BRAIN MR IMAGE SEGMENTATION BY MINIMIZING SCALABLE NEIGHBORHOOD INTENSITY FITTING ENERGY: A MULTIPHASE LEVEL SET APPROACH

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INTRODUCTION

Image segmentation is a fundamental step in quantitative analysis of magnetic resonance (MR) images. Intensity inhomogeneity is often seen in MR images, and these cause considerable difficulties in applying existing image segmentation algorithms. Recently, Li *et al.* [1] proposed a local binary fitting (LBF) model for image segmentation, which is able to handle intensity inhomogeneities better and has been used to segment brain white matter (WM) in MR images. However, the LBF model has difficulties in segmenting gray matter (GM) and cerebral-spinal fluid (CSF) at the same time. In this work, we extend the LBF model to a multiphase level set formulation, so that brain WM, GM and CSF can be segmented simultaneously.

METHODS

In this work, we extend the two-phase level set method described in [1] to a multiphase formulation. We focus on a four-phase formulation, which is enough for brain MR images. In a four-phase level set representation, two level set functions are used to define the following regions: $\{\phi_1>0,\phi_2>0\}$, $\{\phi_1>0,\phi_2<0\}$, $\{\phi_1<0,\phi_2>0\}$, $\{\phi_1<0,\phi_2<0\}$ which form a partition of the image domain into four regions. The segmentation of WM, GM, CSF, and background is then formulated as a problem of finding the optimal partition defined by ϕ_1 and ϕ_2 that minimizes the following energy functional:

$$F(\phi_1,\phi_2,f_1,f_2,f_3,f_4)=\sum_{i=1}^{4}\lambda_i\int_\Omega\int_\Omega K_\sigma(x-y)\left|I(y)-f_i(x)\right|^2 m_i(y)\,dy\,dx+\mu\big(R(\phi_1)+R(\phi_2)\big)+\nu\big(L(\phi_1)+L(\phi_2)\big) \qquad (1)$$

where K_σ is a Gaussian kernel with a scale parameter σ that controls the scale of the neighborhood, $m_1=H(\phi_1)H(\phi_2)$, $m_2=H(\phi_1)(1-H(\phi_2))$, $m_3=(1-H(\phi_1))H(\phi_2)$, $m_4=(1-H(\phi_1))(1-H(\phi_2))$, $R(\phi_i)=\int_\Omega \frac{1}{2}(|\nabla\phi_i|-1)^2\,dx$ is the level set regularization term [2], and $L(\phi_i)=\int_\Omega|\nabla H(\phi_i(x))|dx$ is the arc length term. We call the first term in (1) the scalable neighborhood intensity fitting (SNIF) energy. The kernel function is introduced to utilize local image information. As a result, our method is able to segment brain MR images with intensity inhomogeneities. We use the standard gradient descent method to minimize the above energy for the level set function. The fitting function f_i that minimizes the energy functional can be directly computed from similar close form solutions as in [1]. Our method can be directly applied to the original images without the need for bias correction. Another advantage of our model is that no reinitialization is needed in our method, due to the level set regularization term [2].

RESULTS

In Figure 1, the image in row 1 is from the Motreal Brain-Website [3] with noise level 3% and intensity non-uniformity (INU) 40%. To demonstrate the advantages of our model in terms of accuracy, we compare it with the K-mean algorithm and the Chan-Vese (CV) piecewise constant model [4]. Both the K-mean and CV algorithms rely on the homogeneity of the intensities in each tissue, so we corrected the overall bias by using an expectation-maximization algorithm [5] before applying these segmentation methods. With the ground truth, we can use the Tanimoto coefficient (TC) [6] as a metric to evaluate the performance of the image segmentation algorithms. The TC is always between 0 and 1 by definition, and the larger it is, the better the segmentation. For the image shown in row 1, the TC for WM, GM, and CSF obtained by K-mean algorithm are 0.8957, 0.7804, and 0.7475 respectively. For the CV model, the corresponding TC are 0.8834, 0.7643, and 0.7257. For the proposed SNIF model, the TC for WM, GM, and CSF are 0.9166, 0.82639, and 0.8157 respectively. This comparison shows that our method is more accurate than applying K-mean or CV model to the debiased image. We segment real images obtained at 3T shown in rows 2 and 3, which are two slices (coronal and axial) of a real brain MR image. Obvious intensity inhomogeneities can be seen in these images. Our model has been extended into 3D segmentation. Figure 2 shows a result of 3D segmentation by applying our method to the brain MR image, with (a) and (b) being a 3D surface rendering of the segmented GM and WM respectively.

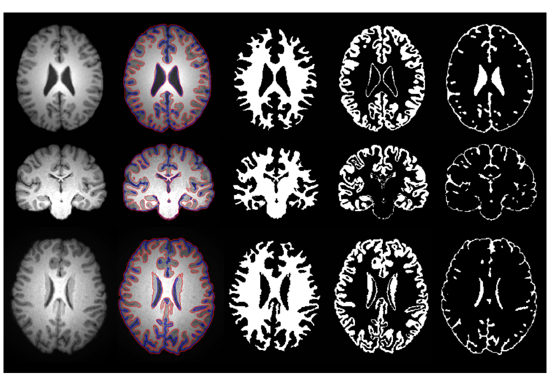
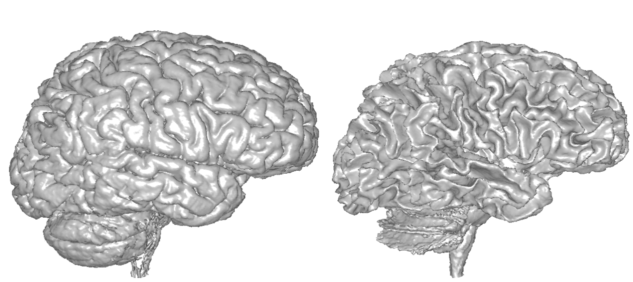


Figure1. Results of 2D segmentation using our method. Column 1: original images. Column 2: segmentation results represented by the zero level contours of ϕ_1 and ϕ_2. Column 3-5: binary maps for the segmentation results for WM, GM, CSF.



(a) (b)

Figure2. Surface rendering of 3D segmentation results. (a) gray matter (b) white matter.

CONCLUSION

We propose a new multiphase level set method for segmentation of brain MR images. The proposed method is able to segment images with intensity inhomogeneities, without the bias field correction. Our method has been applied to brain MR images at 3T. The results show the advantage of our method over alternative methods of segmentation.

RERERENCE

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