Image Enhancement and Space-variant Color Reproduction Method for Endoscopic Images using Adaptive Sigmoid Function

Mohammad Shamim Imtiaz, *IEEE graduate student Member* and Khan A. Wahid, *IEEE Senior Member*

***Abstract*— This paper presents an image enhancement and space-variant color reproduction method based on adaptive sigmoid function for endoscopic image. At first, using YC_BC_R conversion matrix, the color image is separated into luminance and chrominance components. The adaptive sigmoid function with two controlling parameters is applied on the uniformly distributed luminance pixels. The space-variant color reproduction generates new chrominance components by transferring and modifying old chrominance based on texture information. Finally, new luminance and chrominance components are converted into RGB color image. The proposed method highlights some of the tissue and vascular characteristics as well as pit patterns in lesion and polyp. The performance of the proposed scheme is compared with other related methods in terms of image quality, focus value, efficiency of color reproduction and statistic of visual representation.**

***Keywords*— Image enhancement, Color reproduction, adaptive sigmoid function, Endoscopic image**

I. Introduction

Image enhancement and color reproduction play an important role in the improvement of visual quality for endoscopic image diagnosis. New generation endoscopes allow high definition imaging with more details [1]. Capsule endoscopy is a diagnostic tool for examining three portions of small intestine - duodenum, jejunum, and ileum. On the basis of image quality, capsule endoscopy is far behind than high-definition wired endoscopy due to its limited power consumption. Different diseases in GI tract can be prevented and cured through early detection. Improved image quality can increase early detection and reduces the miss rates of detection mucosal or vascular abnormalities. This is why new techniques are being constantly developed to enhance certain mucosal or vascular characteristics so that abnormal growths can be visualized better. Presently, there are few pre-processing and post-processing systems that can somewhat enhance certain mucosal and vascular characteristics. The NBI (Narrow-band imaging) and AFI (Auto florescence imaging) can produce intestinal images with greater details [2]. However, these techniques increase the hardware complexity and power consumption of the endoscopic system. Virtual chromoendoscopy (CE) is another post-processing scheme that decomposes an image into various wavelengths and produces the reconstructed image with enhanced mucosal surface [3]. Several researches have concluded that NBI appears to be a less time-consuming and an equally effective alternative to CE for the detection of neoplasia, but with a higher miss rate [4]. Additionally, neither NBI nor CE improve the adenoma detection or miss rates during screening colonoscopy and no difference is seen in diagnostic efficacy between these two systems.

In this paper, an adaptive sigmoid function based image enhancement and space-variant color reproduction method is proposed which can improve the detection rate of anomalies present in GI images. It is a post-processing scheme and requires no extra hardware in the image acquisition part. It can be applied on any RGB endoscopic images.

II. Proposed Method

The proposed method consists of two stages: adaptive sigmoid function based image enhancement and space-variant color reproduction. Fig. 1 presents the overall diagram of the proposed method. Instead of manipulating R, G and B components, the proposed system first convert the color endoscopic image into $YCbCr$ color space using (1). Later on, Y is used for image enhancement, C_B and C_R for generating new chrominance map.

$$\begin{bmatrix} Y \\ C_B \\ C_R \end{bmatrix} = \begin{bmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \qquad (1)$$

A. Image Enhancement

Sigmoid function is a continuous nonlinear function and often used in neural network when a detail description is lacking. Using $f(x)$ for the input, the sigmoid function is

$$f(x) = \frac{1}{(1+e^{x})} \qquad (2)$$

In the training mode, we have observed that in a certain exponent the image highlights some of the vascular characteristics and mucosa structure but it varies depending on images.

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The authors are with the Department of Electrical and Computer Engineering, University of Saskatchewan, Saskatoon, Saskatchewan, S7N5A9, Canada. (e-mail: khan.wahid@usask.ca).

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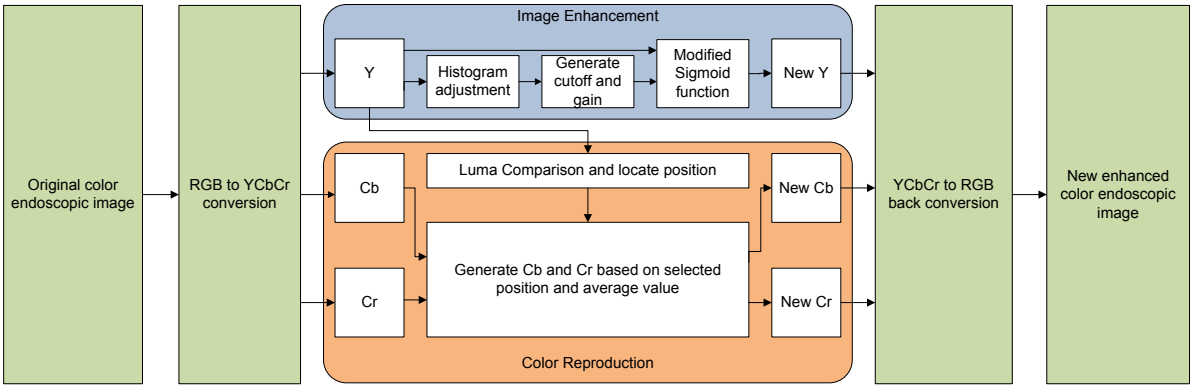


Fig. 1. Block diagram of the proposed method

To control the exponent and limit it to a certain point, we introduced two coefficients in the sigmoid function. Using x for the input, g for gain and k for cutoff, the sigmoid function is given below:

$$f(x) = \frac{1}{\left(1+e^{-g(k-x)}\right)} \qquad (3)$$

By controlling these two parameters, different features of the image can be highlighted. As the proposed function transforms the pixel values adaptively, we named it adaptive sigmoid function. These two parameters are controlled by two different equations which we will discuss later.

Before applying proposed adaptive sigmoid function, the pixels of the image are uniformly distributed using histogram equalization. Let, Y is a given image represented as m by n matrix of integer pixels intensities ranging from 0 to $L-1$. Let, p denotes the normalized histogram of Y with bin for possible intensities.

$$P_z = \frac{Number\ of\ pixels\ with\ intensity\ z}{total\ number\ of\ pixels} \qquad (4)$$

Where, $z = 0,1,2,...,L-1$ gray scale values of image. The uniformly distributed image g is defined as,

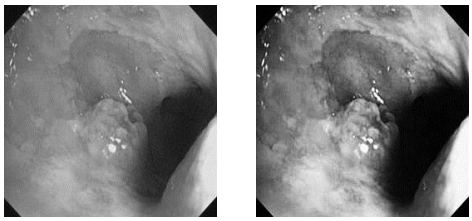
$$g_{i,j} = floor\left((L-1)\sum_{z=0}^{Y_{i,j}} p_z\right) \qquad (5)$$

Where, $floor()$ rounds up the pixel value to the nearest integer. After that, the uniformly distributed pixel values are used to generate the cutoff value k using (6) and gain g using (7). Here, the input x is uniformly distributed pixel.

$$k = \frac{\sum_{i=1,j=1}^{m,n} g_{i,j}(x)}{m \times n} \qquad (6)$$

$$g = A \times \log\left(\frac{S_m}{S_n}\right) \times \frac{\sum_{i=1,j=1}^{m,n} g_{i,j}(x)}{m \times n} \qquad (7)$$

Where, $A = 100$, $S_m = 6$ and $S_n = 5$. These values are heuristically collected from training mode. These values produce the desired exponent which highlights those subtle vascular and mucosa structure in the endoscopic images. From Fig. 2, we can see the mucosa and vascular characterization as well as some pit patterns.



(a) (b)

Fig. 2. (a) Original grey scale image (b) adaptive sigmoid image

B. Color reproduction

In the proposed method, by matching luminance and texture information between pixels of original gray scale images, the chromaticity information has been generated. At the beginning, the luminance and two chrominance have been normalized between 0 – 1 value using (8).

$$f_{norm}(x) = \frac{x - x_{\min}}{x_{\max}} \qquad (8)$$

In the matching process, each pixel of original grey image is subtracted from all the pixels and locates the positions using (9).

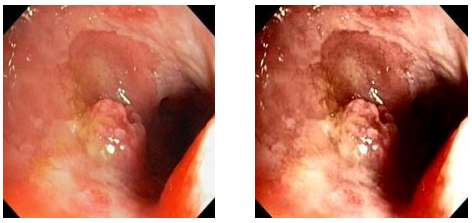
$$[m,n] = locate(f_{i,j}^{or}(x) - f^{or}(x)) \qquad (9)$$

Here, $locate()$ holds the position that is zero, $f_{i,j}^{or}(x)$ is a single pixel of original image and $f^{or}(x)$ are all the pixels. Now based on (9), three scenarios can be occurred. First, it may locate several positions of a single luma. In that case, single Cb has been generated from multiple Cb and a single Cr for multiple Cr using (10).

$$k = \frac{\sum_{i=1}^{n} f(x_i)}{n} \qquad (10)$$

Second, it may locate only one position for a single luma. Then it will generate a single Cb and Cr based on single position. Third, it may not locate any position at all. In that case, it will generate default value 0.5 as Cb and Cr for the corresponding positions. Finally, the new generated Cb, Cr and enhanced luma Y are converted into RGB image using (11). Fig. 3 shows the original image and their corresponding enhanced color image using the proposed method.

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.164 & 0.000 & 1.596 \\ 1.164 & -0.392 & -0.813 \\ 1.164 & 2.017 & 0.000 \end{bmatrix} \begin{bmatrix} Y-16 \\ C_B-128 \\ C_R-128 \end{bmatrix} \quad (11)$$



(a) (b)

Fig. 3. (a) Original color image (b) color reproduced enhanced image

III. Result and Discussion

In order to make a comparative quality assessment study, the proposed scheme is applied on several endoscopic images, collected from Gastrolab [5] and Altas [6]. Later, the performance was evaluated based on Image quality, focus value, efficiency of color reproduction and distortion based on CIE94 and statistic of visual representation.

A. Image quality

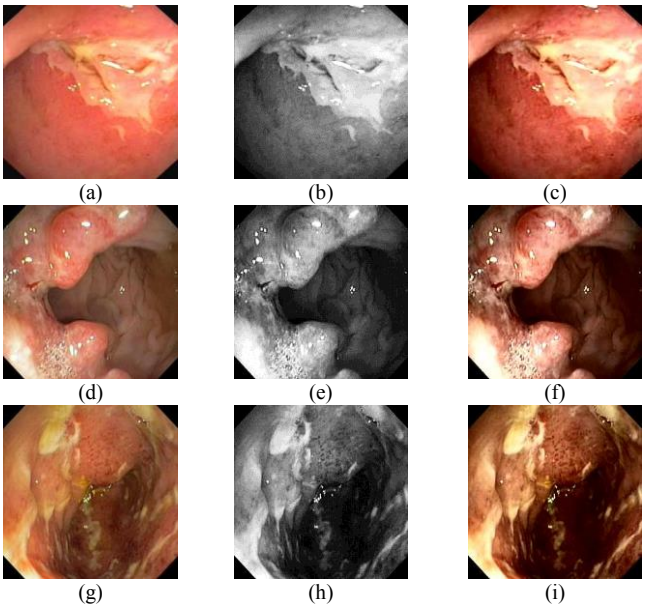
The main focus of this work is to enhance certain vascular and mucosa characterization in endoscopic images. From Fig. 4 shows the original, enhanced and color reproduced images. Here, the images are represented different diseases, such as, (a) defected polyp image, (d) cancer image and (g) crohn disease image. It can be seen that the proposed method highlights some mucosa and vascular characteristics which are not visible in the original images. It has highlighted some pit patterns in lesion and polyp as well. Additionally, the overall contrast and color saturation levels are also improved compare to original images.

B. Focus value

The amount of enhancement and the overall contrast level of the proposed method is evaluated using focus value [7]. It is a mathematical representation of the ratio of AC and DC energy of a DCT image (12).

$$Focus_{value} = \frac{E_{AC}}{E_{DC}} \quad (12)$$

Here, E_{AC} is the energy of AC part and E_{DC} is the energy of DC part of the DCT image. The energy of AC and DC part always carry the information of sharp contours with crisp edges and brightness, respectively. If the overall contrast level is increased, it leads toward a higher focus value and vice versa. This scheme has been applied to two sets of images: original and corresponding reconstructed images. The results are shown in Fig. 5. From the figure, it is clear that the focus value of proposed images is almost three times higher than original images. The average focus value of proposed scheme is 52.17.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 4. (a), (d) and (g) original color image; (b), (e) and (h) proposed enhanced image; (c), (f) and (i) proposed color reproduced image

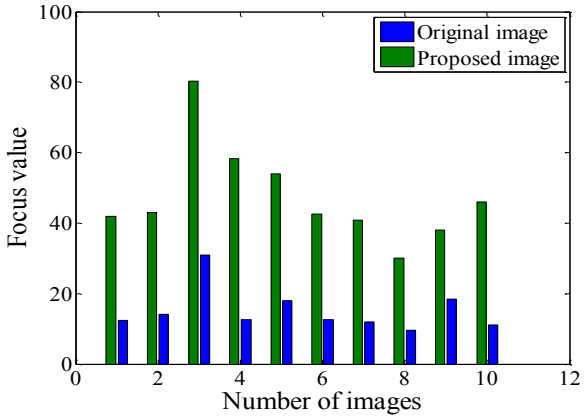


Fig. 5. Focus value of proposed and original images

C. Efficiency of color reproduction and distortion

The efficiency of color reproduction and distortion of proposed scheme is evaluated using delta-E CIE94 (13) [8].

$$\Delta E_{94} = \sqrt{\left(\frac{\Delta L^*}{k_L s_L}\right)^2 + \left(\frac{\Delta C^*_{94}}{k_C s_C}\right)^2 + \left(\frac{\Delta H^*_{94}}{k_H s_H}\right)^2} \quad (13)$$

It is computed between two color images (standard and trial) to define the efficiency of color reproduction and distortion. Therefore, the components of the color difference have positive or negative sign. If $\Delta C^*_{ab} > 0$ then the trial is stronger compare to the standard, whereas if $\Delta C^*_{ab} < 0$ then

the trial is weaker. In our experiment, we have used original image as well as images from other methods [9]-[11]. The results are shown in Table-I.

TABLE I. DELTA-E COLOR DIFFERENCE

Methodology	Image no	Delta-E Color Difference CIE94	
		ΔE^*_{94}	ΔC^*_{ab}
Original and proposed	1	2.14	2.19
	2	2.09	3.99
	3	2.19	4.11
[9] [10] and proposed	1	3.78	3.51
	2	3.49	17.84
	3	3.12	13.87
[11] and proposed	1	4.98	3.11
	2	4.77	14.66
	3	3.91	17.94

From Table-I, it can be noticed that the ΔC^*_{ab} values are positive, that means the proposed images are better. Only the values of ΔE^*_{94} between original and proposed image are approximately 2.3 - which means both of the color reproduction are close to human visual perception. In another word, there is no color distortion between these two images. The ΔE^*_{94} between the other method's images and proposed images are higher which means there is color distortion in either of these images. As the ΔC^*_{ab} values are positive, the color distortion exists in the standard image. Fig. 6 shows the reconstructed images using the proposed and other color reproduction methods.

Proposed [9][10] [11]

Fig. 6. Visual representation of reconstructed images

D. Statistic of visual representation

Finally, we evaluate the performance using statistic of visual representation (SVR) [12]. Usng SVR, the increment or decrement of contrast and luminance level can be mathematically represented. Equations (14) and (15) are used to calculate SVR:

$$C = \frac{\sigma_{out} - \sigma_{in}}{\sigma_{in}} \times 100 \qquad (14)$$

$$L = \frac{L_{out} - L_{in}}{L_{in}} \times 100 \qquad (15)$$

Where, σ_{out} and L_{out} are the variance and average of enhanced image; σ_{in} and L_{in} are the variance and average of original image, respectively. C defines the percentage of increment or decrement of contrast level and L defines the intensity level. All the evaluated results and comparisons are showed in Table-II. From the table, it is noticeable that the proposed scheme can increase the contrast level 143 times higher than the original image, which is higher than other traditional methods. The average intensity level is -8.661 which indicates that the proposed scheme reduces the intensity level. It provides better visualization of the high contrast edges.

TABLE II. STATICTIC OF VISULA REPRESENTATION

Enhancement methods	Contrast measurement	Intensity measurement
Contrast stretching	46.01	45.3
High Boost Filtering	69.54	57.21
Gamma Correction	41.44	45.01
Sigmoid Function	33.5	41.62
Sigmoid Function (gain = 5)	104.81	63.77
Sigmoid Function (gain = 8)	117.01	67.56
Proposed method	143.01	-8.661

IV. CONCLUSION

In this paper, we have proposed an image enhancement and color reproduction method for endoscopic images. Image enhancement is achieved using adaptive sigmoid function on the uniformly distributed gray pixels. The work focuses on highlighting the mucosal and vascular characteristics. The quality of the generated enhanced colored images is evaluated using several standard performance metrics. The results show much higher image quality compared with many existing methods.

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