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Saliency Based Ulcer Detection using Wireless Capsule Endoscopy Diagnosis

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Abstract: Ulcer is one of the most common indications of many serious diseases in the human digestive tract. Especially for ulcers in the small intestine where other methods may not display properly, capsule endoscopy (WCE) is increasingly used in the diagnosis and clinical management. Since WCE generates lots of images of the entire inspection process, computer-aided detection ulcer is considered an essential relief for clinicians. In this work, a CAD system is proposed for fully automated computer in two stages to detect images WCE ulcer. In the first step, a detection method based on the effective prominence superpixel multilevel outline representation candidates proposed ulcer. To find the perceptual and semantically meaningful salient regions, the first image segment in multi-level superpixel segmentations. Each level corresponds to different initial sizes of super pixels region. Then the corresponding prominence according to the characteristics of color and texture of each level superpixel region is evaluated. At the end, we merge the salience maps of all levels together to obtain the final saliency map. The experiment results achieved promising accuracy 94.72% 94.63% sensitivity and, validating the effectiveness of the proposed method. Moreover, the results of the comparison show that our detection system outperforms the methods of prior art in the detection task of the ulcer.

Index Terms: linear-town with limited coding (LLC), multilevel superpixel representation, prominence and the max-sharing method based on prominence.

I. INTRODUCTION

Ulcer is one of the most usual lesions of the gastrointestinal (GI) tract which affects about 10% of people worldwide [5]. It is a chronic inflammatory pain or erosion on internal mucous membranes. Helicobacter pylori and non-steroidal anti-inflammatory drugs (NSAIDs) are considered two major causes of ulcers in the digestive tract. Ulcer itself is not lethal; however, is the symptom of some serious diseases, such as Crohn's disease and ulcerative colitis disease whose complications can cause death [6].

In traditional process of inspection of ulcer, an endoscope is to be inserted into the mouth or anus of the patient by physicians experienced to see the GI tract [17]. Although traditional techniques play an important role to see upper and lower ends of the GI tract, which are highly invasive for patients. Moreover, it is technically difficult for traditional procedures to obtain full access to the small intestine [2].

The revolutionary capsule endoscopy wireless (WCE) provides an alternative way to direct, painless and noninvasive inspection of the small intestine. The WCE commercially available usually consisting of an optical dome, a part of lighting, imaging sensor, batteries, and a radio transmitter frequency as shown in Fig. 1 (a).

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After a WCE is swallowed by a patient, which is pushed by peristalsis slowly travel through the small intestine. For about 8 hours inside the patient's GI tract, the EBB takes 2-4 images per second. These images are compressed and transmitted wirelessly to a recording device attached data the patient's waist. All images can be downloaded and offline examined by doctors to make decisions of diagnosis [9]. An example of the image captured by an ulcer during inspection WCE shown in Fig. 1 (b).

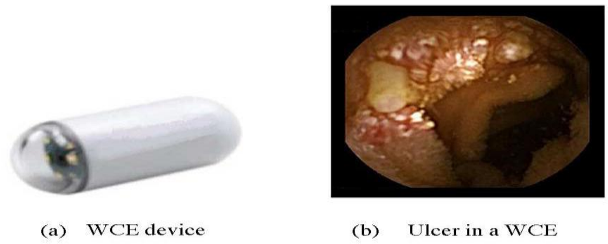

Fig. 1 Wireless capsule endoscopy and one captured image. (a) A typical WCE device. (b) An example image of ulcer

Although WCE has demonstrated significant advantages over traditional endoscopes to inspect the nest ulcer in the small intestine, there are new challenges associated with this technology. WCE creates 55,000 images for each patient, and images captured abnormal occupy only 5% of all the images collected WCE is tedious for the doctors who go through all these images manually frame by frame to detect the abnormal images. Therefore, it is crucial for the design of an automatic system for computer-aided help clinicians to analyze images of the ulcer.

II. RELATED WORK

Image segmentation [3] it is the process of obtaining certain regions of the images. Edge detection identifies the point's border around the required objects. Contour extraction refers to outline the segmented part of the image. In order to make the method useful in practice in clinical trials of the hospital, more tests using a much larger number of data sets are critical to validate the effectiveness and robustness of the WCE images. Furthermore, this study aimed to implement task efficiently for WCE ulcer recognition images as bleeding [8], ulcer and using different tumour detection data set.

2.1. Techniques Used

Image segmentation is the process of dividing an image into multiple parts used to identify relevant information in digital images. In the proposed work, the Gaussian kernel methods used to reduce noise; algorithm canny edge detection is used to produce thick solid edges with reliable values. This method consists mainly of three steps: (1) Gaussian kernel (2) sensing edge (3) segmentation Super pixel.

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2.1.1 Gaussian Kernel

It filtering Gaussian convolution it is performed by each point of the input matrix with a Gaussian kernel and then summing all to produce the output matrix. Invert filter alters the original value of the pixel of color to its inverse value. Each pixel value to their investment value is reversed. Smoothing, also called blur. It is a simple and frequently used image processing operation. This smoothing is used in order to reduce noise. An image grayscale in which the value of each pixel is a single sample, i.e. it only takes intensity information. The images of this type, also known as black and white, are collected exclusively of shades of gray, varying from black to white weakest to the strongest intensity.

2.1.2. Edge Detection

Edge detection in image processing is a tool that detects areas in images with the sudden change of brightness. Used to decrease the amount of data in an image and preserve high threshold pixel for further processing. Detection Canny edge algorithm aims to meet three main criteria:

Low error rate: a good detection meaning only exists edges.

Good location: The distance between the edge pixels detected and the pixels of the actual edge must be minimized.

Minimum response: Only one response per edge detector.

Steps:

i) Filter out any noise: The Gaussian filter is used for this purpose. An example of a Gaussian kernel of size=5 that might be used are shown below:

$$K = \frac{1}{159}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix}$$

ii) Find the intensity gradient of the image: For this, we follow a procedure analogous to Sobel. Apply a pair of convolution masks in x and y directions.

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix}$$

$$G = \sqrt{G_x^2 + G_y^2}$$

$$\theta = arctan(\frac{G_y}{G_x})$$

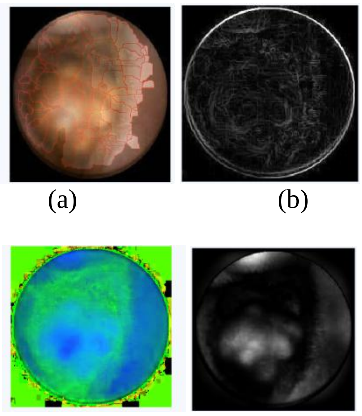
iii) Non-maximum suppression: This removes pixels that are not considered to be part of an edge. Hence, only thin lines (candidate edges) will remain.

iv) Hysteresis: The final step Canny uses two thresholds (upper and lower). If a pixel gradient is greater than the upper threshold, the pixel is accepted as an edge. If a pixel value gradient is below the lower threshold, then it is refused. If the pixel gradient is between the two thresholds, then it will be allowed only if it is attached to a pixel that is above the upper threshold.

2.1.3. Monochrome segmenting

Image segmentation is the process of distributing a digital image into many segments (sets of pixels, also known as Super pixels). Image segmentation is defined as a partition of pixels or blocks of images into homogeneous groups. The goal of segmentation is to simplify and / or change the illustration of an image into something that is more meaningful and easier to evaluate. Image segmentation is commonly used to detect objects and boundaries (lines, curves, etc.). In monochrome images segmentation, each pixel is stored as a single bit 0 or 1.

In this paper, the image containing the region of bleeding was 1 set of labeled sample, no bleeding (ulcer) 2 as the set of sample and tumor as third overall sample. Without filtering process images are not as clear. Invert filter alters the average value of the original pixel color to its inverse value and removal process is able to remove outliers without decreasing the sharpness of the image. Then it is softened applied to reduce noise and to prepare the image for more processing such as segmentation. Grayscale is used to convert color images to gray tones. Detection Canny edge highlights the edge pixels for affected regions are identified effectively. Experimental results show that the proposed method is promising in image enhancement and help doctors diagnose injuries.



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

Fig.2 (a) Superpixel Segmentation(b) Edge Detection (c) HSV Image(d) Texture based ulcer detection

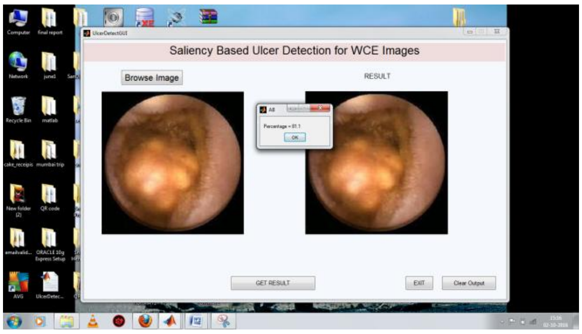


Fig.3 Final Output

III. SALIENT REGION DETECTION

Prominent regions are generally defined as regions that could introduce explicitly the major significant or semantic content. For implicit images with various objects or disorderly scenes, however, there are no uniform metrics that could describe prominence. In this study, as shown in Fig. 1 (b), the WCE images with ulcerative lesions could explicitly distinguished by color and texture contrasts. By exploiting these features, the region detection method can segment projection of the first projection plane region from images WCE. Therefore, the detection method outgoing region is particularly suited to be used as a first step to the problem of recognition of the ulcer.

This paper proposes a framework for abnormalities of the ulcer through estimating the visual prominence based on the contrasts of texture and color. The method of detecting the saliency proposed consists of three main steps. The first step is the segmentation of various levels; the input image is decomposed into several super pixels from a coarse level to a fine of one. Then we carry out estimation of prominence by contrasts of color and texture. At the end, the saliency map is obtained end by merging salience maps of together.

3.1 Segmentation superpixel

A super pixel is defined as a significant entity by grouping spatially neighboring pixels with similar property. The simple iterative linear array (SLIC) is the algorithm superpixel the prior art which outputs desired superpixels regular and compact with low computational cost number.

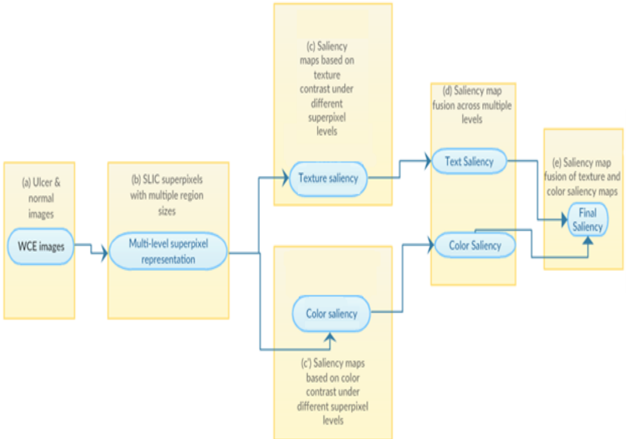
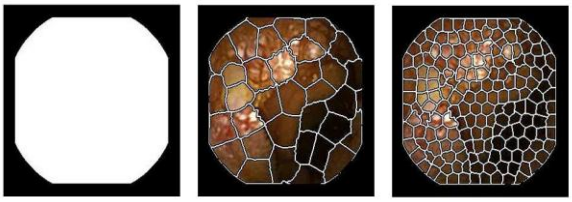


Fig. 4 Illustration of multi-level superpixel saliency extraction method. (a) WCE images as input. (b) Multi-level SLIC superpixel segmentation. (c) Saliency map estimation based on texture contrast. (c') Saliency map estimation based on color contrast. (d) Saliency map fusion for both texture and color saliency. (e) Final saliency map obtained by the fused texture and color saliency maps.

We propose to apply superpixels SLIC as a method of pre-processing for detecting image WCE prominence. Because not only it provides good segmentation results, but also generates appropriate size of image analysis superpixels WCE. In the SLIC method, clustering is performed for the first time and then small isolated groups are combined with the highest neighboring groups for the specific number of superpixels. Each segmented superpixel is used as a processing unit.

The choice of an appropriate number of super pixels for image WCE is empirical and specific cases. This is because too many numbers of superpixels lead to excessive segmentation, while very few superpixels result in the loss of boundary information objects. Furthermore, the use of a single size to segmentation superpixel may not be able to describe the boundary well for some cases. Therefore, one superpixel method multi-level that the first image segments using several different numbers of superpixels (alias, multiple levels of superpixels), all superpixel segmentation fuses at all levels later proposed. The number of super pixels K we tested herein is set to 50, 100, 150, 200 and 250 at each level, resulting in number of L = 5 level.

Figs.5 (b), (c) shows an example of representation of a super pixel image with superpixel WCE number 50 and 250.



(a) Mask (b) 50 superpixels (c) 250 superpixels

Fig.5 Illustration of the mask and the superpixel segmentation of different superpixels. (a) Image mask that outlines useful regions from WCE images. (b) A WCE image is segmented into 50 superpixels; the white lines are the boundaries of each superpixel. (c) The same image is segmented into 250 superpixels.

3.2 Saliency Region Detection Based on Texture

In this paper, texture features of superpixel regions are extracted by using Leung-Malik (LM) filter bank.The LM filter bank is a multi-scale, multi-orientation filter combination with 48 filters. It consists of first and second derivatives of Gaussians at 6 orientations and 3 scales, 8 Laplacian of Gaussian (LOG) filters, and 4 Gaussians. The filter bank is shown in Fig.6.

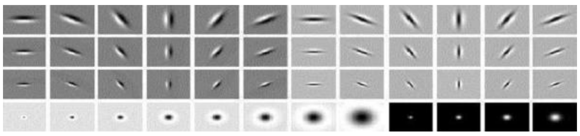


Fig. 6 An illustration of the LM filter bank that is used to extract texture contrast in the WCE images.

Given an image $I_{M \times N}$, the response $R_{M \times N}$ to the m[th] filter w_m out of 48 filters in the LM filter bank can be calculated by,

$$R_m(x,y) = \sum_{s}\sum_{t} \omega_m(s,t) I(x+s, y+t) \quad (1)$$

The texture saliency $^{texture}\hat{S}_l \epsilon \mathbb{R}^{MXN}$ at the l[th] level for the given image is defined as,

$$^{texture}\hat{\mathbf{S}}_l(x,y) = \sum_{j=1, j\neq i}^{N} \frac{\mathbf{D}(i,j)}{\max\limits_{i,j}(\mathbf{D}(i,j))}, \quad (2)$$

Where D (i, j) is the (i, j) entry of the distance matrix D that represents the Euclidean distance between the texture feature vectors $^{texture}F_l(i)$ and $^{texture}F_l(j)$ of the i[th]

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and j[th] regions. Max $_{(i,\ j)}$ (D (i, j)) is to take the maximum within the matrix. The entry (x, y) for the texture saliency matrix ${}^{texture}\hat{S}_l$ represents a pixel within the superpixel region. The texture saliency value for each pixel is set to be the same within the same superpixel region.

Equation (2) indicates that the superpixels whose textures are different from most of the other regions in the image are assigned with a higher value of texture saliency.

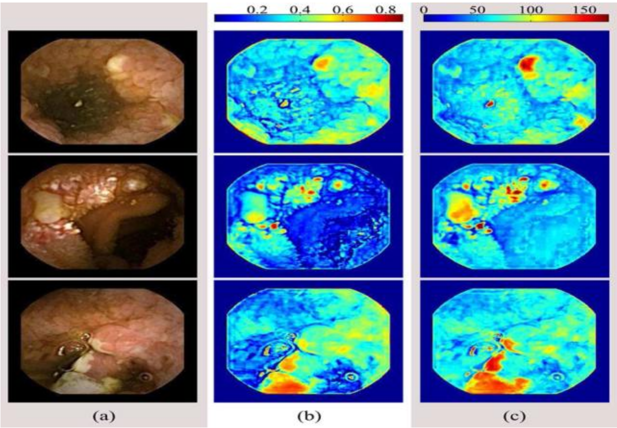

Fig. 7 WCE images with ulcer and the corresponding different color spaces images. (a) Original WCE images. (b, c) Corresponding images of the second components of the HSV and CMYK color spaces, respectively.

3.3 Saliency Region Detection Based on Color

Intuitively, the ulcer in an EBB image shows different color information compared to normal mucosa. However, it is not obvious to select a color component containing the most useful information to express the abnormality of the ulcer. We take a trial and error approach and inspect images ulcer under different color components of different color spaces such as RGB, CIELAB, CIEXYZ, YUV, YIQ, CMYK, HSV and HSI. Accordingly, as shown in Fig. 7, the second components of the WCE transformed images in color spaces HSV and CMYK highlight regions ulcer and mucosal tissues ulcer separately from uninformative parts.

Similar to the texture saliency, the color saliency at level can be obtained by the following equation:

$$ {}^{color}\hat{\mathbf{S}}_l(x,y) = \sum_{j=1, j\neq i}^{N} \frac{\mathbf{D}(i,j)}{\max_{i,j}(\mathbf{D}(i,j))}, \quad (3) $$

Where D (i, j) is the (i, j) entry of the distance matrix D that represents the Euclidean distance between the color feature vectors ${}^{color}F_l(i)$ and ${}^{color}F_l(j)$. Max $_{(i,\ j)}$ (D (i, j)) is to take the maximum within the matrix. The entry for the color saliency matrix represents a pixel within the superpixel region. The value of the prominence of color for each pixel is set to be the same within the same super pixel region. Equation (3) allows the region with a distribution of more different to get more prominent color, and promotes the values of prominence of color regions containing images WCE abnormality.

3.4 Final Saliency Region Fusion

Based on the texture and color prominence introduced into the preceding paragraphs, multilevel derives proposed superpixel method of the prominence of the EBB images in a data fusion way. Given image $I_{M \times N}$, we have computed two saliency maps ${}^{texture}S$ and ${}^{color}S$ based on the texture and color contrast information, respectively. Then the final saliency map can be defined as,

$$ {}^{final}S = {}^{color}S \circ {}^{texture}S \circ K \quad (4) $$

Where o stands for matrix Hadamard product. $K \epsilon \mathbb{R}^{MXN}$ is a Gaussian kernel which is centralized at the image center and gradually declines to the edge to mimic human attention property,

$$ K(x,y) = exp(-\frac{(x-\frac{M}{2})^2+(y-\frac{N}{2})^2}{2\sigma^2} \quad (5) $$

For the simplicity, we use equal standard deviation in both horizontal and vertical directions in this paper. By applying the matrix Hadamard product, the color and the texture saliency maps could be used in an arithmetic manner that only the regions with higher values in both texture and color features could achieve higher values in the final saliency. On the contrary, if a region has high value in only one of the saliency maps, the Hadamard product will eliminate it by simply multiplying a small saliency value to it. In this way, the final saliency map emphasizes the regions due to both color and texture contrasts.

IV. CONCLUSION

The computer-aided detection of ulcers present in the small intestine of the images obtained using capsule endoscopy will result in saving time past medical diagnosis. Gaussian kernel Investing methods such as, the mean elimination, smoothing, Grayscale along with the detection algorithm provides a robust Canny Edge solution because it identifies and locates discontinuities in the pictures. And clearer edges are visible and are easy for doctors to help diagnose bleeding, ulceration and tumor Lesions of the WCE images.

In this paper, we have proposed a two-stage fully automated computerized system for sensing ulcer in WCE images. Superpixel segmentation is performed in the first stage. In the second stage, prominence map is obtained using colour and texture features which are then for ulcer recognition task.

The experiment results promising achieve 94.72% accuracy and 94.63% sensitivity, validating the effectiveness of the proposed Method. Moreover, the experiments showed that the comparison our method outperforms the methods of prior art in the WCE classification task ulcer.

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