HYBRID SEGMENTATION OF COLON BOUNDARIES IN CT IMAGES BASED ON GEOMETRIC DEFORMABLE MODEL

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ABSTRACT

One of the most important stages of virtual colonoscopy is colon segmentation, since an incorrect segmentation may lead to a misdiagnosis. Geometric deformable models (GDM) are found as efficient and attractive tools for structural based segmentation in particular to extract objects with complicated topology. There are two parameters influencing the overall performance of GDM algorithm; the distance between the initial contour and the actual object’s contours and the stopping term which controls the deformation. To overcome these limitations, a two-stage based segmentation is utilized to extract the rough but precise initial contours at first. Then, extracted boundaries are smoothed and fined using a modified GDM algorithm by improving the stopping terms of the algorithm. The proposed method considerably removes false contours obtained during the first stage. The improvement of 6\% on the accuracy of the segmentation method in comparison with region growing method is also achieved.

Index Terms— Virtual colonoscopy, Colonic walls segmentation; geometric deformable model; region-growing; thresholding;

1. INTRODUCTION

Colorectal cancer is one of the important causes of deaths among cancerous patients. Early detection and removal of colorectal polyps via screening is the current prevention method and has been shown to reduce colorectal carcinoma mortality [1,2]. In recent years, virtual colonoscopy with 3D imaging is going to augment conventional colonoscopy as a minimally invasive diagnostic tool for detection of colorectal polyps and cancer.

Since correct definition of colonic walls is essential to localization of polyps and cancerous lesions, one of the most important steps in VC is lumen segmentation. There are basically three anatomical problems which make the colon segmentation a difficult task:

1. The colon is not the only gas filled structure in the abdomen. For example, lower portion of lung are often present in virtual colonoscopy.
2. The existence of different areas that have the same high CT number (intensity) such as bones and contrast enhancement fluid (CEF).
3. Obstructions such as peristalsis, very large lesion and residual feces in the colon.

These difficulties makes the segmentation of colon more complicated specially in situation where an automated algorithm to extract a smooth and precise colon is needed.

Therefore, it seems necessary to utilize hybrid methods based on tissue classification, to extract different tissues within colon clearly, and knowledge based region growing which helps the segmentation process more anatomical based [7, 8, 9]. The differences among these methods are due to classification strategy and anatomy rules applied. Many advanced image segmentation methods employ region growing as the first step to extract the initial contour of the colon. The region growing based segmentation uses the thresholding and connectivity to extract the desired object. Thresholding method typically does not take into account the spatial characteristics of an image and it is sensitive to artifact and intensity inhomogeneities which is the case for colon.

The accuracy of this method is also sensitive to the thresholding level and noise, causing the extracted regions to have holes or become disconnected.

Due to the shortcoming of previous methods in colon segmentation, studies and researches proceed to use structural based methods such as geometric deformable models [4] which starts from an initial contour and follows topological properties of image to reach to the final borders.

The GDM has been used widely as an approach to accurate colon segmentation. The challenges to applying the GDM to colon segmentation are extracting the initial contour and the selection of the stopping term which determines the deformation of the contours.

In this paper, an automated colon boundaries extraction is proposed that utilizes two main stages: The first stage is to extract rough borders of colon to be used as initial contours for the next stage. In the second stage, these
borders are fined and smoothed by applying a modified geometric deformable model.

2. MATERIALS AND METHODS

2.1. Bowel Preparation and Image Acquisition

Preparation of the bowel is essential to produce optimal VC results. For more details the reader can refer to [3].

2.2. First stage: Initial contour extraction

The goal of the first stage is to find initial contour and eliminate extra objects. Figure 1 shows the proposed algorithm.

In below the GDM method is briefly introduced. For more information the reader could refer to [5, 10].

2.3.2. Curve evolution theory

The purpose of curve evolution theory is to study the deformation of curves using only geometric measures such as the unit normal . Let us consider a moving curve

\[ X(s, t) = [x(s, t), y(s, t)] \] (1)

where \( s \) is any parameterization and \( t \) is the time, and denote its inward unit normal as \( N \) and its curvature as \( \kappa \), respectively. The evolution of the curve along its normal direction can be characterized by the following partial differential equation:

\[ \frac{\partial X}{\partial t} = V(\kappa)N \] (2)

where \( V(\kappa) \) is called the speed function, since it determines the speed of the curve evolution.

The most extensively studied curve deformations in curve evolution theory are curvature deformation and constant deformation. Curvature deformation is given by the so-called geometric heat equation:

\[ \frac{\partial X}{\partial t} = \alpha \kappa N \] (3)

where \( \alpha \) is a positive constant. This equation will smooth a curve, eventually shrinking it to a circular point [12].

Constant deformation is given by

\[ \frac{\partial X}{\partial t} = V_0 N \] (4)

where \( V_0 \) is a coefficient determining the speed and direction of deformation.

The basic idea of the geometric deformable model is to couple the speed of deformation (using curvature and/or constant deformation) with the image data, so that the evolution of the curve stops at object boundaries. The evolution is implemented using the level set method. Thus, most of the research in geometric deformable models has been focused in the design of speed functions.

2.3.3. Level set method

The level set method is used to account for automatic topology adaptation, and it also provides the basis for a numerical scheme that is used by geometric deformable models.
We now derive the level set embedding of the curve evolution equation (2). Given a level set function $\phi(x,y,t)$ with the contour $X(s,t)$ as its zero level set, we have:

$$\phi[X(s,t),t] = 0$$  \hspace{1cm} (5)

Differentiating the above equation with respect to and using the chain rule, we obtain

$$\frac{\partial \phi}{\partial t} + \nabla \phi \frac{\partial X}{\partial t} = 0$$  \hspace{1cm} (6)

Where $\nabla \phi$ denotes the gradient of $\phi$.

2.3.4. Speed function

The geometric deformable contour formulation, proposed by Caselles et al. [10] and Malladi et al. [10], takes the following form:

$$\frac{\partial \phi}{\partial t} = \epsilon \|\nabla \phi\|$$  \hspace{1cm} (7)

The curve evolution is coupled with the image data through a multiplicative stopping term $c$. However, when the object boundary is indistinct or has gaps, the geometric deformable contour may leak out because the multiplicative term only slows down the curve near the boundary rather than completely stopping the curve. Once the curve passes the boundary, it will not be pulled back to recover the correct boundary.

To remedy the latter problem an energy minimization formulation to design the speed function is used. This leads to the following geometric deformable contour formulation:

$$\frac{\partial \phi}{\partial t} = c(\kappa + V_0)\|\nabla \phi\| + \nabla c \nabla \phi$$  \hspace{1cm} (8)

Note that the resulting speed function has an extra stopping term $\nabla c, \nabla \phi$ that can pull back the contour if it passes the boundary. We used this type of geometrical deformable contours in our suggested method.

2.3.5. GDM implementation

To implement GMD algorithm, the input data should be first changed to a level set form. In this form the values of pixels which are located on the contour become zero. Pixels located inside and outside of the contour become negative and positive, respectively.

$\Phi$ is level set function and $C$ is stopping function. The relationship between $\Phi$ and $C$ is defined as:

$$\frac{\partial \Phi}{\partial t} = C \|\nabla \Phi\| + \nabla \Phi \nabla C$$  \hspace{1cm} (9)

Conventional function for $C$ is monotonic function

$$C = \frac{1}{1 + \|G_{\sigma}*I\|}$$  \hspace{1cm} (10)

"I" is intensity function and $G_{\sigma}$ is Gaussian filter with $\sigma$ variance. To adjust the sensitivity of algorithm, different functions can be used to make better results for images with different anatomical structures. For example using a function that is more sensitive with respect to image edges may lead to detect the edges arising from the existed noise in the image. To reduce this effect a low pass Gaussian filter can be applied to reduce the effect of noise.

With regard to anatomical conditions of colon, in this research, the following stopping function has been suggested:

$$C = \frac{\lambda}{1 + \epsilon \|G_{\sigma}*I\|}$$  \hspace{1cm} (11)

The main role of $\epsilon_I$ is to weight the gradient vector of the image according to their closeness to the final borders. This factor adaptively controls the speed of convergence by speeding up the curve evolution at the beginning and then to reduce it when the final borders are being extracted. This factor together with $\lambda$ reduce the iteration numbers and time required to obtain enhanced boundaries.

$\epsilon_I$ is defined as follows:

$$\epsilon_I = \begin{cases} K_1, & T_1 < \|G_{\sigma}*I\| < T_2 \\ K_2, & \text{Others} \end{cases}$$

Where $K_1 > K_2$, $T_1$ and $T_2$ is selected in accordance with reinforcing boundaries by $\epsilon_I$.

3. RESULT

The segmentation was performed on two data sets. In Fig.2 and Fig.3 the results of the first and the second stages of segmentation on a single slide of CT scan image are shown. In the first stage false contours are clearly segmented (Green Contours) while in the second stage they are completely removed and the final borders are moved more precisely toward the actual object’s boundaries (Red Contour).

Figure 2. Green contours are results of the first stage segmentation and Red contour is the GDM result
Figure 3. Green contours are results of the first stage. Segmentation and Red contour is the GDM result.

The results are evaluated in two quantitative and qualitative manners. The subjective evaluation was carried out by an expert radiologist to score the final borders of the extracted colon in comparison with manual segmentation. The results are categorized into four groups: Excellent, Good, Fair, and Poor. Table 1 shows the qualitative evaluation applied on 750 slices of CT images.

As the result shows in 87% of cases the output borders were scored as excellent or good which shows the ability of this algorithm to segment the final borders accurately. Quantity evaluation was carried out based on the sensitivity, specificity and the resulting accuracy.

<table>
<thead>
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<th>Parameter</th>
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4. DISCUSSION AND CONCLUSION

In this study an efficient and reliable method for colon segmentation has been proposed. The suggested method exploits the structural properties of the colon by using a deformable model based on a two-stage approach to speed up the total volume segmentation procedure. In the first stage, the initial contours are extracted in a close distance to the actual object using thresholding and region growing approaches. This step has greatly reduced the number of iterations during curve evolution procedures to reach final borders, leading to less computation time.

In the second stage these initial contours are moved to a location with maximum gradient level to perform final borders. The main advantage of this step is the smoothness of the final boundaries because borders are defined based on a level set form by which they can be defined within a single pixel or voxel. As shown in our first results, false contours were greatly removed due to the advantage of using gradient based algorithm like GDM. False contours are resulted from small changes in gray level detected during thresholding methods. These changes become neglected by applying gradient based algorithm.

The suggested algorithm is not able to fully eliminate extra objects obtained in the first stage because the accuracy of the final borders highly depends on the location and preciseness of the initial contours. The accuracy of this method like other deformable methods highly depends on the initial contour because any incorrect location can lead to extracting false contours. It is suggested to use multi-resolution based deformable methods to over come the above limitation which is currently under our investigation.

5. ACKNOWLEDGMENT

We would like to thank Iran Telecommunication Research Center, ITRC for financial support of this project and Research Centre for Science, Technology in Medicine (RCSTIM) Medical Informatics Group for providing valuable resources and Iranian Academic Center for Education, Culture & Reserch IUT branch for this research.

6. REFERENCES