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Thalamus Segmentation from MRI Images by Lagrangian Surface Flow

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Abstract— **In this paper, we present a new thalamus segmentation method for MRI images based on a new type of deformable model–Lagrangian Surface Flow. Given a MRI image, the user can interactively initialize a seed model within region of interest. The model will then start to grow according to both boundary and region information based on the principle of variational analysis. The deformation will stop when an equilibrium state is achieved. Our experiments demonstrate that the new method is robust to image noise and inhomogeneity and will not get stuck into local minima or leak from spurious edge gaps.**

I. INTRODUCTION

Thalamus is the relay center for nerve impulses in the brain. It mediates communication among sensory, motor, and associative brain regions. Axons from almost every sensory system connect here as the last site before the information reaches the cerebral cortex. Information received from the diverse brain regions is passed on to the cortex through the thalamus. Anatomically, thalamus is the largest, most internal structures of the diencephalon consisting of dual lobe masses of gray matter. It is located at the rostral end of the mid brain on each side of the third ventricle. Each lobe is about 4 centimeters. Motor nuclei of the thalamus receive signals from the striatum and cerebellum and project into the motor and premotor areas of the cerebral cortex. The thalamus play a major role in the regulation of consciousness, alertness, arousal, and attention and is thus considered part of the limbic system.

Thalamus segmentation has become more and more essential for a wide range of clinical and research applications. For example, thalamus changes in terms of volume and intensity are involved in a large number of diseases, such as schizophrenia, Parkinson's disease and multiple sclerosis, etc. Manual segmentation is very labor intensive and the result is not reproducible. On the other hand, discrete methods such as thresholding or region growing are not reliable because of the low contrast and discontinuous edges in the MRI images of thalamus.

In this paper, we propose a new semi-automatic framework for thalamus segmentation based on a new type of deformable models–Lagrangian surface flow. Because of the inherent smoothness of the deformable model, the new method is very robust to image noise and inhomogeneity. Unlike previous method which only uses edge information, our method seamlessly integrate both boundary and region information and will not get stuck into local minima or leak from spurious edge gaps.

II. DEFORMABLE MODELS AND MEDICAL IMAGE SEGMENTATION

Segmenting structures from medical images and reconstructing a compact geometric representation of these structures is difficult due to the sheer size of the datasets and the complexity and variability of the anatomic shapes of interest. Furthermore, the shortcomings typical of sampled data, such as sampling artifacts, spatial aliasing, and noise, may cause the boundaries of structures to be indistinct and disconnected. The challenge is to extract boundary elements belonging to the same structure and integrate these elements into a coherent and consistent model of the structure. Among various segmentation techniques, deformable models have been very successful since their invention in late 80's. The mathematical foundation of deformable models stems from the confluence of geometry, physics, and approximation theory. Terzopoulos pioneered the theory of continuous (multi-dimensional) deformable models based on Lagrangian dynamics [7], [9] and formulated deformation energies for generalized splines with controlled continuity [8]. Kass *et al.* [4] introduced the active contour model or "snake", a deformable model which is essentially a 2D spline that minimizes an internal deformation energy subject to external forces derived from images. Later, a voluminous literature on deformable models appear in computer vision, and especially in the field of medical image analysis [5]; for a collection of seminal papers, see [6].

III. THALAMUS SEGMENTATION BY LAGRANGIAN SURFACE FLOW

A. Lagrangian Surface Flow

Our new thalamus segmentation framework is based on a new PDE-based deformable model–Lagrangian surface flow which we recently proposed [2], [1]. Lagrangian Surface Flow is a topology adaptive deformable model that can capture underlying topological structure as well as complicated geometry simultaneously from various datasets (e.g. volumetric images). To ensure the regularity of the model and the stability of the numerical integration process, powerful Laplacian tangential smoothing, along with commonly used mesh optimization techniques, is employed throughout the geometric deformation and topological variation process. The new model can either grow from the inside or shrink from the outside, and it can automatically split to multiple objects whenever necessary during the deformation process. More importantly, Lagrangian surface flow supports level-of-details control through global subdivision and local, adaptive subdivision.

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The general formulation of the Lagrangian surface flow is the following initial-value dynamical system of nonlinear PDEs:

$$\frac{\partial \vec{s}(\vec{p})}{\partial t} = F(t, k, k', f, \ldots)\vec{u}(\vec{p}, t), \qquad \vec{s}(\vec{p}, 0) = \vec{s}_0(\vec{p}) \quad (1)$$

where F is the speed function, t is the time variable, k and k' are the surface curvature and its derivative at the point $\vec{p}$, $\vec{s}_0(\vec{p})$ is the initial surface, $\vec{u}$ is the unit direction vector, and usually it is the surface normal vector. (1) can be either directly provided by the user, or more generally, obtained as a gradient descent flow of the Euler-Lagrange equation of certain energy functionals by the calculus of variations.

B. Thalamus Segmentation

When applying the Lagrangian surface flow for thalamus segmentation, the generic PDE in (1) can be explicitly formulated as the weighted minimal surface flow:

$$\frac{\partial \vec{s}}{\partial t} = (g(s)(v + H) - \nabla g(s) \cdot \vec{n})\vec{n}, \qquad \vec{s}(0) = \vec{s}_0, \quad (2)$$

where $\vec{s} = \vec{s}(t)$ is the 3D deformable surface, t is the time variable, and $\vec{s}_0$ is the initial shape of the surface. Note that H is the mean curvature of the surface, $\vec{n}$ is the unit normal of the surface, and v is a constant velocity that will enable the convex initial shape to capture non-convex, arbitrary complicated shapes. The non-zero velocity term is useful to avoid the model getting stuck into the local minimum during the evolution process. g is a monotonic, non-increasing, non-negative weight function that enables the model to interact with the dataset and will stop the model deformation when it reaches the object boundary. For example, g can be defined as the commonly used 3D edge detector:

$$g(s) = \frac{1}{1 + |\nabla(G_\sigma * I(s))|^2} \quad (3)$$

where I is the volumetric density function, and $G_\sigma * I$ is the smoothed density function by convoluting with a Gaussian filter with variance σ. However, since the thalamus has low contrast, using boundary information alone is not very reliable. It is more preferable to combine the boundary information along with the region information as suggested by Huang et. al [3]. In our experiment we use a different weight function g' which is defined as a linear combination of two functions which corresponds to the boundary and region information, respectively:

$$g'(s) = a_1 g(s) + a_2 g(b(s)), \quad (4)$$

here, a_1, a_2 are the corresponding weighting coefficients. $b(s)$ is the binary image created by the interior probability distribution of the current model, which will be explained in more details in the following section.

C. Algorithm Pipeline

There are four main steps in our Thalamus segmentation framework: (1) Seed initialization; (2) Interior Probability Estimation; (3) Binary Image Creation; (4) Model Growing.

Seed Initialization. First, the user interactively selects a pixel inside the region of interest in the image. Considering the thalamus has an oval shape, a circular contour centered at the pixel can be automatically created and serves as the initial seed model.

Interior Probability Estimation. Then, the intensity probability density function of the interior regions enclosed by the seed surface is estimated. Specifically, we approximate the distribution by a nonparametric method such as the Parzen method because it is differentiable, more generic and can represent complex multi-modal intensity distributions. More specifically, we use the Gaussian kernel as the Parzen window function. Suppose the model M is placed on an image I, the volume of the image region bounded by current model M is V, then the probability of a pixel's intensity value i being consistent with the model interior intensity can be derived as:

$$P(i|M) = \frac{1}{V} \int\int\int \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(i-I(y))^2}{2\sigma^2}}, \quad (5)$$

where σ is a constant specifies the width of the Gaussian kernel.

Binary Image Creation. Next, based on the interior probability density distribution of model M obtained in the previous step, the image intensity probability map P_I of every pixel's intensity is obtained. Then a small threshold (e.g. the mean probability over the entire image domain) is applied on P_I to produce a binary image $B(I)$, in which pixels with probability higher than the threshold have value 1, zero otherwise.

Model Growing. Finally, the model will grow according to Equations (2), (3)) and (4). At each deformation cycle, the model will loop from step 2 to 4 until an equilibrium state is achieved, then the deformation stops and the geometry of the thalamus is extracted from the MRI image.

D. Experimental Results

An example of our thalamus segmentation result is shown in Figure 1 and 2. Each figure shows six snapshots of the model growing process including the initial seed ((a)) and the final shape ((e)). Figure 1 shows the model (green color contour) superimposed with the original image, which Figure 2 shows the same six snapshots superimposed with the binary image (yellow region) created by the interior probability estimation.

IV. Conclusion

We proposed a semi-automatic thalamus segmentation method that is based on a new type of deformable model–Lagrangian Surface Flow. Both the boundary and region information are incorporated in the model evolution process so that the model is very robust to image noise and small gaps. Although only 2D image segmentation result is shown, it is straight forward to extend the current framework into 3D volumetric images. In the future we would also like to apply our new framework for the more challenging task of thalamus nuclei segmentation from the newly available Diffusion Tensor Images.

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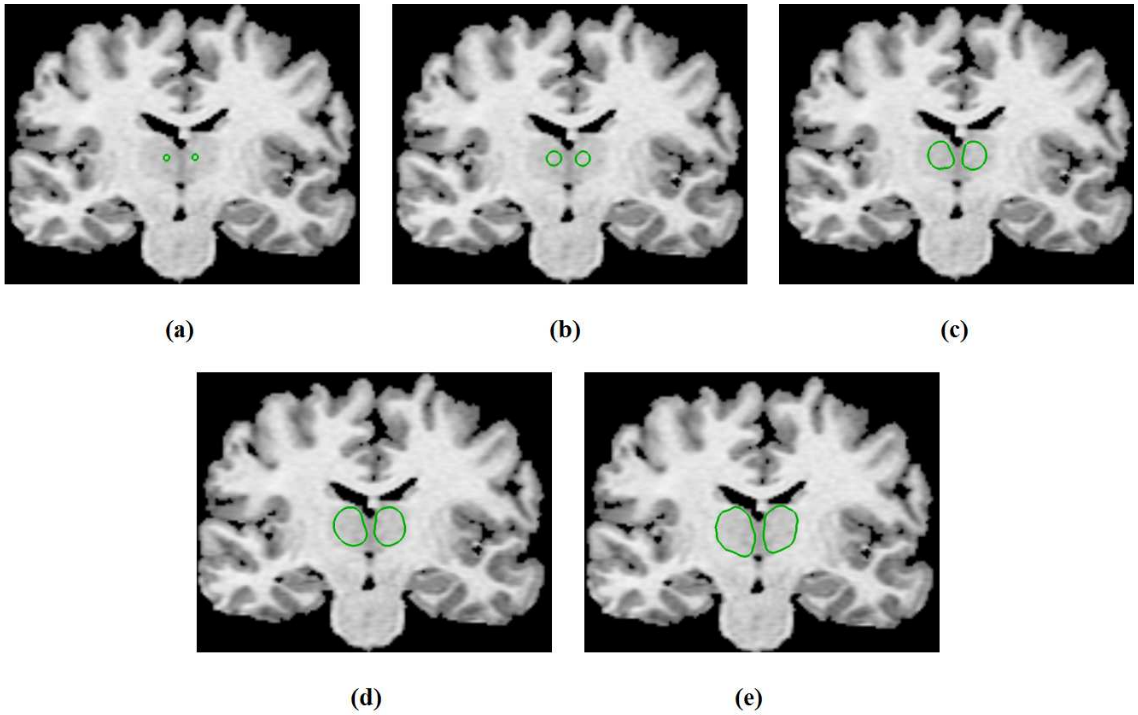

Fig. 1. The model evolution process of the thalamus segmentation superimposed with original image. (a) Initial seed (shown in green color); (b)-(d) three intermediate stages; (e) final extracted shape.

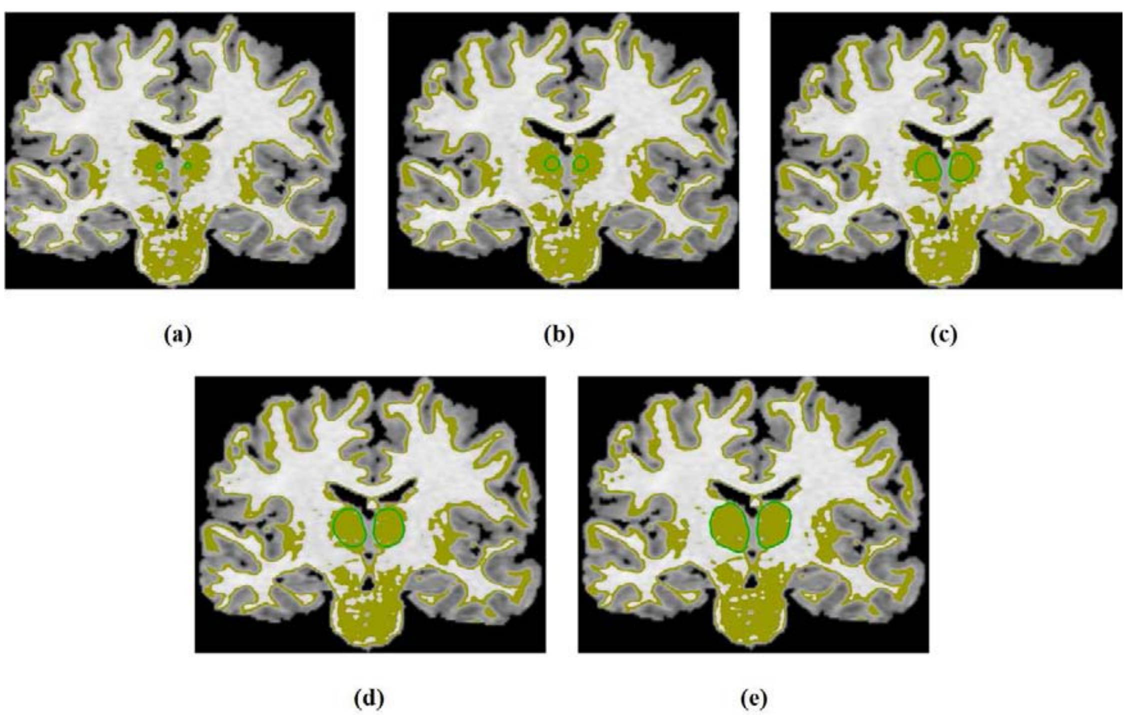

Fig. 2. The same six snapshots of the model evolution process of the thalamus segmentation superimposed with the binary mask (shown as yellow color) created by interior probability estimation.