A Fully Automatic Cerebellum Segmentation Method using an Active Contour Model with Shape Prior

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Introduction

3D visualization and functional analysis of human brain require segmentation of cerebrum and cerebellum from brain magnetic resonance (MR) images. Many methods for brain extraction were developed, but segmentation of the cerebellum from brain region is still difficult. This difficulty mainly comes from partial volume effect that makes the task of delineating the boundary challenging for even neurological experts. Although some algorithms have been proposed, some limitations still exist [1-3]. Especially, [1] is not robust to intensity variation because the algorithm relies on image intensity and edge operator. Moreover, [2] and [3] use active contour and active shape models, respectively, but these algorithms are sensitive to initial template and user-defined parameters. In this paper, we present a fully automatic cerebellum segmentation method using an active contour model with shape priors.

Methods

We first construct a mean shape of the cerebellum using manually segmented cerebellum from several MRI data set. Cerebellum's initial position is then searched, where mutual information between the mean shape and an input image volume is maximized. From the initial position, contours of the mean shape are evolved using the proposed method, which is as follows:

$$
\begin{aligned}
E_{total} &= \alpha E_1 + \beta E_2 + \gamma E_3 \\
E_1 &= \int_\Omega \left((I - c_1)^2 H(\phi) \right) dA + \int_\Omega \left((I - c_2)^2 (1 - H(\phi)) \right) dA + \mu \int_\Omega \left| \nabla H(\phi) \right| dA + v \int_\Omega H(\phi)\, dA \\
E_2 &= d^2(\phi_{template}, \phi) = \int_\Omega \left(H(\phi_{template}) - T[\mathbf{p}](H(\phi)) \right)^2 dA \\
E_3 &= \int_\Omega \left(\partial H(\phi) - \partial I \right)^2 dA
\end{aligned}
\qquad (1)
$$

where I is an input image, E_1 follows the Chan-Vese (CV) model [4], E_2 is a measure of difference between current segmentation result and the mean shape as the first shape prior, and E_3 is a boundary difference energy as the second shape prior. $T[\mathbf{p}]$ is a similarity transform consisting of scaling, translation, and rotation according to the pose parameter ($\mathbf{p}$), and ∂I represents an edge map obtained by a gradient operation of the image I. Furthermore, $H(\cdot)$ means Heaviside function, and $\phi_{template}$ is a level set function for the mean shape. The three parameters α, β, and γ remain constant throughout the evolution.

At first, the evolution of curve from the initial contour begins to decrease E_1. As the contour evolves, the current segmentation result and the mean shape are matched at each iteration resulting in simultaneous update of the pose parameter $\mathbf{p}$ and the level set function ϕ in order to decrease the second term. As the contour approaches the image boundary, the third term can be further minimized, thereby minimizing the total energy as well. Last two terms play roles of shape constraints. Gradient descent algorithm with respect to the $\mathbf{p}$ and the level set function ϕ is used to minimize the total energy.

Result

We evaluated the proposed method using images from BrainWeb [5], 1.5T, and 3T MR scanner as shown in Fig.1. All data was firstly skull-stripped via BET algorithm. We controlled the user-defined parameters (α, β, γ) in Eq.(1) at the first experiment, whereas none of these parameters were controlled in other experiments. We implemented the proposed method using MATLAB. For most images, the number of iterations was up to 200, and the computation time was about 15 seconds per slice on an Intel Core 2 CPU at 2.66GHz with 2GB of main memory.

Although the cerebellum's boundary of BrainWeb and 1.5T data was generally indistinguishable due to the partial volume effect, the segmentation results showed fine performance. The experimental results for 3T data provide better performance since the boundary of 3T data is more clearly shown compared to the boundary of 1.5T data.

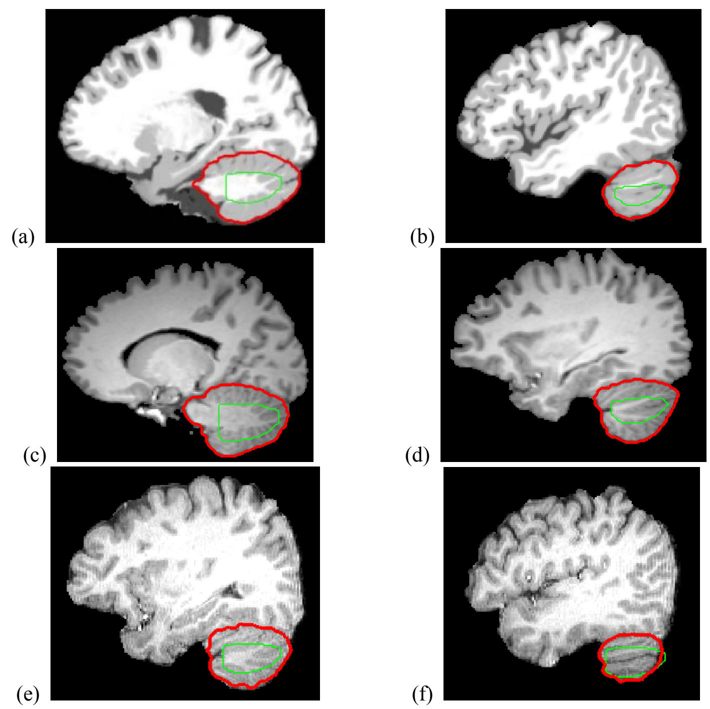

Fig. 1 Experimental results of the proposed method. Green and red lines represent initial contour and segmentation result, respectively. (a) and (b): BrainWeb data, (c) and (d): 1.5T MRI data, (e) and (f): 3T MRI data

Discussion

We presented the cerebellum segmentation algorithm using active contour model based on Chan and Vese (CV) model. Two constraints as shape prior were utilized to prevent over-segmentation by CV model. The experimental results showed well segmented results of the boundary between cerebrum and cerebellum.

References

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