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An Adaptive Level Set Evolution for the Analysis of Ventricle Variations in Alzheimer MR Images

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Abstract: ***Alzheimer's disease (AD) is a common form of dementia and it is fatal neurogenerative disorder resulting in atrophy of brain regions.MR imaging is a very important tool in diagnosing AD. The enlargement of ventricles due to neuronal loss is a significant characteristic of AD. In this work, ventricular expansion in Axial, Saggital and Coronal views of MR images is analyzed by segmenting the ventricles. Due to intensity inhomogeneties segmentation techniques are to be more sensitive to capture variations in the structural boundaries. Intensity inhomogeneties may cause considerable difficulties in image segmentation. In order to overcome this difficulty we propose a region based active contour model that draws upon intensity information in local regions at a controllable scale. A data fitting energy is defined in terms of a contour and this energy is incorporated into level set formulation. Due to kernel function intensity information in local regions is extracted to guide the motion of the contour. The size and shape of the ventricles in AD subjects are apparently enlarged in the axial view than in the sagittal and coronal views. Segmentation of dilated ventricle is a key step in the diagnosis of AD***.

Keywords: Alzheimer's disease (AD), Image segmentation, Intensity inhomogeneity, level set method, active contour model

1. Introduction

Alzheimer disease is a neuro generative disorder that causes severe cognitive and memory impairment problems. According to world Alzheimer report 35.6 million people suffers from AD. The stepwise diagnosis of this disease includes memory loss, language deterioration and problems day to day life execution. Ventricles are filled with cerebrospinal fluid(CSF) that supply nutrition to brain and provide major physical support. Ventricles expand due to neuronal loss. The shape based analysis of ventricles can act as structural biomarker for the early diagnosis of AD. Magnetic resonance imaging(MRI) is anon-invasive diagnostic tool with high spatial resolution. Ventricle volume has been measured using region growing method. The existing segmentation approaches suffer from inherent complexities .The concavity of the ventricle region and its variations in the size and shape affect the accuracy of the segmentation. Active contour models have extensively applied to image segmentation which has several desirable advantages compared to other classical methods. First, active contour models can achieve sub-pixel accuracy of object boundaries.[5]Second,active contour models can be easily formulated under aprincipled energy minimization frame work. Third, they can provide smooth and closed contours as segmentation results.

For medical images, intensity inhomogeneity is usually due to technical limitations or artifacts introduced by the object being imaged. In particular, the inhomogeneitiesin magnetic resonance (MR) images arise from then on-uniform magnetic fields produced by radio-frequency coils as well as from variations in object susceptibility. Segmentation of such MR images usually requires intensity inhomogeneity correction as a preprocessing step [6]. Level set functions(LSF) are active contour models that undergo evolution to capture complex topological changes. To maintain the stability during the evolution, reintialization is employed. In this paper the modified regularized rate equation is adopted as the rate equation in the variational level set framework.

We define Region-scalable fitting (RSF*)* energy functional in terms of a contour and two fitting functions that locally approximate the image intensities on the two sides of the contour. The optimal fitting functions are shown to be the averages of local intensities on the two sides of the contour. The region-scalability of the RSF energy is due to the kernel function with a scale parameter, which allows the use of intensity information in regions at a controllable scale, from small neighborhoods to the entire domain. This energy is then incorporated into a variational level set formulation with a level set regularization term. In the resulting curve evolution that minimizes the associated energy functional, intensity information in local regions at a certain scale is used to compute the two fitting functions and, thus, guide the motion of the contour toward the object boundaries. As a result, the proposed model can be used to segment images with intensity inhomogeneity. Due to the level set regularization term in the proposed level set formulation, the regularity of the levelset function is intrinsically preserved to ensure accurate computation for the level set evolution and final results, and avoid expensive reinitialization procedures. The structure of the paper is arranged as follows: section I included the introduction and section II included the methodology of the proposed scheme. The implementation of the proposed method is explained in Section III. Section IV included the results. Conclusions are shown in Section V.

2. Methodology

A. Active Contour Model

The intensity inhomogeneity can be mainly observed in Brain MR images and the vessel images.For an image I(x,y) on the image domain **Ω**, they propose to minimize thefollowing energy:

$$\mathcal{F}^{CV}(C,c_1,c_2) = \lambda_1 \int_{\text{outside}(C)} |I(\mathbf{x}) - c_1|^2 d\mathbf{x} + \lambda_2 \int_{\text{inside}(C)} |I(\mathbf{x}) - c_2|^2 d\mathbf{x} + \nu |C| \quad (1)$$

Where outside(C) and inside (C)represent the regions outside and inside the contour C, respectively, and c_1 and c_2 are two constants that approximate the image intensity in outside(C) and inside (C). We call the first two terms in (1) the global fitting energy. This energy can be represented by a level set formulation, and then the energy minimization problem can be converted to solving a level set evolution equation [7].

A level set function Φ and two smooth functions $u^+$and u^- that are defined on the regions outside and inside the zero level contour of a level set function Φ, respectively. The energy functional has a data fitting term, which describes the approximation of the image by $u^+$and u^- in their corresponding sub regions and smoothing term forces them to be smooth. We propose a region-based model using intensity information in local regions at a controllable scale. The kernel function and its localization property play a key role in the proposed method. Consider a given vector valued image I:$\Omega \longrightarrow \Re^d$

where Ωis the image domain, and d≥1 is the dimension of the vector I(x). In particular, d=1 for gray level images, while d=3 for color images. The choice of the kernel function K is flexible. In this paper, Gaussian kernel is chosen as

$$K_\sigma(\mathbf{u}) = \frac{1}{(2\pi)^{n/2}\sigma^n} e^{-|\mathbf{u}|^2/2\sigma^2} \quad (2)$$

With scale parameter σ>0

B. Level Set Formulation

In level set methods, the zero level set of a Lipschitz function Φ which is called a level set function. In this paper, the level set function Φ take positive and negative values outside and inside the contour C, respectively. Let H be the Heaviside function, then the energy functional can be expressed as

$$\mathcal{E}(\phi, f_1, f_2) = \sum_{i=1}^{2} \lambda_i \int \left(\int K_\sigma(\mathbf{x}-\mathbf{y}) |I(\mathbf{y}) - f_i(\mathbf{x})|^2 M_i(\phi(\mathbf{y})) d\mathbf{y} \right) d\mathbf{x} + \nu \int |\nabla H(\phi(\mathbf{x}))| d\mathbf{x} \quad (3)$$

where the last term $\nu \int |\nabla H_\varepsilon(\phi(\mathbf{x}))| d\mathbf{x}$ computes the length of the zero level contour of Φ. Note that this length term has been commonly used for the regularization of the zero level contour [7].[8].

To preserve the regularity of the level set function, which is necessary for accurate computation and stable level set evolution, we introduce a level set regularization term in level set formulation. As proposed in [10], we define the level set regularization term as

$$\mathcal{P}(\phi) = \int \frac{1}{2}(|\nabla \phi(\mathbf{x})| - 1)^2 d\mathbf{x} \quad (4)$$

which characterizes the deviation of the function from a signed distance function. Therefore, we propose to minimizethe energy functional

$$\mathcal{F}(\phi, f_1, f_2) = \mathcal{E}_\epsilon(\phi, f_1, f_2) + \mu \mathcal{P}(\phi) \quad (5)$$

where is a positive constant. To minimize this energy functional, its gradient flow is used as the level set evolution equation.

C. Energy Minimization

The standard gradient descent (or steepest descent)method is used to minimize the energy functional. The gradient flow equation as follows:

$$\frac{\partial \phi}{\partial t} = -\delta_\epsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + \nu \delta_\epsilon(\phi) \operatorname{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \mu \left(\nabla^2 \phi - \operatorname{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right)\right) \quad (6)$$

The above equation (6) is the level set evolution equation to be solved in the proposed method. The term $-\delta_\epsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2)$ is derived from the data fitting energy, and, therefore, is referred to as the data fitting term. This term plays a key role in the proposed model, since it is responsible for driving the active contour toward object boundaries. The second term $\nu\delta_\epsilon(\phi)\operatorname{div}(\nabla\phi/|\nabla\phi|)$ has a length shortening or smoothing effect on the zero level contour, which is necessary to maintain the regularity of the contour. This term is called the arc length term. The third term $\mu(\nabla^2\phi - \operatorname{div}(\nabla\phi/|\nabla\phi|))$ is called a level set regularization term, since it serves to maintain the regularity of the level set function.

3. Implementation

The level set function Φcan be simply initialized as a binary step function which takes a negative constant value $-c_0$ inside a region R_0 and a positive constant valuec_0 outside, for a constant c_0 >0.We choose c_0 = 3 in the experiments shown in this paper. The advantage of using binary step function as the initial level set function is that new contours can emerge easily and the curve evolution is significantly faster than the evolution from an initial function as a signed distance map. In our implementation, the functions f_1 and f_2 are updated at every time step before the update of the level set function. To compute the convolutions more efficiently, the kernel can be truncated as aωxω mask, where is the smallest odd number no less than 4σ . For example, given a scale parameter σ=3, the size of the mask is 13x13.

There are four convolutions in the numerators and denominatorsin (7). However f_2 can be written as

$$f_2 = \frac{K_\sigma * I - K_\sigma * [H_\epsilon(\phi) I]}{K_\sigma * \mathbf{1} - K_\sigma * H_\epsilon(\phi)} \quad (7)$$

Where 1 is the constant

In practice, the Heaviside H function approximated by a smooth function Hε definedby

$$(H_\epsilon(x) = \frac{1}{2}\left[1 + \frac{2}{\pi}\arctan\left(\frac{x}{\epsilon}\right)\right]$$

T

$$(\ \delta_\epsilon(x) = H'_\epsilon(x) = \frac{1}{\pi}\frac{\epsilon}{\epsilon^2 + x^2}.$$

There are totally four convolutions can be computed at each iterations in the above implementation.

4. Results and Discussion

The proposed method has been tested for MR images in transaxial and coronal views for normal as shown in Fig.1

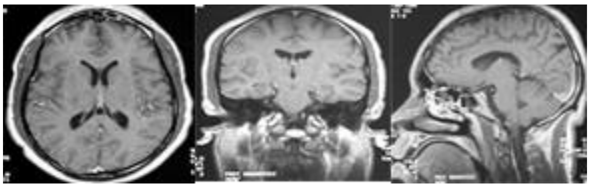

Figure 1: The T1 weighted Normal MR images in (a) Transaxial(b) Saggital and (c) Coronal views

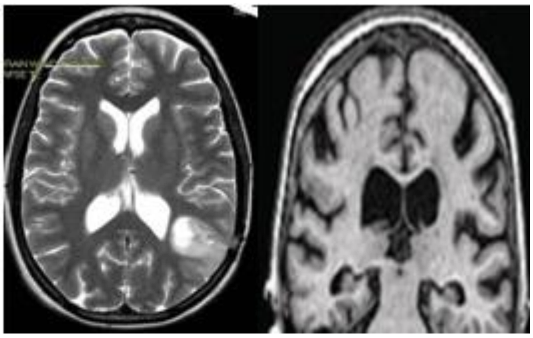

Figure 2: The T2 weighted AD MR images in (a) Transaxialand (b) T1 weighted Coronal views

The following parameters are used in this paper:σ=3,λ_1=λ_1=0.1,time step Δt=0.1,μ=1 and υ=0.001x255x255.In general, a smaller scale can produce more accurate location of the object boundaries.

Figure 3: Final contour of transaxial view.

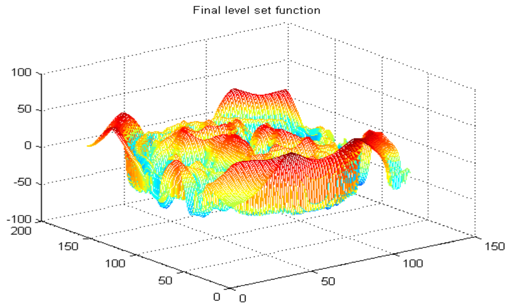

Figure 4: Level set function of transaxial 3D view

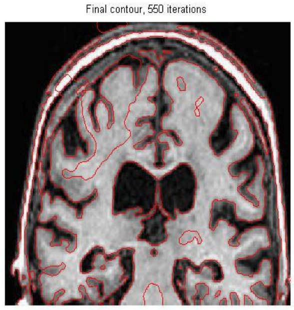

Figure 5: Final contour of coronal view

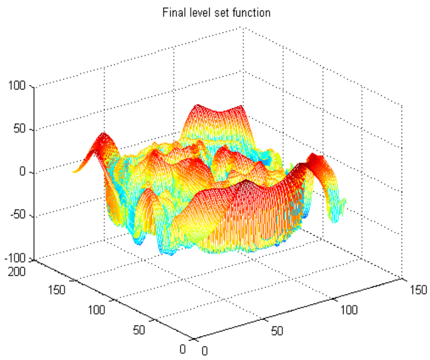

Figure 5: Level set function of coronal 3D view

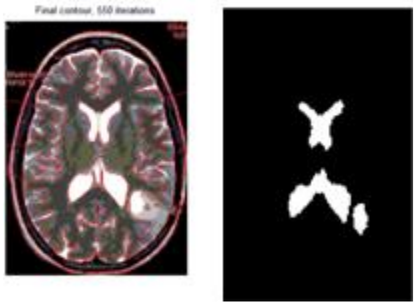

Figure 6: Segmentation of enlarged ventricle (AD MR image) in transaxial view

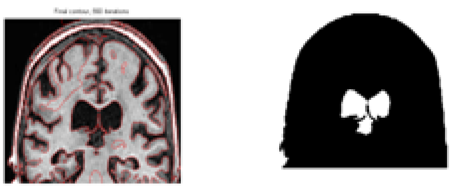

Figure 7: Segmentation of enlarged ventricles (AD MR image) in coronal view

The segmented ventricle regions exhibit distinct morphological variations between the normal and AD subjects. It is also observed that the sizes of the ventricles in the AD subjects are noticeably enlarged in tranaxial view when compared to normal subjects of sagittal and coronal views.

5. Conclusion

The intensity inhomogeneity often occurs in MR images. MRI demonstrates actual pathology of brain disorder due to its high resolution.AD is a common form of dementia. These images have the same subjects but different distribution of intensities. We have presented an active contour model that draws upon intensity information in local regions at a controllable scale. Ventricle enlargement is a productive biomarker of AD. The proposed model is able to segment enlarged images with intensity inhomogeneity and has desirable performance with images with weak object boundaries. In this work ventricular expansion in axial, sagittal and coronal views of MR images. The proposed level set method able to segment ventricles In all the three views. The feature extracted from segmented ventricles in the axial view is used for the diagnosis of the AD disease.

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