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Medical Image Segmentation Using a Combined Approach

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Abstract- In this paper, we present a combined approach designed for automated segmentation of radiological image, such as CT, MRI, etc, to get the organ or interested area from the image. This approach integrates region-based method and boundary-based method. Such integration reduces the drawbacks of both methods and enlarges the advantages of them. Firstly, we use fuzzy connectedness method to get an initial segmentation result. Then we use Voronoi Diagram-based to refine the last step's result. Finally we use level set method to handle some vague or missed boundary, and get smooth and accurate segmentation. This hybrid approach is automated, since the whole segmentation procedure doesn't need much manual intervention, except the initial seed position selection for fuzzy connectedness segmentation.

Keywords: segmentation, region-based, boundary-based, fuzzy connectedness, Voronoi Diagram, level set

1.0 Introduction

Internal organ segmentation from different kinds of image modalities is an essential step for many anatomy and pathology studies. A variety of segmentation methods have been developed over past several years. There are two main segmentation techniques, region-based and edge-based. Region-based method tries to divide the image into regions and classify the pixels as inside, outside or on the boundary according to its position and surrounding structure. Edge-based method uses a numerical test for image gradient or curvature, or other properties to classify pixels.

The fuzzy connectedness-based method [8] is one kind of region-based techniques. Medical image is considered fuzzy. It is composed by signal intensities specific to different tissue types, noise, blurring, background variation, partial voluming, and certain acquisition-specific effects. The fuzzy connectedness-based method assigns fuzzy affinities to the target object. The affinity is computed as the weight sum of some characters. They are the intensity, the intensity gradient in the neighbourhood of the pixel to capture the intensity features and patterns of intensity variations. The weight can also be dynamically adaptive for the homogeneity and the gradient energy functions [9]. The adaptive weights introduce shift-variance to the definition of fuzzy connectedness, and decrease user interaction. The other region-based segmentation algorithm is to divide an image into regions, classify each region as either inside or outside the target object. For the boundary region between two classifications, the dividing and classifying procedure will be repeated till the boundary is satisfied the segmentation of target. [10] describes such a region-based method. It makes use of Voronoi diagrams to perform the division on the image. And [11] improves this method so that the final result can be produced in a few iterations.

Snake method [1] is one kind of boundary-based techniques. In this method, there is an energy function to qualify the difference between model and the edge in the image. The model starts with a coarse initialization, by minimizing the energy function with smoothness constraints, and attempts to align this boundary to the edge in the image. To avoid the propagation of the model sticking locally, the initial model should be set near the solution. Prior model [2] adapts an "average shape" as a prior term in active contour model. A statistical model of shape variation can be constructed by finding corresponding points across a set of training images [3]. The prior information can combine the shape of an object and its neighbours [4]. However, for the energy function model, it is difficult to handle the situation, when the topological of the contour changes during the evolution. Level set method [5] solves this problem by computing the evolution in one higher dimension. This method is combined in active contour methods in [6], [7]. Level set evolution with fixed propagation direction is either initialized inside or outside sought objects, and the propagation force is opposed by a strong gradient magnitude at image discontinuities. The internal force is strong enough to act against to global smoothness and leaks through gaps when the boundary is miss or fuzzy. This is the region competition, where two adjacent regions compete for the common boundary.

We have developed a new method to segment the organ from image. It integrates region-based techniques and edge-based techniques. The process starts from an initial seed inside the target object, and uses the fuzzy connectedness method [8] to get an estimation of the object's boundary. Then with the Voronoi diagram (VD), the image is redefined to outside, inside or boundary regions by the region classification method. After it, the boundary will be extracted to fill in the missing boundary and to override the spurious boundary data with a deformable surface model. Our hybrid method amplifies the strengths of both region-based and edge-based techniques but reduces the weaknesses of them.

2.0 Hybrid Approach

We present a hybrid approach for medical image segmentation. This approach requires minimum user interactions. It starts with fuzzy connectedness method to get the region, which contains the target object. Then with automatically homogeneity statistics, the VD-based algorithm will generate an estimation of boundary in a few iterations. After that, the level-set method will find the accurate boundary for the segmentation procedure. In the following sections, we will introduce the each algorithm that composes our hybrid approach.

2.1 Fuzzy Connectedness Algorithm

Medical image captured by devices is inherent fuzzy. The fuzzy property is caused by both the capture procedure and the anatomical objects hang together. The fuzzy setting notion is developed by J. K. Udupa in [8]. It is considered that the object should be defined formally in the fuzzy setting so that the data inaccuracies can be handled beyond mere visualization to object segmentation, manipulation, and analysis. The fuzzy affinities are defined to the target object during classification. The affinity between two elements in an image (e.g. pixels, voxels, spels) is defined via a degree of adjacency and the similarity of their intensity values. The aim of fuzzy connectedness is to capture the specific intensity patterns related to the target object.

We define a scene over a fuzzy digital space (Z^n, α) as a pair $\varsigma = (C, f)$, where C is a n-dimensional array of spels (spatial elements – pixels or voxels) and f is a function in the domain C. Its range is a subset of the closed interval [0, 1], $f : C \rightarrow [0,1]$. Fuzzy affinity k is any reflexive and symmetric fuzzy relation in C, that is:

$$\begin{aligned} & k = \{((c,d), \mu_\kappa(c,d)) | (c,d) \in C\} \\ & \mu_\kappa : C \times C \rightarrow [0,1] \\ & \mu_\kappa(c,c) = 1, \forall c \in C \\ & \mu_\kappa(c,d) = \mu_\kappa(d,c), \forall (c,d) \in C \end{aligned} \tag{1}$$

μ_κ can be written as follows generally:

$$\mu_\kappa(c,d) = h(\mu_\alpha(c,d), \mu_\varphi(c,d), \mu_\phi(c,d), c, d), \quad \forall (c,d) \in C$$

where: $\mu_\alpha(c,d)$ represents the degree of coordinate space adjacency of c and d; μ_φ represents the degree of intensity space adjacency of c and d; and μ_ϕ represents the degree of intensity gradient space adjacency of c and d to the corresponding target object features. Fuzzy k - connectedness K is a fuzzy relationship in C, where $\mu_\kappa(c,d)$ is the strength of a path is the strongest path between c and d, and the strength of a path is the smallest affinity along the path. The hard binary relation K_θ based on the fuzzy relation K is used to define the notion of a fuzzy connected component.

$$\mu_\kappa(c,d) = \begin{cases} 1 & iff\ \mu_\kappa(c,d) \geq \theta \in [0,1] \\ 0 & otherwise \end{cases} \tag{2}$$

Let O_θ be an equivalence class of the relation K_θ in C. A fuzzy k -component Γ_θ of C of strength θ is a fuzzy subset of C defined by the membership function:

$$\mu\Gamma_\theta = \begin{cases} f(c) & \mathit{iff}\ c \in O_\theta \\ 0 & otherwise \end{cases} \quad (3)$$

The equivalence class $O_\theta \subset C$, such that for any $(c,d) \in C$, $\mu_\kappa(c,d) \geq \theta, \theta \in [0,1]$, and for any $e \in \{C - O_\theta\}, \mu_\kappa(c,d) < \theta$. The notation $[O]_\theta$ denotes the equivalence class of K_θ that contains O for any $O \in C$. The fuzzy k-component of C contains O, denoted $\Gamma_\theta(O)$. It is a fuzzy subset of C, whose membership function is given by:

$$\mu\Gamma_{\theta(O)} = \begin{cases} f(c) & \mathit{iff}\ c \in [O]_\theta \\ 0 & otherwise \end{cases} \quad (4)$$

A fuzzy $k\theta$-object of ς is a fuzzy k-component of ς of strength θ. For any spel $O \in C$, a fuzzy $k\theta$-object of ς that contains O is a fuzzy k-component of ς of strength θ that contains O. Given k, O, θ, and ς, a fuzzy $k\theta$-object of ς of strength $\theta \in [0,1]$ containing O, for any $O \in C$, can be computed via dynamic programming.

In a generic implementation of fuzzy connectedness for

$c, d \in C : \mu_\kappa(c,d) = h(\mu_\alpha(c,d), f(c), f(d), c, d)$

where c, d are the image locations of the two pixels, $\mu_\alpha(c,d)$ is an adjacency function based on the distance of the two pixels, and $f(c)$ and $f(d)$ are the intensity of pixels c and d, respectively. In this general form, $\mu_\kappa(c,d)$ is shift-variant. In other words, it is dependent on the location of pixels c and d. A more specific and shift-variant definition for a fuzzy affinity was introduced in [8]:

$$\mu_\kappa(c,d) = \mu_\alpha(c,d)\begin{bmatrix} \omega_1 h_1(f(c), f(d)) + \\ \omega_2 h_2(f(c), f(d)) \end{bmatrix} \quad (5)$$

$$\mu_\kappa(c,c) = 1$$

where, $\mu_\kappa(c,d)$ is a linear combination of $h_1(f(c), f(d))$ and $h_2(f(c), f(d))$, with $\omega_1 + \omega_2 = 1$. The three features taken into consideration are: the adjacency between the pixel $\mu_\alpha(c,d)$, the intensity of the pixels $h_1(f(c), f(d))$, and the gradient of the pixels $h_2(f(c), f(d))$.

The adjacency function $\mu_\alpha(c,d)$ is assumed to be a hard adjacency relation, such that:

$$\mu_\alpha(c,d) \begin{cases} 1 & if \quad \sqrt{\sum_i (c_i - d_i)^2} \leq 1 \\ 0 & otherwise \end{cases} \quad (6)$$

where $c_i (0 \leq i \leq n)$ are the pixel's coordinates in n dimensions. The functions h_1 and h_2 are Gaussian functions of $\frac{1}{2}(f(c) + f(d))$ and $|f(c) - f(d)|$, respectively, such that:

$$h_1(f(c), f(d)) = e^{-\frac{1}{2}\left[\frac{\frac{1}{2}(f(c)+f(d)) - m_1}{s_1}\right]^2} \quad (7)$$

$$h_2(f(c), f(d)) = e^{-\frac{1}{2}\left[\frac{(|f(c)-f(d)|) - m_2}{s_2}\right]^2}$$

where m_1 and s_1 are the mean intensity and standard deviation of the intensity of the sample region, and m_2 and s_2 are the mean and standard deviation of the gradient of the sample region. The weight values can be captured by some improved methods so that the only manual work is to select the seed pixel.

2.2 Voronoi Diagram-Based Algorithm

The second part in our hybrid approach is Voronoi diagram (VD)-based segmentation algorithm. Voronoi diagrams are useful for the image segmentation. This algorithm divides the Voronoi regions repeatedly according to the homogeneity classifier for the medical image segmentation. And the classifier for different tissue type is generated from the regions that segmented by the fuzzy connectedness based method mentioned above.

The definition of the Voronoi Diagram is detailed described in [12]. We give a brief review of it here. Let S be a set of N points in the plane, indexed by $i \in \{1, \ldots, N\}$. The Voronoi region associated to one point $p_i \in S$ denoted by $Vor_S(p_i)$ is the set of the pointes closer to p_i than to any other points of S. According to this definition it is easy to show that each Voronoi region is polygonal and convex as an intersection of the half-plane. Let us denote $H(p_i, p_j)$ the half-plane containing

p_i that is defined by the perpendicular bisector of $\overline{p_i p_j}$. It is written as below:

$$Vor_S(p_i) = \bigcap_{i \neq j} H(p_i, p_j) \quad (8)$$

The Voronoi diagram is defined by the set of all Voronoi polygons.
An interesting property is that the dual graph of the Voronoi diagram is the Delaunay graph with the following properties: the Delaunay graph is

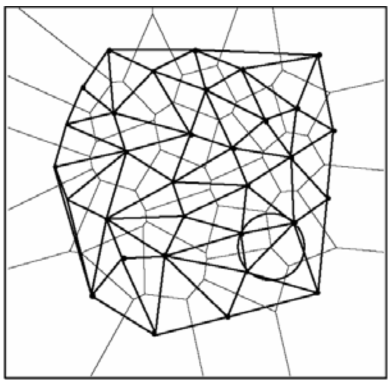

Figure 1: Voronoi polygons and Delaunay triangulation. The circle does not contain any point of S (Black dots) in its interior.

a triangulation such that each circle C circumscribed by every triangle $\overline{p_i p_j, p_k}$ does not contain any point of S in its interior. The proof is that assume there exists a point p_i of S in the interior of C. Then the distance between the centre c of C and p_l is smaller than the distance between c and any $p_n \in S, n \neq l$. According to the definition of a Voronoi polygon, c belongs to the interior of $Vor_S(p_l)$, which is contradictory.
As the continue step in our hybrid approach, the Voronoi diagram-based segmentation method processes the image based on the result of last step, fuzzy connectedness-based segmentation. The last step has got the initial segmented area of the target object. It offers the following step the statistic homogeneity classifier for the exterior part, interior part and boundary. By adding some seed points, the image will be divided into some regions as Voronoi diagram. For each region, the homogeneity classifier will reclassify it to exterior, interior or boundary. For the boundary region, connecting the seed points as Delaunay triangulation, the boundary outline is formed. This procedure can be repeated in a number of iterations till the boundary is accurate enough. The pseudocode for the algorithm is shown as Figure 2.

1. Input some points in the image
2. Compute Voronoi Diagram of those points
3. Classify each region as interior, exterior or boundary
4. Compute Delaunay triangulation and show the connection of the boundary regions
5. Add seeds to the edges and inside of boundary regions
6. Goto 2 until a specified number of iterations procedures are processed or user quits

Figure 2: Pseudocode for VD-based Segmentation Algorithm

This algorithm is quite robust. Normally in a few iterations, the accuracy of the boundary outline computed by this method is acceptable. Since it is region-based algorithm, the search procedure can only be concentrated on the specified area by the result of last step. It improves the algorithm both in speed and in accuracy.

2.3 Level Set Method

The third part of our hybrid approach is level set method. Level set method solves the topology modified problem that snake method is difficult to handle. Level set front evolution with fixed propagation direction is either initialized inside or outside sought objects, and the propagation force is opposed by a strong gradient magnitude at image discontinuities. At location of missing or fuzzy boundaries, the internal force is often strong enough to counteract global smoothness and leaks through these gaps.
A level set model specifies a surface as a level set (iso-surface) of a scalar volumetric function, $\phi : U \mapsto \Re$, where $U \subset \Re^3$ is the range of the surface model. Thus, a surface S is

$$S = \{s | \phi(s) = k\}, \quad (9)$$

and k is the isovalue. In other words, S is the set of points s in $\Re^3$ that compose the k th iso-surface of ϕ . The embedding ϕ can be specified as a regular sampling on a rectilinear grid. The surfaces may propagate with (timevarying) curvature-dependent speeds. The surfaces are viewed as a specific level set of a higher-dimensional function ϕ, so that the name level set methods. Level set methods provide the mathematical and numerical mechanisms for computing surface deformations as isovalues of ϕ by solving a partial differential equation on the 3D grid. That is, the level set formulation provides a set of numerical methods that describes how to manipulate the greyscale values in a volume, so that the isosurfaces of ϕ move in a prescribed manner.

There are two different approaches to defining a deformable surface from a level set of a volumetric function as described in equation (9). Either one can think of $\phi(s)$ as a static function and change the iso-value $k(t)$ or alternatively fix k and let the volumetric function dynamically change in time, i.e. $\phi(s,t)$. Following the second approach, we can mathematically express the dynamic model as

$$\phi(s,t) = k . \qquad (10)$$

To transform this definition into partial differential equation that can easily be solved by standard numerical techniques, we differentiate both sides of equation (10) with respect to time t, and apply the chain rule:

$$\frac{\partial \phi(s,t)}{\partial t} + \nabla \phi(s,t) \cdot \frac{ds}{dt} = 0 . \qquad (11)$$

Equation (11) is sometimes referred to as a "Hamilton-Jacobi-type" equation and defines an initial value problem for the time-dependent ϕ. Let ds/dt be the movement of a point on a surface as it deforms, such that it can be expressed in terms of the position of $s \subset U$ and the geometry of the surface at that point, which is, in turn, a differential expression of the implicit function, ϕ. This gives a partial differential equation (PDE) on ϕ : $s \equiv s(t)$

$$\frac{\partial \phi}{\partial t} = -\nabla \phi \cdot \frac{ds}{dt} \equiv -\nabla \phi \cdot F\left(s, D\phi, D^2\phi, \cdots\right) \quad (12)$$

where F is user-defined "speed" term which generally depends on a set of order-n derivatives of ϕ, $D^n\phi$ evaluated at s, as well as other functions of s. Typically $F(x)$ combines a data term with a smoothing term, which prevents the solution from fitting too closely to noise-corrupted data. There are a variety of surface-motion terms that can be used in succession or simultaneously in a linear combination to form $F(x)$. For example, it can combine the attraction term with smooth term as weighting factors. So that the surface can be attracted following the gradient of grey scale features, at the same time kept its smoothness.

Level set models have a number of practical and theoretical advantages over conventional surface models, especially in the context of deformation and segmentation. Level set models are topologically flexible; they easily represent complicated surface shapes that can, form holes, split to form multiple objects, or merge with other objects to form a single structure. These models can incorporate many of degrees of freedom, and therefore they can accommodate complex shapes. Indeed, the shapes formed by the level sets of ϕ are restricted only by the resolution of the sampling. Thus, there is no need to re-parameterize the model as it undergoes significant changes in shape.

3.0 Implementation of Hybrid Approach

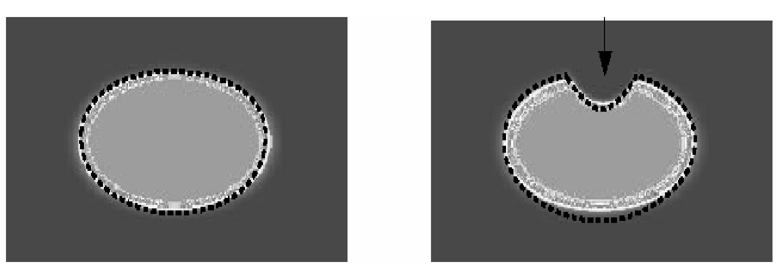

Figure 3. Level set models represent curves and surfaces implicitly using grey scale images. For example an ellipse is represented as the level set of an image (left). To change the shape of the ellipse we modify the grey scale values of the image by a PDE (right)

The approach integrates three methods, fuzzy-connectedness, VD-based algorithm and level set method. The concept of each algorithm has been described above. The fuzzy connectedness algorithm is used to find the broad outline of the target tissue. It might be not so precise. The segment result offers a set of statistics automatically to define the homogeneity operator. The homogeneity operator is used in the next step, VD-based algorithm as classifier. The second step enhances the result of the first step since fuzzy-connectedness algorithm will stick locally. The VD-based algorithm improves the boundary to the target. The third step is level-set method. This deformable surface model refines the output from the second step. It extracts boundary data to fill in the missing boundary data and to override the spurious boundary data due to image noise. So it keeps the boundary preciseness and smoothness also.

For the first step, the fuzzy connectedness algorithm segments a sample of the target tissue, and generates statistics, average and variance. To initialize the fuzzy connectedness algorithm, the user clicks on the image and selects one small square region inside the target tissue. This initial seed is used to compute the fuzzy connectedness by dynamic programming. User also decides the strength of the fuzzy connectedness by adjusting the factor value in its threshold range. From the segmented sample of the tissue, the largest relative difference in mean value and in variance value between the object and its background are selected. The homogeneity operator for the VD-based algorithm uses the expected mean/variance values of the object together with tolerance values, for classifying the internal and external region.

For the second step, the VD-based algorithm computes an initial VD by adding random points in the image. Then every region in VD is classified to as internal or external region by homogeneity operator. Those external regions having at least one internal region neighbour are identified as boundary region. The boundary region is processed iteratively by the VD-based algorithm until the boundary is precise enough or user chooses quit.

For the third step, the output of the second step is the coarse segmentation of the target issue. The boundary separates the region of interest and its background during last two steps. However, the boundary is not smooth enough, since the medical image could have noise, the anatomical structure could be complex, and the capture procedure could also introduce blurs. Level set model has two kinds of forces. External force makes the front to propagate to the boundary of the target according to the image grey level. Internal force makes the front to keep certain smooth to fit the total energy requirement. The level set model works on the output of the second step. It needs a small number of iterations to converge.

4.0 Result of Hybrid approach

In this section, we present the result from experiments of the hybrid approach. In the following example, we segment the MRI proton density brain image. The result of each step is shown following. We want to segment the light part of the original image. As the first step, fuzzy connectedness method gets sample of target object. But it is not the whole object. The segmentation procedure stops locally since the grey level variance. The second step improves the segmentation result of the first step. The segmented area covers the whole target tissue. However, the boundary is quite rough since the image might contain some noise. The third step refines the rough boundary of the last step. The final segmentation result gets both precise and smooth property of the boundary of the target tissue.

5.0 Conclusions and Future Work

In this paper, we report a hybrid approach for medical image segmentation. This approach integrates region-based and edge-based segmentation method. There are three components in this hybrid approach, fuzzy connectedness method to get the sample of the target tissue, VD-based method to find the boundary of the target tissue and its background, level set model to improve the boundary to be precise and smooth. The hybrid approach offers the greater robustness than either technique alone.

In the current system, as alternative, user can adjust some parameters to get good result. In the future, we will improve the algorithms to make it more automatically. And the algorithm should be expanded to three dimensions in order to segment 3D volume. For each component of our hybrid approach, there exists expanded version in 3D. However, such expanding increases the complexity largely. And simple fusing of these three algorithms in

3D situation like in this paper will not be robust. So better strategy should be developed in 3D.

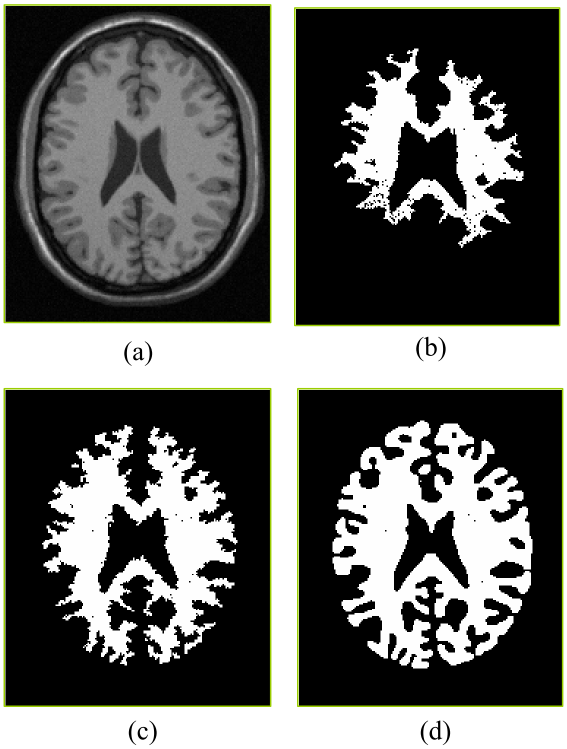

Figure 4. This figure shows one example of our hybrid approach. The image (a) is one MRI proton density brain image. The following images (b), (c), (d) are the result of three segmentation steps, respectively

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