Actual Brain Midline Detection using Level Set Segmentation and Window Selection

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***Abstract*—Detection of actual brain midline is essential for accurate estimation of midline shift due to traumatic brain injury. An effective method to estimate the actual midline is to use the positions of the identified ventricles. In this work, a level set algorithm combined with Ventricle Window Selection Algorithm and Ventricle Identification Algorithm is proposed to detect the ventricular system in computed tomography (CT) images. The system automatically selects appropriate slices from numerous raw slices and confines the focus to the region of interest prior to segmentation. The variational level set method performs ventricle segmentation without any requirement of re-initialization or intensity-homogeneity of CT images. Combined with ventricle identification, the level set segmentation successfully extracts ventricle contours and estimates actual midline. Experimental results assessed on 391 CT slices of 40 patients support that the proposed system is accurate (90%) and useful for clinical practice.**

Keywords-actual midline; ventricle; CT slice; window selection; level set segmentation

I. INTRODUCTION

Automated actual midline detection precedes accurate midline shift estimation, which is a key clinical index to assess the severity of Traumatic Brain Injury. Midline Shift is known to be highly correlated with elevated Intracranial Pressure levels (ICP) [1]. Computer-aided estimation of the actual brain midline using medical images has attracted a great deal of attention [2-4]. Using quadratic Bezier curve [5] in CT image segmentation, the model introduced by Liao et al., is simple and effective, but it suffers from low accuracy when CT slices show spontaneous intracranial hemorrhage [5]. Chen et al. proposed a method based on Gaussian Mixture Model and template matching to detect the ventricle system on brain CT image. This method has high-accuracy but is time-consuming during the computation of brain midline estimation [6, 7]. Variational level set method overcomes the intrinsic limitation of re-initialization and high sensitivity on intensity-homogeneity [8]. It has been widely used in medical image processing [9, 10].

In this work, a system based on variational level set segmentation combined with Ventricle Window Selection Algorithm (VWSA) and Ventricle Identification Algorithm (VIA) has been proposed, for ventricle detection and midline estimation. The system achieves higher accuracy with less time consumption on midline estimation as compared to other proposed methods.

The rest of this paper is organized as follows: the methodology is introduced in Section II, results are presented and discussed in Section III, and the conclusion of this work is given in Section IV.

II. METHODOLOGY

A flowchart of the four-step algorithm for actual midline estimation is shown in Figure 1.

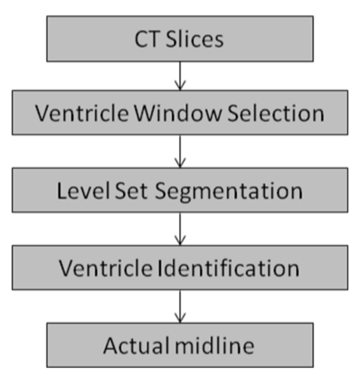

Figure 1. Flowchart of actual midline estimation

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First, Ventricle Window Selection Algorithm is run with all raw CT slices to select appropriate ones. Second, utilization of the level set segmentation effectively extracts candidate contours. Subsequently, the right and left lateral ventricles are determined in ventricle identification. Lastly, the brain midline is estimated using the position of the ventricles.

2.1 Ventricle Window Selection Algorithm (VWSA)

In clinical practice, even though dozens of CT images can be acquired from the head CT scans of each patient, only a few of these slices contain clear ventricle information owing to appropriate scan position. Hence, Ventricle Window Selection Algorithm (VWSA) is designed to narrow down the selection of relevant CT slices and confine the region of focus.

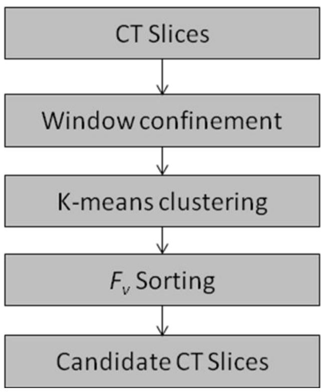

Figure 2. Flowchart of Ventricle Window Selection Algorithm (VWSA)

Raw CT slices may contain too much noise and other irrelevant tissue information, which affects the visibility of ventricles. Moreover, since the speed of contour evolution in subsequent level set segmentation largely depends on size of image, narrowing down the region of interest can accelerate the algorithms throughput. Therefore, as the flowchart shows in Figure 2, the first step of VWSA is confining the focus of operation to a window within a fixed area in the upper center of the brain. We set a window with size of 140*200 pixels. Because of anatomical characteristics and observations during the algorithm development process, this region contains ventricles and is hardly affected by skull or by the presence of other tissues. Using K-means clustering on the gray scale of every pixel, the pixels belonging to the ventricle class are distinguished from all other pixels within the window. In order to evaluate the visibility of ventricles in slices, a new measure, called Ventricle Fidelity Measure (F_v), has been introduced in this study. F_v is a proportion defined by the number of pixels labeled as the ventricle class over the total number of pixels in the window. The larger the Ventricle Fidelity Measure is, the more visible the ventricle should be within the image. Three slices with the largest F_v values are selected as the candidate slices for the following detection.

2.2 Ventricle segmentation based on level set method

Region-based geometric active contour model implemented by variation level set method [9] is used in ventricle contour detection.

Here, we consider a two-dimensional gray level image $I:\Omega \rightarrow \Re$, where $\Omega \subset \Re^2$ is the image domain and I is the image intensity [9]. C represents closed contour in the 2-D image domain ($C \subset \Omega$) and segments the image into two regions: $\Omega_1 = outside(C)$ and $\Omega_2 = inside(C)$. Contour C can be expressed by the zero level set of a Lipschitz function $\varphi:\Omega \rightarrow \Re$, which is a level set function. The energy function $F(\varphi, f_1, f_2)$, which is subject to minimization is defined as;

$$F(\varphi, f_1(x), f_2(x)) = \varepsilon_f(\varphi, f_1(x), f_2(x)) + v|C(\varphi)| + \mu P(\varphi) \quad (1)$$

where the fitting energy ε_f minimizes the gray value variance in separated phases, the contour length $|C(\varphi)|$ smoothes the curve, and the internal energy $\mu P(\varphi)$ helps stabilize curve evolution. $f_1(x)$ and $f_2(x)$ reflect the intensity in the region with center x. With a fixed f_1 and f_2, the energy function $F(\varphi, f_1, f_2)$ in (1) can be minimized by solving the gradient flow equation as follows:

$$\begin{aligned}\frac{\partial \varphi}{\partial t} &= -\delta_\varepsilon(\varphi)(\lambda_1 \int K_\sigma(x-y)|I(x)-f_1(y)|^2 dy \\ &\quad -\lambda_2 \int K_\sigma(x-y)|I(x)-f_2(y)|^2 dy \\ &\quad + v\delta_\varepsilon(\varphi) div(\frac{\nabla\varphi}{|\nabla\varphi|}) + \mu(\nabla^2\varphi - div(\frac{\nabla\varphi}{|\nabla\varphi|}))\end{aligned} \quad (2)$$

with

- $\delta_\varepsilon(\varphi)(\lambda_1 \int K_\sigma(x-y)|I(x)-f_1(y)|^2 dy - \lambda_2 \int K_\sigma(x-y)|I(x)-f_2(y)|^2 dy$ being the data fitting term;
- $v\delta_\varepsilon(\varphi) div(\frac{\nabla\varphi}{|\nabla\varphi|})$ represents the arc length term; and
- $\mu(\nabla^2\varphi - div(\frac{\nabla\varphi}{|\nabla\varphi|}))$ is the level set regularization term.

The segmentation used in this work is based on the level set evolution equation (2). Further details can be found in [9]. Level set regularization term effectively eliminates time consumption due to re-initialization, which is one of the main purposes of using this method in segmentation.

Using the variational level set method in segmentation, candidate contours are extracted from the candidate CT slice. Generally, two ventricle contours is expected to be found corresponding to the right and left lateral ventricles. However, due to the complexity of CT images, in practice, more (or less) than two contours are possibly found. Therefore, we need the following ventricle identification process to identify the actual ventricles.

2.3 Ventricle identification and actual midline estimation

As the flowchart shows in Figure 3, the first step of the VIA is to identify the right and left lateral ventricle contours from a set of contours obtained from level set segmentation. We remove the unclosed contours using the Connected Component Algorithm (CCA) [11]. Assume that n-candidate

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contours are retained in the VWSA window. If n equals 0 or 1, it means that either no ventricle or a mangled ventricle image is displayed in the CT slice. The algorithm automatically skips this slice and moves back to VWSA to compute on the next candidate slice. In the case where two or more candidate contours are found, the two contours with the largest length are chosen as the right and left lateral ventricles.

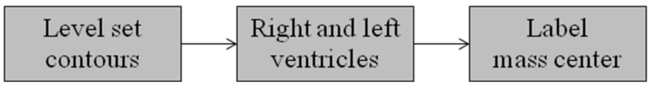

Figure 3. Flowchart of ventricle identification

In order to determine the mass center of a contour, the moment m_{pq} [12] with the order of $p+q$ of the digital image Γ is defined as below,

$$m_{pq} = \sum_{j=1}^{n}\sum_{i=1}^{m} i^p \cdot j^q \cdot \Gamma_{ij}, \quad (p = 0,1; q = 0,1) \tag{3}$$

where Γ_{ij} is the image intensity of the element at the ith row and the jth column in the matrix Γ. This means that Γ_{ij} equals 1 when the element is on the contour, else equals 0. Then, the coordinate of the mass center (x, y) [12] of the object contour is given by

$$\begin{cases} x = \dfrac{m_{10}}{m_{00}} \\ y = \dfrac{m_{01}}{m_{00}} \end{cases} \tag{4}$$

Finally, the step of estimating the actual midline can be performed. Assuming that the right and left lateral ventricles have the mass center positions of (x_1, y_1) and (x_2, y_2), respectively, the actual midline is believed to be at the middle of the two ventricles and have the slope K as shown below;

$$K = -tan\frac{(x_2 - x_1)}{(y_2 - y_1)} \tag{5}$$

III. RESULTS AND DISCUSSION

3.1 Data

The dataset in this study contains 391 axial CT scan slices acquired across 40 patients with cases of both mild and severe Traumatic Brain Injuries.

3.2. Results of Ventricle Window Selection Algorithm

Ventricle Window Selection Algorithm (VWSA) is aimed at selecting the most appropriate slices and confining the window of focus. Figure 4 shows that three CT slices with the largest F_v values are selected as candidate slices from a patient's CT scans. As can be seen, the first candidate slice Figure 4-(a) with the largest F_v, shows ventricles more clearly than the other two. In our experiment, 30 out of 36 cases, in which ventricle boundaries were correctly extracted with segmentation, obtained their actual midline using the VWSA slice with the top F_v.

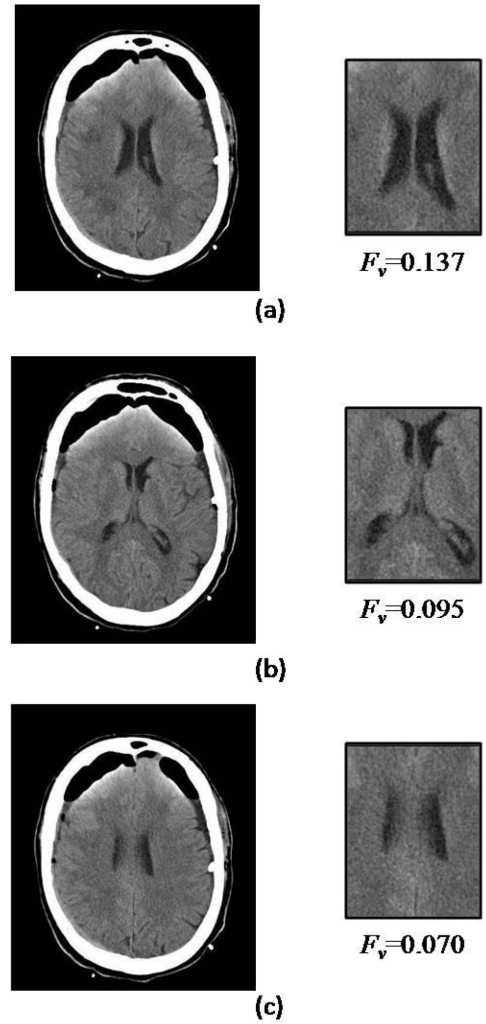

Figure 4. Results for Ventricle Window Selection Algorithm: three candidate slices are selected from one patient's CT images.

With the focus region confined from whole image to only the VWSA window, the time-cost associated with level set segmentation is greatly reduced. Additionally, the contour evolution becomes much easier due to the avoidance of the artifacts present outside the windowed region.

3.3 Level Set Segmentation

The algorithm has been implemented in Matlab on a PC with Intel core I7 3.40 GHz processor with 8GB RAM. The initial level set function φ assigns the value 2 for all the pixels within the VWSA window. The parameters of the level set function are set as follows, λ_1=1, λ_2=1, σ=3.0, time step Δt=0.1, μ=1, and v=0.001×255×255.

Figure 5 depicts the results of the level set method at various iterations. It demonstrates how the algorithm evolves from the initial stage 0 iteration to the final stable contour at iteration 200. The images from the left to right shows 0, 50, 100, and 200 iterations in level set evolution, respectively. The evolution becomes stable after 200 iterations. From the above results, it can be seen that the level set segmentation

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successfully extracts the final contours that match the ventricles boundary well. It provides a good foundation for the subsequent ventricle identification and midline estimation.

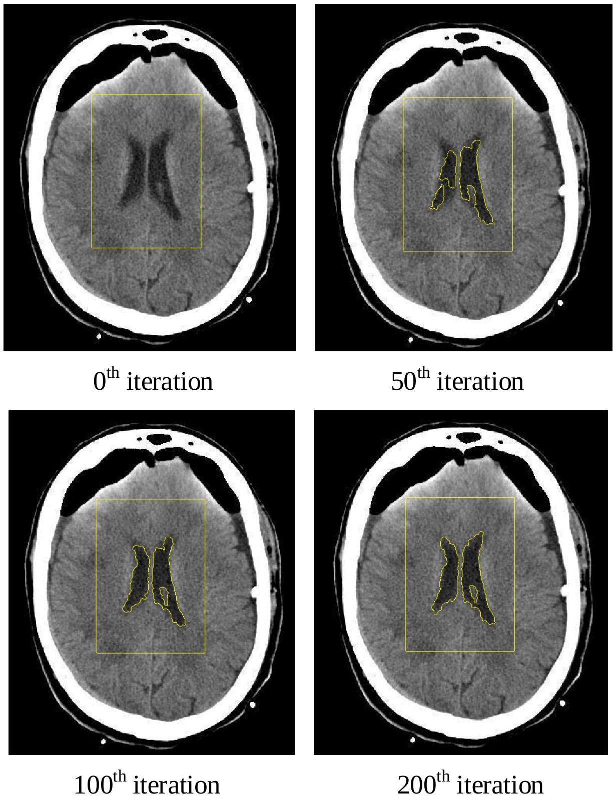

Figure 5. Contour evolution using the level set algorithm. From left to right images show different levels of iterations.

In this work, the average CPU time used on the level set evolution on one candidate CT slice is 129.2 seconds. In order to test the computational cost of the algorithm, we compare the experimental results of the level set segmentation and the Gaussian Mixture Model (GMM) method [7] on the same database under the same hardware configuration. It is found that the level set segmentation takes 17% lesser computational time as compared to the GMM method.

3.4 Ventricle identification and actual midline estimation in post-processing

The ventricle identification and midline estimation process is shown in Figure 6. Three candidate contours are extracted by level set segmentation (Figure 6-a). VIA selects the largest two to represent the left and right lateral ventricles. Then, their mass centers, calculated by (11), are labeled in Figure 6-b. According to the positions of the ventricle mass centers, the actual midline is estimated and shown in Figure 6-c.

The collaborating physicians manually labeled the actual midline for every patient in the database. With a strict definition of accuracy, which is an allowed error of three pixels in the horizontal direction and two degrees of the rotation angle, the accuracy of the midline estimation of our system is 90%, which is much higher than 87.5% using GMM method in [7].

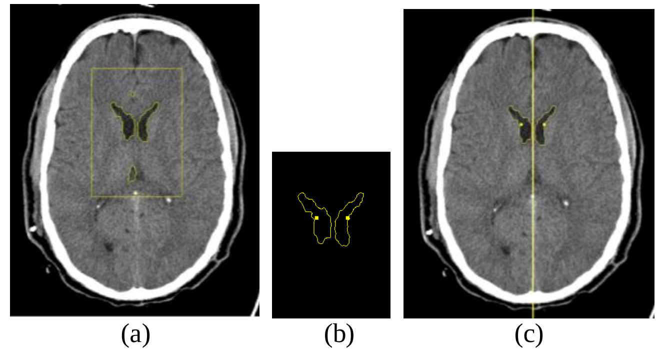

Figure 6. Ventricle identification and midline estimation. (a) The candidate contours extracted by level set segmentation, (b) ventricle contour identification and mass ceters determination, (c) midline estimation.

IV. CONCLUSION

In this work, an actual midline detection system based on the level set segmentation and window selection has been proposed. The Ventricle Window Selection Algorithm not only selects appropriate CT slices containing clear ventricle information but also confines the focus of operation. It greatly enhances the efficiency of the whole system by reducing processing time for the level set segmentation. The variational level set segmentation model, combined with the ventricle identification process, successfully extracts ventricle contours. Actual midline is estimated by the positions of the ventricle contours. With physician's validation, the results show a high accuracy of 90% for midline estimation. This makes the new system viable in clinical settings.

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