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Robustness of an adaptive MRI segmentation algorithm parametric intensity inhomogeneity modeling

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A R T I C L E I N F O

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A B S T R A C T

We propose an unsupervised segmentation algorithm for magnetic resonance images (MRI) endowed with a parametric intensity inhomogeneity (IIH) correction schema and the on-line estimation of the image model intensity class means. The paper includes an extensive experimentation that shows that the algorithm is robust in the sense that it converges to good image segmentations despite the initial estimation of the image model intensity class means. The algorithm is, therefore, highly automatic requiring no interactive tuning to obtain good image segmentations, an appealing property in clinical environments. The IIH field and intensity class means estimation consists of the gradient descent of the restoration error of the intensity corrected image. Our algorithm does not work on the logarithmic transformation of the image, thus allowing for the explicit distinction between the smooth multiplicative field and the independent and identically distributed additive noise at each image voxel.

1. Introduction

Magnetic resonance images (MRI) allows to visualize with great contrast the soft tissues in the body and has revolutionized the capacity to diagnose the pathologies that affect them [1]. It is based on the phenomenon known as nuclear magnetic resonance (NMR). The image results from the aggregated measurements of the tissue composition at the molecular level. MRI are expected to be piecewise constant except for partial volume effects in the tissue boundaries and the additive noise. Thus, once the expected intensities of each tissue are known, we can built up a good approximation to the optimal Bayesian classifier of minimum classification error assuming that the intensity distribution is a mixture of Gaussians whose means are the tissue expected intensities, to perform the image segmentation task. However, several imaging conditions introduce an additional multiplicative noise factor, referred to as the intensity inhomogeneity (IIH) field in the literature. The sources of IIH are generally divided in two groups [2]: (a) related to properties of the MRI device such as static field inhomogeneity, radio frequency signal energy spatial distribution and others. (b) Related to the imaged object itself such as the specific magnetic permeability and dielectric properties of the imaged object.

A broad taxonomy of MRI IIH correction algorithms divides them between parametric and non-parametric algorithms. The first ones use a parametric model of the IIH field [3–5]. The non-parametric algorithms [6–9] perform a non-parametric estimation of the IIH bias, usually, a smoothing of the restored image classification residuals.

From the point of view of the estimation approach, the two approaches which have produced the greater number of works devoted to this issue are the Bayesian image processing algorithms and the fuzzy clustering. Bayesian algorithms [4,7,9–11] perform the maximum A posteriori (MAP) estimation of either the IIH field or the classification image, or both. The approach needs the formulation of an *a priori* model of the images and/or the inhomogeneity field probability density, and the conditional probability density of the observed image. The probability density of the observed image conditioned to the voxel classification and the inhomogeneity field is usually assumed to be Gaussian. The *a priori* model of the MRI images is sometimes specified by a Markov random field (MRF) that formalizes the smoothness constraints on the image classification [4,7]. In [9,10] modeling the bias as a Gaussian distributed random vector leads to the Expectation Maximization estimation algorithm of the inhomogeneity field. The Hidden MRF proposed in [11] is essentially identical to the MRF *a priori* probability density model of [7].

Fuzzy clustering algorithms [6,12,13] perform the estimation of the image classification minimizing an objective function given by the voxel quantization error weighted by the fuzzy membership coefficients. The algorithms estimate the membership coefficients, the intensity class means and the IIH bias through this minimization process.

We have been previously working on parametric approaches to IIH modeling, estimation and correction, following the approach

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[3,5] of modeling the IIH field with 2D or 3D Legendre polynomials. In [14] we did propose a gradient descent algorithm of the restoration error of the image corrected with an estimation of a parametric IIH bias. The error function gradient is formulated relative to the IIH field model parameters. In this paper, is also formulated the error function gradient relative to the tissue intensity class means and we explore the robust response of the algorithm to random initial mean values. Uncertainty about the correct mean class intensities can be due to the variations on the imaging pulse sequence parameters or to the change from one machine to another. A robust segmentation algorithm able to obtain useful estimations of the class means is a needed step to obtain more automated segmentation procedures.

The image model and the algorithm is described in Section 2. Experimental results on simulated brain MRI volumes are presented in Section 3. In Section 4 we discuss the relationship of the algorithm with precedent algorithms. Finally, conclusions and further work are presented in Section 5.

2. Description of the algorithm

We will denote $\mathbf{y} = (y_i; i \in I)$ the observed image and $\mathbf{x} = (x_i; i \in I, x_i \in \Omega)$ the classification image, where $i \in I \subset \mathbb{N}^3$ is the voxel site in the discrete lattice of the image support for 3D images, and $\Omega = \{\omega_1, \ldots, \omega_c\}$ is the set of tissue classes in the image. The assumed image formation model is the following one:

$$y_i = \beta_i \cdot r_i + \eta_i, \tag{1}$$

where β_i is the multiplicative noise due to the IIH, r_i is the clean signal associated with the true voxel class x_i and η_i is the additive noise. In MRI we have the additional restriction that the reflectance values belong to a discrete (small) set, $\Gamma = \{\mu_{\omega_1}, \ldots, \mu_{\omega_c}\}$, so that $r_i = \mu_{x_i}$. Each μ_ω is the signal intensity mean value associated with a homogeneous tissue.[1]

Definition 1. The robust MRI segmentation and IIH correction problem is the problem of estimating the image segmentation $\mathbf{x}$, the values of the intensity class means Γ, and the IIH multiplicative field $\boldsymbol{\beta} = (\beta_i; i \in I)$ from $\mathbf{y}$.

2.1. The GradClassLeg algorithm

We call GradClassLeg [14] our own proposition of an IIH correction and voxel classification algorithm according to its definition as the Gradient descent of Classified images corrected by products of Legendre polynomials. We assume that IIH field model is a linear combination of 3D products of Legendre polynomials [3,5] given by

$$\beta_i(\mathbf{p}) = \sum_{j=0}^{m} \sum_{k=0}^{m-j} \sum_{l=0}^{m-k-j} p_{jkl} P_j(i_x) P_k(i_y) P_l(i_z), \tag{2}$$

where $i = (i_x, i_y, i_z)$ and $P_k(.)$ is a discretization of the Legendre polynomial of degree k that is consistent with the image size in each dimension, and $\mathbf{p} = \{p_{jkl}\}$ is the vector of the linear combination coefficients. The expression in Eq. (2) takes into account the symmetries in the composition of the bias, assuming that the volume discretization is identical in each spatial dimension. Then number of parameters that compose $\mathbf{p} = \{p_{jkl}\}$ is $n = (m+1)((m+2)/2)((m+3)/3)$. Given an IIH field estimation $\hat{\beta}$ we consider the image correction error relative to the intensity class means as the objective function

$$e(\mathbf{p}, \Gamma) = \sum_{i \in I} \left(\frac{y_i}{\widehat{\beta}_i(\mathbf{p})} - \mu_{x_i} \right)^2. \tag{3}$$

That is, we compute the restoration error as the difference between the predicted intensity associated with the tissue class and the observed intensity after bias correction.

GradClassLeg is a gradient descent algorithm of this error function on the vector of parameters $\mathbf{p}$ of the IIH field model

$$\mathbf{p}_{t+1} = \mathbf{p}_t + \boldsymbol{\alpha}_t^{\mathbf{p}} \nabla_{\mathbf{p}} e(\mathbf{p}, \Gamma), \tag{4}$$

and on the intensity class means

$$\Gamma_{t+1} = \Gamma_t + \boldsymbol{\alpha}_t^{\Gamma} \nabla_{\Gamma} e(\mathbf{p}, \Gamma). \tag{5}$$

Eq. (4) gives the estimation $\hat{\mathbf{p}}$ of the IIH field model parameters starting from a random initial model, Eq. (5) gives the estimation $\hat{\Gamma}$ of the intensity class means, starting either from a random initial set of values or from a good guess. The IIH field parameter gradient vector in Eq. (4) is a vector $\nabla_{\mathbf{p}} e(\mathbf{p}, \Gamma) = \{(\partial/\partial p_{jkl}) e(\mathbf{p}, \Gamma)\}$, where each of its components is of the form

$$\frac{\partial}{\partial p_{jkl}} e(\mathbf{p}, \Gamma) = \sum_{i \in I} \left(\frac{y_i}{\widehat{\beta}_i(\mathbf{p})} - \widehat{\mu}_{\widehat{x_i}} \right) \frac{-y_i P_j(i_x) P_k(i_y) P_l(i_z)}{\widehat{\beta}_i^2(\mathbf{p})}, \tag{6}$$

where $\widehat{x}_i = \operatorname{argmin}_\omega \{y_i / \widehat{\beta}_i(\mathbf{p}) - \mu_\omega\}$ is the estimation of the classification of each voxel based on the current estimation of the class intensity means. The intensity class means gradient vector in Eq. (5) is a vector $\nabla_{\Gamma} e(\mathbf{p}, \Gamma) = \{(\partial/\partial \mu_\omega) e(\mathbf{p}, \Gamma)\}$ where each of its components is of the form

$$\frac{\partial}{\partial \mu_\omega} e(\mathbf{p}, I) = \sum_{i \in I | \widehat{x_i} = \omega} -\frac{1}{2} \left(\frac{y_i}{\widehat{\beta}_i(\mathbf{p})} - \widehat{\mu}_\omega \right). \tag{7}$$

3. Computational experiment results

The experimental data is composed of simulated brain MRI volumes [15] obtained from the BrainWeb Internet site [16] at the McConnell Brain Imaging Center of the Montreal Neurological Institute, McGill University. The advantage of working with the simulated volume is that it is possible to compute the classification accuracy relative to the ground truth classes effectively defined in the generation model. There are available simulated brain MRI volumes corrupted with synthetic IIH fields with magnitude 20% and 40% of the original clean image. For short we will call them 20% and 40% IIH volumes. Using the voxel class information provided in the site we have masked out the pixels not belonging to the three classes of interest: white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). We have also downsampled the volume to allow for extensive experiments in a reasonable time frame. The GradClassLeg parameters are set to $\alpha^{\mathbf{p}} = 0.01$, $\alpha^{\Gamma} = 0.1$, and the maximum number of iterations allowed is 100. Initial IIH field parameter vector value $\hat{\mathbf{p}}$ is set to zero. The initial intensity class means $\hat{\Gamma}$ are generated with uniform probability in the interval $[0, 100]$ and ordered in ascendent order to preserve the meaning of the intensity classes for the purposes of visualization and computation of validation indices. The natural ascending order of intensities is CSF, GM and WM. If this order corresponds to ascending number of class, the visualization will not need further labeling neither for the human inspection nor for the computation of the Tanimoto coefficient.

To give a quantitative evaluation of GradClassLeg we have computed the Tanimoto (also known as Kappa or Dace) coefficient, as defined in [4,13], for the CSF, GM and WM tissue classes.

[1] Obviously the existence of such a thing as an homogeneous tissue is dependent on the imaging resolution, and always a source of critical debate.