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Original contribution

A novel approach to segmentation and measurement of medical image using level set methods

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ABSTRACT

The study proposes a novel approach for segmentation and visualization plus value-added surface area and volume measurements for brain medical image analysis. The proposed method contains edge detection and Bayesian based level set segmentation, surface and volume rendering, and surface area and volume measurements for 3D objects of interest (i.e., brain tumor, brain tissue, or whole brain).
Two extensions based on edge detection and Bayesian level set are first used to segment 3D objects. Ray casting and a modified marching cubes algorithm are then adopted to facilitate volume and surface visualization of medical-image dataset. To provide physicians with more useful information for diagnosis, the surface area and volume of an examined 3D object are calculated by the techniques of linear algebra and surface integration. Experiment results are finally reported in terms of 3D object extraction, surface and volume rendering, and surface area and volume measurements for medical image analysis.

1. Introduction

Medical images, such as magnetic resonance (*MRI*), computed tomography (*CT*), and ultrasound (US) images, are extensively used in surgical planning, early lesion detection, and preoperative diagnosis. With the active development of high-tech imaging equipment and high-speed computing software, the demand for more advanced medical diagnostic imaging has also been on the rise. In conventional medical diagnosis, physicians rely on a sequence of two-dimensional (2D) medical images to speculate on the locations and volumetric structures of organs or tumors in patients and to investigate the disease according to the examined symptoms. However, the medical images of organs, internal structures, or suspected tumors may overlap in the 2D projections to such an extent that normal vision is obstructed. Manual segmentations, on the other hand, are extremely labor-intensive. In response to these limitations, continuous efforts have been invested to develop solutions capable of achieving more accurate extraction and visualization. In recent years, modern technologies have been applied to diagnostic medical imaging to introduce advanced tools now routinely used in clinical work. Nevertheless, image-based medical diagnosis continues to present steep challenges putting into question the efficacy of existing extraction approaches for special parts of human body.

The brain, the most complex organ in the human body, is made up of a highly sophisticated network of neurons that serves as the center of the nervous system. The brain's structure is composed of three major anatomical regions, the forebrain, the midbrain, and the hindbrain. The brain also contains a ventricular system, which consists of four ventricles: two lateral ventricles, a third ventricle, and a fourth ventricle. The ventricles are filled with cerebrospinal fluid (*CSF*) and are continuous with the spinal canal. The human cerebrum (brain) is formed by two cerebral hemispheres separated by a groove (i.e., the medial longitudinal fissure). The brain can thus be described as being divided into left and right cerebral hemispheres. The cerebral hemispheres containing cerebral cortex are linked by the corpus callosum, a very large bundle of nerve fibers. Its shell part is constituted by the nerve cell bodies, gray matter (*GM*) of gray color. The inner part is mainly composed of fiber tract, white matter (*WM*) of nearly white color. Numerous nerve fibers in the brain together form a fiber tract, so that they can pass signals to and from the brain around the gray matter or send signals between different regions in the brain hemisphere.

In spite of its low incidence, brain tumor reports a dreadfully high mortality rate and has accordingly been considered as an incurable disease [1,2]. Once a brain tumor is growing, it invades healthy surrounding tissues rapidly, and the boundary between the tumor and the healthy surrounding tissues remains so indistinct and obscure that it is highly difficult to perceive the solid outline of the tumor and its structural and spatial relationships with the surrounding tissues. In addition, existence of image speckles, noise, or blur caused by imaging modality, or high-noisy and low-contrast effects on the tumor itself may seriously cripple physicians' ability in judging the presence of tumor, thereby losing the optimal timing for accurate diagnosis and effectual treatment.

The paper focuses on the development of three key techniques containing segmentation (extraction), surface/volume rendering, and

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quantitative estimation of volume and surface area. Of the various methods available for medical-image segmentation, the level set algorithm is known for its ability to achieve better results. In the front-propagation approach proposed by Malladi et al. [3], a speed function consisting of both advection and curvature-dependent terms is applied onto the propagating curves. When the propagating curves are getting closer to the target boundaries, the speed function is expected to gradually slow down to zero. The active contour model with an edge detector is given as

$$\frac{\partial \phi}{\partial t} = G(x,y)(F_A + F_G)|\nabla \phi| \text{ with } G(x,y) = \frac{1}{1+|\nabla G_\sigma * g(x,y)|}, \tag{1}$$

where F_A is the advection term, F_G the curvature-dependent term, $\nabla\phi$ a gradient of the level set function ϕ, $G(x,y)$ the edge detector, and $|\nabla G_\sigma * g(x,y)|$ denotes the absolute value of the image convolved by a Gaussian smoothing filter of standard derivation σ. Chan and Vese [4] presented a different active contour model by incorporating region-based information into their energy function without relying on the gradient to stop the propagation process. The model is given as

$$\frac{\partial \phi}{\partial t} = \delta_0(\phi)\left[\nu\, div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) - \mu - \lambda_1 (g-c_1)^2 + \lambda_2 (g-c_2)^2\right], \tag{2}$$

where g refers to the image gray levels, $\delta_0(\varphi)$ the Dirac measure, c_1 the average of g inside the propagating curve, and c_2 the average of g outside the propagating curve; $\nu \geq 0$, $\mu \geq 0$, and $\lambda_1, \lambda_2 > 0$ are fixed parameters. Chan and Vese further proposed a method, called four-phase Chan-Vese model [5], to segment the image into four distinct regions. The basic idea is to use two level set functions and the model is given as

$$\begin{aligned}\frac{\partial \phi_1}{\partial t} = \delta_\varepsilon(\phi_1)\Big\{\nu\, div\left(\frac{\nabla\phi_1}{|\nabla\phi_1|}\right) - \Big[\left((u_0-c_{11})^2-(u_0-c_{01})^2\right)H(\phi_2) \\ + \left((u_0-c_{10})^2-(u_0-c_{00})^2\right)(1-H(\phi_2))\Big]\Big\},\end{aligned} \tag{3}$$

and

$$\begin{aligned}\frac{\partial \phi_2}{\partial t} = \delta_\varepsilon(\phi_2)\Big\{\nu\, div\left(\frac{\nabla\phi_2}{|\nabla\phi_2|}\right) - \Big[\left((u_0-c_{11})^2-(u_0-c_{10})^2\right)H(\phi_1) \\ + \left((u_0-c_{01})^2-(u_0-c_{00})^2\right)(1-H(\phi_1))\Big]\Big\},\end{aligned} \tag{4}$$

where ϕ_1 and ϕ_2 are the two level set functions, u_0 denotes the image, ν is a fixed non-negative constant; $H(\phi_i) = \begin{cases} 1, & \text{if } \phi_i \geq 0, \\ 0, & \text{if } \phi_i < 0, \end{cases}$ $\delta_\varepsilon(\phi_i) = \frac{d}{d\phi_i}H(\phi_i), i = 1, 2$, and $\begin{cases} c_{11} = \text{mean}(u_0) \text{ in } \{\phi_1 > 0, \ \phi_2 > 0\}, \\ c_{10} = \text{mean}(u_0) \text{ in } \{\phi_1 > 0, \ \phi_2 < 0\}, \\ c_{01} = \text{mean}(u_0) \text{ in } \{\phi_1 < 0, \ \phi_2 > 0\}, \\ c_{00} = \text{mean}(u_0) \text{ in } \{\phi_1 < 0, \ \phi_2 < 0\}. \end{cases}$

Ayed and Mitiche [6] developed a curve evolution method allowing the effective number of regions to vary during curve evolution. This level set functional used a region merging prior embedding an implicit region merging in curve evolution. Bernard et al. [7] developed a formulation of active contours based on level set where the implicit function is modeled as a continuous parametric function expressed on a B-spline basis. Based on the theory of curve evolution, the geodesic active contour (*GAC*) was started by Caselles et al. [8]. Since then, a great variety of *GAC* models [9,10] have been developed in response to the ever-increasing demands on image segmentation. In the model, the curve is propagated by the means of velocity and the velocity function that is a function of the curvature, and it contains two terms. One is related to the regularity of the curve and the other moves the curve toward the boundaries. The model is given as

$$\frac{\partial \phi}{\partial t} = \left(c + div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right)g|\nabla\phi| + \nabla g \cdot \nabla\phi, \tag{5}$$

where c is constant for weight for balloon/pressure force (if c is a positive value, the contours will shrink and vice versa), g denotes the edge indicator function, and $\nabla g \cdot \nabla\phi$ denotes the projection of an attractive force vector on the normal of the curve. Gout et al. [11] further combined the ideas developed by the *GAC* model with an interpolation constraint for creating interpolation conditions to help the evaluation process of the level set function obtain more accurate segmentation.

The second technique related to the proposed method is the rendering algorithm. Generally, rendering techniques can be divided into two major categories: surface rendering [12] and volume rendering [13–15]. Surface rendering treats the object as having a surface of a uniform color and it mathematically models the object with surface primitives. The interior of the object is thus not described. Surface rendering can be a good choice when users are mainly interested in perceiving the surface of a three-dimensional (3D) target. To extract a surface from a volume dataset, marching cubes algorithm is the most frequently used technique. The basic principle behind the algorithm is to subdivide space into a series of small cubes. Then the algorithm marches through each of the cubes, testing the corner points and replacing the cube with an appropriate set of polygons. The total of the generated polygons would be a surface approximating the described target. Compared to surface rendering, volume rendering allows users to see the inhomogeneity inside objects and is therefore more suitable for medical imaging. Volume rendering is typically used to generate images that represent an entire 3D dataset in 2D images. It is a powerful tool for gaining insight into the human body. The focus of this paper is on image-order volume rendering that is often referred to as ray casting.

For analyzing medical images concerning brain tumor and tissue, boundary detection, reconstruction, visualization, and geometry information measurement are four indispensable approaches. In addition, the shape, margin, and size of a brain tumor play significant roles in judging whether the tumor is benign or malignant. To measure tumor size, Macdonald and *RECIST* criteria [16,17] are two of the most widely used standards. Based on 2D measurement, the Macdonald criteria concentrate on the length and width of a tumor to assess response to cancer therapy. Attempting to simplify and standardize the objective response criteria, *RECIST* criteria use 1D measurement, instead of 2D measurement, based on the greatest length of tumor region. Kanaly [18] used gray-scale within the area of a brain image as the correction basis, combined with the critical value, to measure tumor size. Fuzzy-connectedness [19,20] is also a useful method for measuring the tumor volume in *MRI* images.

Patel and Doshi [21] reviewed various clustering methods used for brain tumor segmentation. Taheri et al. [22] presented a threshold-based level set segmentation for 3D brain tumor segmentation which employs a speed function that does not require density function estimation and is obtained by minimal user interaction. Corso et al. [23] developed a method for detecting and segmenting brain tumor and edema in multichannel magnetic resonance volumes. Wang et al. [24] proposed an approach, called fluid vector flow (*FVF*) active contour model, to solve the problems of insufficient capture range and poor convergence for concavities. Experiments on brain tumor images show that *FVF* produced accurate segmentation. Belaid et al. [25] used a speed term based on local phase and local orientation to derive a level set method whose inclusion of Cauchy kernels as a pair of quadrature filters for feature extraction makes the algorithm robust to speckle noise and low contrast for ultrasonic image. Based on Markov random fields, an extensively used model for medical image segmentation, Held et al. [26] proposed a segmentation algorithm capturing three features of special importance for *MRI* images - non-parametric distributions of tissue intensities, neighborhood correlations, and signal inhomogeneities - to achieve tissue classification in a brain. The fact that various methods, notably the