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A proved FCM for Brain MRI segmentation and bias estimation

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Abstract This paper proposes a new energy minimization framework for simultaneous estimation of the intensity inhomogeneities and segmentation. Intensity inhomogeneities estimation and image segmentation are simultaneously achieved by calculating the result of minimizing this energy. Furthermore, in order to reduce the effect of the noise, the membership ratios are adapted by using nonlocal information. Experimental results show that our method can obtain more accurate results.

Key words: Non-local Information, Basis Function, Bias field, FCM, Noise

1 Introduction

Magnetic resonance imaging (MRI) is a helpful method for diagnoses of brain illness, such as Alzheimer's disease and schizophrenia. In MRI data analysis, precise segmentation of different tissues plays an pivotal role for brain studies. Although many algorithms have been reported, automated segmentation still remains a difficult task due to the intensity corruption caused by noise and intensity inhomogeneity.

Recently, an increasing number of people utilize segmentation based approaches to estimate intensity inhomogeneities [1]. Wells et.al [2] extended the framework of maximum likelihood classification to estimate the bias field. The model has the disadvantage of being computationally intensive and requiring initialization of explicitly modeled classes [3].

Some methods introduce the fuzzy c-means (FCM) method and modify the objective function to segment images meanwhile estimating the bias field. Pham [4] used first and second-order regularization terms to ensure the smoothness and continuity of the estimated bias field. However, it is hard to find the exact coefficient of the smoothing term to obtain accurate results. Ahmed et.al.[5] incorporated spatial information by adding a spatial regularization term that enabled the class membership of a pixel to be influenced by its neighbors. This approach proved tolerant to salt and pepper noise, resulting in smoother segmentation. However, a regularization parameter also needed to determine.

In this paper, we propose a new energy minimization approach for simultaneous tissue classification and bias field estimation. The energy function depends on the patch information, the coefficients of the basis functions, the membership functions

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and the centroids of the tissues in the image. Bias field estimation and image segmentation are simultaneously achieved as the result of minimizing this energy.

2 Method

We proposed a new objective function, which preserves the advantages of FCM while taking the bias field into account. In this paper, we only propose the function for 2D images, because it is similar for 3D data. The function is written as:

$$E = \int_{\Omega} \sum_{k=1}^{K} \int_{\Omega} W(x, y) u_k^q(y) dy \left\| J(x) - B(x) v_k \right\|^2 dx \qquad (1)$$

where $u_k(x) \in \{[0,1] \mid \sum_{k=1}^{K} u_k(x) = 1, \forall x\}, \forall x\}$. $W(x, y)$ is a weight function, which depends on the similarity between the neighborhood of x and y, to reduce the effect of the noise.

The similarity between x and y depends on the neighborhood x and y. x is a fixed size square window with width 2×p + 1 centered at x. y is centered at y with the same width as x. The point y with a more analogous neighborhood will have a larger weight. Broadly speaking, if the neighborhoods of two pixels x and y are similar, it is more probable that these pixels belong to the same tissue and so the weight function increases. Conversely, if these two pixels are quite different in the original image, the influence of the weight function should be decreased, since there is a lower probability that the pixel y might have a strong influence on the classification of the current pixel x. The weight function is defined as:

$$W(x, y) = e^{-\frac{\left\| \Delta x - \Delta y \right\|_2^2}{h^2}} \qquad (2)$$

where h acts as a filtering parameter to control the decay of the exponential function, $\left\| \Delta x - \Delta y \right\|_2^2$ is the Euclidean distance, broadly speaking a small neighborhood around a pixel may match neighborhoods around other pixels within the same image. In practical implementation, the spatial neighborhood is often restricted in a small search window with radius r for computational purpose, instead of the entire image domain Ω .

Because the bias field B is usually very smooth across the whole image, we assume that B belongs to a family of smooth functions. We have chosen B to be a linear combination of L smooth basis functions $s_1, s_2, ..., s_L$, , which has been shown in [6]:

$$B(x) = \sum_{l=1}^{L} w_l s_l(x) \qquad (3)$$

where $w_l \in R$, $l = 1, ..., L$, are the combination coefficients. Orthogonal polynomials are usually used as the basis functions, which satisfy

$$\int_{\Omega} s_i(x) s_j(x) dx = \delta_{i,j} \qquad (4)$$

where $\delta_{i,j} = 1$ for $i = j$ and $\delta_{i,j} = 0$ for $i \neq j$.

In this paper, we use Legendre polynomials as the basis functions. In 2-D, we selected products of Legendre polynomials *P* in *x* and *y* as the basis functions si. The image coordinates are scaled to the range [−1, 1]. For Legendre polynomials up to the degree *m*, the size *L* of the parameter vector is given for the 2-D case by *L* = (*m* + 1)(*m* + 2)/2. The parameters $w_1, w_2, ..., w_L$ and $s_1, s_2, ..., s_L$ can be represented in the form of column vectors, i.e. $w = (w_1, w_2, ..., w_L)^T$ and $S(x) = (s_1(x), s_2(x), ..., s_L(x))^T$. Consequently, the energy function above can be updated as

$$E = \int_\Omega \sum_{k=1}^{K} \int_\Omega W(x,y) u_k^q(y) dy \left\| J(x) - w^T S(x) v_k \right\|^2 dx \qquad (5)$$

The objective function E can be minimized in a fashion similar to the standard FCM algorithm. Taking the first derivatives of E with respect to u, v and w and setting them to zero results, we can obtain:

$$u_k^{\#}(x) = \frac{\dfrac{1}{\left(\int_\Omega W(x,y)(J(x) - w^T S(x) v_k)^2 dy\right)^{\frac{1}{q-1}}}}{\sum_{k=1}^{K} \dfrac{1}{\left(\int_\Omega W(x,y)(J(x) - w^T S(x) v_k)^2 dy\right)^{\frac{1}{q-1}}}} \qquad (6)$$

$$v_k^{\#} = \left(\frac{\int_\Omega \int_\Omega W(x,y) u_k^q(y) J(x) dxdy}{\int_\Omega \int_\Omega W(x,y) u_k^q(y) w^T S(x) dxdy}\right) \qquad (7)$$

$$w^{\#} = A^{-1} G \qquad (8)$$

where $A = \int_\Omega \int_\Omega \sum_{k=1}^{K} W(x,y) u_k^q(y) S(x) S(x)^T dxdy$ is an $L \times L$ matrix, where *L* is the number of the basis functions. $G = \int_\Omega \int_\Omega \sum_{k=1}^{K} W(x,y) u_k^q(y) J(x) S(x) dxdy$ is a vector.

The entire procedure correcting the bias field and segmenting the image into different clusters can be summarized in the following steps.

Step 1. Initialize v, u and w;

Step 2. Update *u* to $u^{\#}$ by Eq. 6;

Step 3. Update *w* to $w^{\#}$ by Eq. 8;

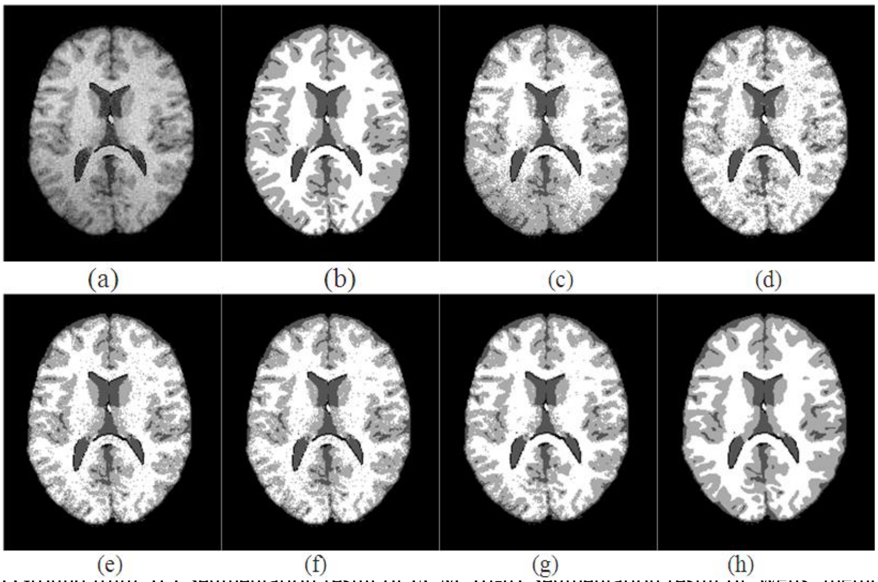
Step 4. Update *v* to $v^{\#}$ by Eq. 7;

Step 5. Check convergence criterion. If convergence has been reached, stop the iteration, otherwise, go to Step 2.

3 Implementation and Experimental Results

Fig.1 shows the segmentation results of a simulated MR image, which was created with the MRI simulator (Brain Imaging Center at the Montreal Neurological Institute, McGill University, mcgill). There are many advantages for using these synthetic images rather than real image data for validating segmentation methods. These advantages include prior knowledge of the true tissue types and control over image parameters such as mean intensity values, noise, and bias field.

We compared our method with FCM and other six segmentation based methods: Wells' method [2], Leemput method [3], AFCM method [4], Li method [6]. Fig.1 shows the segmentation results of the 87th transaxial image with the noise levels 5% and intensity inhomogeneity level 80%. Fig.1 (a) is the initial image. Fig.1 (b) is the ground truth. Fig. 1(c) is the segmentation result of FCM method. It can be seen that, due to the effect of the bias field, some of the WM tissues have be misclassified into GM. Fig. 1(d-f) are the segmentation results of Leemput's method, Wells' method and Li's method. These three techniques can reduce the effect of the bias field, however, they only use the intensity distribution information, which makes these three methodologies sensitive to the noise. The segmentation result of the AFCM method is exibited in Fig. 1(g). This method extends the FCM method to reduce the effect of the bias field and uses the neighbor information to reduce the effect of the noise. However, it is an isotropic method, which makes it unable to reduce the effect of strong noise. Apart from it, when the size of the neighbor increases, the method will lose structure information of brain tissues. Fig.2(h) is the reuslts of our method. Our method can obtain more accurate reulsts by using nonlocal inofrmation.



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(b) Ground truth, (c) Segmentation result of FCM, (d-h) Segmentation result of Wells' method, Leemput's method, Li's method, AFCM method and our method, respectively.

4 Conclusions

In this paper, we have presented a new energy minimization framework for simultaneous bias field estimation and segmentation. Experimental results have shown that our method outperforms other segmentation methods when segmenting images with intensity inhomogeneities and noise.

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