## LETTER An Interleaved Otsu Segmentation for MR Images with Intensity Inhomogeneity

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**SUMMARY** The MR image segmentation is always a challenging problem because of the intensity inhomogeneity. Many existing methods don't reach their expected segmentations; besides their implementations are usually complicated. Therefore, we originally interleave the extended Otsu segmentation with bias field estimation in an energy minimization. Via our proposed method, the optimal segmentation and bias field estimation are achieved simultaneously throughout the reciprocal iteration. The results of our method not only satisfy the required classification via its applications in the synthetic and the real images, but also demonstrate that our method is superior to the baseline methods in accordance with the performance analysis of JS metrics.

*key words:* intensity inhomogeneity, bias field estimation, Otsu segmentation, energy minimization

#### 1. Introduction

Since magnetic resonance imaging (MRI) has been a crucial visualization tool for clinical diagnosis, a great deal of attention has been paid to the MR image segmentation. Therefore, various methods, e.g., thresholding, region growing, statistical models, boundary-based methods [10] and clustering-based methods, have been proposed and applied in the MR image segmentation in recent years. However, the intrinsic imaging issues, e.g., bias field and noise, are challenging enough for the automatic MR image segmentation, which often cause the severe tissue misclassifications [8]. Additionally, it is the intensity inhomogeneity, namely bias filed, that results in many difficulties in medical image analysis such as registration and segmentation.

There are two kinds of the existing bias field correction methods, i.e., prospective methods [2] and retrospective methods [5]. The former can correct the intensity inhomogeneity caused by the MR scanners. On the other hand, the latter mainly rely on the information of the MR image itself, where the useful information on anatomy and intensity inhomogeneity is integrated. For most of the retrospective, the final bias correction and tissue segmentation are sensitive to the estimation initialization.

Consequently, we use a new interleaved method which

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combines the extended Otsu segmentation with bias field estimation in an energy minimization. There is no voting strategy in the proposed method in contrast with the interleaved KNN one [11]. So the time consumption of our method is less than the one of interleaved KNN method. In light of the applications in the real and the synthetic MR images, the proposed method greatly decreases or eliminates the misclassifications compared with the two baseline methods, unified segmentation and FANTASM. Furthermore, experimental results also demonstrate the accuracy and effectiveness according to the performance analysis of JS metrics.

The remainder of this letter are organized as follows: In Sect. 2, we explain the MR image model and the interleaved framework for the Otsu segmentation and bias field estimation. The experimental results and quantitative evaluations are subsequently shown in Sect. 3. Finally, the conclusion is made in Sect. 4.

#### 2. Method

#### 2.1 MR Image Model

According to an MR image model [6], [8], an MR image with bias field can be modeled as

$$I(x) = b(x)J(x) + n(x)$$
(1)

where I(x) is the observed image, b(x) the bias field, J(x) the intrinsic image, and n(x) additive noise.

In general, we assume that the above model has the following properties:

(A1) The bias field varies slowly in the image domain, denoted as  $\Omega$ .

(A2) The voxels with the same physical property can be considered as a constant in the same tissue region.

Given the assumption (A1), the bias field can be approximated by a linear combination of basis functions. Let  $g_1(x), \dots, g_M(x)$  be the set of basis functions defined in the image domain. The bias field can be defined as:

$$b(x) = \sum_{i=1}^{M} w_i g_i(x) = \mathbf{w}^T \mathbf{g}(x)$$
(2)

where  $\mathbf{g}(x) = (g_1(x), \dots, g_M(x))^T$  is the vector form of basis functions,  $\mathbf{w} = (w_1, \dots, w_M)^T$  is the coefficient vector for the basis functions, and M is the number of basis functions employed in this work.

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According to the assumption (A2), a piece constant map is approximate to the intrinsic image, which takes a constant value  $c_i$  in the *i*-th tissue region  $\Omega_i$ . The regions  $\{\Omega_i\}_{i=1}^N$  make up the partition of the image domain in the sense of  $\bigcup_{i=1}^N \Omega_i = \Omega$  and  $\Omega_i \cap \Omega_j = \emptyset$  for  $i \neq j$ . Thus,

$$J(x) = \mathbf{c}^T \mathbf{u}(x) \tag{3}$$

where  $\mathbf{c} = (c_1, \dots, c_N)^T$  is the constant vector, and the membership function vector  $\mathbf{u}(x) = (u_1(x), \dots, u_N(x))^T$  has the following properties

$$u_i(x) = \begin{cases} 1, & x \in \Omega_i \\ 0, & \text{else} \end{cases}$$
(4)

and

$$\sum_{i=1}^{N} u_i(x) = 1.$$
 (5)

#### 2.2 Extended Otsu Method

Since the major focus of this work is to identify white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) in the normal brain MR image after skull stripping, we present an extended Otsu segmentation to perform the tissue classification, which is a thresholding method [1] that could assign voxels to three classes.

Let 0, 1, 2,  $\dots$ , L - 1 denote the L distinct intensity levels in an image of V voxels, and  $n_i$  notates the number of voxels with intensity *i*. Then, the normalized histogram has components  $p_i = n_i/V$ . Provided that the two thresholds  $t_1$ ,  $t_2$  are selected to threshold the input image into three classes,  $C_1$ ,  $C_2$  and  $C_3$ . The probability  $P_1$  that a voxel is assigned to class  $C_1$  is based on the sum  $P_1 = \sum_{i=0}^{t_1} p_i$ . Similarly, the probability of class  $C_2$  and  $C_3$  occurring are  $P_2(t_1, t_2) = \sum_{i=t_1+1}^{t_2} p_i$ 

and  $P_3(t_1, t_2) = \sum_{i=t_2+1}^{L-1} p_i$ , respectively. Then the mean intensity value of voxels threshold to class  $C_i$  is

$$m_j(t_1, t_2) = \frac{1}{P_1(t_1, t_2)} \sum_{i \in C_j} i p_i$$
(6)

and the average intensity of the entire image

$$m_G = \sum_{i=0}^{L-1} i p_i$$
 (7)

In order to evaluate the "goodness" of the thresholds  $t_1, t_2$ , we define the interclass variance

$$\sigma_B^2(t_1, t_2) = \sum_{i=1}^3 P_i (m_i - m_G)^2$$
(8)

and the optimal thresholds are the value,  $t_1^*$  and  $t_2^*$ , that maximizes  $\sigma_B^2(t_1, t_2)$ :

$$\sigma_B^2(t_1^{\star}, t_2^{\star}) = \max_{0 \le t_1 \le t_2 \le L-1} \sigma_B^2(t_1, t_2)$$
(9)

# 2.3 The Interleaved Iteration between Otsu Segmentation and Bias Field Estimation

To seek the optimal intrinsic image and bias field, the interleaved iteration includes two reciprocal iterative processes, viz, a more accurate tissue segmentation could enhance a better estimated bias field and vice versa.

#### Optimization of u(x) and c

Given a segmentation result  $I_{thresholding}$  obtained from the extended Otsu method, we can optimize the membership functions  $\mathbf{u}(x)$  and constants  $\mathbf{c}$  as

$$\hat{u}_i(x) = \begin{cases} 1, & I_{thresholding}(x) = i \\ 0, & \text{else} \end{cases}, i = 1, \cdots, N$$
(10)

and

$$\hat{c}_i = \frac{\sum\limits_{x \in \Omega} I(x)u_i(x)}{\sum\limits_{x \in \Omega} u_i(x)} \qquad i = 1, \cdots, N.$$
(11)

#### **Optimization of w**

An energy minimization framework [8] is introduced to optimize **w**. Firstly, an energy is defined as

$$F(\mathbf{u}, \mathbf{c}, \mathbf{w}) = \sum_{x \in \Omega} \left| I(x) - (\mathbf{w}^T \mathbf{g}(x))(\mathbf{c}^T \mathbf{u}(x)) \right|^2$$
(12)

By fixing **u** and **c**, we can partially differentiate  $F(\mathbf{u}, \mathbf{c}, \mathbf{w})$  with respect to the variable **w**:

$$\frac{\partial F(\mathbf{u}, \mathbf{c}, \mathbf{w})}{\partial \mathbf{w}} = 0 \tag{13}$$

Hence,

$$\hat{\mathbf{w}} = \left(\sum_{x \in \Omega} \mathbf{g}(x) \mathbf{g}(x)^T (\mathbf{c}^T \mathbf{u}(x))^2\right)^{-1} \left(\sum_{x \in \Omega} I(x) \mathbf{g}(x) (\mathbf{c}^T \mathbf{u}(x))\right)$$
(14)

#### **Bias field correction**

Motivated by the bias field estimation from the optimization of **w**, the bias corrected image  $\hat{I}_c$  can be given by

$$\hat{I}_c(x) = \frac{I(x)}{\hat{\mathbf{w}}^T \mathbf{g}(x)}.$$
(15)

#### 2.4 Implementation

The entire procedure of the proposed method is described as below

**Step1.** Initialize  $I_c = I$ ;

**Step2.** Apply the extended Otsu method on  $I_c$  to get  $I_{thresholding}$ , and calculate  $\hat{\mathbf{u}}(x)$  and  $\hat{\mathbf{c}}$  according to Eq. (10) and Eq. (11);

Step3. Update w in accordance with Eq. (14);

**Step4.** Obtain the bias corrected image  $\hat{I}_c$  according to Eq. (15);

Step5. Check the converge criterion. If the converge

has been reached, stop the iteration; otherwise, update  $I_c$  to  $\hat{I}_c$  and go to step 2.

### 3. Results

The proposed method is applied to the synthetic and the real images with intensity inhomogeneity. The real images are acquired from 3T scans, whose size is  $192 \times 256 \times 160$  voxels, with a voxel size of  $0.9375 \times 0.9375 \times 1$  mm. The synthetic images were generated from a famous simulation brain database—BrainWeb [3] whose size is  $181 \times 217 \times 181$  voxels, with a voxel size of  $1 \times 1 \times 1$  mm.

#### 3.1 Experimental Results

We first compare the proposed method with the noninterleaved Otsu method through their applications in the synthetic and the real images in Fig. 1, which shows individually the synthetic image and its results in the top row, and the real image and its results in the bottom row. It can be seen that there are serious misclassifications of the noninterleaved Otsu method, whereas the results of our method are consistent with the brain anatomy.

Secondly, the results of our method for the synthetic and the real images are shown in Fig. 2. The top and the second row show the results of synthetic images, while the third and the bottom row show the results of real images. As shown in this figure, the segmentation results are consistent with the brain anatomy, and the intensities within each tissue are homogeneous in the bias corrected images.

We further compare our method with three methodsthe unified segmentation [9] and FANTASM [5] and the interleaved KNN method. Unified segmentation and FAN-TASM are two baseline-methods. Figure 3 and Fig. 4 show the comparison of the synthetic and the real images, respectively. The original images, the segmentation results, estimated bias fields and bias corrected images are shown from left to right, respectively. In view of the two group figures, the segmentation results from our method is nearly similar to the interleaved KNN method, and higher agreement with the brain anatomy than FANTASM and the unified segmentation.

Fig. 1 The comparisons of our method with the non-interleaved Otsu method. The original images, the results of the proposed method and the non-interleaved Otsu method are shown from left to right, respectively.

#### 3.2 Quality Evaluation

To further evaluate the performances of our method, Jaccard similarity (JS) [7] and coefficient of variation (CV) [4] are introduced below.

JS is defined as the ratio of the intersection of two regions to their union.



**Fig.2** The results of our method on the synthetic and the real images. The segmentation results, the estimated bias fields and the bias corrected images are shown in the second, third and right column, respectively.



**Fig.3** Comparisons for the synthetic image shown in the left column. The segmentation results, estimated bias fields and bias corrected images are shown in the second, third and right column, respectively. The results of FANTASM, the unified segmentation, the interleaved KNN method and our method are shown in the top, second, third and bottom row, respectively.



**Fig. 4** Comparisons for the real image shown in the left column. The segmentation results, estimated bias fields and bias corrected images are shown in the second, third and right column, respectively. The results of FANTASM, the unified segmentation, the interleaved KNN method and our method are shown in the top, second, third and bottom row, respectively.



$$JS(\Omega_1, \Omega_2) = \frac{|\Omega_1 \cap \Omega_2|}{|\Omega_1 \cup \Omega_2|} \tag{16}$$

where  $\Omega_1$  is the segmented region by the algorithm, and  $\Omega_2$  is given by the ground truth. The closer the JS value is to 1, the more accurate the segmentation is.

20 synthetic images with different levels of intensity inhomogeneity and noises are used to evaluate the segmentation accuracy. The comparison of JS value for GM and WM are shown in Fig. 5. Thence, our method has better performances than the two baseline methods in terms of JS value. However, the interleaved KNN method is a little better than our method.

The definition of CV is the ratio of standard deviation  $\delta$  to mean value  $\mu$  under the same selected tissue class

$$CV(\Omega) = \frac{\delta(\Omega)}{\mu(\Omega)} \tag{17}$$

The smaller CV value indicates the better bias field correction. We tested CV value on 20 synthetic images and 12 3T real images. The comparisons of CV index are shown in Fig. 6. In consideration of Fig. 6, our method has an overall better performance of bias correction than the two baseline methods. The interleaved KNN method has a similar result



to ours.

#### 4. Conclusion

In this letter, we have offered an interleaved Otsu method to segment the MR image with bias field, which combines the extended Otsu segmentation and bias field estimation in an energy minimization. During the interleaved iteration, the segmentations of our method achieve the expected classifications of MR images with intensity inhomogeneity in most cases, excluding the MR images severely corrupted by noise. Based on the results of our method's applications in the real and the synthetic images with bias field, the comparisons are exemplified that our method is more accurate and more effective than the others in view of JS metrics.

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