ISSN 1746-7659, England, UK
Journal of Information and Computing Science
Vol. 9, No. 4, 2014, *pp*. 262-266

Hippocampus Segmentation via active contour model

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(*Received February 21, 2014, accepted October 3, 2014*)

Abstract. Since hippocampal volume measurement is often used in studying Alzheimer's disease to assess disease progression, automatic hippocampus segmentation is an important task in clinical applications. However, it is a challenging task due to its small size, complex shape, fuzzy boundaries, partial volume effects, and anatomical variability. In this paper we propose a new segmentation method to segment the hippocampus from brain MRI images automatically.This proposed method presents a new region-based signed pressure force function, which can efficiently stop the contours at weak boundary. Experimental results show that the model can fast and effectively segment the intensity inhomogeneous images.

Keywords: hippocampus; Image segmentation; active contour; Chan-Vese.

1. Introduction

Segmentation of anatomical structures from medical images, such as MRI and CT, has found numerous applications. Current image-based diagnosis, therapy evaluation, surgical planning and navigation highly depend on the segmentation procedure. Medical expert's time though, is both limited and valuable to perform manual segmentations, which also lack reproducibility. The need for automatic segmentation in medical images and its challenging nature, are the main reasons that attract researchers on the topic.

The main challenges of the topic arise from the fact that neighboring structures share the same intensity characteristics and weak boundaries. This exactly is the case with the hippocampus and amygdala complex (Fig. 1). Evidences that alterations of hippocampus and amygdala could serve as potential biomarkers for mental diseases [1], have increased the interest for automated methods that would accurately, robustly and reproducibly segment those structures.

The existing active contour models can be categorized into two classes: edge-based models [1–5] and region-based models [6–10]. The edge-based models utilize image gradient as an additional constraint to stop the contours on the boundaries of desired objects. Usually, a stopping function is used to attract the contours to the desired boundaries. In order to enlarge the capture range of the force, a balloon force term is often incorporated into the evolution function, which controls the contour to shrink or expand. However,it is difficult to choose a proper balloon force. Region-based models aim to identify each region of interest by a certain region descriptor to guide the motion of the active contour. One of the most popular region-based models is the CV model [6], which has been successfully used in binary phase segmentation with the assumption that each image region is statistically homogeneous. However, the CV model does not work well for the images with intensity inhomogeneity. Vese and Chan extended their work in [9] to utilize multiphase level set functions to represent multiple regions. These models are called the piecewise constant (PC) models. Nonetheless, both the CV and the PC models have the drawback described above.

Those models though, solely depend on current information, i.e. the image at hand. However, in medical image analysis prior information is critical for understanding and segmentation of anatomical structures, since their shape shares common characteristics over the population.

This paper is organized as follows: section 2 describes the proposed segmentation method; section 3 performs extensive experiments to verify the proposed method; and section 4 shows the conclusion of this paper

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This paper is sponsored by the open fund of Jiangsu Provincial key laboratory for interventional medical devices (JR1405).

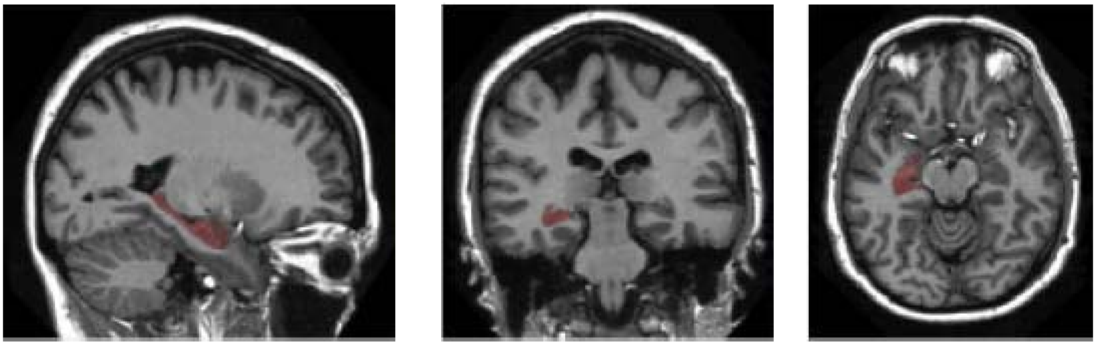


Figure 1. MRI of a brain with highlighted the hippocampus structures.

2. The Proposed Hippocampus Segmentation Method

In this paper, we propose an improved region-based active contour model in a variational level set formulation.

2.1. CV model

Chan and Vese [2] proposed an active contour model which can be seen as a special case of the Mumford–Shah problem [3]. For a given image I in domain Ω, the CV model is formulated by minimizing the following energy functional:

$$E_{\varepsilon}^{cv}(c_1,c_2,\phi)=\lambda_1\int_{\Omega}\left|u_0(x)-c_1\right|^2 H_{\varepsilon}(\phi(x))dx+\lambda_2\int_{\Omega}\left|u_0(x)-c_2\right|^2(1-H_{\varepsilon}(\phi(x)))dx\ \ (x,y)\in\Omega \qquad (1)$$

where c_1 and c_2 are two constants which are the average intensities inside and outside the contour, respectively. With the level set method, we assume

$$\begin{cases} C=\{(x,y)\in\Omega:\phi(x,y)=0\}, \\ inside(C)=\{(x,y)\in\Omega:\phi(x,y)>0\}, \\ outside(C)=\{(x,y)\in\Omega:\phi(x,y)<0\}, \end{cases} \qquad (2)$$

$$c_1(\phi)=\frac{\int_{\Omega}I(x,y)\cdot H(\phi)dxdy}{\int_{\Omega}H(\phi)dxdy},\quad c_2(\phi)=\frac{\int_{\Omega}I(x,y)\cdot(1-H(\phi))dxdy}{\int_{\Omega}(1-H(\phi))dxdy} \qquad (3)$$

By incorporating the length and area energy terms into Eq. (1) and minimizing them, we obtain the corresponding variational level set formulation as follows:

$$\frac{\partial\phi}{\partial t}=\delta_{\varepsilon}(\phi)\left[\mu div(\frac{\nabla\phi}{|\nabla\phi|})-\lambda_1(u_0-c_1)^2+\lambda_2(u_0-c_2)^2\right] \qquad (4)$$

where $\mu\geq 0$, $\lambda_1>0$, $\lambda_2>0$ are fixed parameters, μ controls the smoothness of zero level set, ν increases the propagation speed, and λ_1 and λ_2 control the image data driven force inside and outside the contour, respectively. ∇ is the gradient operator. $H(\phi)$ is the Heaviside function and $\delta(\phi)$ is the Dirac function.

The CV model has good performance in image segmentation due to its ability of obtaining a larger convergence range and being less sensitive to the initialization. If the intensities with inside C or outside C are not homogeneous, the constants c1 and c2 will not be accurate. As a consequence, the CV model generally fails to segment images with intensity inhomogeneity.

2.2. LRCV model

To overcome this drawback, Liu et.al proposed local region based CV model (LRCV) based on CV model. The energy functional of this model is

$$E(c_1(x),c_2(x),C)=\lambda_1\int_{in(C)}\left(I(x)-c_1(x)\right)^2dx+\lambda_2\int_{out(C)}\left(I(x)-c_2(x)\right)^2dx+\mu L(C) \qquad (5)$$

where g_k is Gaussian kernel function, $c_1(x)$ and $c_2(x)$ are shown:

$$\begin{cases} c_1(x) = \dfrac{\int_\Omega g_k(x-y)(I(y)H(\phi(x)))dy}{\int_\Omega g_k(x-y)H(\phi(\mathrm{y}))dy} \\ c_2(x) = \dfrac{\int_\Omega g_k(x-y)(I(y)(1-H(\phi(x))))dy}{\int_\Omega g_k(x-y)(1-H(\phi(x)))dy} \end{cases} \tag{6}$$

We can get the following local region-based flow:

$$\frac{\partial\phi(x,t)}{\partial t} = \delta(\phi)\left[\lambda_1(I(x)-c_1(x))^2 + \lambda_2(I(x)-c_2(x))^2 + \mu div(\frac{\nabla\phi}{|\nabla\phi|})\right] \tag{7}$$

Although LRCV can handle with the inhomogeneous images, it takes more time to compute $c_1(x)$ and $c_2(x)$. Furthermore, LRCV takes the local information into account, therefore it is sensitive to the initial contour.

2.3. The proposed method

Our method combines the advantages of the CV model and the LRCV model by taking the local and global intensity information into account. In this section, we will detail our active contour model based on local and global region-based energy for image segmentation.

The functional is re-defined as:

$$\begin{aligned} E(c_1(x),c_2(x),C,k) = {} & \lambda_1(k)\left[\int_{in(C)}\left(I(x)-d_1\right)^2dx + \int_{out(C)}\left(I(x)-d_2\right)^2dx\right] \\ & + \lambda_2(k)\left[\int_{in(C)}\left(I(x)-e_1(x)\right)^2dx + \int_{out(C)}\left(I(x)-e_2(x)\right)^2dx\right] \end{aligned} \tag{8}$$

where k is iteration times, $\lambda_1(k)$ and $\lambda_2(k)$ is the corresponding weight coefficients, the other variables are defined :

$$\begin{cases} d_1 = \dfrac{\int_\Omega I(x)H(\phi(x))dx}{\int_\Omega H(\phi(x))d\mathrm{x}} \\ d_2 = \dfrac{\int_\Omega I(x)(1-H(\phi(x)))dx}{\int_\Omega (1-H(\phi(x)))dx} \end{cases} \tag{9}$$

$$\begin{cases} e_1(x) = \dfrac{\int_\Omega g_k(x-y)(I(y)H(\phi(x)))dy}{\int_\Omega g_k(x-y)H(\phi(\mathrm{y}))dy} \\ e_2(x) = \dfrac{\int_\Omega g_k(x-y)(I(y)(1-H(\phi(x))))dy}{\int_\Omega g_k(x-y)(1-H(\phi(x)))dy} \end{cases} \tag{10}$$

The final level set evolution equation is show below:

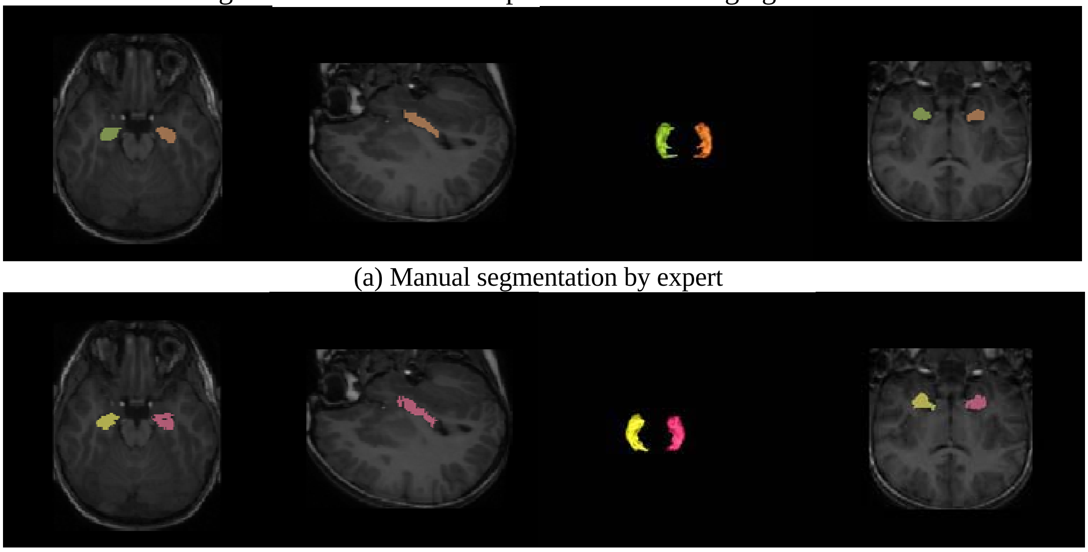
$$\frac{\partial\phi(\mathrm{x},t)}{\partial t} = \delta(\phi)(\lambda_1(k)(-\left(I(x)-d_1\right)^2 + \left(I(x)-d_2\right)^2) + \lambda_2(k)(-\left(I(x)-e_1(x)\right)^2 + \left(I(x)-e_2(x)\right)^2) \tag{11}$$

3. Experimental results

Our algorithm is implemented in Matlab 7.0 on a 2.8-GHz Intel Pentium IV PC. Extensive experiments are performed to validate the proposed method. First, we compare the proposed model with the other models in hippocampus segmentation, as shown Fig.3.

3.1. Evaluation and comparison with manual segmentation

Figure 2 shows the segmentation result using the proposed method. Visual inspection of the segmentation results was performed by comparing “gold standard” and automatic segmentation on the hippocampus. It can be seen that the automatic segmentation result is acceptable and encouraging.



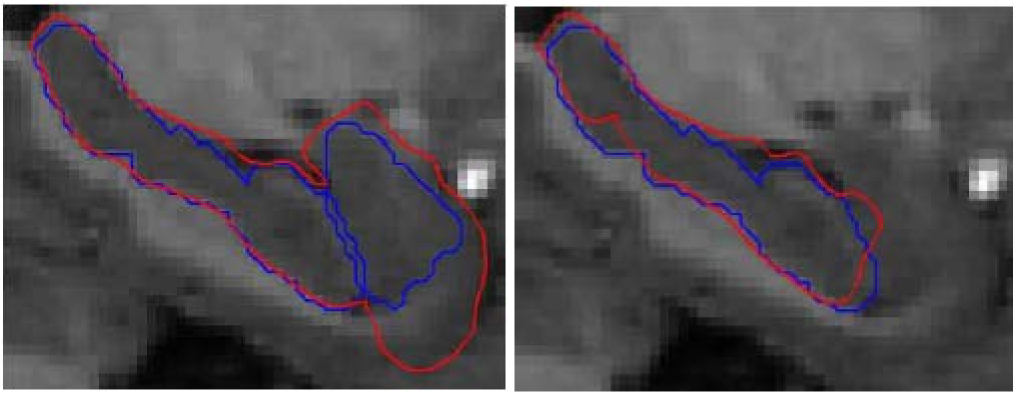
(a) Manual segmentation by expert

(b) Automatic segmentation using the proposed method

Figure 2. Comparison of manual and automatic segmentation on the hippocampus

3.2. The comparison of the other methods

The proposed algorithm was evaluated in the context of the leave-one-out procedure. For every excluded test image, a new hippocampus spatial distribution map and GDHB map was generated. For comparison purposes, results of the combined framework of CV and proposed model have been calculated, which will be abbreviated as SP in the following.



(a) (b)

Figure 3. (a) Segmentation result of the Chan-Vese model (red contour) that leaks from the hippocampus-amygdala boundary (blue contours) on a central slice of the hippocampus. (b) Segmentation result of the proposed model.

Since it is hard to obtain real MRI images of the human brain with known segmentation results of the internal structures, a quantitative assessment of the performance of the segmentation method requires the use of simulated data with known segmentation as the gold standard. The synthetic images came from the deformed SPL reference image, which was deformed using an analytic harmonic deformation approach [11].

4. Conclusion

A combination of local affine transformation and Demons free-form transformation is used to segment the hippocampus automatically in this paper. The segmentation results on both the simulated data and the real data are encouraging. It indicates that the proposed method could be a solution for segmenting such brain internal structures which lack clearly defined intensity boundaries from human MRI images. Compared to global affine transform and simple histogram match, the selected local affine transform with intensity correction simultaneously provide a better initial conditions to the Demons registration algorithm. Furthermore, the results on the simulated data are superior to that on the real data due to the nice intensity correspondence between the homologous structures. It can be concluded that the image gray level of the corresponding structures plays an important role in registration based segmentation using intensity metric.

Acknowledgements

This work was supported by the grant from Natural Science Research Key Project of Jiangsu Provincial Colleges and Universities, No. 11KJA460001, the Jiang Su Qing Lan project and fund of Huai'an 533 project.

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