A VARIATIONAL FRAMEWORK FOR 3D COLONIC POLYP VISUALIZATION IN VIRTUAL COLONOSCOPY

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ABSTRACT
Colorectal cancer includes cancer of the colon, rectum, anus and appendix. Since it is largely preventable, it is extremely important to detect and treat the colorectal cancer in the earliest stage. Virtual colonoscopy is an emerging screening technique for colon cancer. One component of virtual colonoscopy, image pre-processing, is important for colonic polyp detection/diagnosis, feature extraction and classification. This paper introduces a general variational approach based framework for a computer aided diagnosis system for colorectal cancer. It includes techniques for 3D colon segmentation, 3D colon object reconstruction by iso-surface generation, and 3D centerline extraction. The proposed framework has been validated on 22 real CT Colonography datasets.

Index Terms— CT Colonography, Image Pre-processing, 3D Segmentation, 3D Object Reconstruction

1. INTRODUCTION
In most cases, colorectal cancers develop slowly and normally take a period of several years to grow from the earliest lesion to an advanced cancer. Adenocarcinomas account for about 95 percent of colorectal cancers, arising from the intestinal epithelial cells that line the colon and rectum.

Colorectal cancer is largely preventable. Several screening tests, including the digital rectal exam, fecal occult blood test (via guaiac or fecal immunochemical test), flexible sigmoidoscopy, double-contrast barium enema, and colonoscopy are recommended for all people age 50 and above. Currently, optical colonoscopy is considered the gold standard for colorectal cancer screening. During optical colonoscopy, a thin flexible video endoscope is inserted into the patient’s rectum and advanced to the cecum. Inspection of the colon for polyps generally occurs during the withdrawal phase of the colonoscopy. Although a colonoscopy can detect more than 90% of colorectal cancers, it is invasive, sometimes uncomfortable, the preparation is inconvenient, and inability to reach the cecum results in an incomplete exam [1].

Computed tomographic colonography (CTC), also known as virtual colonoscopy (VC), is a computer-based alternative to optical colonoscopy. It has evolved rapidly over the past decade due to advances in manufacturing of high-resolution helical spiral computed tomography scanners. VC has many advantages, including relative lack of invasiveness, lower incidence of complications and side effects, patient tolerability and preference [2]. VC is not intended to replace traditional optical colonoscopy [3, 4, 5], but rather to complement it by providing an additional mechanism for providing CTC screening. Benefits of VC include visualization of neighboring structures outside the colon, visualization of difficult anatomical locations (i.e. behind flexures), the ability to bypass high grade stenoses, and providing an alternative to colonoscopy in those patients who either refuse optical colonoscopy or cannot tolerate it due to severe illness.

The computer aided diagnosis (CAD) for colorectal cancer screening normally consists of colon segmentation, 3D colon object reconstruction and visualization, polyp detection, feature extraction and benign/malignant polyp classification.

The literature has introduced several sophisticated image segmentation procedures. Most are based on two concepts: thresholding and connectivity [6]. Tagged CT colonography uses thresholding for digital stool subtraction. When contrast enters the colon and tags residual fluid, electronic cleaning can occur. Electronic cleaning [7, 8] served as a very useful technique to balance CT values in fluid-filled lumen parts and others filled with air, and to remove the contrast fluid. However, some artifacts were generated which affected image interpretation. Yoshida and Nappi [9] designed a CAD framework to detect and classify the colonic polyps by using shape index and curvedness. The first stage of their CAD system involved colon segmentation, consisting of two major steps: 1) anatomy based extraction and 2) colon based anal-
ysis. Recently, Summers [6] proposed an entire framework for hybrid segmentation of colon tissue in CT colonoscopy. It achieved good segmentation results, however it consisted of eight different steps, so the processing time was very long.

This paper introduces a general framework for image pre-processing techniques. We focus on the adaptive level sets segmentation techniques, colon iso-surface generation and rendering, and 3D centerline generation for navigation. The proposed framework has been evaluated on 22 real CT colonography (CTC) datasets. Experimental results have shown 100% accuracy for detection of colonic polyps with sizes of 6 mm and above.

2. METHODS

2.1. Basic Level Sets

Given a curve $\Gamma$, it can be embedded into a higher dimension function $\Phi$ as $\Gamma = \{ X : \Phi(X) = 0 \}$ [10]. The curve is defined as the zero level of the implicit function. If we add time $t$ to the function, curves (fronts) evolution function is changed to $\Phi = \Phi(X, t)$.

$$\Phi_t + F|\nabla \Phi| = 0$$

where, $F$ is the velocity field.

Under discrete case, the level sets evolution is governed by Equation 2.

$$\Phi(t + \Delta t) = \Phi(t) - F \Delta t |\nabla \Phi|$$

where, $|\nabla \Phi|$ is the norm of gradient of curve $\Phi$. If $F > 0$, the original curve shrinks, while it expands when $F < 0$. And the curve does not change, if $F = 0$.

Normally, $F = \pm 1 - \varepsilon \kappa$, where, $\kappa$ is the curvature, and $\varepsilon$ is the parameter controlling the bending of the curve.

2.2. Adaptive Level Sets Technique

For the bi-model system in this paper, we use Gaussian distributions for the colon (foreground) and non-colon tissues (background).

For each class $i (i = 1, 2)$, the mean $\mu_i$, variance $\sigma_i^2$, and the prior probability $\pi_i$ are updated during each iteration as follows.

$$\mu_i = \frac{\int H_\alpha(\Phi_i) I(X) dX}{\int H_\alpha(\Phi_i) dX}$$

$$\sigma_i^2 = \frac{\int H_\alpha(\Phi_i) (\mu_i - I(X))^2 dX}{\int H_\alpha(\Phi_i) dX}$$

$$\pi_i = \frac{\int H_\alpha(\Phi_i) dX}{\sum_{i=1}^{2} \int H_\alpha(\Phi_i) dX}$$

where, $X = (x, y, z)$ is a 3D point. $H_\alpha(\bullet)$ is the Heaviside step function as a smoothed differentiable version of the unit step function. $I(X)$ is the input image. $\sum_{i=1}^{2} \pi_i = 1$.

Finally, the classification decision at $X$ is based on the Bayesian criteria.

$$i^*(X) = \arg\left(\max_i 1, 2(\pi_i p_i(I(X)))\right)$$


2.3. Colon Iso-surface Generation

After colon segmentation to an entire CTC data, the colon object is reconstructed by searching the iso-surface from the segmented colon tissue using the Marching Cube algorithm. This procedure is accomplished by Visualization ToolKit (VTK) 5.0 under Windows XP. The VTK is an open source and freely available software system for 3D computer graphics and medical image visualization (http://www.vtk.org).

2.4. 3D Centerline Extraction

The 3D centerline is considered as the optimal path for navigation inside the 3D colon object. The 3D centerline is generated by the work [12]. This paper assumes that there only exists a single 3D centerline, which connects between the cecum and rectum inside the colonic lumen.

Consider the minimum-cost path problem that finds the path $C(s) : [0, \infty) \rightarrow \mathbb{R}^n$ that minimizes the cumulative travel cost from a starting point $A$ to some destination $B$ in $\mathbb{R}^n$. If the cost $U$ is only a function of the location $X$ in the image domain, the cost function is called isotropic, and the minimum cumulative cost at $X$ is defined as

$$T(X) = \min \int_A^B U(C(s)) ds$$

The path which gives the minimum integral is the minimum cost path. The solution of Equation 7 is a nonlinear partial differential equation known as the Eikonal equation.

$$|\nabla T(X)| F(X) = 1.0$$

where $F(X) = 1/U(X)$, and $T(X)$ is the time when the front crosses $X$.

Let $A$ and $B$ be medial voxels. Assume that $A$ is a point source $P_S$ that transmits a high speed front Equation (9), where $\lambda(X)$ is a medial descriptor function that distinguishes medial voxels from others and $\alpha$ controls the curvature of the front at medial voxels.

$$F(X) = e^{\alpha \lambda(X)} \geq 0$$

$$\lambda(X) = \frac{2.0}{1.0 + ||V_\alpha(X)||^{0.05}} - 1$$
where, $\|V_n(X)\| = \|V(X)\| - \|V(X)\|_{\text{min}}$ and $V(X)$ is the gradient vector field (GVF) \[13\].

The propagating front is monotonically increasing in time; there is only one global minimum over the cumulative cost field $T$, that is $P_{S_t}$, which has zero travel time. Then, the path between $B$ and $A$ can be found by backtracking from $B$ along the gradient of $T$ until $A$ is reached. The extraction process is the solution of the ordinary differential equation (ODE) in Equation 11. $C(t)$ traces out the $CS$, which is found by solving Equation 11 using the second order Runge-Kutta method. The error of the method is $O(h^3)$, where $h$ is the integration step. $h$ is set to 1.0.

$$\frac{dC}{dt} = -\frac{\nabla T(X)}{\|\nabla T(X)\|}, \quad C(0) = B \quad (11)$$

3. RESULT AND DISCUSSION

We validate the proposed method on 22 CTC datasets. One has been provided by the 3DR Inc., Louisville, KY, and the rest 21 CTC datasets have been received from the Virtual Colonoscopy Center, Walter Reed Army Medical Center, Washington, DC. The patients underwent a standard 24-hour colonic preparation by oral administration of 90 ml of sodium phosphate and 10 mg of bisacodyl; then consumed 500 ml of barium (2.1 percent by weight) for solid-stool tagging and 120 ml of Gastrografin to opacify luminal fluid \[14\]. A four-channel or eight-channel CT scanner (GE LightSpeed or LightSpeed Ultra) was used. The CT protocol included 1.25 mm to 2.5 mm collimation, 15 mm/second table speed, and 100 mAs and 120 kVp scanner settings. Each dataset contains 400 ~ 500 slices and the spatial resolution is $1.0 \times 1.0 \times 1.0mm^3$.

The segmentation accuracy has been evaluated by calculating the overlap between the results by manual and algorithm segmentations in Equation 12. One CTC dataset was manually segmented under guidance of an experienced radiologist. Then, the accuracy $\eta$ is calculated as follows.

$$\eta = \frac{S_a \cap S_m}{S_a \cup S_m} \quad (12)$$

where, $S_a$ and $S_m$ denote the results by manual and algorithm segmentation.

The average accuracy of the whole CTC dataset has achieved 98.40%.

After colon segmentation, all the iso-surfaces are reconstructed, and due to the space limitation, only four examples hereafter are shown in Figure 1.

All the centerlines are generated as shown in Figure 2.

In Table 1, we show the volume size, vertices number and execution time of dataset load-in, 3D segmentation & reconstruction, and 3D centerline generation for each dataset. We find that all the vertices numbers range from 2.5 Million to about 7.0 Million.

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<th>Dataset</th>
<th>Volume</th>
<th>Vertices No.</th>
<th>Time</th>
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<tr>
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</tr>
<tr>
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![Fig. 1. 3D colon surfaces reconstructed from the four segmented colon datasets](image-url)

A significant colonic polyp is defined as one larger than 5 mm in diameter. The polyps no less than 6 mm are only focused. For the 13 colonic polyps with sizes of 6 mm and above in the 22 clinical CTC datasets, they are all found by the proposed framework, and compared with the reported ground truth. Four presented examples in Figure 3 show that the proposed framework can find and identify colonic polyps.

4. CONCLUSION

This paper describes a variational framework as the basis for clinical validation of fly-over visualization and polyp finding. It relies upon adaptive level sets based colon segmentation, colon iso-surface generation, and 3D centerline extraction. The proposed framework has been successfully validated on 22 real CTC datasets.
5. REFERENCES


