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SOM for intensity inhomogeneity correction in MRI

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Abstract. Given an appropriate imaging resolution, a common Magnetic Resonance Imaging (MRI) model assumes that object under study is composed of piecewise constant materials, so that MRI produces piecewise constant images. The intensity inhomogeneity (IIH) is modeled by a multiplicative inhomogeneity field. It is due to the spatial inhomogeneity in the excitatory Radio Frequency (RF) signal and other effects. It has been acknowledged as a greater source of error for automatic segmentation algorithms than additive noise. We propose a new non parametric IIH correction algorithm where the Self Organizing Map (SOM) is used to estimate the IIH field.

1 Introduction

Magnetic Resonance Imaging (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 [5]. MRI has a high spatial resolution and provides much information on the anatomical structure, allowing quantitative pathological or clinical studies, the derivation of digitized anatomical atlases and also the guide before and during the therapeutic intervention. Given an appropriate imaging resolution, a common MRI model assumes that the object under study is composed of piecewise constant materials, so that MRI would produce piecewise constant images. Under this model, once the expected intensities of each tissue are known, we can obtain 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: the intensity inhomogeneity (IIH) field. This effect may come from inaccurate positioning of the patient or inhomogeneities in the RF signal energy spatial distribution. Conventional clustering algorithms [6] can cope with the additive noise, but the multiplicative inhomogeneity field has catastrophic effects on their performance. 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 [4, 10, 14]. The non parametric algorithms [1, 11, 13, 16] perform a non-parametric estimation of the inhomogeneity field which is computed as the smoothed restored image classification residuals. A general non parametric algorithm for IIH correction is the lowpass filtering in the log-domain, which is

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equivalent to homomorphic filtering [8] in digital image processing for the correction of illumination inhomogeneity. However, it is of no use for MRI because there is a great overlap between the IIH field and the image Fourier spectra. The IIH correction algorithms in MRI are composed of two steps. One is a method for the IIH field estimation and the other is a classification algorithm applied to the image obtained removing the IIH field. In this paper the classification step is performed by a simple minimum distance classifier to the assumed class intensity means corresponding to the reference tissues. The field estimation is performed applying a SOM adaptation rule. In this paper we do not deal with the simultaneous estimation of the class intensity means and the IIH field.

Section 2 contains the definition of the algorithm. Section 3 contains some experimental results, and section 4 contains some conclusions and further work directions.

2 Description of the algorithms

We will denote $\mathbf{y} = (y_i; i \in I)$ the observed image and $\mathbf{c} = (c_i; i \in I, c_i \in \Omega)$ the classification image, where $i \in I \subset \mathbb{N}^2$ is the pixel site in the discrete lattice of the image support for 2D images, and $\Omega = \{\omega_1, ..., \omega_c\}$ is the set of tissue classes in the image. The assumed image formation model is the following one

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

where β_i is the multiplicative inhomogeneity field, x_i is the clean signal associated with the true pixel class c_i and η_i is the additive noise. In MRI we have the additional constraint that the signal intensity values belong to a discrete (small) set, $\Gamma = \{\mu_{\omega_1}, ..., \mu_{\omega_c}\}$, so that $x_i = \mu_{c_i}$. The IIH correction problem is the problem of estimating the image segmentation $\mathbf{c}$ and the inhomogeneity multiplicative field $\beta = (\beta_i; i \in I)$ from $\mathbf{y}$. In some algorithms the correction and estimation is performed on the image logarithm. If we discard the additive noise term, we have that the model in equation (1) becomes:

$$\log y_i = \log \beta_i + \log x_i. \tag{2}$$

The multiplicative field β becomes an additive term usually named *bias field*. The distinction between the two image formation models is not as trivial as may appear at first sight, because the log-model in equation (2) implies that the additive noise term η_i has been taken care of previously by means of some linear or non-linear filtering technique, i.e.: anysotropic filtering [7, 12], otherwise the model does not apply. However, in [9] a strong case was made against previous filtering of the image.

We assume the image formation model in eq. 1, and that the intensity class means $\Gamma = \{\mu_{\omega_1}, ..., \mu_{\omega_c}\}$ are known, the problem of IIH estimation becomes the following minimization problem:

$$\min_{\beta_i} \sum_i \left(\frac{y_i}{\beta_i} - \mu_{c(i)} \right)^2$$

where $c(i) = \arg\min_k \left\{ \left\| \mu_k - \frac{y_i}{\beta_i} \right\| \right\}$. That is, we try to minimize the quantization error over the IIH corrected image. We have the additional constraint that the estimated IIH field must be smooth. This smoothness constraint can be expressed in several ways:

1. $\max_{j \in N(i)} \|\beta_i - \beta_j\| < \varepsilon$. The IIH field value differences between a pixel site and its neighbors are arbitrarily small.
2. $\sum_{j \in N(i)} \|\beta_i - \beta_j\| < \varepsilon$. The sum of the IIH field value differences between a pixel site and its neighbors is arbitrarily small.
3. $\forall i, j, k; |i - j| < |i - k| \Rightarrow \|\beta_i - \beta_j\| < \|\beta_i - \beta_k\|$. There is a topological preservation relation between the pixel site index space and the intensity value space.

The last condition resembles the SOM topological preservation property. We propose to use a SOM-like estimation procedure. The logarithm is monotonic transformation, therefore the minimization problem in eq. 2 can be rewritten as follows:

$$\begin{aligned} \min_{\beta_i} \sum_i \left(\frac{y_i}{\beta_i} - \mu_{k(i)} \right)^2 &= \min_{\beta_i} \sum_i \left(\log \left(\frac{y_i}{\beta_i} \right) - \log \mu_{k(i)} \right)^2 = \\ &= \min_{\beta_i} \sum_i \left(\log y_i - \log \beta_i - \log \mu_{k(i)} \right)^2 \end{aligned}$$

If we consider a gradient descent rule for the minimization of this error function when the pixel components of the IIH field are assumed independent, we obtain the following rule:

$$\triangle \log \beta_i = -2\alpha \left(\log y_i - \log \beta_i - \log \mu_{k(i)} \right)$$

where $0 < \alpha < 1$ as usual. If we take into account the smoothness constraint as formulated in condition 3 above, then we can propose the following gradient descent rule as an approximation to minimizing the error in eq. 2 with the constraint of a smooth IIH field:

$$\triangle \log \beta_j = -2\alpha_j \left(\log y_i - \log \beta_i - \log \mu_{k(i)} \right); j \in N(i)$$

Like in the SOM, the neighboring pixels are updated along with the selected pixel. The algorithm is a stochastic gradient descent in which the rule of eq. 2 is applied to a randomly selected pixel i. The gain parameters α_j can be constant for all the neighboring pixels, but a better approach is to make them Gaussian shaped. An annealing process, shrinking the neighborhood radius as the estimation proceeds.

It must be clearly stated that our approach follows a path that differs from other previous applications of SOM to MRI segmentation, like [2, 15]. There, the SOM is used to estimate the intensity class means, either in multispectral or single modality images. In these works, the existence of IIH fields is not taken into account. Most of these papers report an overestimation of the number of classes in the image. This is a natural effect when the IIH field is not considered. On the other hand, in this work we assume the intensity class means provided, focusing on the estimation of the IIH field.

3 Experimental results

In this section we present the experimental results of a new non parametric IIH correction algorithm based on the Self Organizing Map (SOM). We have compared the IIH correction capacity between the proposed algorithm and the state of the art Wells algorithm [16]. The experimental data is composed of 84 slices of simulated brain images, divided into three main groups of 28 consecutive slices that correspond to sagittal, coronal and axial slices respectively. These images are IIH corrupted versions of a clean volume which has been downloaded from the BrainWeb site [3] at the McConnell Brain Imaging Centre of the Montreal Neurological Institute, McGill University. The IIH fields were randomly generated linear combinations of 2D Legendre polynomials.

Figure 1 plots the correlation between the IIH correction results of both algorithms. We can observe that greatest correlation between the Wells algorithm and our algorithm correspond to the coronal slices (images #29 to #56), whereas the lowest ones occur in the sagittal slices. Overall the correlation between the results of both algorithms is greater than 0.9 for the images tested, that means that our approach compares well with state of the art algorithms. Figure 2 (a) shows one coronal slice of a clean simulated volume. Figures 2 (b), 3 (a), 3 (b) show the result of applying the Canny Edge Detection algorithm over the clean slice, the corrected slice using the proposed algorithm and the corrected slice using the Wells algorithm respectively.

4 Conclusions

We have proposed an algorithm for IIH field estimation in MRI. Our algorithm is based on a topological preservation formulation of the smoothness constraint on the IIH field. The resulting estimation rule is very similar to SOM rule, where the neural units are all the pixels of the image. We have tested the approach over MRI simulated images and we have compared its IIH correction capacity with a state of the art algorithm, obtaining encouraging results. Our algorithm obtains results comparable to the Wells algorithm, with a substantial reduction in time. Further work will be addressed to experiment with real brain images and volumes to study the fine detail of the convergence of the algorithm.

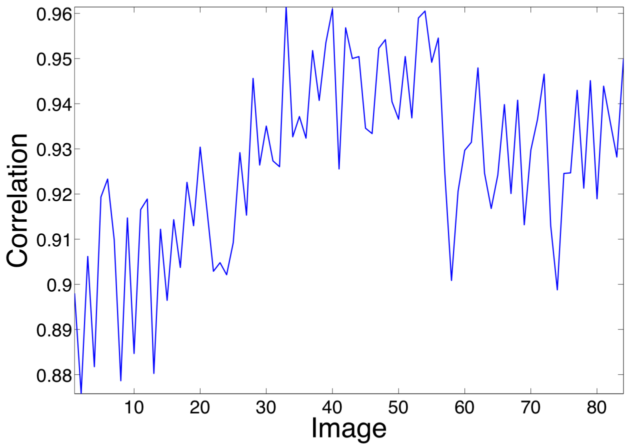

Fig. 1: Correlation between proposed algorithm and Wells Algorithm.

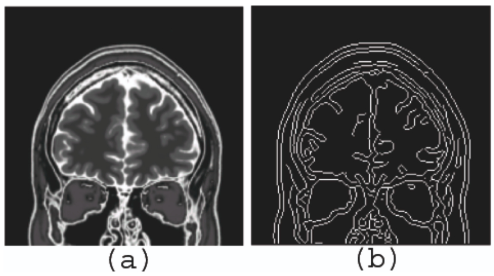

Fig. 2: (a) A slice of clean simulated volume , (b) corresponding edge detection.

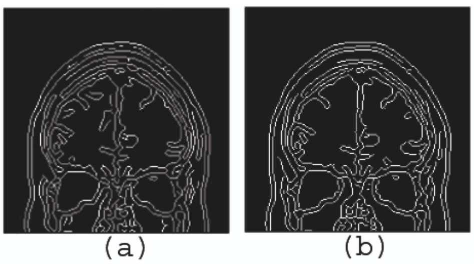

Fig. 3: Edge detection over the slice corrected by our algorithm (a) and the corrected by Wells Algorithm (b).

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