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A Robust Energy Minimization Algorithm for MS-Lesion Segmentation

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Abstract

The detection of multiple sclerosis lesion is important for many neuroimaging studies. In this paper, a new automatic robust algorithm for lesion segmentation based on MR images is proposed. This method takes full advantage of the decomposition of MR images into the true image that characterizes a physical property of the tissues and the bias field that accounts for the intensity inhomogeneity. An energy function is defined in term of the property of true image and bias field. The energy minimization is proposed for seeking the optimal segmentation result of lesions and white matter. Then postprocessing operations is used to select the most plausible lesions in the obtained hyperintense signals. The experimental results show that our approach is effective and robust for the lesion segmentation.

Keywords

Multiple sclerosis lesion; MR; Bias field; True image; Energy minimization

1 Introduction

Multiple Sclerosis (MS) is a chronic and inflammatory disease, which causes morphological and structural changes to the brain. MS could cause various central nervous system dysfunctions such as numbness or weakness of a limb, in coordination, vertigo or visual dysfunction. Therefore, it is very important for radiologists to accurately detect MS lesions and follow-up the numbers, locations, and areas of MS lesions for diagnosis of each patient [1].

Automatization of MS lesion segmentation is highly desirable with regard to time and complexity and visually vague edges of anatomical borders. Their shapes are deformable, their location and area across patients may differ significantly [2–5]. There are many automatic and semiautomatic approaches for brain segmentation [6, 7], Similar to those methods, the MS lesions segmentation approaches include a variety of methods such as

region partitioning, markov random field model, adaptive outlier detection and feature extraction [8–11]. Wu et al. [12] proposed an intensity-based statistical k-nearest neighbor (k-NN) classification which combined with template-driven segmentation and partial volume artifact correction (TDS+) for segmentation of MS lesions subtypes and brain tissue compartments. Geremia et al. [13] proposed a multi-channel MR intensities (T1, T2, FLAIR), knowledge on tissue classes and long-range spatial context to discriminate lesions from background. Abdullah [14] proposed a trained support vector machine (SVM) to discriminate between the blocks in regions of MS lesions and the blocks in non-MS lesion regions mainly based on the textural features with aid of the other features.

In this paper, we proposed a novel algorithm for automatic lesion segmentation from MR images in an energy minimization and intensity information framework. This method is an extension of Li et al.'s algorithm in [15], which only segments the normal tissues from T1 W images. There are three main steps in our proposed method shown in Fig. 1. Skull stripping methods remove non-brain voxels from the image to simplify the following lesion segmentation. The BET method [16] which employed from the FSL library is used for skull stripping first, and then an energy minimization approach is proposed to segment Gray matter(GM) class and estimate the bias field from original images, finally lesion segmentation can be compute automatically from the intensity information of the GM class.

2 Method

2.1 Image Model

Base on a generally accepted MR image model [17], the intensity inhomogeneity in an MR image can be modeled as a multiplicative component of an observed image described by

$$I(x) = b(x)J(x) + n(x) \quad (1)$$

where $I(x)$ is the intensity of the observed image at voxel x , $J(x)$ is the true image, $b(x)$ is the bias field that accounts for the intensity inhomogeneity in the observed image, and $n(x)$ is additive noise with zero-mean.

In this model, the true image $J(x)$ is approximately a constant c_i for x in the i -th tissue. We denote by Ω_i the region where the i -th tissue is located. Each region (tissue) Ω_i can be represented by its membership function u_i , which satisfy $\sum_{i=1}^N u_i(x) = 1$. Given the membership functions u_i and constants c_i , the true image J can be approximated by

$$J(x) = \sum_{i=1}^N c_i u_i(x) \quad (2)$$

More generally, MS lesions are considered as the fourth type of tissue, in addition to GM, WM, and CSF. Therefore, the N is set to 4 here. Due to the partial volume effect, the fuzzy

membership functions with values between 0 and 1 represent a soft segmentation result. It should satisfy

$$\begin{cases} 0 \leq u_i(x) \leq 1 & x \in \Omega_i \\ \sum_{i=1}^N u_i(x) = 1 \end{cases} \quad (3)$$

We represent the coefficients $w_1; \dots; w_M$ by a column vector $w = (w_1; \dots; w_M)^T$, where $(\cdot)^T$ is the transpose operator. The basis functions $g_1(x); \dots; g_M(x)$ are represented by a column vector valued function $G(x) = (g_1(x); \dots; g_M(x))^T$. Thus, the bias field $b(x)$ can be expressed in the following vector form

$$b(x) = w^T G(x) \quad (4)$$

The above vector representation will be used in our proposed energy minimization method for bias field estimation, which allows us to use efficient vector and matrix computations to compute the optimal bias field derived from the energy minimization problem [15].

2.2 Energy Formulation

According to [15], the energy minimization formulation can be defined as follows:

$$F(b, J) = \int_{\Omega} |I(x) - b(x)J(x)|^2 dx \quad (5)$$

From Eqs. (2) and (4), the energy function $F(u, c, w)$ is rewritten as:

$$F(u, c, w) = \int_{\Omega} \sum_{i=1}^N |I(x) - w^T G(x) c_i|^2 u_i(x) dx \quad (6)$$

In many applications, it is preferable to have fuzzy (or soft) segmentation results. To achieve fuzzy segmentation, we modify the energy function F in (6) by introducing a fuzzifier $q \geq 1$ to define the following energy:

$$F(u, c, w) = \int_{\Omega} \sum_{i=1}^N |I(x) - w^T G(x) c_i|^2 u_i^q(x) dx \quad (7)$$

2.3 Energy Minimization

The energy minimization can be achieved by alternately minimizing $F(u, c, w, q)$ with respect to each of its variables given the other two fixed. The minimizer of $F(u, c, w, q)$ in each variable is given below.

Optimization of c

For fixed w and $u = (u_1; \dots; u_N)^T$, the energy $F(u; c; w)$ is minimized with respect to the variable c . Therefore, the estimated intensity mean of j -th tissue can be expressed as

$$\hat{c}_i = \frac{\int_{\Omega} I(x)b(x)u_i^q(x)dx}{\int_{\Omega} b^2(x)u_i^q(x)dx}, \quad i = 1, \dots, N \quad (8)$$

Optimization of w

For fixed c and u , we minimize the energy $F(u, c, w)$ with respect to the variable w . This can be achieved by solving the equation $\frac{\partial F}{\partial w} = 0$. It is easy to show that

$$\frac{\partial F}{\partial w} = -2r + 2Sw \quad (9)$$

where r can be given by

$$r = \int_{\Omega} G(x)I(x) \left(\sum_{i=1}^N c_i u_i^q(x) \right) dx \quad (10)$$

where S is an $M \times M$ matrix,

$$S = \int_{\Omega} G(x)G^T(x) \left(\sum_{i=1}^N c_i^2 u_i^q(x) \right) dx \quad (11)$$

Given the solution of this equation $\hat{w} = A^{-1}v$, the vector $\hat{w}$ can be explicitly expressed as

$$\hat{w} = \left(\int_{\Omega} G(x)G^T(x) \left(\sum_{i=1}^N c_i^2 u_i^q(x) \right) dx \right)^{-1} \int_{\Omega} G(x)I(x) \left(\sum_{i=1}^N c_i u_i^q(x) \right) dx \quad (12)$$

With the optimal vector $\hat{w}$ given by (11), the estimated bias field is computed by

$$\hat{b}(x) = \hat{w}^T G(x) \quad (13)$$

Optimization of u

By fixing c and w , the energy $F(u; c; w)$ is minimized with respect to the variable u .

It can be shown that

$$\hat{u}_i(x) = \frac{(|I(x) - c_i b_i(x)|^2)^{\frac{1}{1-q}}}{\left(\sum_{i=1}^N |I(x) - c_i b_i(x)|^2 \right)^{\frac{1}{1-q}}}, \quad i = 1, \dots, N \quad (14)$$

Each variable is updated with the other two updated in the previous iteration. The optimizations of c , w and u are performed in an iterative process for minimizing the energy $F(u, c, w, q)$.

2.4 Lesion Extraction

Lesions are hyperintense signals on the FLAIR sequence, therefore the intensity information is used to give a preliminary segmentation of the lesions which can be compute automatically from the properties of the GM class. Let $\Omega_1 \subset \mathbb{R}^2$ be the GM domain. $I: \Omega_1 \subset \mathbb{R}^2$ be a given gray level image. Lesions can be obtained as follows

$$\mu_{lesion} = \frac{\int_{\Omega_1} I(x) \cdot u_{lesion}(x)}{\int_{\Omega_1} u_{lesion}(x)} \quad (15)$$

$$\sigma_{lesion} = \sqrt{\frac{\int_{\Omega_1} (I(x) - \mu_{lesion}(x))^2}{\int_{\Omega_1} \mu_{lesion}(x)}} \quad (16)$$

$$S_{lesion} = \begin{cases} 1, & \mu_{lesion} + \beta \cdot \sigma_{lesion} \\ 0, & others \end{cases} \quad (17)$$

where μ_{lesion} is mean of the GM domain, and σ_{lesion} is standard deviation of the GM domain, S_{lesion} is the lesion segmentation results, β is a constant coefficient.

3 Result and Discussions

The proposed method has been tested on the images from University of Pennsylvania, section of biomedical image analysis (SBICA). There are 33 training cases which were

provided with manual segmentation from different experts. The manual segmentations can be viewed as ground truth (GT) to evaluate the automatic lesion segmentations method.

3.1 Experiment Results

Our method has been validated with FLAIR image. We have tested our method on 33 real data sets. All of test data used in our method are the typical MR image with high level of intensity inhomogeneity and strong noise.

Figure 2 shows the process of lesion segmentation, lesions and white matter can be obtained by energy minimization, then lesions can be extracted from the intensity information of them. The normal tissue segmentation obtained by our method is not sufficiently accurate, as the contrast between white matter and gray matter in FLAIR images is very low. However, the errors in the normal tissue segmentation do not affect the satisfactory segmentation for MS lesions.

As it is seen from Fig. 3, there is a good correlation between the input image and the resulted image, although the input images have the obvious intensity inhomogeneity and noise, our method carries out the desirable lesion segmentation result. Moreover, the results of our method does not rely on the type and volume of MS lesion.

3.2 Quantitative Evaluation

The specificity [18] indicates the ability of the segmentation to identify negative results. The fewer the number of false positives (FP), the greater value the specificity of the segmentation. It is defined as

$$Specificity = \frac{TN}{TN + FP} \quad (18)$$

$$TN = |\overline{MS} \cap \overline{Seg}| \quad (19)$$

$$FP = |Seg - MS| \quad (20)$$

where TN is true negative, which is the number of voxels marked as non-MS in both sets, and FP is the false positive, which is the number of voxels only appeared in automatic segmentation. MS is the manual segmentations, and Seg is the segmentation result by our method.

We tested specificity, false negative rate for the 33 sets of flair MR images. The results of these indexes are listed in Table 1. It can be seen that the specificity value of our method to the 33 cases approaches 1 for the manual segmentation. Therefore, the lesion segmentation results from our method are similar to the manual segmentations for most of cases.

Dice's coefficient (DC) is used to measure the similarity of automatic segmentation results and ground truth. For two regions S_1 and S_2 , Dice's coefficient is defined as twice the shared information (intersection) over the sum of cardinalities, and calculated based on the similarity of lesion regions [19]. Even though the manual segmentations cannot be considered to be the same as ground truth, they are still a good way of comparing the automatic lesion segmentation. A larger DC value suggests a better automatic segmentation result.

$$DC = \frac{2|S_1 \cap S_2|}{|S_1| + |S_2|} \quad (21)$$

From Fig. 4 we can see that the DC values between different parameter beta. It can be seen from this figure that the DC value of our method is higher with $\beta = 1.5$ than those of other values.

4 Conclusion

In this paper, we have presented a robust energy minimization algorithm for MS-lesion segmentation. Except the skull stripping, our method does not require other pre-processing steps for the input images. Experimental results on the real MR images have demonstrated the superior performance of our method in terms of segmentation accuracy and efficiency. Our method does not depend on the type and volume of lesions. Finally, we wish to extend our approach and apply it to other tasks and modalities in medical imaging.

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Fig. 1.

The proposed approach for fully automatic segmentation of MS lesions.

Fig. 2.

Result of applying the proposed algorithm to the image of a patient with moderate lesion load: (a), (d), (g) input image, (b), (e), (h) result of energy minimization, (c), (f), (I) result of lesion extraction

Fig. 3. Result of applying the proposed algorithm to the image of a patient with moderate lesion load: (a), (c), (e), (g), (i), (k), (m), (o) input image, (b), (d), (f), (h), (j), (l), (n), (p) result of our method.

Fig. 4.
The comparison of DC value based on the manual segmentation from different parameter values.

Table 1

The detail index of our method with the manual segmentation

Data	Specificity	Data	Specificity	Data	Specificity
Case 01	0.9632	Case 12	0.9231	Case 23	0.9349
Case 02	0.9561	Case 13	0.9364	Case 24	0.9773
Case 03	0.9374	Case 14	0.9644	Case 25	0.9441
Case 04	0.9585	Case 15	0.9531	Case 26	0.9642
Case 05	0.9433	Case 16	0.9534	Case 27	0.9586
Case 06	0.9571	Case 17	0.9413	Case 28	0.9533
Case 07	0.9587	Case 18	0.9448	Case 29	0.9444
Case 08	0.9531	Case 19	0.9537	Case 30	0.9322
Case 09	0.9634	Case 20	0.9461	Case 31	0.9541
Case 10	0.9161	Case 21	0.9277	Case 32	0.9201
Case 11	0.9264	Case 22	0.9338	Case 33	0.9101