_1 is shown in Fig. 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 which can be seen in Fig. 1.

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 Fig. 1(d) is shown in Fig. 1(f) and the corresponding image is shown in Fig1.(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 given in section 2.4, 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 Fig. 1(f) is shown in Fig. 1(h) and the corresponding image is shown in Fig 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 Fig. 1(h) is shown in Fig. 1(j) and the corresponding image is shown in Fig 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 Fig. 1(j) is shown in Fig. 1(l) and the corresponding image is shown in Fig 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 an 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 .

$$I_1 = I_0 \cdot M_5 \quad (3)$$

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

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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 Fig. 1(m). It can be seen that the result is more accurate than the coarse 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.(4) to judge whether the elements, which were connected with the GM, belonging to the GM.

$$M_7(x) = \begin{cases} 0, & \text{if } J(x) < T, \\ 1, & \text{else} \end{cases} \quad (4)$$

where T is a threshold based on the images, $J(x) = \exp(-(\|\mu_x - \mu\| + \|\sigma_x - \sigma\|))$, $\mu, \mu_x, \sigma, \sigma_x$ 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 Fig. 1(a) is shown in Fig. 1(n).

$$I_{end} = I_0 \cdot M_{end} \quad (5)$$

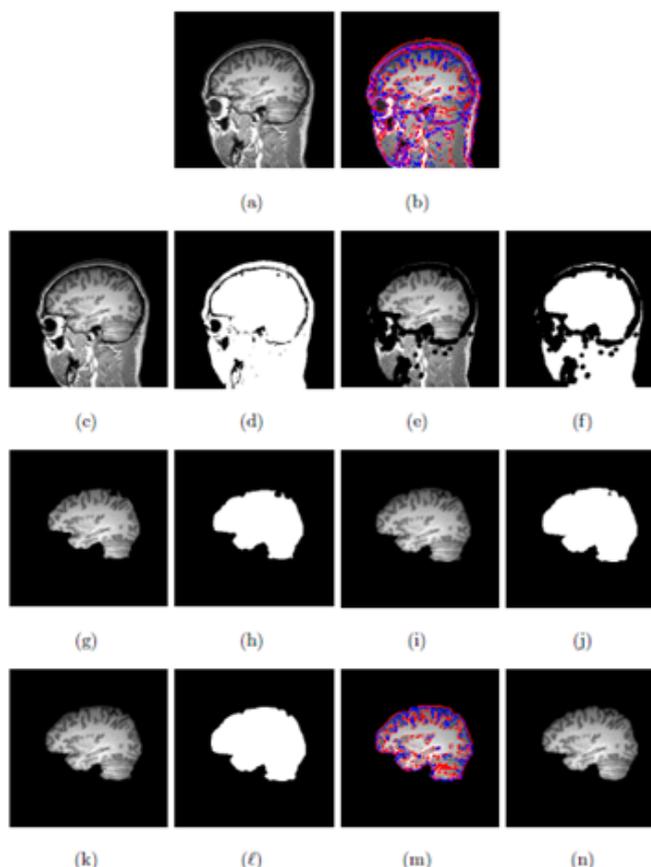


Fig. 1. An example of the skull stripping procedure of a brain MR image. (a) is one of the initial image. (b) is the result of the ISBEM. (c) is the background removed and tissues with the lower intensity removed image. (d) is M1. (e) is the result after applying a morphological binary erosion. (f) is 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.

2.4 Table Method

The image data can be classified into different groups by using ISBEM. With the classified information, some non-brain tissues, whose intensities are different from those of brain tissues, can be disregarded or removed. However, some non-brain tissues that are still marked in the table M_2 , have similar intensities to those of brain tissues. In order to separate brain tissues from those non-brain tissues, we propose a table method to find brain tissues efficiently as described in the following steps.

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Step 1 Construct a zero matrix FH (same size as M_2). In M_2 , brain tissues and some non-brain tissues with similar intensities are marked as one and remaining elements are made zero. The brain tissues and the non-brain tissues locate in different regions.

Step 2 Calculate the centroid $P(\bar{x}, \bar{y}, \bar{z})$ of M_2

$$\begin{aligned}\bar{x} &= \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \sum_{z=0}^{l-1} xM_2(x, y, z) / \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \sum_{z=0}^{l-1} M_2(x, y, z) \\ \bar{y} &= \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \sum_{z=0}^{l-1} yM_2(x, y, z) / \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \sum_{z=0}^{l-1} M_2(x, y, z) \\ \bar{z} &= \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \sum_{z=0}^{l-1} zM_2(x, y, z) / \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \sum_{z=0}^{l-1} M_2(x, y, z)\end{aligned}\tag{6}$$

where m, n, l are the size of M_2 .

Step 3 Look for the area around $P(\bar{x}, \bar{y}, \bar{z})$ to find an element $P_{seed}(x, y, z)$, where $M_2(x, y, z) = 1$. We assume that the brain tissues locate in the center of the MR brain image, and P_{seed} is regarded as an element of the brain tissues. Set $FH(location(P_{seed})) = 1$.

Step 4 Construct a stack H initialized to contain the location of P_{seed} .

Step 5 Repeat the operations below until H is null:

The top element of H is removed and its six adjacent elements l_p , $p = 1, 2, 3, 4, 5, 6$, are analyzed. If $M_2(l_p) = 1$ and $FH(l_p) = 1$, we set $FH(l_p) = 1$ and put l_p into H . When H is null, all the elements of the brain tissues have been marked as one in FH . In the matrix FH , the brain tissues are marked as one and nonbrain tissues are marked as zero.

3 Results

For all four data sets, the ground truth was defined as GM+WM. Manual, expert segmentation containing GM, WM and subcortical structures (inclusive of cerebellum) was already included in the real MR data. The Brainweb give the ground truth of the image data created with the MRI simulator.

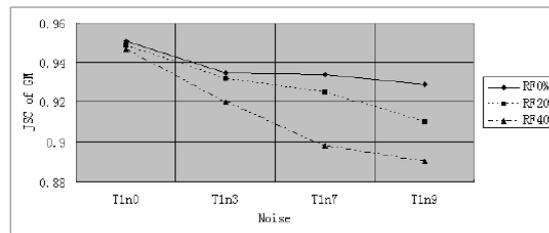
In order to compare each manually skull-stripped outcome to the outcome of each automated method, the Jaccard similarity coefficient (JSC) is used to measure degree of correspondence, or overlap. The JSC is formulated as:

$$JSC(R_1, R_2) = \frac{|R_1 \cap R_2|}{|R_1 \cup R_2|} \quad (7)$$

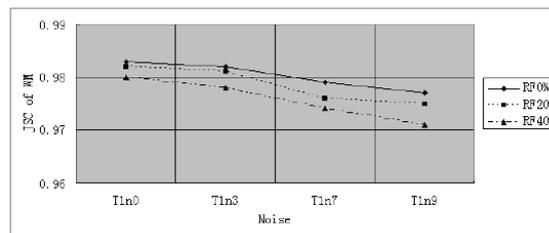
where R_1 is the area of brain region of the manually skull-stripped image slice and R_2 is the area of brain region of the corresponding image slice skull stripped using the compared skull-stripping tool. A JSC of 1.0 represents complete overlap or agreement, whereas an index of 0.0 represents no overlap.

3.1 Segmentation of SBMR image

SBMR images with different noise and heterogeneity levels were segmented using our method. Fig. 2 depicts the average brain tissue segmentation accuracy using our method on SBMR images with different noise levels and heterogeneities. Fig. 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 from 0% to 9% and the RF levels increased from 0% to 40%.



(a)



(b)

Fig. 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

4 Conclusions

In this work we developed and implemented a skull stripping algorithm which is basically designed for T1 weighted anatomic images. This brain segmentation

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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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