AUTOMATIC POLYP DETECTION FROM CT COLONOGRAPHY USING MATHEMATICAL MORPHOLOGY

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ABSTRACT:

In this paper we present and develop a set of algorithms, mostly based on morphological operators, for automatic colonic polyp detection applied to computed tomography (CT) scans. Initially noisy images are enhanced using Morphological Image Cleaning (MIC) algorithm. Then the colon wall is segmented using region growing followed by a morphological grassfire operation. In order to detect polyp candidates we present a new Automatic Morphological Polyp Detection (AMPD) algorithm. Candidate features are classified as polyps and non-polyps performing a novel Template Matching Algorithm (TMA) which is based on Euclidean distance searching. The whole technique achieved 100% sensitivity for detection of polyps larger than 10 mm and 81.82% sensitivity for polyps between 5 to 10 mm and expressed relatively low sensitivity (66.67%) for polyps smaller than 5 mm. The experimental data indicates that our polyp detection technique shows 71.73% sensitivity which has about 10 percent improvement after adding the noise reduction algorithm.

1. INTRODUCTION

Colon cancer death is among increasing causes of death (Jemal et al., 2004). Most colorectal cancer mortalities can be prevented by early detection and removal of colonic polyps (Robert Van Uiterta et al., 2006). A way to diagnose colonic polyps is to screen colon via colonoscopy. Figure 1 is a digital photograph from conventional colonoscopy showing a colonic polyp.

Figure 1. Colonic polyp from conventional colonoscopy

Although colonoscopy provides a precise means of colon examination, it is time-consuming, expensive to perform, and requires great care and skill by the examiner. Moreover, since colonoscopy is an invasive procedure, there is a fatal risk of injury to colon. In comparison with colonoscopy, Computed Tomography scanning is a technique for non-invasively performing colon cancer screenings. According to radiologists, it is not that simple to distinguish colon wall and successively colonic polyps from CT slices. Therefore, automatic polyp detection can make diagnostic processes reach a general level, not depending highly on the experts' special skills. In this regard, Vining et al., 1997 proposed a method to detect the colonic polyps by analysing the local curvature of the colon surface attaining 73% sensitivity. Summers et al., 2001 developed a method that identifies the convex surfaces that protrude inward from the colon by evaluating the principle and mean curvature of the colon surface. Their method achieved 29% to 100% sensitivity. Yoshida et al., 2002 proposed to use features such as the shape index (cup, rut, saddle, ridge, and cap) and curvedness values on small volume of interest and apply fuzzy clustering for polyp detection. They reported 89% sensitivity. Paik et al., 2000 proposed a technique based on contour normal intersection to detect surface patches along the colon wall and shows 85% to 90% sensitivity. Kiss et al., 2002 combined the surface normal distribution and sphere fitting to produce 90% polyp sensitivity for polyps higher than 6mm. Kiss et al., 2003 employed the slope density function to discriminate between polyps and folds and their technique shows 85% sensitivity for polyps higher than 6mm. Paik et al., 2004 developed a new technique based on surface normal overlap. Acar et al., 2001 suggested a method that detects spherical patches by Hough Transform and the algorithm analyses them using the optical flow to decide if they are polyps or not. Other interesting automated CAD techniques include the work of Gokturk et al., 2001, Acar et al., 2002, Wang et al.,

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2004, Jerebko et al., 2003, Kiraly et al., 2004 and Tarik et. al., 2006.

All the above mentioned CAD techniques show different levels of accuracy and indicate that future investigations are needed in order to obtain a robust technique for polyp detection. In this paper we propose two new algorithms for detecting and classifying polyp candidates. We also improve the experimental results by adding a morphological image cleaning algorithm introduced by Richard Alan Peters II, 1995. The presented polyp detection technique shows relatively high sensitivity for polyps larger than 5 mm.

2. ALGORITHMS

2.1 Noise Reduction

CT images may be considered noisy due to low radiation dose requirements and other processing stages. Image enhancement through noise reduction is a fundamental problem in image processing which leads to better looking images to the interpreters. Noise reduction is an image restoration problem in that it attempts to recover an underlying perfect image from a degraded copy. To meet this purpose, we apply the Morphological Image Cleaning (MIC) algorithm introduced by Richard Alan Peters II, 1995 since it is capable of preserving small features while removing noise and scanner artifacts and enhancing images. MIC smoothes the image in a number of size-bands by computing the pixel wise average of the open-close and the close-open of image with disk shaped structuring elements of different diameters (OCCO filter). Let I be the original image and Z the corresponding structuring element:

$$OCCO\,(I;Z) = \frac{1}{2}\left((I \circ Z) \bullet Z\right) + \frac{1}{2}\left((I \bullet Z) \circ Z\right) \qquad (1)$$

After that, it subtracts these bands out of its previous image to create residuals. Let S_j be the result of smoothing I with filters of size d_j, then D_j is the j'th residual image:

$$D_j = S_j - S_{j-1} \qquad (2)$$

These outputs are signed images. Positive residuals are called top hat images and negative ones are called bot hat. Then, it segments the residuals into features and noise regions by cleaning up top hat and bot hat images. And finally, adds the features back to the smoothed version of the original image under the following order: bright features are put back in smoothed image by adding to it the sum of all the cleaned-up top hats and the dark features are put back by subtracting from it the sum of all the cleaned-up bot hats. Ideally, this results in an image whose edges and other features are as sharp as the original yet has smooth regions between them.

2.2 Segmentation

The segmentation algorithm includes two separate steps; first, extracts the colonic wall applying a region growing algorithm (Gonzalez et al., 1993). This idea comes from the fact that CT images show high intensity difference between air and tissue. Therefore air insufflated colon lumen can be segmented applying a simple region growing. In some situations that the colon is collapsed due to either residual materials and water or insufficient insufflations, we are obliged to use multiple seed points for each part. The seeded region growing is done at the fixed intensity threshold of -800HU; proposed by Sadleir et al., 2002.

We assume the diagnostically region of interest as about five pixels outside the colon wall so that no information is lost. Thus in the second step we apply a morphological grassfire operation proposed by Gokturk et al., 2001 on the image. This algorithm finds points that are at equal distance from a layer of points (the extracted colon wall pixels).This determines the colon wall region within a 5 pixel margin (five pixels outside and five pixels inside). But we just need the outside pixels since the inside layer may cover the surface candidates. Therefore we can mark and subtract the inner added pixels from the result gotten before performing grassfire operation.

2.3 Feature Extraction

Having colon wall segmented we have to detect polyps on the colon surface. Polyp detection algorithms are under development to help diagnosis processes. These approaches include use of overlapping surface normals (Paik, 2001; Paik et al., 2004), curvatures (Summers et al., 2000; Yoshida et al., 2001), sphere model fitting (Gokturk et al. 2000), vector field analysis (Acar et al., 2002) and statistical classification techniques such as support vector machines (Gokturk et al., 2001) or neural network (Jerebko, 2003). Here we present a novel Automatic Morphological Polyp Detection (AMPD) algorithm. This algorithm marks polyp candidates (potentially containing folds) on images and determines their boundaries as inputs to the final stage.

Mathematical morphology is a theoretical model for digital images built upon lattice theory and topology. Various image processing techniques can be implemented by combining only a few simple morphological operations. AMPD algorithm begins by eroding the image with a small size (in this work 3) square structuring element to reduce very small brighter components on darker background and this will effect the image the same in all directions because of its symmetric structuring element. Let I be the image and H the structuring element. So the erosion of I by H is defined as:

$$I \Theta H = \{x : (H)_x \subset I\} \qquad (3)$$

$I \Theta H$ is composed of points that when H is moved to these points, every point of H is contained in I.

It then operates area opening process which is a filter removing the components with area smaller than a definable parameter, the connectivity is given by a structuring element. As polyps seem like branches connected to colon wall at a perpendicular orientation, they can be removed by this procedure considering a proper structuring element (SE) and area parameter.

If I is the image, a the area parameter and B_c the structuring element, then the area opening of I with respect to a and B_c is defined as:

$$I \circ (a)_{Bc} = \bigvee_{B \in B_{Bc,a}} I \circ B \qquad (4)$$

The structuring element that we use is a cross structuring element (4-connected). The area parameter is determined by computing the minimum area of connected boundaries inside the colon wall. The connected boundaries knowing as closed edges are simply derived using Marr-Hildreth operator (Marr et al., 1980). Marr-Hildreth operator locates edges at zero crossings of the image that is first smoothed with a Gaussian mask and then the second derivative is calculated; or we can convolve the image with the Laplacian of the Gaussian, also known as the LoG operator:

$$\nabla^2(G \otimes I) = \nabla^2 G \otimes I \tag{5}$$

The Marr-Hildreth operator is used since it is symmetric and finds edges in all directions and also zero crossings of the second derivatives always form closed contours which we need. They are so simple to be determined as well; all to be done is to look for a sign change.

Next, area top-hating is performed to subtract the result from the original image. Let the result of area top-hating be J:

$$J = I - \left(I \circ (a)_{Bc}\right) \tag{6}$$

After that, it performs opening operator using a structuring element with the same size and shape as the primary erosion structuring element in order to smooth contours of the image and eliminate false touching.

$$\begin{aligned} &J \circ H = (J \Theta H) \oplus H \\ &\text{where } \oplus = \text{dilation operator} \\ &\qquad\quad \Theta = \text{erosion operator} \end{aligned} \tag{7}$$

Morphological opening is then followed by a global threshold using Otsus' method (Otsu, 1979) in which the threshold is chosen to minimize intraclass variance of black and white pixels. This threshold is used to discard extra parts and make a binary version of the images passed through opening operator. After extraction of polyp candidates this way, their boundaries are simply identified by determining black pixels adjacent to white ones. Figure 2 illustrates an example result of performing AMPD and Figure 3 gives an overview of the algorithm.

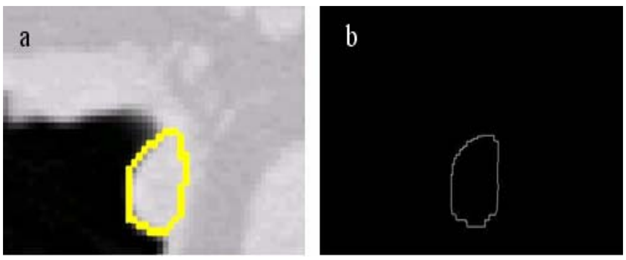

Figure2. Polyp detection a) colonic polyp specification on CT scan b) extracted colonic polyp by AMPD

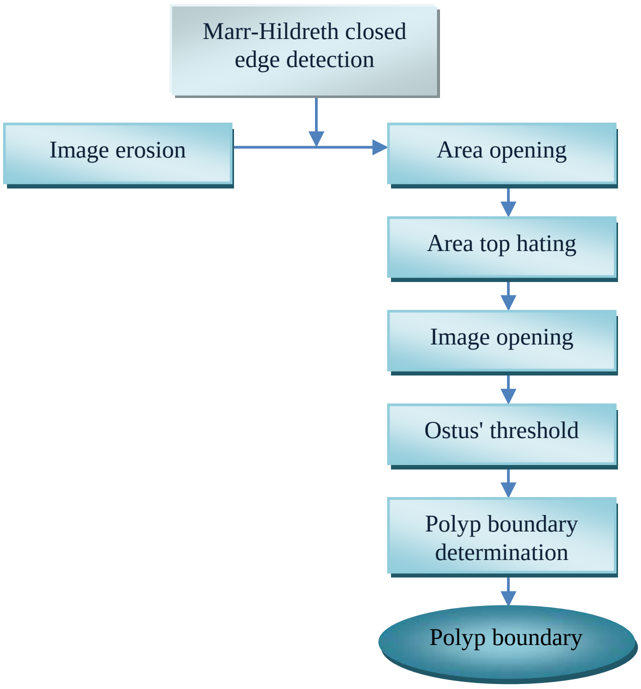

Figure 3. Overview of AMPD algorithm

2.4 Classification

Classifying candidate features as polyps and non-polyps completes the detection process. For polyp/fold classification we present a novel Template Matching Algorithm (TMA) which is based on Euclidean distance searching regarding that typical model for polyps can be assumed either spherical or ellipsoidal. The algorithm requires two polyp templates including a local window and a template pattern. One pattern is determined to be a circle and the other one, an ellipse (Figure 4).

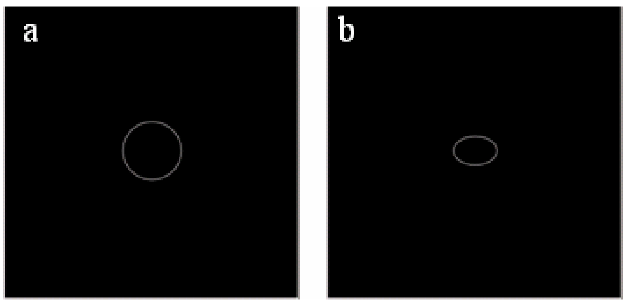

Figure 4. Polyp templates a) circle pattern b) ellipse pattern

The window size is considered to be equal to the largest polyp candidate and pattern templates' sizes are selected to be as small as the smallest segmented component. In order to find required sizes we calculate area within each segmented boundary in the image. Area of on pixels in an image is computed by summing the areas of each pixel in the image. The area of an individual pixel is determined by looking at its 2-by-2 neighborhood. There are six different patterns, each representing a different area: Patterns with zero on pixels (area = 0), Patterns with one on pixel (area = 1/4), Patterns with two adjacent on pixels (area = 1/2), Patterns with two diagonal on pixels (area = 3/4), Patterns with three on pixels (area = 7/8), Patterns with all four on pixels (area = 1) (Pratt et. al., 1991).

After construction of polyp templates, we first detect spherical shaped polyps. The window, containing the circle pattern, is moved across the entire image. Whenever, the circle pattern is located inside a mask of 'on' pixels, the algorithm computes Euclidean distances between the points on the template and the points on the lesion boundary, at predefined intervals (D).

Then, for each boundary a 360/D-length vector of distances is formed. The standard deviation is calculated for each vector. In the case the test circle is centered within a polyp, distances between the circle perimeter and lesion boundary points become nearly equal. Therefore the standard deviation of the corresponding distance vector approaches a small value. Thus, spherical polyps are distinguished from other lesions using an experimental threshold T on the standard deviations. Any cluster having the standard deviation smaller than T is considered to be polyp.

In order to detect ellipsoidal polyps, the template with ellipsoid pattern is moved across the image containing remained clusters. Whenever a closed boundary is located inside the local window, the algorithm computes all Euclidean distances between any two pixels located on the lesion boundary and finds maximum distance. The direction having the maximum distance is assumed to be the major axis of potential ellipse. Orientation of such direction is calculated and the pattern ellipse is then rotated to get the same orientation. Then, it is possible to calculate the Euclidean distances between the points on the template and the points on the lesion boundary at symmetric intervals. Next, a histogram of number of pixels with a given distance versus distance values can be constructed for each cluster. If lesion is an elliptical shaped polyp, then the distances follow the symmetry property of ellipse. Thus, the standard deviation for its corresponding histogram takes a small value. The same as the first step, classifying procedure is done using a threshold T' on the standard deviations. Any cluster with the standard deviation smaller than T' is classified as polyp.

3. RESULTS

In this section, we discuss the results that we obtained by performing our computer-aided colonic polyp detection system when applied to 20 real data sets. First we assess the effect of noise reduction on detection process by testing the technique not including MIC algorithm. The results are summarized in table 1. Next, we examined the complete set of algorithm, containing all four steps. Table 2 shows the performance of our polyp detection technique.

As the results express, adding the noise reduction algorithm improved the total sensitivity rate by about 10 percents. Main table-table 2- shows that technique achieved 100% sensitivity for detection of polyps larger than 10 mm which are the most important types of polyps to be detected in clinical studies. For polyps ranging from 5 to 10 mm there is almost high true positive where a sensitivity rate of 81.82% is achieved. Also our experiment shows a relative low sensitivity (66.67%) for polyps smaller than 5 mm. totally, the experimental data indicates that our polyp detection technique shows a sensitivity rate of 71.73%.

Polyp type	**Total number of polyps**	**True positive**	**sensitivity**
$\geq 10\ mm$	3	3	100%
$[5-10)mm$	11	8	72.73%
$< 5\ mm$	30	17	50.67%
flat	2	0	0%
total	46	28	60.87%

Table 1. Results of performing the technique without noise reduction

Polyp type	**Total number of polyps**	**True positive**	**sensitivity**
$\geq 10\ mm$	3	3	100%
$[5-10)mm$	11	9	81.82%
$< 5\ mm$	30	20	66.67%
flat	2	1	50%
total	46	33	71.73%

Table 2. Results of performing the complete technique

4. CONCLUSION

We have presented and developed a set of algorithms for automatic colonic polyp detection including four stages: noise reduction, colon wall segmentation, feature extraction and finally polyp/fold classification. The morphological image cleaning algorithm smoothes the images while preserving their important features. Colon wall segmentation is done to determine the colon wall region within a 5 pixels margin. Feature extraction is done by AMPD algorithm applying morphological operators and our polyp/fold classification algorithm (TMA) is a template matching algorithm based on Euclidian distance searching.

The proposed system for colonic polyp detection shows almost high sensitivity for medium and large polyps which means polyps between 5 to 10 mm and larger than 10 mm. it expressed total sensitivity of 71.73% which is about 10 percent higher than the case without image cleaning.

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