# Active Contour Segmentation of Polyps in Capsule Endoscopic Images

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***Abstract*—Capsule endoscopy (CE) has been used as a reliable diagnostic measure for detecting polyps in the gastrointestinal (GI) tract. In this paper, we propose an automated framework for efficient segmentation of such polyps from endoscopic images. The segmentation is a challenging task owing to differences in-context in each frame. Principal componet pursuit (PCP) followed by a well-known active contour (AC) model is used in the proposed segmentation method. The PCP is used for specularity removal and background subtraction task in our method. A preprocessing algorithm is proposed to improve the performance of the PCP technique via removing bigger specular regions. Finally, the polyp regions are localized using the AC model in each frame. The experimental results show that the proposed method provides a good performance in localizing the polyps. The polyp regions, which are well illuminated in image produces better result using our proposed method.**

***Index Terms*—Capsule endoscopy, polyps, PCP, specularity, active contour**

## I. Introduction

Segmentation of polyps in endoscopic images requires assigning one label to polyp parts and another label to other parts. Numerous attempts have been made over years in this field still segmentation remains as a challenging task. Broadly, state of the art approaches for image segmentation are divided into three groups: Region based, contour based and amalgamation of the mentioned methods. Region based techniques divide the whole images into number of homogeneous regions. One of such techniques is Markov Random Field [1], where the prior probability captures the contextual constraints that neighboring pixels have similar properties. This method has strong mathematical background and known for its robustness. Since it considers every pixel and calculates its probability of being belonging to a particular class makes it computationally expensive.

Contour based method is popularly known to be Active contour model or snakes [2]. Gradient vector flow (GVF) [3] is extension of the snake which can reach to boundary concavities with use of regularization term. The other advantage of GVF is that, seed of the snake need not to be initialized close to boundary of the object to be detected. The main limitation of these methods are that, they are very much sensitive to outliers and snake may stuck to local minima in the image. In case of endoscopy image, there is a possibility that a snake may stuck to tissues that mimic the shape of polyps. Active contour without edges with level set formulation [4] has been extensively used for segmentation. In [10] diagnosis of pathological vocal folds has been studied using modified active contour model. In this model, the authors have formulated the curve evolution as a minimization problem solved by graph cut optimization. The curve converges such that it has minimal intensity variation around the mean inside and outside the curve. In this paper, we make use of Chan-Vese method [4] on pre-processed endoscopy image for polyp segmentation.

The main purpose of this paper can be summarized as follows: we proposed a two step procedure to remove specularity in endoscopy image. We decomposed image into low rank and sparse form using Principal component pursuit (PCP) [5], where sparse matrix represents specular regions. Further, it was used to subtract non polyp parts from the image. Finally, we applied active contour in the whole background subtracted image for segmentation. This paper is organized as follows: We introduce the underlying principles of Active contour segmentation and pre-processing steps in section II. In section III, we discuss the experimental results. Finally, section IV concludes the paper.

## II. Methodology

### A. Active contour model

The fundamental idea behind active contour model or snake is to evolve a curve defined by some constraints of the images, in order to detect the object of interest. The curve evolves until it converges on the boundary of the object. Let $\Omega$ denotes bounded subset of $\mathbb{R}^2$, and $\partial\Omega$ as its boundary. Suppose $u_o : \bar{\Omega} \rightarrow \mathbb{R}$ be a given image, the image is parameterized by the curve $C(s) : [0,1] \rightarrow \mathbb{R}$

In the original snake model, the evolving curve stops when it finds the largest curve in the image. A functional of the output of an edge detector is the criterion for convergence. In the boundary of the object, it has maximum gradient i.e. lowest functional value which forces the evolving curve to stop there.

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The snake model thus becomes a minimization problem given by Eq. (1)

$$E(C) = \alpha \int_0^1 |C'(s)|^2 ds + \beta \int_0^1 |C''(s)|^2 ds - \lambda \int_0^1 |\Delta u_0 C(s)|^2 \quad (1)$$

where, $\alpha$, $\beta$ and $\lambda$ are weights. The first two terms represent the internal energy of the image, which restrict the curve not to deform quickly. The last term is the external force, which impels the curve to come near object boundary. The term $|\Delta u_0 C(s)|$ is a functional of edge detector which is a decreasing function depending upon gradient of image $u_0$. So, the Eq.(1) can easily be defined as a minimizing function that would try to find the curve that has maximum value $u_0$ while making the curve smooth around the object boundary.

The main limitation of this method is that, the curve may find a local minima. If the curve is initialized far from the object boundary than it would result incorrect segmentation. There have been lots of variants to this model proposed over years but active contour without edges by Chan and Vese [4] is the most popular one.

The Chan-Vese segmentation model is combination of Mumford-Shah functional [6] with level set formulation. This model segments an image by minimizing an energy function given by Eq.(2)

$$E(C, c_1, c_2) = \mu.Length(C) + \lambda_1 \int_{inside(C)} |u_0(x,y) - c_1|^2 dxdy + \lambda_2 \int_{outside(C)} |u_0(x,y) - c_2|^2 dxdy \quad (2)$$

where $\mu \geqslant 0, \lambda_1, \lambda_2 > 0$ are constant parameters. $c_1$ and $c_2$ are average intensity values inside and outside the the curve $C$. So, Eq.(2) becomes an minimization problem that would find the best curve for object segmentation.

In this paper, we use this formulation for segmenting polyp. As an endoscopy image frame is rich in texture and regions are not homogeneous, applying this segmentation techniques would not work well. So preprocessing is an inevitable task.

### B. Specularity Removal and Background Subtraction

In this section, we will discuss about Low rank and Sparse representation of an image. We formulated this for specularity removal and non-polyp region subtraction from an endoscopic image to facilitate polyp segmentation.

An image, represented by matrix $I$ can be decomposed to its low rank $L$ and sparse $S$ matrix [5].

$$I = L + S \quad (3)$$

If the matrix $I$ contains glossy and noisy values than the sparse matrix $S$ would contain these elements. The recovery of low rank matrix from the noisy matrix is achieved through the *Principal Component Pursuit (PCP)* a version of *Robust PCA* [5]. The formulation of PCP is given by Eq. (4)

$$\text{minimize } \|L_*\| + \lambda \|S\|_1 \quad \text{s.t. } L + S = M \quad (4)$$

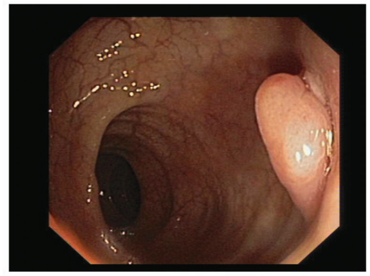

Fig. 1. Typical endoscopic image with specular regions. Image taken from CVC clinic-DB [9].

will solve for $L$ and $S$. $\|L_*\|$ represent the nuclear norm and $\|S\|_1$represent $l_1$ norm of matrix respectively. This convex optimization problem (Eq.4) is solved by using *Augmented Lagrangian Multiplier* (ALM) algorithm [7] [8]. The ALM method to solve this PCP problem is now formulated as Eq. (5)

$$l(L, S, Y) = \|L_*\| + \lambda \|S\|_1 + \langle Y, I - L - S \rangle + \frac{\mu}{2} \|I - L - S\|_F^2 \quad (5)$$

where $Y$ is the Lagrange multiplier matrix. We applied this methodology to get specular free image and further non-polyp regions were suppressed to facilitate segmentation using Chan-Vese algorithm. PCP can only remove small specular regions in an image. Endoscopic images suffer from illumination variation and have large specular patches. A typical endoscopic image of colon is shown in Fig. 1.

In order to make these patches as small as possible, we proposed a 2 stage process. In stage 1, large specular patches were removed. In second stage, the small artifacts were removed by PCP approach. This PCP approach was also used for subtraction of non-polyp region from the image. Finally, segmentation was done using Chan-Vese model, with initial contour defined over the whole image. The whole process is discussed in the next section.

## III. Experimental Results

All the experiments were conducted on CVC clinic database from MICCAI 2015 Sub-challenge on Automatic Polyp Detection [9]. CVC-ClinicDB is a database of frames, extracted from colonoscopy videos. The experiment was conducted with Matlab 2016b on intel i3 @1.8 GHz processor. In stage 1, After reading the image in its usual RGB format, we converted it into gray scale. The logic behind this is the observation that the pixels which fall under specular region, preserve their property of being high intensity region even in gray scale. This step is simply to locate those pixels. In order to locate the proper pixels with high intensity values, we need to have an estimate of the average intensity of the image. Using this rough estimate, we set a threshold of 98 percentiles, such that the pixels having intensity values greater than that threshold will be recognized as specular pixels and will be stored and further processed for rectification. After that, a window of

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median filter of size 33×33 was slided across each channel of the original image and stored the newly filtered image. In the final step, the pixels detected as specular ones were replaced with corresponding median-filtered value.

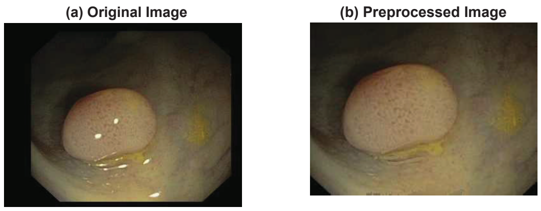


Fig. 2. Specularity removal in endoscopic image after pre-processing stage.

The resultant image is specular free yet some artifacts are present in the boundary of specular regions. We then took the advantage of PCP for its ability to remove small specular regions from an image.

In this stage, the pre-processed image was decomposed to form low rank and sparse using PCP approach. We are now

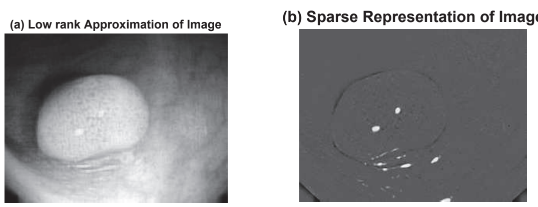


Fig. 3. Decomposed Low Rank and Sparse representation of images with pre-processing stage 1.

comparing the results of decomposition if the image were not gone through stage 1.

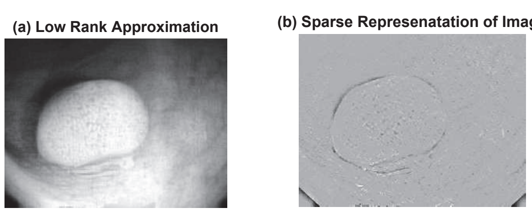


Fig. 4. Decomposed Low Rank and Sparse representation of images without pre-processing stage 1.

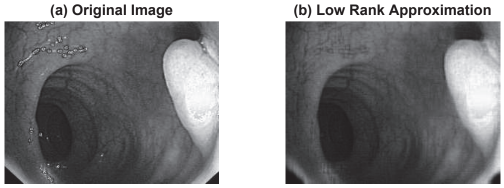


Fig. 5. Decomposed Low Rank representation of image with pre-processing stage 1.

From the experiment, it is observed that the sparse matrix highlights the specular regions. In the original formulation of PCP, a number of images of a particular scene with different illumination are stacked as column matrix which is decomposed. In our case, we applied on a single endoscopic image which is not an optimized decomposition. The endoscopic image is highly corrupted with noise. The sparse matrix represents specular regions and gray values for other parts of image.

In endoscopic imaging, polyps regions are generally highly illuminated than other parts of colon. With this assumption, we found an empirically relation between decomposed matrices to remove low illuminated non-polyp regions. The relation is given by Eq. (6)

$$B = I - \alpha.S \tag{6}$$

The value of $\alpha$ need to be set manually to get different level of back ground subtraction. We applied the Chan-Vese segmenta-

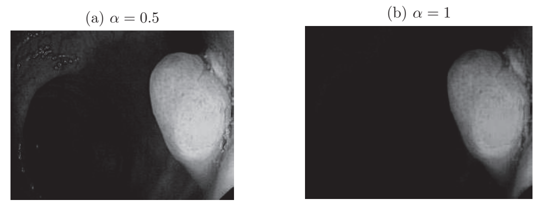


Fig. 6. Background subtracted image with different values of $\alpha$

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tion with length parameter $\mu$ set as 0.2. Initial contour location is an important factor in this frame work. We initialized the contour whole across the image with holes around. After 1800 iteration the results are shown in Fig. 7

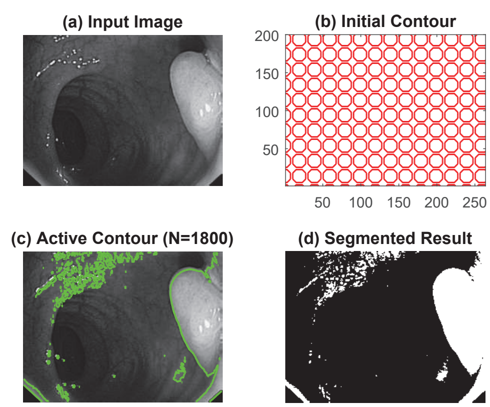


Fig. 7. Active contour segmentation without subtracting background from original endoscopic image. Note that N denotes the number of iterations.

Now, we chose different values of $\alpha$ and went for background subtraction using Eq. (6). Upon these background subtracted images we applied active contour for segmenting the polyps. The results are shown in Fig. 8. Finally, we chose $\alpha = 1$ which almost segment the polyp region. The active contour was applied on it. Results are shown in Fig. 9. Our proposed frame work is well suited for segmenting

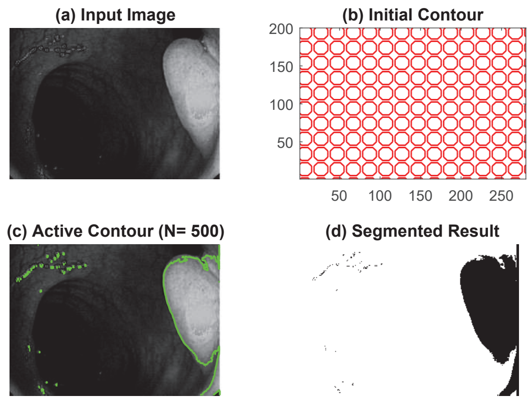


Fig. 8. Active contour segmentation with subtracting background from original endoscopic image. Note that N denotes the number of iterations for value of $\alpha = 0.5$.

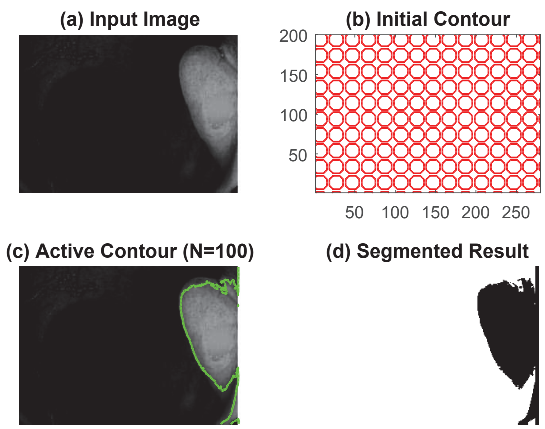


Fig. 9. Active contour segmentation with subtracting background from original endoscopic image. Note that N denotes the number of iterations for value of $\alpha = 1$.

polyps regions which are highly illuminated than other parts of image frame. If non-polyp regions are also have high intensity along with the polyp regions than this would result in over segmentation. Result of such case is shown in Fig. 10. The over segmented image can further be used as input to other segmentation model like Markov Random Field (MRF) for better result.

## IV. Conclusion

In this paper, we propose a multistep approach for polyp region segmentation in endoscopic image frames. A pre-processing step is devised before applying PCP for image decomposition. With this preprocessing, PCP better approximates the image with low rank and sparse representation. We then introduce an empirical formulation for non-polyp region subtraction from the image which facilitates better segmentation. Our proposed model works well with polyps region having high illumination. In some cases it gives over

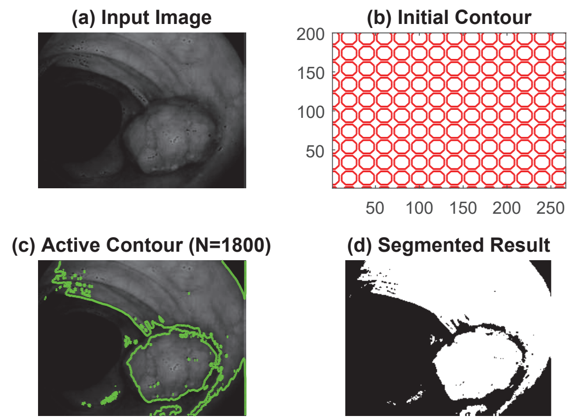


Fig. 10. Active contour segmentation with subtracting background from original endoscopic image. Note that N denotes the number of iterations for value of $\alpha = 1$.

segmented results which can be used as an input for other robust segmentation technique such as MRF based segmentation. As the endoscopic image has highly non homogeneous regions the energy functional for active contour must be properly formulated. In future we would incorporate other image features into the active contour formulation for better segmentation output.

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