Determining Candidate Polyp Morphology from CT Colonography using a Level-set Method

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Abstract:
In this paper we propose a level-set segmentation for polyp candidates in Computer Tomography Colongraphy (CTC). Correct classification of the candidate polyps into polyp and non-polyp is, in most cases, evaluated using shape features. Therefore, accurate recovery of the polyp candidate surface is important for correct classification. The method presented in this paper, evolves a curvature and gradient dependent boundary to recover the surface of the polyp candidate in a level-set framework. The curvature term is computed using a combination of the Mean curvature and the Gaussian curvature. The results of the algorithm were run through a classifier for two complete data-sets and returned 100% sensitivity for polyps greater than 5mm.

Keywords: Colonic polyp segmentation, level set, curvature.

1 Introduction

Computer Tomography Colonography (CTC) is a rapidly evolving, non-invasive method for the early detection of colorectal polyps. The extraction of candidate polyp surface from the colonography scan is a primary and important step in candidate polyp classification. Such a classification step is necessary due to the high frequency of false positive (FP) polyp detection's which are apparent in previous computer aided diagnostic techniques. In such a classification problem, accurate surface extraction is one of the key issues and is the basis for this study.

Much of the previous work in polyp extraction uses local curvature and shape constraints to determine polyp candidates and to establish morphology [1–3]. This type of classification encounters difficulty when determining folds, a naturally occurring instance in the colonography exam. Yao et al. [4] proposed a segmentation of method which used a knowledge guided deformable model to extract the surface of the polyp and compared it to manual segmentation of experts. The knowledge was provided by the curvature of the deformable model and the signal intensities of the pixels surrounding the polyp. The segmentation was performed in 2D and the 2D images were combined together to create the local 3D volume.

In this paper we describe a method for the accurate segmentation of polyp candidate surface using a level-set segmentation method. The level set is a deformable surface that evolves under a force that includes gradient and curvature. We exploit the curvature property in the evolution to extract only the surface of the candidate polyp to avoid over segmentation of the colon wall. The segmentation is performed in 3D and the extracted surface contains just the points from the colon wall.

The following sections describe the level-set method in more detail, with the evolving force defined. Section 2 describes the extraction of the polyp surface candidates from the 3D volume data. In section 3 the initialisation of the level-set is discussed. Section 4 details the implementation of the level-set to polyp candidate surface extraction. The results section provides the performance of the system after it is applied to real data. The point-to-point error between the extracted surfaces and manually delineated for some polyps is given. Also, a data-set is analysed and the resulting surfaces classified into polyp and non-polyp. An overview of the complete segmentation scheme can be seen in Figure 1.

2 Convex Surface Extraction

Initially, the colon is segmented using a seeded 3D region growing algorithm that was applied to segment the air voxels, which assures the robust identification of the colon wall. In some situations the colon is collapsed due to either insufficient insuflation or residual water. In order to address this issue we have developed a novel colon segmentation algorithm that is able to correctly identify the colon segments using knowledge about their sizes and location within the body in all imaging conditions. After the identification of the colon wall, for each colon wall voxel the surface normal vector is calculated using the Hummel-Zucker operator [5]. The normal vectors sample the local orientation of the colonic surface and the suspicious candidate structures that may resemble polyps are extracted using a simple convexity analysis. In this regard, the colonic suspicious surfaces have convex properties and are determined using the 3D histogram and Gaussian distribution of the Hough points (full details about this developed algorithm can be found in [6]). This method is able to correctly identify all polyps above 3mm but it is worth nothing that this is achieved at a cost of high level of false positives. In order to reduce the level of false positives, the surface is extracted using a level-set method and the results are classified using a statistical

morphological features.

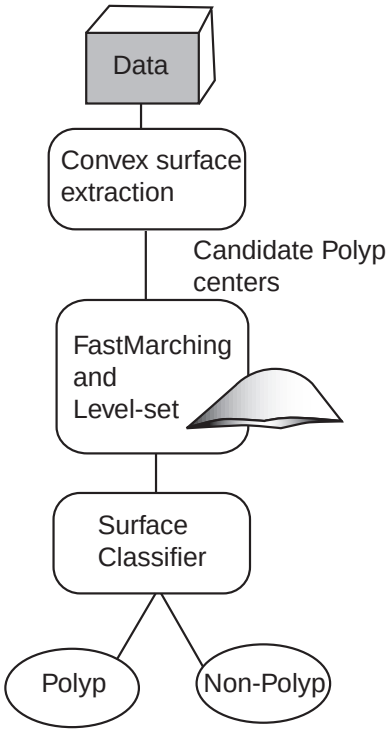


Figure 1: Flow-chart of proposed algorithm

3 Level-Set Initialisation. Fast-Marching Algorithm

The formulation of the problem is conceptually simple. The evolving curve or front Γ, evolves as the zero level-set of a higher dimensional function ϕ. This function deforms with a force F that is dependent on both curvature of the front and external forces in the image. The force acts in the direction of the normal to the front.

$$\begin{aligned} \phi_t + F|\nabla\phi| &= 0 \\ \phi(x,y,t=0) &= given \end{aligned} \tag{1}$$

Our implementation is a standard two step approach which includes a fast-marching initial step to speed up the segmentation. Fast marching is a special case of the above equation where $F(x,y) > 0$. Let $T(x,y)$ be the time that the front Γ crosses the point (x,y). The function $T(x,y)$ then satisfies the equation;

$$|\nabla T|F = 1 \tag{2}$$

which simply says that the gradient of the arrival time is inversely proportional to the speed of the surface. The T function is evaluated using the diffusion and attraction to pixels within the front. The front grows out from its initial position to points with the smallest value of $T(x,y)$. The $T(x,y)$ function is then updated and and continued until the front does not grow.

4 Level-Set Analysis

The theory behind level-set segmentation is largely based on work in partial differential equations and the propagation of fronts under intrinsic properties such as curvature [7, 8]. By extending the dimensionality of the problem to N+1,where N is the initial dimension of the problem, some advantageous properties can be exploited. Representing the boundary as the zero level set instance of a higher dimensional function ϕ, the effects of curvature can be easily incorporated. ϕ is represented by the continuous Lipschitz function $\phi(s,t=0) = \pm d$, where d is the signed distance from position s to the initial interface Γ_0 (see Equation 3). The distance is given a positive sign outside the initial boundary ($D\ \Omega$), a negative sign inside the boundary ($\Omega \setminus \partial\Omega$) and zero on the boundary ($\partial\Omega$).

$$\phi(s) = \begin{cases} -d & \forall s \in \Omega \setminus \partial\Omega \\ 0 & \forall s \in \partial\Omega \\ +d & \forall s \in R^n \setminus \Omega \end{cases} \tag{3}$$

From this definition of ϕ, intrinsic properties of the front can be easily determined, like the normal $\vec{n} = \pm\frac{\nabla\phi}{|\nabla\phi|}$.

Since curvature of the polyp should be a pertinent factor in the segmentation evolution, particular emphasis is given to this measure. The mean curvature (H), is connected to the physical evolution of soap bubbles and the heat equation. While smooth, it may not necessarily be convex and can lead to singularities.

$$H = \nabla \cdot \frac{\nabla\phi}{|\nabla\phi|} \tag{4}$$

Gaussian curvature (K), has also being used to model physical problems such as flame propagation. It has being shown that a convex curve evolves to a point under curvature evolution, but it can also be shown that evolution of non-convex surfaces can be unstable.

$$K = \frac{\nabla\phi^T \text{Adj}\ (\mathbf{H}(\phi))\nabla\phi}{|\nabla\phi|^2} \tag{5}$$

where $\mathbf{H}(\phi)$ is the Hessian matrix of ϕ, and Adj($\mathbf{H}$) is the adjoint of the matrix $\mathbf{H}$.

In this paper we purpose to use Neskovic and Kimia's [9] measure of curvature which involves both mean and Gaussian. In this approach, the direction of flow is obtained from the Mean curvature while the magnitude of the flow is dictated by the Gaussian curvature. This is appropriate as the Mean curvature alone can cause singularities and extracts the strictly convex surface of the polyp candidate.

$$\kappa = sign(H)\sqrt{K + |K|} \tag{6}$$

Using this value for κ, the level set is iteratively updated within a defined narrow band around the segmented boundary to increase efficiency. The following equation details the update parameters

$$\phi_{t+1} = \phi_t + k_I(1 - \varepsilon\kappa)|\nabla\phi| + \beta\nabla I \cdot \nabla\phi \tag{7}$$

where ε and *beta* are user defined parameters (see Table 1), κ is the curvature term defined in Equation 6 and k_I is the gradient dependent speed term and is given by $\frac{1}{1+\nabla I}$. The third term, $\nabla I \cdot \nabla \phi$ represents the attractive force vector normal to the front. The level-set segmentation is performed in 3D.

Possible polyp candidate centres are calculated over the entire data set by calculating the normal vectors at each voxel on the lumen wall. Polyp candidates are defined as regions of high convexity, therefore the centres for possible polyp candidates are located at points that contain high concentration of normal intersections (**ref tarik**).

The level set is initialised at the polyp candidate centres and grows outwards until a boundary is encountered. The convex surface is maintained by placing a high influence on the curvature parameter. Once the level-set has converged or completed its iterations, the surface of the polyp candidate is taken as all boundary points that have an associated gradient. This ensures that just the lumen surface is extracted.

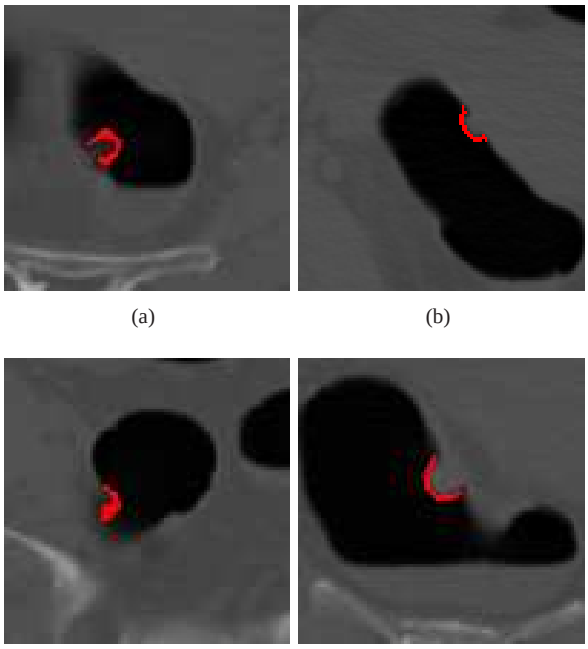
5 Classifier

Once the true surface of the polyp candidates has being extracted, they are passed to a classifier to determine whether they are polyps or folds. The classifier is a statistical model of known polyps and folds and uses statistical features of the candidates morphology such as least squares ellipsoid fitting error, normalised distribution of the surface curvature and the Gaussian sphere radius [6]. These features are used to classify the candidate polyp surfaces into polyps or folds using a feature normalised nearest neighbour classification scheme [10]. The classifier was trained with 64 polyps and 354 folds that were selected as true positives by a radiologist.

6 Results

The segmentation algorithm described above was performed on a full CTC data set, converted to isotropic dimensions using cubic interpolation. In total 181 polyp candidates were tested through the volume. Visual representations of the segmentation are shown in Figure 2 and the extracted surface volume renderings are shown in Figure 3. Table 1 lists the user defined parameters used in the level-set algorithm. From this table it can be seen that curvature is given a large influence to maintain the convexity of the polyp candidate surface. The narrow bandwidth is given a small value of 10 to increase the efficiency of the update.

A classifier, trained on expertly categorised unseen data, is then used to determine whether the extracted surface is classified as polyp or non-polyp. Small folds in the colon lumen are the main cause of detecting a false positive. It can be clearly seen in Figure 3 that fold surface is extracted is saddle shaped and thus can be easily classified using its shape characteristics.



(a) (b) (c) (d)

Figure 2: Images above show the segmentation of the convex polyp candidate. The bottom left image shows the segmentation of a fold.

Table 1: Control parameters used in the level-set segmentation.

Index	Control Parameters	Values
1	Fast-Marching Iterations	3
2	Level-set Iterations	10
3	Level-set ε	0.5
4	Level-set β	0.08
5	Level-set Narrow bandwidth	10

Table 2 shows the measured point-to-curve error between the automatic segmentation results against those found from a manual segmentation of the small number of polyp candidates. Indicated on the table are the average error, standard deviation of the error and the root-mean-square of the error. This error is measured in pixels where each pixel has sub-millimeter dimensions.

Table 3 gives the results on two real patient supine data sets. From the high number of polyp surface candidates(181 and 191), a relatively low number are detected (6 and 3). The results show a sensitivity of 100% for all polyps 5mm. Normally, in a clinical situation, polyps below 5mm are discarded in the classification. One cause for our method missing smaller polyps, are their low curvature difference between the polyp and the colon wall, therefore some colon wall is taken into the candidate surface (see Figure 4). Also note, the low number of false

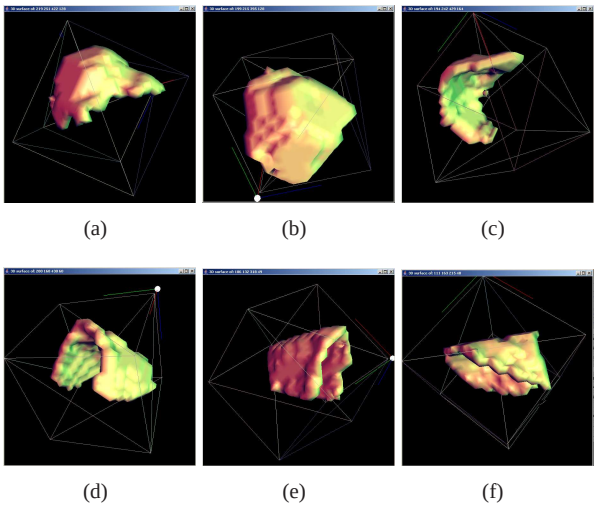
Table 2: Point-to-curve errors between manually segmented data and our method.

Average	Std. Dev.	RMS
0.298	0.587	0.661

Table 3: Performance Analysis for Polyp Classification. True positive (TP) and False Positive (FP).

Data	Size	Detected	TP	FP	Missed
Data 1 Supine	>5mm	6	3	3	0
(181 surf.)	$\leq$ 5mm	0	0	0	2
Data 2 Supine	>5mm	3	2	1	0
(191 surf.)	$\leq$ 5mm	0	0	0	2
Total		9	5	4	4

positives present in the analysed data.



(a) (b) (c)

(d) (e) (f)

Figure 3: Images above show the polyp candidate renderings of the extracted surface. Figures *(a)-(c)* show correctly classified polyps, where Figures *(d)-(f)* show correctly classified folds.

7 Conclusion

In conclusion, the accurate segmentation described in this paper is the first important step in the classification of polyp candidates into polyp and fold. This paper describes a method for the extraction of accurate polyp candidate surfaces using a level-set segmentation. The level-set is initialised using the distribution of surface normal vectors and the resulting surfaces are classified into polyp and non-polyp. The level-set evolution is constrained by image gradients and by the curvature of the boundary and is able to perform robust polyp segmentation in all imaging conditions. The segmentation is performed in 3D and the results are presented and discussed.

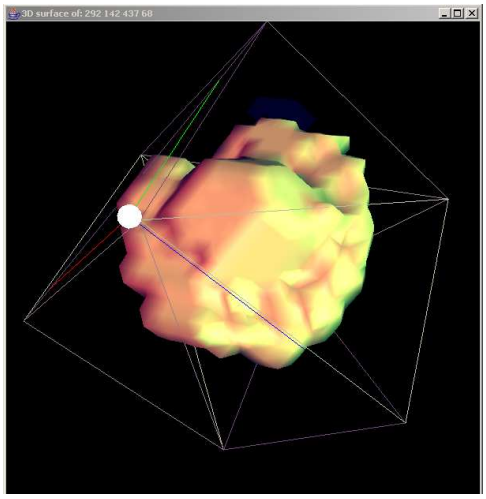


Figure 4: One of the $\leq$5mm polyps misclassified due to the inclusion of colon wall in the surface extraction.

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