A RVR-based Method for Bias Field Estimation in Brain Magnetic Resonance Images Segmentation

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Abstract— **This paper presents a relevance vector regression (RVR) based parametric approach to the bias field estimation in brain magnetic resonance (MR) image segmentation. Segmentation is a very important and challenging task in brain analysis, while the bias field existed in the images can significantly deteriorate the performance. Most of current parametric bias field correction techniques use a pre-set linear combination of low degree basis functions, the coefficients and the basis function types of which completely determine the field. The proposed RVR method can automatically determine the best combination for the bias field, resulting in a good segmentation in the presence of noise by combining with spatial constrained fuzzy C-means (SCFCM) segmentation. Experiments on simulated T1 images show the efficiency.**

Keywords— **Bias field, segmentation, relevance vector regression, spatial constrained fuzzy C-means, estimation.**

I. INTRODUCTION

Correctly segmenting brain images into gray matter (GM), whiter matter (WM) and cerebrospinal fluid (CSF) plays an important role in brain magnetic resonance (MR) image analysis. In the presence of bias field, we will get a poor segmentation with intensity based methods. In general, bias field, also known as gain field or intensity inhomogeneities, manifests as a slow varying multiplicative field across the whole image. How to properly model the bias field and then correct it to get a pleasant segmentation remains a challenging task up to now.

Various methods have been proposed to solve this problem. They are usually categorized into two groups: prospective methods and retrospective methods. Prospective methods treat intensity corruption as a systematic error of the MRI acquisition process that can either be minimized by acquiring additional images of a uniform phantom, or by devising special image sequences and so on, but they don't take patient movement into account. Retrospective methods are relatively general. These methods mainly rely on the information of the acquired image in which useful anatomical information and information on the intensity inhomogeneity are integrated. In which, filtering methods assume the intensity inhomogeneity is a low-frequency artifact that can be eliminated by low-pass filtering [1], but the assumption fails for most MR images. Histogram based methods operate directly on image intensity histograms, such methods are based on constrained minimization of image information [2]. But it requires several input parameters and a tissue model . Typically, parametric surface fitting methods attracted many authors' attention. These methods fit a parametric surface to a set of image features that contain information on intensity inhomogeneity, and merge with segmentation [3] to get a pleasant result. Some studies modeled the bias field as a polynomial field [4], a stack of B-spline surfaces with constraints [5], a mixture of legendre polynomials [6] and so on. These methods are often done by determining the order of the functions in advance, setting the parameters according to the order and then optimizing them. Their main drawback lies in that we do not know the exact order or how many basis functions we should choose to approximate the objective bias field.

With the relevance vector regression (RVR), we can overcome the drawback to get a reasonable bias field and a pleasant segmentation at the same time. RVR was firstly proposed by M. Tipping [7]. It is a general Bayesian framework [8] for obtaining sparse solutions to regression task, and it provides us with the best parameters automatically under the given kernel form. Specially we use Gaussian function as the kernel in this paper. Together with spatial constrained fuzzy C-means (SCFCM) segmentation [9], which takes neighborhood as regularization and leads the solution toward piecewise-homogeneous labeling, we integrate the goals into an energy function, then update the bias field and centroids alternatively. And finally we get a reasonable bias field and a pleasant segmentation.

The reminder of the paper is organized as follows. The proposed model and methods are presented in Section II. Section III is denoted to the applications of our proposed method to brain MR image segmentation. The conclusions are given in Section IV.

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II. MODEL AND METHODS

The observed magnetic resonance imaging (MRI) signal often can be formulated as

$$Y_i = X_i \times B_i + NO_i, \quad \forall i \in \{1,2,\cdots,N\}, \tag{1}$$

where Y_i, X_i, B_i and NO_i stand for the observed, true intensities, the bias field and the noise at the ith voxel, respectively. And N is the total number of voxels in the MRI. Denoising the image, by a logarithm transform of (1) we get

$$y_i \approx x_i + b_i, \quad \forall i \in \{1,2,\cdots,N\} \tag{2}$$

with $y_i = log(Y_i)$, $x_i = log(X_i)$ and $b_i = log(B_i)$. It may be problematic to estimate either x or b without the knowledge of the other. Also we can see that if (x,b) is a solution to the estimation, so does $(x+cM, b-cM)$ with any constant c. Here, M is the matrix with all entries equal to one. In this paper, the basic assumptions are that b is a slowly varying field across the whole image with mean zero and x can be approximated by a piecewise-constant image. Under these assumptions, we can estimate both x and b by using an iterative algorithm based on RVR and fuzzy logic.

A fuzzy C-means (FCM) based energy function is adopted to achieve the goal in this paper. The energy function can be expressed as

$$\begin{aligned} J_p = &\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^p \|y_k - b_k - v_i\|^2 + \\ &\frac{\alpha}{N_R}\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^p \Big(\sum_{y_r \in \mathcal{N}_k} \|y_r - b_r - v_i\|^2\Big), \end{aligned} \tag{3}$$

where u_{ik} denotes the probability the kth intensity belonging to the ith cluster with $\sum_{i=1}^{c} u_{ik} = 1$, v_i is the ith cluster value, c is the number of clusters, N is the number of intensities, $p \in [1,\infty)$ is the fuzzy index, $\mathcal{N}_k$ is the neighborhood centered at y_k, N_R is the number of $\mathcal{N}_k$ and the effect of the neighbor term is controlled by α (big for low-SNR images). Our goal is to minimize J_p with respect to $\{u_{ik}\}$, $\{v_i\}$, $\{b_k\}$, with the bias field modeled as a linear summation of Gaussian kernels. With $\alpha = 0$, we get the standard FCM objective function. Such function is minimized when high membership values are assigned to voxels whose intensities are close to the centroid of the its particular class, and low membership values are assigned when the voxel data is far from the centroid. When $\alpha > 0$, we allow the labeling of a voxel to be influenced by the labels in its immediate neighborhood [10].

Minimization of the method proposed in this paper consists of four steps.

First of all, the cerebrums of the images gotten from the BrainWeb [11] are removed using a histogram-based method. We set intensities below some pre-set value to be the background value, and then apply morphological operators to remove the skull, leaving the region compose of GM, WM and CSF. In the following steps, we focus on this region.

In the second step, we calculate the histogram of the region of interest (ROI) which is smoothed by a Gaussian filter. Then we use a RVR method to fit the resulting curve, and get the local maximums as the initial centroids which are also transformed into the log-space. Usually we get more centroids than needed, because the intensities have a wide range below the intensity of gray matter. With the centroids, we use a C-means method to get a piecewise constant image ECI with clusters v. By the way, RVR is very convenient for implementation, as its Matlab toolbox can be downloaded from [12].

The third step is the main step. We model the bias field as a linear combination of Gaussian functions. We can choose many points as the kernel centers and their corresponding values as the inputs, for example, 1×10^3 points uniformly distributed in the ROI, and then RVR is used to get an estimated bias field which is a best combination of much less kernel functions. We integrate the bias field to the objective energy function, and then update alternatively with the fuzzy partition matrix and cluster prototypes by SCFCM.

More specifically, letting $D_{ik} = \|y_k - b_k - v_i\|^2$ and $\gamma_i = \sum_{y_r \in \mathcal{N}_k} \|y_r - b_r - v_i\|^2$, we repeat the followings until convergence:

1. $BF = y - ECI$, filter BF with a pre-set window and then perform RVR for bias field approximation to get an estimated bias field EBF.

2. $CI = y - EBF$, perform SCFCM to get new partition matrix and cluster prototypes. We do it in a general way: Taking the first derivatives of J_p with respect to u_{ik} and v_i, then setting them to zero, we get:

$$\begin{aligned} u_{ik}^* &= \frac{1}{\sum_{j=1}^{c}\Big(\frac{D_{ik}+\frac{\alpha}{N_R}\gamma_i}{D_{jk}+\frac{\alpha}{N_R}\gamma_j}\Big)^{\frac{1}{p-1}}}, \\ v_i^* &= \frac{\sum_{k=1}^{N} u_{ik}^p\big((y_k - b_k) + \frac{\alpha}{N_R}(\sum_{y_r \in \mathcal{N}_k}(y_r - b_r)\big)}{(1+\alpha)\sum_{k=1}^{N} u_{ik}^p}, \end{aligned} \tag{4}$$

with the partition matrix we can get the new ECI.

3. Check the stopping criterion. The convergence rule usually is that the norm of difference between the new prototypes and the latest one is less than a pre-set small constant ε,

$$\|V_{new} - V_{old}\| < \varepsilon. \tag{5}$$

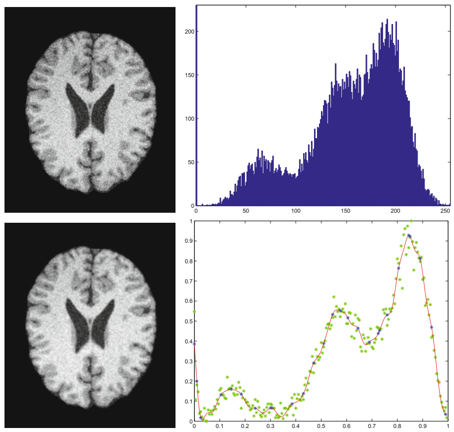

Fig. 1: The image with 9% noise and 40% intensity non-uniformity is shown on the upper left. Its corresponding histogram is shown on the upper right.The smoothed image and its RVR fitting are shown on the down row. The regress function is shown in red and the relevance vectors in blue.

Refine the centroids if necessary. If the difference of two centroids after exponential transform is less than some threshold η, then merge one centroid to the other, and change the ECI accordingly.

At last, we change ECI and EBF to the original space with exponential transform. Post-processing ECI to get the final desired image.

III. Results and discussions

In this section, we test the proposed method on simulated brain MR images. The MR images simulate the appearance and image characteristics of the T1-weighted images. We can validate our segmentation method by using simulated images so that we can have prior knowledge of the true tissue types and control the image parameters like mean intensity values, noise and intensity inhomogeneities. All of images used in this paper are downloaded from [13]. We got T1 weighted volumetric MR scans, $181\times217\times181$ voxels, sized $1\times1\times1$ mm. In all examples, we set the parameter α to be 0.85, $p=2$, a 3×3 window centered at each pixel for image intensities averaging, 5×5 for bias field values averaging, $\varepsilon=0.001$ and $\eta=1$. For high SNR images, we set $\alpha=0.7$.

Fig.1 shows the original image with 9% noise and 40% intensity non-uniformity. Apparently, RVR does a good fitting of the histogram with just a few relevance vectors, and we can easily determine local maximums as initial centroids. In Fig.2, the piecewise constant image and the estimation of the multiplicative bias field resulting with the presented algorithm are shown on the upper row. These images were obtained by scaling the values to a suitable range. Three classes of the brain image corresponding to CSF, GM and WM getting from the piecewise constant image are shown in the middle row and the corresponding standard maps from BrainWeb are shown on the down row. From comparison of the second row and third row of Fig.2, we can see that we have gotten a reasonable and pleasant result.

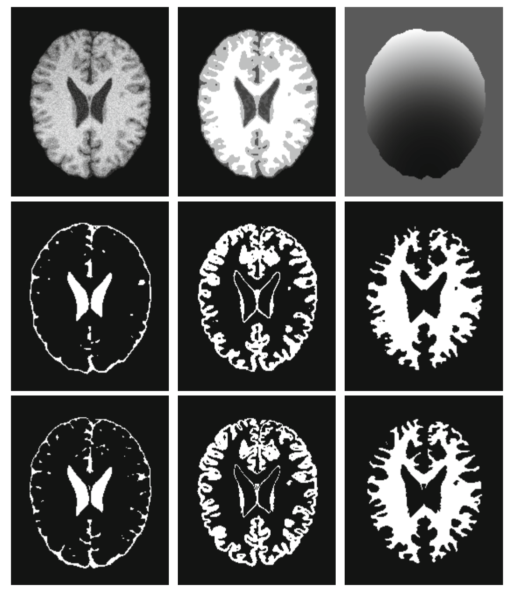

Fig. 2: The original image is shown on the top left followed by the piecewise constant image and estimated bias field on the top row. The respective *CSF*, *GM* and *WM* of the image are presented in the middle row, while the corresponding ground trues are shown in the down row.

In order to show a quantitative comparison between the results getting from the method proposed in this paper and the ground true classes, we detailed the segmentation accuracy with different conditions of noise and bias field in Table 1. With the method in step one, we can not guarantee to remove all irrelevant structures, and it mainly affect the segment result of CSF. So we do not consider the accuracy of CSF. The GM and WM segmentation accuracies are measured by using an average overlap metric (AOM)[14], which is a quantitative evaluation of performance. Overlap metric is defined for a given voxel class assignment as the sum of the number of voxels that both have the class assignment in each segmentation divided by the sum of voxels where either segmentation has the class assignment. This is the same as the Tanimoto coefficient. The AOM can be expressed as follow:

$$AOM=\frac{N(I\cap J)}{N(I\cup J)}\times100\%, \quad (6)$$

where $N(I\cap J)$ denotes the number of voxels that both images I and J have the class assignment, $N(I\cup J)$ denotes the

Table 1: Segmentation results on T1-weighted data under different conditions of noise and bias field.

Noise	Bias	WM	GM	Overall
3%	20%	0.908	0.793	0.851
5%	20%	0.905	0.789	0.847
7%	20%	0.905	0.796	0.850
9%	20%	0.894	0.770	0.832
3%	40%	0.898	0.792	0.845
5%	40%	0.891	0.781	0.836
7%	40%	0.891	0.773	0.832
9%	40%	0.886	0.763	0.824

number of voxels where either segmentation has the class assignment. This metric approaches a value of 1.0 for results that are very similar and near 0.0 when they share no similarly classified voxels.

According to Zijdenbos statement [15] that AOM indicates excellent agreement when it is above 0.7, from the above results we can see that the proposed method is feasible and robust to bias field and noise. Though the accuracy decreases when noise and bias increase, the accuracy stays above 0.7.

From the experiments, we find that: when the algorithm comes to convergence, the bias field can be approximated by a linear combination of about three to five kernel functions in general.

IV. Conclusions

In this paper, we have demonstrated a RVR based parametric approach to the bias field estimation in brain MR images segmentation. It aims to correctly model the bias field and segment the brain image more accuracy. The experiments in different situations were implemented on the simulated T1 images and we got pleasant results. Especially for GM, we got an accuracy around 0.9. In the future, we will utilize basis functions other than gauss function to model the bias field, generalize the method from 2D to 3D images and combine with other modalities to improve the segmentation accuracy.

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