A Multi-Objective Framework for Brain MRI Threshold Segmentation

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***Abstract*—In this paper, a novel framework for brain MRI threshold segmentation based on multi-objective model is proposed. Two classical techniques named Otsu's method (OTSU) and maximum entropy method (MET) are selected as the objective function based on their opposite characteristics when processing brain MRI with different levels of noise and bias field. The proposed method aims at finding trade-off solutions when segmenting images with noise and bias field. MOEA/D which has low computational complexity and high accuracy is used as the fundamental optimization tool. The Pareto front is approximated by optimizing OTSU and MET simultaneously. We employee the angle based method to find knee point as the final solution which contains more information from Pareto front. The experiments are carried on BrainWeb dataset to verify the performance of proposed framework. The segmentation results also indicate the effectiveness of the new approach.**

***Keywords*-brain image; image segmentation; multi-objective optimization; MOEA/D; threshold; magnetic resonance image**

I. Introduction

Over the last few decades, the rapid development of medical imaging method plays an important role in medical treatment, such as computed topography (CT), magnetic resonance (MR) imaging, ultrasound, positron emission tomography (PET) for diagnosis, therapeutic schedule and clinical studies. In general, brain MRI is utilized to estimate the size of the brain tissues. It is sensitive in detecting brain abnormalities such as cerebral infarction, brain tumors, or infections [1]. However, it is a tedious and complex task for clinicians to analysis the large and complex magnetic resonance image datasets. It is necessary to use computers to assist radiological experts in MRI analysis and evaluation.

Image segmentation is a critical step in image processing which determines the accuracy of the following work. Many different segmentation techniques with application to brain MRI have been developed and can be grouped as follows: (i) manual segmentation; (ii) intensity-based methods; (iii) atlas-based methods; (iv) surface-based methods ; (v) hybrid segmentation methods [2]. Threshold based method is simple and effective, and good survey can be found in [3]. Otsu's method (OTSU) [4] proposed in 1979 segments image by maximizing the variance between various classes. Kapur's

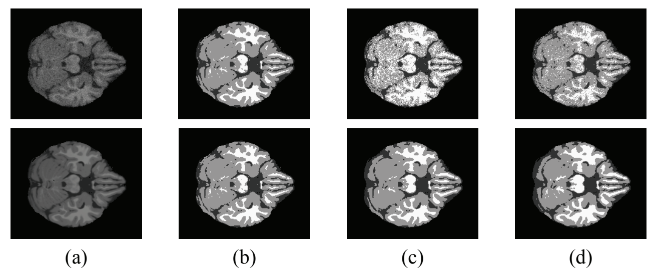

Figure 1. (a) Original image with 9% noise and original image with 40% bias field. (b) Ground truth. (c) Segmentation result by OTSU. (d) Segmentation result by MET.

method (MET) [5] optimize the entropy function to obtain the optimal segmentation result.

For Brain MRI, the segmentation algorithm is supposed to overcome two difficulties called noise and bias field due to the effects of imaging equipment. OTSU and MET show opposite performance when the image is mixed with noise and bias field. OTSU is stable and reliable when segmenting image with bias field, however sensitive to noise. MET shows stability performance processing images with noise, but exhibits poor performance with image containing bias field. Good results are obtained by forming the segmentation problem as a multi-objective model [6], [7], [8], [9]. In the lights of [6], [7], [8], [9], and the contradictory characteristics of OTSU and MET, we propose a framework for brain MRI threshold segmentation based on multi-objective optimization (TSMF). MOEA/D [10] is employed to obtain the Pareto front by optimizing the multi-objective optimization functions OTSU and MET simultaneously. Then, a suitable solution called knee point is obtained by angle based method [11].

The remainder of this paper is organized as follows. Section 2 introduces Otsu's method, Kapur's method and multi-objective optimization. Section 3 gives description of the proposed framework. Results are presented in Section 4. Section 5 concludes this paper.

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II. Preliminary

A. Otsu's method

OTSU is a nonparametric and unsupervised method with a simple structure. The basic principle of Otsu's method is to divide the image into two different classes by maximizing the difference between classes. In general, the pixels in a given picture can be represented in L gray levels $[1, ..., L]$. The probability of occurrence of pixel at level i is denoted as p_i. Suppose the pixels of an image are expected to be spitted into two classes which are $C_0 = [1, ..., k]$ and $C_1 = [k+1, ..., L]$ by a threshold k. The probabilities distributions of C_0 and C_1 can be expressed as follows.

$$\omega_0 = \sum_{i=1}^{k} p_i \tag{1}$$

$$\omega_1 = \sum_{i=k+1}^{L} p_i \tag{2}$$

The mean levels of class C_0 and C_1 are shown in Eq.(3) and Eq.(4) respectively.

$$\mu_0 = \sum_{i=1}^{k} ip_i/\omega_0 \tag{3}$$

$$\mu_1 = \sum_{i=k+1}^{L} ip_i/\omega_1 \tag{4}$$

The total mean level of the original image can be calculated as follows.

$$\mu_T = \sum_{i=1}^{L} ip_i \tag{5}$$

Finally, OTSU defines the total variance of levels in Eq.(6) which is adopted in our proposed framework to evaluate the quality of the threshold.

$$\eta = \sigma_B^2/\sigma_T^2 \tag{6}$$

where

$$\sigma_B^2 = \omega_0\omega_1(\mu_1 - \mu_0)^2 \tag{7}$$

$$\sigma_T^2 = \sum_{i=1}^{L} (i - \mu_T)^2 p_i \tag{8}$$

Then, the segmentation problem is formed as an optimization problem. The optimal threshold is obtained by maximizing the total variance of levels function.

B. Kapur's method

Entropy is used to quantify the amount of necessary information to describe the macrostate of a system. The method is based on the assumption that the pixels in separate categories have different independent probability densities. In the case of binary classification problems, the pixels of given image is supposed to be classified into two categories C_0 and C_1 at threshold k. The accumulated probabilities P_A and P_B of the two classes C_0 and C_1 can be formulated as follows.

$$P_A = \sum_{i=1}^{k} p_i \tag{9}$$

$$P_B = \sum_{i=k+1}^{L} p_i \tag{10}$$

Then, we give the entropy description of an image in Eq.(11).

$$H(I) = H(C_0) + H(C_1) \tag{11}$$

where

$$H(C_0) = -\sum_{i=1}^{k} \frac{p_i}{P_A} \log_2 \frac{p_i}{P_A} \tag{12}$$

$$H(C_1) = -\sum_{i=k+1}^{L} \frac{p_i}{P_B} \log_2 \frac{p_i}{P_B} \tag{13}$$

Consequently, the entropy based method is able to be generalized in the case of N classes in Eq.(14) ,where C_i represents the ith class.

$$H(I) = \sum_{i=1}^{N} H(C_i) \tag{14}$$

C. Multi-objective optimization

A multi-objective optimization technique deals with problems containing more than one objective function at the same time. The general form of multi-objective problem(MOP) is defined in Eq.(15).

$$\begin{array}{lll} Min & f_n(\mathbf{x}), & n = 1, 2, ..., N \\ subject\ to & g_i(\mathbf{x}) = 0, & i = 1 \ldots m_e \\ & g_j(\mathbf{x}) \leq 0, & j = 1, 2, ..., m \\ & x_k^{(L)} \leq x_k \leq x_k^{(U)}, & k = 1, 2, ..., K \end{array} \tag{15}$$

Where $f(x)$ is the objective function subject to constraints $g(x)$, m_e and m are numbers of equality and total constraints respectively. And the variable lower bounds $x_k^{(L)}$ and upper bound $x_k^{(U)}$ restrict each decision variable x_k to take value in the suitable range.

In this paper, there are two objective to be optimized simultaneously described in Eq.(16).

$$\min\{(f_1(x), f_2(x))\} \tag{16}$$

Algorithm 1 A Multi-Objective Framework for Brain MRI Threshold Segmentation

Input: The segmented image I, number of classes N
Output: The knee solution.

1: Initialize the population $P = \{v_1, \cdots, v_p\}$ which contains p individuals of $N-1$ dimension.
2: The value of P is rounded to the nearest integer and sorted in ascending order.
3: Update P by maximizing Eq. (6) and Eq. (14) simultaneously using MOEA/D.
4: **for** $j = 1$ **to** p **do**
5: Reproduce new offspring v_j and update the neighboring solutions. For more information, please refer to[10].
6: **end for**
7: Obtain the Pareto front and an angle based method is used to obtain the knee solution.
8: Return the knee solution.

For multi-objective optimization problems, it is necessary to note that the objectives are conflicting to each other. In the context of multi-objective optimization, Pareto dominance is used to define the optimality of solutions. The solution $x^{(1)}$ is said to dominate the other solution $x^{(2)}$ if and only if $f_i(x^{(1)}) \leq f_i(x^{(2)})$ for $i = 1$ or $i = 2$, and there are at least one index $j \in \{1, 2\}$ satisfied $f_i(x^{(1)}) < f_i(x^{(2)})$. If a solution x^* cannot be dominated by any other solution, x^* is called Pareto-optimal. Pareto-optimal front is defined in the objective space which the corresponding variable in the decision space is Pareto-optimal solution. A solution x^* is said to be weakly Pareto-optimal if no solution can strongly dominate x^*. In our method, we are interested in finding the knee point from weakly Pareto-optimal solutions.

III. TSMF Algorithm

Based on the fact that OTSU and MET focus on different aspects during the process of Brain MRI segmentation. Entropy exhibits better performance when the image suffers from serious noise while OTSU shows poor stability. However, the accuracy offered by OTSU is higher than MET dealing with image influenced by intense bias field. This motivates our approach which aims to obtain a robust algorithm when processing brain MRI with noise and bias field.

OTSU and entropy are selected as segmentation criteria to be optimized simultaneously. For multi-objective problems, evolutionary algorithm is proved to be well suited since this technique is able to dispose multiple solutions at the same time [12], [13]. The popular method MOEA/D [10] is used as the fundamental optimization technique to solve the multi-objective problem. In the proposed framework, MOEA/D is modified to adapt to our problem which the solution is composed with integer threshold. We select the knee solution according to the angle based method [11] from the Pareto front optimized by MOEA/D. Therefore, a threshold is determined. It is necessary to note that our method segments the image automatically while the final threshold usually need to be manually decided in the existing methods.

IV. Experiments

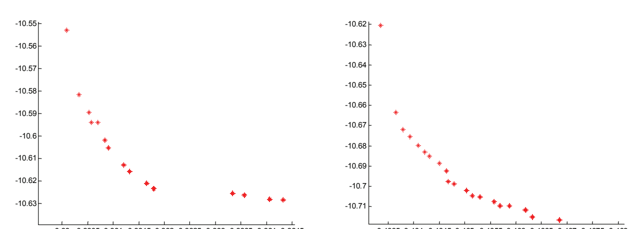
In this section, the experiments are carried out on the well-known BrainWeb [14], [15] database which provides a variety of slice thicknesses simulated brain MR images with different noise levels, and levels of intensity inhomogeneity. The ground truth is also provided to evaluate the performance of various image segmentation methods. We segment the image into cerebrospinal fluid (CSF), white matter (WM) and gray matter (GM). All experiments have been performed in 64-bit matlabR2011a on a PC (Intel Core i7-4790 CPU, 3.60GHz, 8 GB RAM, 64-bit Windows 7 operation system).

A. Experiment settings

We choose the brain MRI image with T1 modality, 1mm slice thickness, 9% noise and 40% intensity non-uniformity to verify the proposed method. The number of segmentation classes is 3. In addition, the population size is set as 200 and the iteration is 400.

In order to evaluate the performance of algorithm, we select similarity measure Dice [16] to quantify the overlap between the segmentation result A_i and the given ground truth B_i of the ith class as shown in Eq.(17). The range of Dice is (0,1). The accuracy of segmentation is high if Dice is close to 1.

$$\rho_i = \frac{2|A_i \cap B_i|}{|A_i| + |B_i|} \tag{17}$$



(a) (b)

Figure 2. Pareto front obtained by TSMF on test image of slice=50 (a) and slice=53 (b).

Table I
DICE VALUES OF GM, WM AND CSF SEGMENTED BY TSMF AND TSMPSO

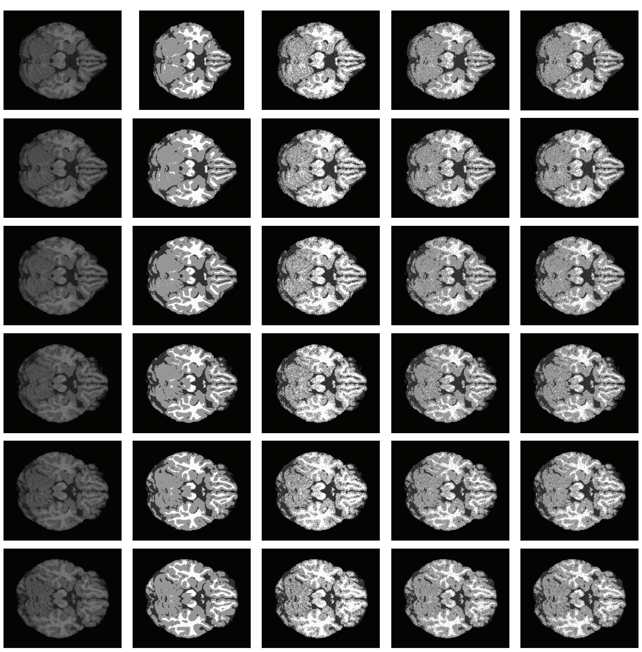
slice	TSMF CSF	TSMF GM	TSMF WM	TSMPSO CSF	TSMPSO GM	TSMPSO WM
50	**0.853**	**0.892**	**0.747**	0.848	0.855	0.710
51	**0.851**	**0.881**	**0.743**	0.846	0.849	0.708
52	**0.858**	**0.892**	**0.742**	0.856	0.857	0.719
53	**0.859**	**0.885**	0.754	0.815	0.853	0.754
54	**0.858**	**0.885**	**0.755**	0.856	0.825	0.679
55	0.846	**0.884**	**0.757**	**0.849**	0.868	0.747
56	**0.839**	**0.878**	**0.775**	0.839	0.856	0.750
57	**0.836**	**0.872**	**0.780**	0.835	0.851	0.760
58	**0.844**	**0.865**	0.776	0.838	0.847	**0.777**
59	**0.844**	**0.865**	**0.807**	0.843	0.856	0.806

B. *The effect of TSMF*

Firstly, the Pareto front calculated by MOEA/D is plotted in Fig. 2. For convince, We convert the problem into a standard form for finding the minimum. It can be clearly seen that the solutions on the Pareto front distribute uniformly. Therefore, MOEA/D is proved to be a suitable technique to brain segmentation.

Secondly, the segmentation results from slice 50 to slice 55 selected from test MR images are collected in Figure 3 . From the results, the proposed method is capable of getting the proper thresholds of test images. It is obvious that the proposed method works well and the stability is quite good.

Finally, we compare the proposed method TSMF with other effective state-of-art method TSMPSO proposed in [6] combined with knee point selection by angle based method used in our framework. The parameters popsize and the iteration are set as 200 and 400 respectively. Table 1 presents the Dice results of TSMF performed on the selected brain MRI dataset from slice 50 to slice 59. The better results are marked in bold. It can be seen that our framework shows effective performance since TSMF gets higher Dice value 8 out of 10 test images. For slice 55, TSMF exhibits better performance with respect to the segment result of GM and WM. For slice 59, gains better solution on the results of CSF and GM. Overall, TSMF is superior to the compared method.



(a) (b) (c) (d) (e)

Figure 3. Illustration of (a) six simulated T1-weighted 1 mm brain MR images with 40% bias field and 9% noise. (b) Ground truth and segmentation results obtained by applying (c) OTSU, (d) MET, (e) TSMF.

V. CONCLUSION

In this paper, we suggested a robust automatic framework TSMF for brain MR image segmentation based on the contradictory characteristic of OTSU and MET when segmenting brain MRI with intense level of noise and bias field. It attempts to find a knee point of Pareto front to obtain a suitable threshold for segmentation. Our experimental results confirmed that TSMF is effective for threshold segmentation on brain MRI. In the future work, we plan to apply the proposed algorithm to deal with nature images.

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