Original Article

Barrett's Mucosa Segmentation in Endoscopic Images Using a Hybrid Method: Spatial Fuzzy c-mean and Level Set

Abstract

Barrett's mucosa is one of the most important diseases in upper gastrointestinal system that caused by gastro-esophagus reflux. If left untreated, the disease will cause distal esophagus and gastric cardia adenocarcinoma. The malignancy risk is very high in short segment Barrett's mucosa. Therefore, lesion area segmentation can improve specialist decision for treatment. In this paper, we proposed a combined fuzzy method with active models for Barrett's mucosa segmentation. In this study, we applied three methods for special area segmentation and determination. For whole disease area segmentation, we applied the hybrid fuzzy based level set method (LSM). Morphological algorithms were used for gastroesophageal junction determination, and we discriminated Barrett's mucosa from break by applying Chan-Vase method. Fuzzy c-mean and LSMs fail to segment this type of medical image due to weak boundaries. In contrast, the full automatic hybrid method with correlation approach that has used in this paper segmented the metaplasia area in the endoscopy image with desirable accuracy. The presented approach omits the manually desired cluster selection step that needed the operator manipulation. Obtained results convinced us that this approach is suitable for esophagus metaplasia segmentation.

Keywords: *Adenocarcinoma, algorithms, Barrett's mucosa, cardia, endoscopy, esophagogastric junction, fuzzy logic, gastroesophageal reflux, metaplasia, segmentation*

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Introduction

Upper gastrointestinal endoscopy is one of the most frequent medical procedures; evaluating patients with gastro-esophageal reflux disease (GERD) makes a large proportion of these procedures all over the world. This disorder is quite frequent but may less likely be erosive esophagitis and rarely be a clinically significant medical problem, i.e., mucosal change into specified intestinal metaplasia that is called Barrett's mucosa that consequently may change into cancer.

In diagnostic esophagogastroduodenoscopy of GERD cases, a physician looks for (a) finding and grading erosive esophagitis (b) searching possible etiology including sliding hiatal hernia and its size, and (c) detecting and measuring abnormal mucosa in gastro-esophageal junction (GEJ), i.e., Barrett mucosa.

To reach each of the goals of scopy in GERD, there is a need for measurement of the length or width of parts of image that a physician observes during the procedure considering baseline and landmarks, for the purpose of (i) detecting anatomical GEJ or Z line (ii) marking highest border of red-colored mucosa and (iii) considering its irregular or broken shape traditionally called breaks and tongues.

In the current study as a pilot investigation, we tried to map endoscopically suspected Barrett's mucosa especially its upper border considering its possibly broken-line shape; this may then facilitate further measurements according to clinically accepted classifications of erosive esophagitis (i.e., Los Angles) and Barrett mucosa (i.e., Prague).[1] Our study showed that very few image analysis methods have been performed in this area. Hence, we were motivated to do research on Barrett's mucosa in endoscopic images.

Medical image segmentation is challenging due to weak resolution and poor contrast.[2] The image segmentation algorithms are normally based on some characteristics obtained from an image such as gray level, color, pattern, texture, depth, or motion.[3-5] One of the most accurate image segmentation methods that is widely used is level set method (LSM) that is

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numerical techniques which can follow the evolution of interfaces. LSMs can be divided into two main categories, named as edge-based models that use image gradients to detect the boundaries and region-based models that utilize the statistical information to control the evolution of contour to detect boundaries. LSMs fail to achieve desired segmentation when an image contains several blocks with gradual variations in pixel intensities.[4]

One of the most popular clustering algorithms, fuzzy c-means (FCMs) algorithm, is an unsupervised technique which has been successfully used in many fields such as clustering and segmentation. However, there are some deficiencies in FCM algorithm. Therefore, several modifications have been proposed to improve the performance of FCM algorithm.[5]

Due to complexity in medical image segmentation especially in esophagus endoscopic images neither LSM nor FCM algorithm alone can be relied upon to obtain a perfect result. Some hybrid intelligent systems have used fuzzy clustering to facilitate level set segmentation. Rastgarpour *et al*. used hybrid method to segment brain tumor, brain tissue, with inhomogeneous intensity.[6] Anitha and Peter used fuzzy based level set to detect mammogram mass.[7] Li *et al*. used fuzzy based level set for different medical image segmentation such as brain white and gray matter, liver and tumors.[8] Balla-Arabé proposed a robust combined level set and fuzzy clustering for inhomogeneous image segmentation.[9] Although an LSM based on FCM clustering can suppress problems such as noise sensitivity and poor boundaries but the operators still have to select initial boundary manually and set proper parameters for optimal segmentation.[8,10] Hence, we proposed combined fuzzy based LSM to segment the esophagus endoscopic images. In this method first, we applied spatial FCM (SFCM) on the given image and then obtained result served as an initial contour for LSM to obtain more accurate segmentation of the image.

In this paper, we improve the FCM based level set segmentation algorithm for full automatic medical image segmentation especially for Barrett's mucosa endoscopy image segmentation.

Materials and Methods

Patient geometric data were selected from a set of several 24-bit esophagus endoscopy image series of patients that had endoscopy procedure in one of the author's clinic. Selected images have resolution of 240 × 320 × 3 pixels. The implemented MATLAB program runs in a computer with dual-core 2.53 GHz CPU and 4G of RAM. The graphical block diagram of the proposed approach has been showed in Figure 1.

Preprocessing

Before applying the automatic combined method for image segmentation, an enhancement procedure was performed.

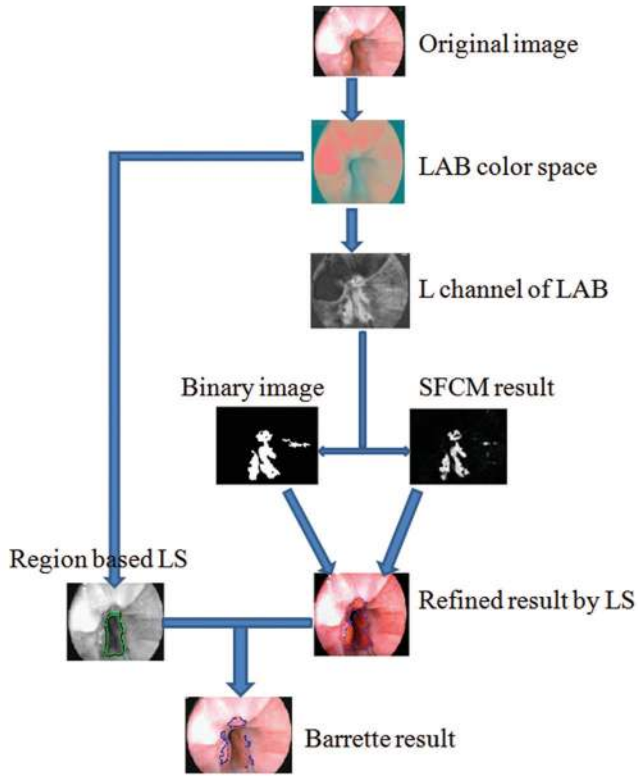

Figure 1: The graphical block diagram of proposed Barrett's mucosa segmentation method

Since the obtained images are represented by close contrast values, so the histogram equalization method was applied to enhance the image contrast globally. However, because of the nature of color image, the color space was converted from RGB to LAB, and only luminance (L) channel was used for equalization without changing other channels (because L contains information about lightness and A and B are color-opponent dimensions). The enhanced image was fed to the segmentation algorithm.

Spatial fuzzy C-mean algorithm

FCM clustering is an unsupervised method that the centroid and domain of each sub-clusters are estimated iteratively to minimize the predefined cost function. The main goal behind this method is to distribute the data into clusters that minimizes the dissimilar properties in each cluster. The FCM algorithm has been widely applied for medical image processing such as image segmentation, image enhancement.[11,12] The FCM algorithm classifies pixels of data sets into clusters using a distance function. For an FCM clustering with Euclidian distance function, with c clusters, the FCM cost function is defined as follows:[13-15]

$$J=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}d_{ij}^{2}=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}d_{ij}^{2}\left\|x_j-v_t\right\|^2 \quad (1)$$

where x_j is the specific image pixel and u_{ij} represents the membership of j_{th} pixel in the i_{th} cluster, v_i is the centroid of i_{th} cluster, $\|\cdot\|$ denote a norm metric, and m is a parameter that controls the fuzziness of the obtained segmentation results. The membership function represents the probability of belonging of a pixel to a specific cluster that satisfies this condition $\sum_{i=1}^{c} u_{1,j} = 1 \forall j = 1,\ldots n$. The membership P value of a pixel is dependent on the distance between the pixel and centroid of its cluster. Membership function and centroid of clusters are updated iteratively as below:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|x_j - v_i\right\|^2}{\left\|x_j - v_k\right\|^2}\right)^{\frac{2}{m-1}}} \tag{2}$$

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{3}$$

in an image, neighboring pixels have high correlation with each other. Therefore, if we applied a method that uses the spatial information, so we can utilize neighboring pixels information to suppress noise and artifact effect. In the SFCM algorithm, using spatial information, the algorithm is robust to noise and disturbance. Chuang *et al*. proposed an SFCM algorithm that uses spatial information in fuzzy membership directly by:[14,16]

$$u_i = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^{c} u_{kj}^p h_{kj}^q} \tag{4}$$

where h contains spatial information and p and q are parameters that control the importance of u and h. The spatial information h can be defined as:

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik} \tag{5}$$

where NB (x_j) denotes a local window centered on image pixel x_j.

Level Set Method

The LSM is a powerful numerical method for tracking interfaces and boundaries that use the PDE equations. This method originally presented by Osher and Sethian to track sliding interfaces.[17] It has been used quite widely in signal and image processing fields such as image segmentation.[16] The benefit of the LSM is performing numerical computation including curves and surfaces on a Cartesian grid. The LSM against FCM starts with an initial curve or surface and push it perpendicular to itself at a defined speed. In the LSM, ϕ (x, y, t) is the height of the surface at position (x, y) and time t. To find the movement of interface, we first require:

$$\phi\,(x(t), t) = 0 \tag{6}$$

For a general curve, C can be defined as a signed distance function to C

$$\phi\,(x, y) = \begin{cases} \phi \geq \text{if } (x, y) \in \text{inside C} \\ \phi < 0 \text{ if } (x, y) \in \text{outside C} \\ \phi = 0 \text{ if } (x, y) \in \text{ C} \end{cases} \tag{7}$$

Signed pressure force formulation

Zhang *et al*. introduced a new region-based signed pressure force (SPF) function to control the zero level set at weak boundaries.[18] The region-based methods have two great advantages. First, region-based methods are less sensitive to image noise and give higher accuracy for images with blurred edges and boundaries. Second, they are not affected by the placement of initial curve. The proposed LSM using SPF formulation is introduced as follows:

$$\frac{\partial \phi}{\partial t} = \text{SPF}(I(x)) \cdot \alpha \left|\nabla \phi\right| \tag{8}$$

where SPF function is defined as:

$$\text{SPF}(I(\text{x})) = \frac{I(x) - \frac{c_1 + c_2}{2}}{\max\left(\left|I(x) - \frac{c_1 + c_2}{2}\right|\right)} \tag{9}$$

c_1 and c_2 are constants which are the average intensities inside and outside the contour respectively that are defined as:

$$c_1 = \frac{\int_{\Omega} I(x) H(\phi)\, dx}{\int_{\Omega} H(\phi)\, dx} \tag{10}$$

$$c_2 = \frac{\int_{\Omega} I(x) \cdot (1 - H(\phi))\, dx}{\int_{\Omega} 1 - H(\phi)\, dx} \tag{11}$$

H(ϕ) is the Heaviside function.

Chan-vase method

In this section, we shortly explain about the proposed region-based algorithm by Chan and Vese.[19] We use region information in this method to detect objects whose boundaries are not well defined by gradient and edge information. In this method at first, an evolving curve C in Ω (as the boundary of an open subset ω of Ω) has to be defined. Assume that the image I_0 is represented by two regions of piecewise constant intensities. Let c0 denote the boundary object; then we have $I_0 \approx I_0^i$ inside the object, and $I_0 \approx I_0^o$ outside the object. Now we can write the energy function as:[19]

$$F_1(C)+F_2(C)=\alpha\int_{\text{inside}(c)}\left|u_0(x,y)-c_1\right|^2 dxdy + \beta\int_{\text{outside}(c)}\left|u_0(x,y)-c_2\right|^2 dxdy \quad (12)$$

where c_1 and c_2 are defined in LSM, C is any variable curve, α and β are. So the boundary of object is the minimizer of the fitting energy:

$$\inf_c\left\{F_1(C)+F_2(C)\right\}\approx 0\approx F_1(C)+F_2(C) \quad (13)$$

for example, if the curve C is outside the object, then F_1 (C) > 0 and F_2 (C) ≈ 0. On the other hand, if the curve (C) is inside the object, then F_1 (C) ≈ 0 and F_2 (C) > 0. Finally, the fitting energy is minimized if C ≈ C0. For our purpose, we regularized internal and external energy in a way, boundary evolution stops where it has steep, abrupt changes. Therefore, in this study, we selected α = 2 for more smoothness. This basic remark is showed in Figure 2.

Proposed algorithm

The level set and FCM methods can be used for multidimensional image segmentation separately. Recently, new hybrid approaches have been developed, but for final segmentation, we must select the desired cluster manually.[8] In this paper, we propose a new method to segment the Barrett´s mucosa in esophagus endoscopy image. We first converted the original image to a binary one with a proper threshold which was obtained by Otsu method, and then we calculated the correlation coefficient of the FCM output clusters with the binary image:

$$r=\frac{\sum_i\sum_j(I_{ij}-\bar{I})(BW_{ij}-\overline{BW})}{\sqrt{\sum_i\sum_j(I_{ij}-\bar{I})^2\sum\sum(BW_{ij}-\overline{BW})}} \quad (14)$$

where $\bar{I}$ and $\overline{BW}$ are the mean of FCM cluster and binary image, respectively. The cluster with the high correlation coefficient is selected as the desired cluster to feed the LSM as initial contour, and the output of the LSM would be the whole disease area. Parallel to this algorithm, the region based active contour is applied to the original image for determining Barrett's mucosa in the final step. In the final step, to obtain Barrett's mucosa area, the output of region-based active contour is subtracted from the output of LSM.

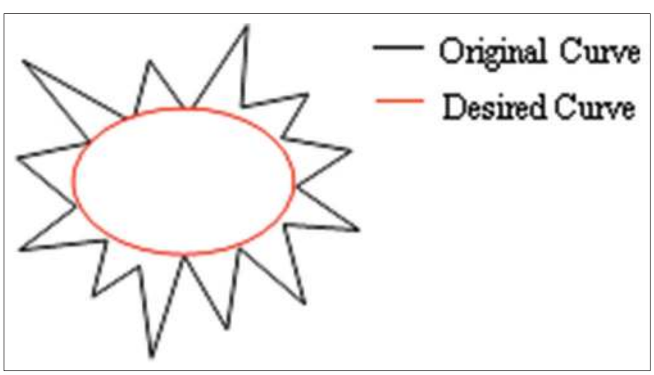

Figure 2: Basic remark, black line is original curve and the red line is desired curve

Finally, for evaluation, we compare our obtained results with manual segmentation results that have been done by gastroenterologist as a gold standard. For quantitative evaluation we compute accuracy of the proposed method.

Results

In this section, we express our experiment results on esophagus endoscopic images. As illustrated above for Barrett's mucosa segmentation we applied a hybrid method. We used two types of LSM, LSM with SPF formulation and Chan-Vase method for all disease segmentation and GEJ detection, respectively. Then we determine break region for further evaluation.

Figure 3 illustrates the Barrett's mucosa segmentation in endoscopic images. FCM and LSMs fail to segment this type of medical images due to weak boundaries if used separately. In contrast, the hybrid model FCM and SPF formulation LSM with correlation approach have been able to segment the Barrett's mucosa in endoscopic images with acceptable accuracy. Obtained results have been showed below.

In the next step, we used Chan-Vase model to determine the break region in Barrett's mucosa, in this step, we determine the external and internal energy in which way that the model stops in areas with high changes in boundaries. Then the obtained results are subtracted from those ones that were obtained from the hybrid step. The results were shown in Figure 4.

For evaluation, we compare the obtained results from proposed method with manual segmentation as a gold standard by calculating dice metric of segmented areas. There was more than 95% agreement between algorithm results and gold standard segmentation. The obtained results have been showed in Table 1.

Discussion

Analysis and processing of the esophagus endoscopy image is one of the challenging fields in medical image processing due to noise and light reflection. Hence, in the current work, we proposed a full automatic hybrid method for segmentation of the suspicious endoscopic Barrett's mucosa. Since the different endoscopy device images have different features and topologies so model tuning was required at first. We successfully applied combined SFCM with SPF formulation based LSM for dysplasia area segmentation.

Table 1: Barrett's mucosa segmentation performance

	Case 1	Case 2	Case 3	Case 4
Accuracy	95.53%	94.66%	96.32%	95.13%

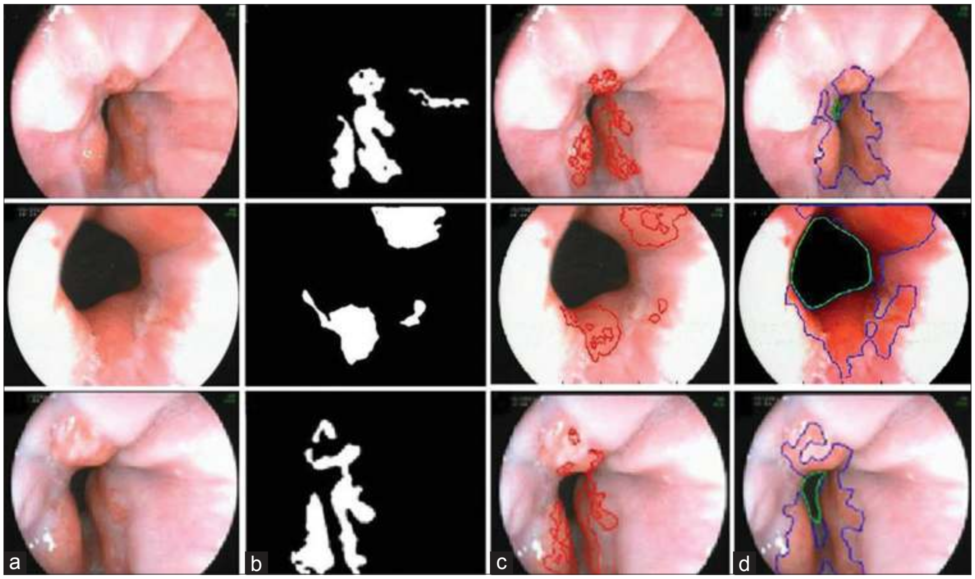

Figure 3: Illustration of the automatic method (a) original images, (b) the binary images of the original images, (c) the desired FCM output clusters and (D) the output of the level set method, blue and green contours represent the Barrett's mucosa and base line respectively

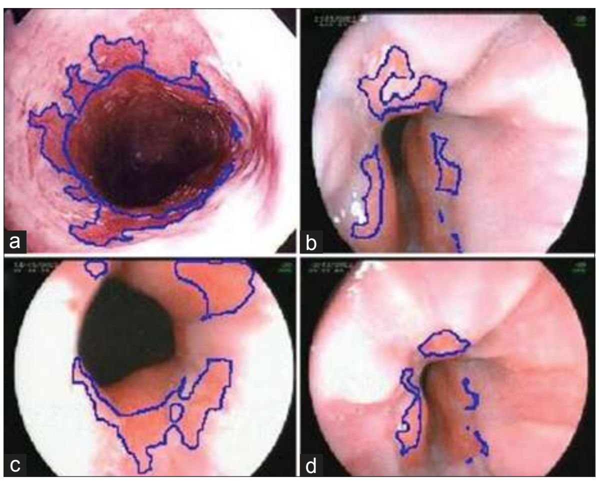

Figure 4: The Barrett's mucosa esophagus segmentation

Furthermore, combination of hybrid approach with Chan-Vase segmentation method segments the break part properly. In Chan-Vase segmentation method, we regularized internal and external energy in a way that boundary stops where it has steep abrupt changes. With this approach first we can introduce break's starting points, second by subtracting Chan-Vase segmentation method from hybrid method break regions are determined. The presented approach omits the manually desired cluster selection step that needed operator manipulation. Obtained results show that this approach can segment Barrette´s mucosa disease images properly and automatically. As have been showed in Figures 3 this algorithm can segment the disease and determine the baseline for disease progress evaluation. Furthermore, our method could segment the endoscopic Barrett to determine the length and surface of the disease.

A report on single-endoscopist detection of GEJ point showed high accuracy in a small group of patients[20] but when considering esophagitis or Barrett's mucosa we need to calculate the length and a simulation study on a sample of expired and trainee endscopists showed over/underestimation of length in 5/6 of measurements.[21] On the other hand, there is a problem with inter-observer reliability especially in short lengths; a study in Asian gastroenterologist showed ICC values for Barrett's segment <1 cm were as low as 0.18.[22] This shows the need for an automated method of measurement in GEJ endoscopy to detect columnar lined epithelium and erosions with perfection.

We may conclude that this algorithm seems to be proper for GEJ endoscopy image segmentation. There are some potential limitations in current study: First, we focused on upper border of segment and measuring Barrett's mucosa needs perfect setting of GEJ that is defined by upper border of gastric folds as American gastroenterologists do, not the lower limit of palisade esophageal vessels as Japanese doctors do; second, when calculating the length of Barrett's mucosa we need a set of push-in and pull-out images since the height is variable based on which type of image is analyzed.[23] In future works, we want to measure the dimensions of the segment quantitatively to assist the gastroenterologist.

Conclusion

We proposed fuzzy based level set method for segmentation and evaluation of Barrett´s mucosa. In future works, we want to measure the dimensions of the segment quantitatively to assist the gastroenterologis.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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