Unsupervised Abnormality Detection Using Saliency and Retinex based Color Enhancement

Farah Deeba, Shahed K. Mohammed, Francis M. Bui, Khan A. Wahid

Abstract—**An efficient and automated abnormality detection method can significantly reduce the burden of screening of the enormous visual information resulting from capsule endoscopic procedure. As a pre-processing stage, color enhancement could be useful to improve the image quality and the detection performance. Therefore, in this paper, we have proposed a two-stage automated abnormality detection algorithm. In the first stage, an adaptive color enhancement method based on Retinex theory is applied on the endoscopic images. In the second stage, an efficient salient region detection algorithm is applied to detect the clinically significant regions. The proposed algorithm is applied on a dataset containing images with diverse pathologies. The algorithm can successfully detect a significant percentage of the abnormal regions. From our experiment, it was evident that color enhancement method improves the performance of abnormality detection. The proposed algorithm can achieve a sensitivity of 97.33% and specificity of 79%, higher than state-of-the-art performance.**

I. Introduction

Since the inception of first commercial capsule endoscopy (CE) in 2000 [1], the non-invasive and painless technology has been the first-line diagnostic tool for examining the entire gastrointestinal tract, specifically for the screening of small bowel diseases [2]. An endoscopic capsule, which is a swallowable wireless miniaturized camera, captures and transmits 14,000-72,000 images at a frame rate of 2-6 fps while it travels through the gastrointestinal (GI) tract [3], [4]. The large amount of visual information requires 45 minutes to 4 hours of careful screening by the CE reader since abnormalities might be visible in only a few frames [5].

To make the time consuming screening procedure easier and shorter, additional reading software features have been incorporated, for example, Suspected Blood Indicator (SBI) and QuickView by Given Imaging Ltd [3]. However, the sub-optimum performance of these screening tools limits their use as rather supportive tools [3]. Implementation of color enhancement techniques at chip level or at post-processing stage is another approach to improve the image quality and diagnostic yield. Fuji Intelligent Color Enhancement (FICE, Fujinon Inc.) system, ALICE (A Large Ion Collider Experiment, Intromedic Co.) and I-scan are the examples of commercially used post-processing color enhancement algorithms which have exhibited promises to increase diagnostic yield [3], [6].

*Research supported by NSERC.

Farah Deeba, Shahed K. Mohammed, Francis M. Bui and Khan A. Wahid are with the Department of Electrical and Computer Engineering at the University of Saskatchewan, Canada (e-mail:{farah.deeba, shahed.mohammed, francis.bui, khan.wahid}@ usask.ca).

Investigation of the color enhancement techniques for improving the visualization and diagnostic yield from CE images have attained much attention of researchers in recent years. In [7], a color enhancement method based on Retinex theory has been proposed for endoscopic images. In [8], the efficacy of I-scan to detect neoplasia has been demonstrated. A color enhancement method to enhance the color tone and highlight the vascular and mucosa structure has been proposed in [9]. In [6], a comparative study among endoscopic image enhancement techniques shows that these techniques can significantly improve the stereo matching and classification performance.

Computer-aided abnormality detection from endoscopic images has remained another major focus for the researchers in past 15 years, with an emphasis to detect specific types of abnormality, e.g., bleeding, ulcer or tumor. Nevertheless, a few attempts have been made to emulate the approach of physician in practical clinical setting, i.e., differentiate between normal and abnormal frames [10], [11]. However, from the literature review, it is evident that there is a gap between these two research directions, namely color enhancement and automatic abnormality detection. An abnormality detection method incorporating color enhancement would be important in two ways: (1) it would provide a quantitative measure of the performance improvement achievable by a certain color enhancement method and (2) a better abnormality detection system can be designed with resulting enhanced CE images.

In this paper, we propose a two-stage fully automated unsupervised abnormality detection algorithm for CE images to bridge the gap between color enhancement methods and automated abnormality detection. In the first stage, the CE images are adaptively enhanced using a color enhancement method based on Retinex theory [7]. In the second stage, a saliency detector [12] detects the salient regions corresponding to clinically significant regions in the CE images. To our knowledge, it is the first attempt to combine a color enhancement technique with an unsupervised abnormality detection system for CE images. Another important contribution of our work is that the proposed saliency detection algorithm is able to localize the abnormality by detecting significant part of the region corresponding to abnormality, contrary to the previous saliency based abnormality detection methods [10], [13], where salient points from both normal and abnormal regions are selected and later classified by a classifier.

The rest of the paper is organized as follows: In section II, the proposed methodology has been described. In section III, the experiment and the results are presented. Finally, in section III, the conclusions of the study are summarized.

978-1-4577-0220-4/16/$31.00 ©2016 IEEE

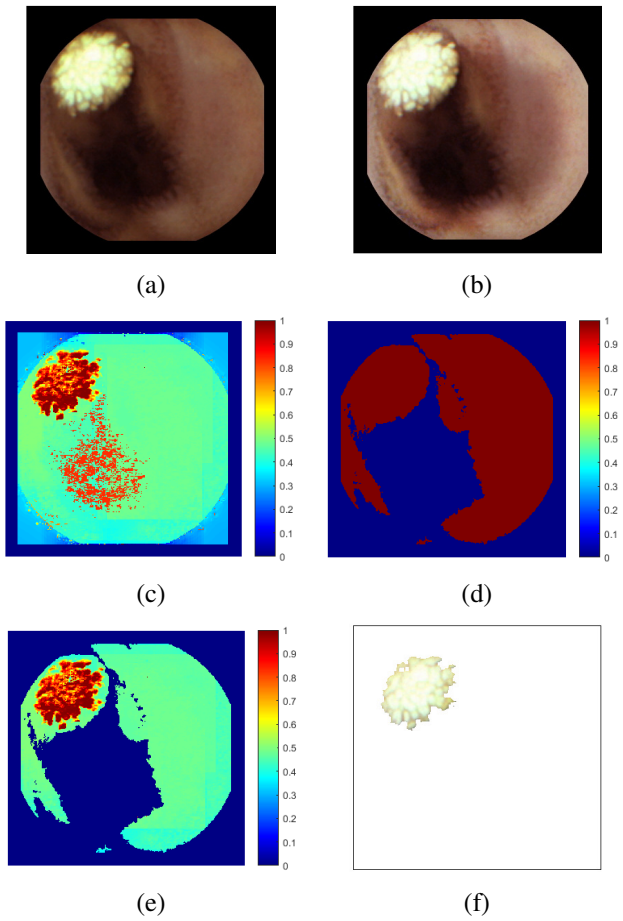


Fig. 1. Steps of the proposed algorithm: (a) Original image containing abnormality (lymphangiectasia), (b) image enhanced with Retinex, (c) saliency map S obtained from the color enhanced image, which highlights a part of lumen along with the region of clinical interest, (d) binary image $H(I_{gray} - T_{otsu})$ after applying Otsu's thresholding, (e) final saliency map, M, (f) resulting "abnormal" region after applying the binary classification, C.

II. Proposed Methodology

A. Adaptive Color Enhancement based on Retinex Theory

Capsule endoscopic images suffer from inhomogeneous brightness, poor contrast and different artifacts (specular reflection and vignetting) due to the uncontrolled motion of the capsule and dynamic illumination condition [6, 7]. Furthermore, for a saliency based abnormality detection approach, it is desirable to apply a pre-processing method to enhance the saliency of clinically significant regions. Therefore, in this paper, we perform an adaptive color enhancement step based on Retinex theory on the CE images [7]. Based on the assumption that human visual system can recognize and match colors under a wide range of different illuminations, Retinex theory decomposes a given image into reflectance image and the illumination image, and enhanced image is achieved by adaptively processing the illumination image. In this paper, the variational approach proposed in [7], [14] has been adopted to implement Retinex color enhancement.

B. Salient Region Detection

The underlying principle of saliency detection is motivated by the attention mechanism of human visual system, which enables us to focus on general salient objects without prior training. The detection of salient regions could be very significant for medical images as they are likely to correspond to the abnormalities. As color is the most important cue to discriminate between majority of pathologies from normal tissues for capsule endoscopic images [13], we adopt a modified saliency detection method based on the measurement of semi-local color contrast [12]. The method applies a sliding window approach, where the saliency of a point in the window is estimated by determining the conditional probability of the point of being represented by the intensity distribution of the window compared to the distribution of the surrounding area. Thus the resulting saliency map reflects the color contrast between the semi-local window and the surrounding area. From our experiment, we find that the choice of color plane for saliency calculation is an important factor. In the original saliency detection algorithm [12], RGB color plane was used for natural scene. However, HSV and Luv planes have been found to be more suitable to result in saliency maps close to human perception for endoscopic images.

C. Classification

From the saliency map S (Fig. 1 (c)), it can be seen that some unwanted regions (for example, lumen, turbid fluid, trash, etc.) are also detected as salient regions. To discard the uninformative regions, we apply Otsu's thresholding method to the original intensity image, I_{gray} and multiply it to the saliency map, S :

$$M = H(I_{gray} - T_{otsu}) \cdot S \tag{1}$$

where T_{otsu} is the global threshold determined using Otsu's method and H is the Heaviside step function:

$$H(x) = \begin{cases} 0, & if\ x < 0 \\ 1, & if\ x > 0 \end{cases} \tag{2}$$

The application of H and the multiplication in (1) are pixel-wise. Finally, an adaptive threshold $T_{adaptive}$ is applied on each pixel x of the resulting saliency map M to perform the binary classification, which is defined as:

$$C_{ij} = \begin{cases} "normal", & if\ M_{ij} < T_{adaptive} \\ "abnormal", & if\ M_{ij} > T_{adaptive} \end{cases}, \quad 1 \le i \le N_x, 1 \le j \le N_y \tag{3}$$

Here, N_x and N_y are respectively the width and height of the frames in pixels. The scalar threshold, $T_{adaptive}$ is defined by the following equation:

$$T_{adaptive} = \max\left(\left(\max_{i,j} M_{ij} - T_{\text{var}}\right), L\right) \tag{4}$$

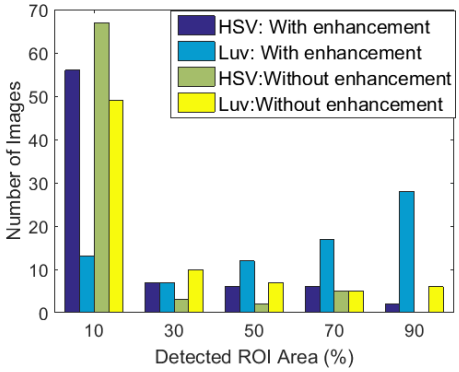


Fig. 2. ROI detection performance for four different cases.

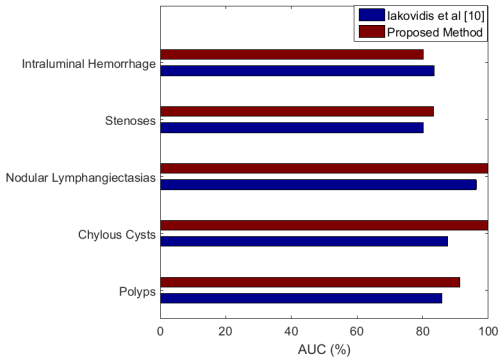


Fig. 3. Comparison of AUC per pathology obtained using the method proposed by Iakovidis [10] and our method.

Here, L is the lower limit of the threshold $T_{adaptive}$ and T_{var} is the only parameter, which will be optimized in the training stage. In Fig. 1, the result of performing each step of our proposed algorithm on a representative image containing lymphangiectasia has been demonstrated.

III. Experiments and Results

A. Dataset

For the proper validation of our experiment, we require a dataset along with the pixel level annotation performed by the clinical experts. To this end, we select a publicly available expert annotated dataset [2], [10], [13], [15]. The dataset includes 77 images with abnormal findings and 100 images without visible abnormalities, including intestinal content such as bubbles and/or luminal debris or opaque fluid, to simulate the real-world clinical scenario.

B. Experimental Results

The proposed method in this paper has two stages: (1) enhance images using adaptive color enhancement method based on Retinex theory and (2) Salient Region detection. To evaluate the effect of enhancement on the salient region detection, we performed each experiment for both cases, namely, with and without applying enhancement. Again, HSV and Luv color spaces exhibit desirable performance for salient map calculation. Therefore, we experimented with both of these color spaces to quantitatively measure their performance.

The proposed method is distinct from previous abnormality detection methods [10], [13] in the way that this method does not simply detect frame-wise abnormality on the basis of few detected abnormal pixels. Rather, our proposed method can localize the abnormality by detecting a significant portion of the region-of-interest (ROI). Additionally, where the previous methods require feature extraction and classification from the selected salient points, the proposed method can classify between normal and abnormal pixels by applying a simple thresholding on the resulting saliency map.

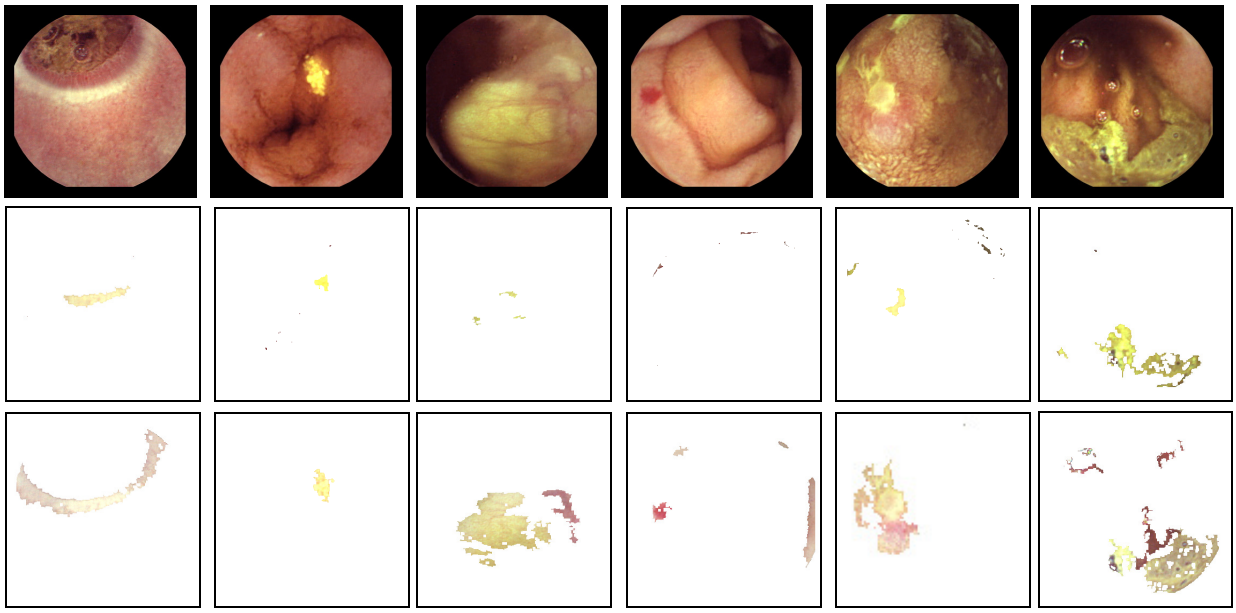
For the dataset used in this paper, the set of ground truth images annotated by experts is available. Therefore, we calculate the percentage of ROI detected by this method:

$$Detected\ ROI\ (\%) = \frac{The\ area\ of\ \ ROI\ extracted\ by\ proposed\ method}{The\ area\ of\ \ ROI\ in\ ground\ truth\ image} \times 100\%$$

The result has been shown in Fig. 2, where it can be seen that color enhancement significantly improves the detection of ROI. By applying color enhancement and selecting Luv color space, we can achieve the best ROI detection performance, with detection of 80%-100% ROI compared to ground truth for approximately 50% of the total images. In Table 1, the sensitivity and specificity obtained for different pathologies have been listed, which again shows the advantage of using enhancement and Luv color space for improved performance with a sensitivity of 97.33%. We compare our result with the one obtained from the method proposed in [10]. From Fig. 3, it can be seen that our method can achieve better result for most of the pathologies. In Fig. 4, some examples of abnormality detection with and without applying color enhancement have been showed. For all cases, color enhancement significantly improves ROI detection. Among different abnormalities, superior

TABLE I. Experimental Results Obtained for Different Pathologies

Performance Metric	Pathology	Without Enhancement		With Enhancement	
		HSV	*Luv*	*HSV*	*Luv*
Sensitivity (%)	Stenoses	33.33	60	66.67	100
	Chylous Cysts	75	100	100	100
	Lymphangietasias	88.89	100	100	100
	Polypoid	50	50	50	100
	Bleeding	60	40	40	80
	Angiectasia	37.04	33.33	44.44	85.19
	Ulcer	11.11	11.11	33.33	88.89
	Total	45.45	61.04	58.44	**97.33**
Specificity (%)	Normal	98	65.0	95	**79.0**



(a) (b) (c) (d) (e) (f)

Fig. 4. Example of abnormality detection using proposed method. Top: Original image; Middle: Detected region without enhancement (Luv); Bottom: Detected region with enhancement (Luv); (a) Stenoses; (b) Lymphangietasias; (c) Chylous Cysts; (d) Angiectasia; (e) Ulcer; (f) Normal, where the algorithm incorrectly labels a region as abnormal.

performance can be achieved for abnormality with high contrast. However, for abnormalities with low contrast, e.g., bleeding, the performance is sub-optimum. For normal images containing intestinal contents, the algorithm can incorrectly detect some visually salient region, thus degrading the specificity performance.

The two-stage algorithm takes 0.007 seconds for executing the color enhancement algorithm and 7.2 seconds for implementing the salient region detection algorithm per image. The algorithm was implemented using MATLAB 2015a in a 3.4 GHz Intel Core i7 processor.

IV. Conclusion

We presented an automated abnormality detection system, which is applicable for a wide range of pathologies and has the potential to reduce the burden of manual screening. In this paper, we explored the potential of color enhancement methods to improve the diagnostic yield of computer-aided detection systems. We have achieved significant improvement in detection performance by the use of Retinex based color enhancement method. The adoption of Luv color space along with color enhancement can achieve sensitivity of 97.33%. Though the specificity performance is not optimum due to the presence of visually salient intestinal objects in normal images, a pre-processing stage to eliminate uninformative frames can solve this problem. In future, we will investigate to incorporate uninformative frame elimination techniques and other color enhancement methods to further improve the performance.

References

[1] G. Iddan, G. Meron, A. Glukhovsky, and P. Swain, "Wireless capsule endoscopy.," *Nature*, vol. 405, no. May, p. 417, 2000.

[2] D. K. Iakovidis and A. Koulaouzidis, "Software for enhanced video capsule endoscopy: challenges for essential progress," *Nat. Rev. Gastroenterol. Hepatol.*, vol. 12, no. 3, pp. 172–186, 2015.

[3] A. Koulaouzidis, E. Rondonotti, and A. Karargyris, "Small-bowel capsule endoscopy: A ten-point contemporary review," *World J. Gastroenterol.*, vol. 19, no. 24, pp. 3726–3746, 2013.

[4] C. Van de Bruaene, D. De Looze, and P. Hindryckx, "Small bowel capsule endoscopy: Where are we after almost 15 years of use?," *World J Gastrointest Endosc*, vol. 7.1, pp. 13–36, 2015.

[5] S. K. Lo, "How Should We Do Capsule Reading?," *Tech. Gastrointest. Endosc.*, vol. 8, no. 4, pp. 146–148, 2006.

[6] M. Computing, "Comparative Study of Image Enhancement Techniques," vol. 2, no. January, pp. 11–21, 2013.

[7] H. Okuhata, et. al. "Application of the real-time Retinex image enhancement for endoscopic images," *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 2013, pp. 3407–3410, 2013.

[8] A. Hoffman, et al. "Recognition and characterization of small colonic neoplasia with high-definition colonoscopy using i-Scan is as precise as chromoendoscopy," *Dig. Liver Dis.*, vol. 42, no. 1, pp. 45–50, 2010.

[9] T. H. Khan, S. K. Mohammed, M. S. Imtiaz, and K. A. Wahid, "Color reproduction and processing algorithm based on real-time mapping for endoscopic images," *Springerplus*, vol. 5,1, p. 17, 2016.

[10] D. K. Iakovidis and A. Koulaouzidis, "Automatic lesion detection in capsule endoscopy based on color saliency: Closer to an essential adjunct for reviewing software," *Gastrointest. Endosc.*, vol. 80, no. 5, pp. 877–883, 2014.

[11] S. Hwang, "Bag-of-visual-words approach to abnormal image detection in wireless capsule endoscopy videos," *Lect. Notes Comput. Sci.*, vol. 6939, no. 2, pp. 320–327, 2011.

[12] E. Rahtu and J. Heikkila, "A simple and efficient saliency detector for background subtraction," *2009 IEEE 12th Int. Conf. Comput. Vis. Work. ICCV Work. 2009*, pp. 1137–1144, 2009.

[13] D. K. Iakovidis and A. Koulaouzidis, "Automatic lesion detection in wireless capsule endoscopy - A simple solution for a complex problem," in *Image Processing (ICIP), 2014 IEEE International Conference on. IEEE*, 2014, pp. 2236–2240.

[14] R. Kimmel, et al. "A variational framework for retinex," *Int. J. Comput. Vis.*, vol. 52, no. 1, pp. 7–23, 2003.

[15] Koulaouzidis and D. K. Iakovidis, "KID: Koulaouzidis-Iakovidis Database for Capsule Endoscopy." http://is-innovation.eu/kid.