An Automatic Bleeding Detection Scheme in Wireless Capsule Endoscopy Based on Histogram of an RGB-Indexed Image

T. Ghosh[1], S. A. Fattah[1*], C. Shahnaz[1], and K. A. Wahid[2]
[1]Bangladesh University of Engineering and Technology, Bangladesh
[2] University of Saskatchewan, Saskatchewan, Canada
[*]E-mail: fattah@eee.buet.ac.bd

Abstract—**Wireless capsule endoscopy (WCE) is one of the most effective technologies to diagnose gastrointestinal (GI) diseases, such as bleeding in GI tract. Because of long duration of WCE video containing large number images, it is a burden for clinician to detect diseases in real time. In this paper, an automatic bleeding image detection method is proposed utilizing construction of an index image incorporating certain level of information from each plane of RGB color space. Distinguishable color texture feature is developed from index image by histogram. Support vector machine (SVM) classifier is employed to detect bleeding and non-bleeding images from WCE videos. From extensive experimentation on real time WCE video recordings, it is found that the proposed method can accurately detect bleeding images with high sensitivity and specificity.**

Keywords— Wireless capsule endoscopy, bleeding detection, color histogram, indexed image, supported vector machine (SVM).

I. INTRODUCTION

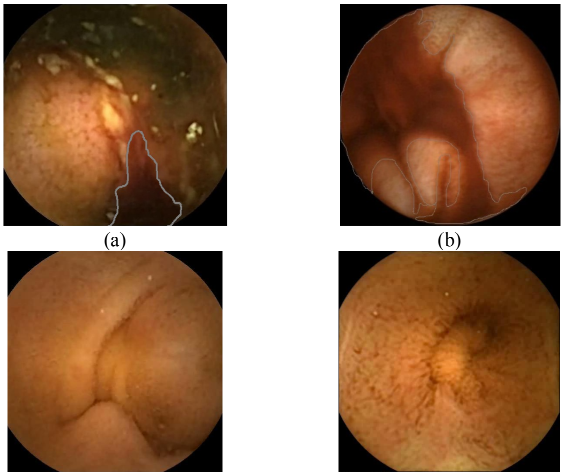
Automatic bleeding detection plays an important role in identifying candidate video frames in wireless capsule endoscopy and thereby helps physicians in diagnosing gastrointestinal (GI) diseases [1]. The WCE is getting immense popularity as it has been proved to be the best choice of investigation for visualizing the entire small gut [2], [3]. It can directly show the entire small intestine without any pain, sedation, or air insufflations. That is why it is widely used in many hospitals to detect status of stomach and whole intestine.

Capsule Endoscopy was invented by Given Imaging Company in 2000 [4]. Patients can swallow the capsule easily due to its small size as 11 mm in diameter and 26 mm in length. The capsule contains an embedded color camera, image sensor, a wireless transmitter, battery and lights. When a subject swallows this capsule its camera takes around 57,000 color images with 2 frames per second during its 8 hours of journey in the GI tract. The images are transmitted to the base receiver and restored in a computer. After collecting all images, physician diagnoses the images to see if any of them has the symptoms of diseases like bleeding and determines its location in that particular WCE image. This reviewing process usually takes two hours to complete [5]. Sometimes symptom of diseases may be present in only 2 frames or images of the video and it may be missed by the physicians because of oversight. Furthermore, there may be some bleeding regions and abnormal characters that cannot be recognized by naked eyes due to their size or distribution. All these problems motivate researchers to develop the computer aided intelligent bleeding detection technology to reduce the burden of physicians [6]. With its gradually wide applications, some efforts have been made to detect bleeding images form the WCE videos so as to decrease the burden of doctors. Suspected blood indicator (SBI) is a technique to detect bleeding from WCE images but its sensitivity and specificity are found not very satisfactory [7], [8]. In [9], color histogram based bleeding detection scheme is introduced where support vector classification is used. Because of its algorithmic complexity, it is too intricate to be practical in clinical use. In [5], a three layer multilayer perceptron (MLP) neural network is used to detect bleeding regions in WCE images and a satisfactory overall performance is achieved. However, it is to be mentioned that the MLP is evolved from linear perceptron which has poor robustness and anti-interference ability. Back propagation (BP) neural network is used to detect bleeding in [10]. Nevertheless BP neural network is slow to process images, and is not feasible to process large amount of WCE images. The method reported in [6] employs probabilistic neural network (PNN) to detect bleeding images. This method utilizes color texture feature of bleeding regions which is extracted in RGB and HSI color spaces. As per the reported results, the sensitivity is good at image level but specificity is not up to the mark. Recently in [11], an automatic bleeding detection method is proposed based on color statistical features extracted from histogram probability, which offers satisfactory overall accuracy, but sensitivity and specificity are not reported.

The objective of this paper is to develop an efficient algorithm to detect bleeding in the WCE video recordings. First construct a representative image plane containing intensity information from all three planes, instead of using information from a single plane which is called index image. Then certain level of bit value information of different RGB planes alone with grayscale and index image histogram are investigated for bleeding and non-bleeding video frames. Apart from index images histogram values are taken as proposed features. For the purpose of classification, support vector machine (SVM) classifier is employed. The proposed bleeding detection algorithm is tested on several images extracted from WCE videos of various subjects.

II. PROPOSED METHOD

Color is a perceptual property that human visual system utilizes to measure the electromagnetic spectrum. There are different color scheme for representing color images and depending on the nature of images, a particular color scheme with a set of color spaces are generally chosen. A common



(a) (b)

(c) (d)

Figure 1. Bleeding and non-bleeding WCE images. (a),(b) Bleeding images (the region in the grey boundary denotes bleeding region); (c),(d) non-bleeding image.

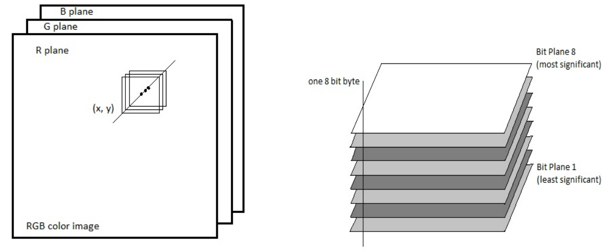
Problem of WCE image is illumination changes due to the battery weakening of the capsule over time. The RGB is the most common device based color space and WCE devices use RGB color space. The typical bleeding and non-bleeding WCE images are shown in Fig. 1. For a better understanding in the bleeding images (Fig. 1(a) and (b)), border line surrounding the red bleeding zone is drawn. The difference between bleeding and non-bleeding zones is quite visible in the figure simply based on color. Hence, color features play an important role in bleeding detection. In what follows, the proposed feature extraction scheme consisting of the bit-plane slicing and color histogram technique is presented. SVM classifier is implemented to detect bleeding and non-bleeding images.

A. Feature Extraction from Color Histogram of Index Image

In RGB color system, each pixel $c(x, y)$ of a color WCE image consists of three primary color components. Considering that the color components are function of coordinates (x, y), one may express $c(x, y)$ as

$$c(x,y)=\begin{bmatrix} c_R(x,y) \\ c_G(x,y) \\ c_B(x,y) \end{bmatrix}=\begin{bmatrix} R(x,y) \\ G(x,y) \\ B(x,y) \end{bmatrix}. \tag{1}$$

For an image of size $M \times N$, there are MN such vectors, $c(x,y)$, for $x = 0, 1, 2, \ldots., M-1$; $y = 0, 1, 2, \ldots., N-1$. The value of each color component, say $R(x,y)$, varies from 0 to 255, which is composed of 8 bits (one byte). In Fig. 2(a), three different planes are shown. Considering 8 bits separately, each one of the RGB plane can be considered as being composed of eight 1-bit planes, which is demonstrated in Fig. 2(b). Here the eighth plane indicates the most significant bit (MSB) and the first plane indicates the least significant bit (LSB). Instead of considering all eight planes, one may consider only the MSB or two planes, MSB and the next one. For the purpuse of classifying a pixel into one of the



(a) (b)

Figure 2. Indexed image construction from RGB planes: (a) Spatial marks for RGB color image; (b) Bit-plane representation of an 8-bit R color plane

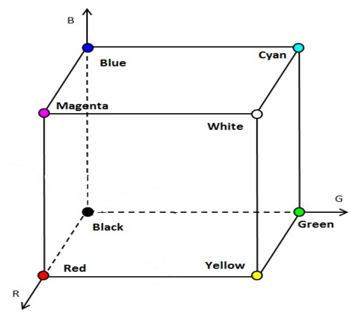


Figure 3. Cartesian coordinate system of RGB color space

two classes, bleeding and non-bleeding, it is observed that use of eight planes (considering 256 different values for a pixel) may not be necessary and even makes the task difficult. If only one bit (MSB) plane is considered from each color space, there could be only two possibilities (0 and 1) of each bit resulting in $2^3 = 8$ different choices. As each pixel is now represented by three MSBs from three color spaces, using Cartesian coordinate system, the color subspace of interest can be represented by a cube as shown in Fig. 3. As per standard color scheme, eight colors obtained in this system are indicated in the figure. Use of the MSB of a color plane is, in fact, equivalent to considering normalized values 0 and 1 for each color space, where 0 represent the intensity range 0 to 127 and 1 represent the intensity range 128 to 255. For each pixel, MSB information from all three planes is taken into consideration and the corresponding pixel is now assigned a new three bit value. The given WCE image is now transformed into a different plane where the pixels are indexed with $3L$ bits where L indicates the number of bits (starting from MSB) to be considered from each color plane resulting in 2^{3L} combination for each pixel. The WCE image in the transformed plane is termed as index image.

In order to capture spatial distribution of different colors, in the proposed scheme combined color plane histogram approach is employed. Instead of considering the color distribution in one plane, information for constructing histogram is extracted from the index image plane described above. A color histogram represents the number of occurrence of each color in the whole plane. It is expected that the pattern of histogram for bleeding images remains consistently similar and that of non-bleeding images differs significantly. For better understanding, considering the bleeding and non-bleeding images considered Fig. 1, eight bin histograms

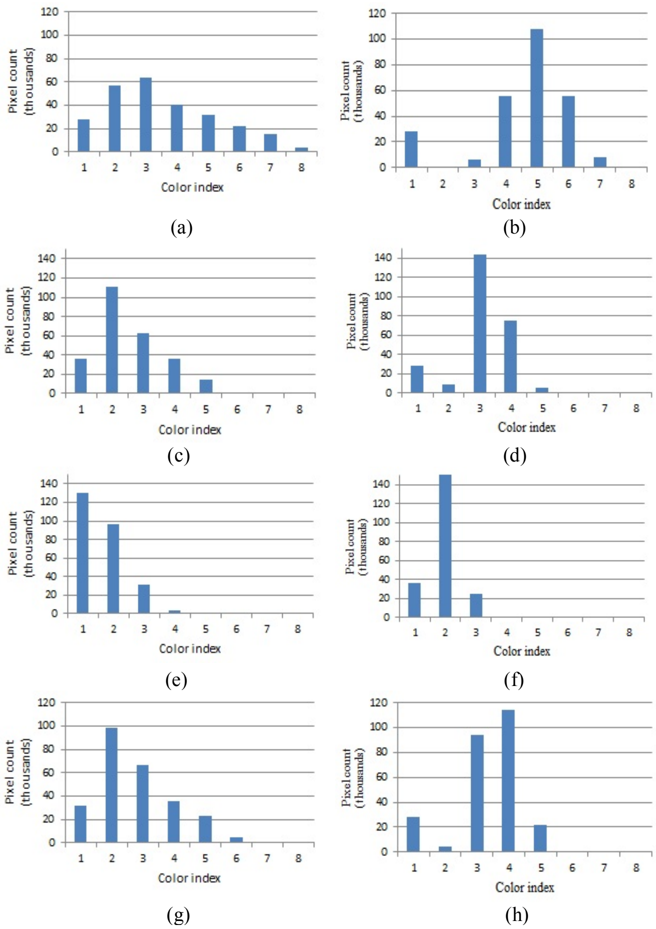


Fig. 4. Color histogram. (a) R-plane (bleeding); (b) R-plane (non-bleeding); (c) G-plane (bleeding); (d) G-plane (non-bleeding); (e) B-plane (bleeding); (f) B-plane (non-bleeding); (g) grayscale (bleeding); (h) grayscale (non-bleeding).

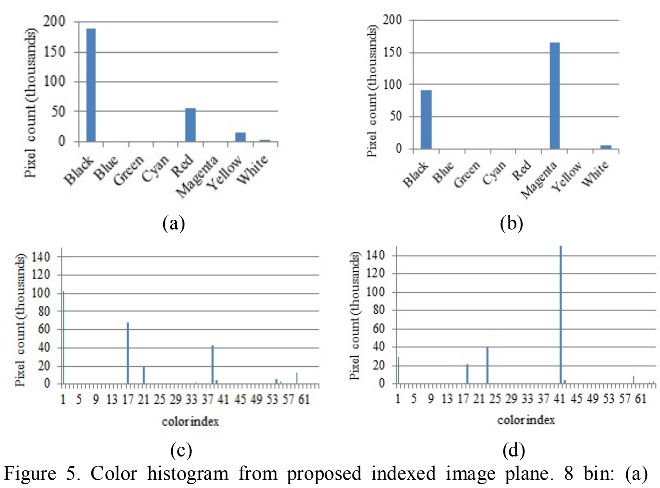


Figure 5. Color histogram from proposed indexed image plane. 8 bin: (a) bleeding and (b) non-bleeding. 64 bin: (c) bleeding and (d) non-bleeding.

Constructed from different individual color planes are first shown in Fig. 4. In this figure R, G, B three planes and the gray scale plane are shown separately. Next in Fig. 5, for the same WCE images, histograms constructed from index image plane are shown considering 8 bins and 64 bins. For 64-bin color histogram, pixel value in each plane is divided as 0 to 63, 64 to 127, 128 to 191 and 192 to 255 and represented by two bits ($L = 2$). It can be observed that the classification task is more difficult if histogram of an individual plane (R, G, B, grayscale) is used. However, the histogram obtained by using index image offers better between class separation. Hence, a set of occurrence values of each color in the index image histogram is proposed to be used as potential feature for classifying bleeding and non-bleeding images. In order to construct the feature vector, L bits (starting from MSB) of a pixel from each plane are taken and placed in sequential manner to construct the transformed pixel value of the index image plane.

B. *SVM Based Classification*

Bleeding detection is a two class problem. In the proposed method, the support vector machine (SVM) is used to classify the test WCE image. Accuracy, sensitivity, and specificity for different kernel function, as linear, polynomial, and Gaussian Radial Basis function are calculated. Extensive experimentation is carried out using leave one out cross validation technique to classify a given WCE image into one of the two classes, namely bleeding or non-bleeding.

The key component in support vector machine (SVM) learning is to identify a set of representative training vectors deemed to be the most useful for shaping the (linear or nonlinear) decision boundary. These training vectors are called support vectors. Considering a training dataset which consists of color texture features of N images $\boldsymbol{x}_i$, where each M dimensional feature vector $\boldsymbol{x}_i = x_i(n)$, $n = 1, \ldots, M$ is associated with a teacher value or class label. Given a discriminant function $f(\boldsymbol{x}) = f(\boldsymbol{w}, \boldsymbol{x})$, the objective is to find an M dimensional decision vector $\boldsymbol{w} = [w_1 \;\; w_2 \; \ldots \; w_{\mathrm{M}}]^{\mathrm{T}}$ so that $f(\boldsymbol{x}_i)$ can best match with teacher value y_i, with all the training dataset taken into consideration. Considering 2 class problem, all the training vectors $\boldsymbol{x}_i$ satisfy the following inequalities:

$$\begin{aligned} \boldsymbol{w}^T \boldsymbol{x}_i + b &\geq +1, \text{ for all positive } \boldsymbol{x}_i \\ \boldsymbol{w}^T \boldsymbol{x}_i + b &\leq -1, \text{ for all negative } \boldsymbol{x}_i \end{aligned} \tag{2}$$

An error term is defined as $\varepsilon_i \equiv \boldsymbol{w}^T \boldsymbol{x}_i + b - y_i$. The main objective here is to create a maximum margin to separate the two opposite classes. Considering the kernel function $K(\boldsymbol{x}, \boldsymbol{y})$ and empirical vector $\boldsymbol{a}$, the discriminant function is defined as

$$f(\boldsymbol{x}) = \sum_{i=1}^{N} a_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b. \tag{3}$$

Here a nonlinear kernel function can also be adopted.

III. SIMULATION RESULT AND DISCUSSION

Dataset contains 2250 color images from 30 WCE videos, which are publicly available in [12]. 450 of them show a sign of bleeding and other 1800 detected as non-bleeding. 50 bleeding images along with 200 non-bleeding images are used for training, and remaining 400 bleeding and 1600 non-bleeding images are used for test purpose. These images have 576×576 pixels. After removing dark zones outside the circular desired zone, it becomes 512×512 pixels. These

TABLE I. PERFORMANCE VARIATION AT DIFFERENT HISTOGRAM BINS

Proposed method Histogram bins	Accuracy (%)	Sensitivity (%)	Specificity (%)
8 bins	68.20	66.75	68.56
16 bins	85.55	85.25	85.63
32 bins	86.20	89.25	85.44
64 bins	85.75	87.75	85.25
128 bins	94.50	93.00	94.88
256 bins	90.20	85.50	91.38
512 bins	91.35	86.50	92.56

images are used to find the features of training dataset, which are used in SVM trainer. For the purpose of testing, remaining 2000 images are used. By investigating several bleeding and non-bleeding WCE images available in [12], color histogram values of different bins are used.

There are four cases about the detection result of bleeding and non-bleeding images. The bleeding image will be possibly detected as non-bleeding image, which is called false non-bleeding recognition (Fnb). In a similar way, when the non-bleeding images are detected as bleeding images, it is called false bleeding recognition (Fb). The other two cases are the true bleeding recognition (Tb) and the true non-bleeding recognition (Tnb). In order to assess the capability of the bleeding detection method, sensitivity, specificity, and overall accuracy are calculated as follows [6]

$$\text{Sensitivity} = \frac{\sum Tb}{\sum Tb + \sum Fnb} \tag{4}$$

$$\text{Specificity} = \frac{\sum Tnb}{\sum Tnb + \sum Fb} \tag{5}$$

$$\text{Accuracy} = \frac{\sum Tb + \sum Tnb}{\sum Tb + \sum Fnb + \sum Tnb + \sum Fb} \tag{6}$$

Table I. illustrates proposed method accuracy, sensitivity, and specificity. 8 bin color histogram shows poor accuracy and sensitivity. But higher order histogram shows better accuracy, sensitivity, and specificity. Performance is investigated for different bin values of color histogram. Among of them 128 bin color histogram features shows best result, with an accuracy 94.50%, sensitivity 93.00% and specificity 94.88%. For fair comparison, in all three methods, experiments are carried on using the same classifier, i.e., SVM. The comparison results are demonstrated in Table II. It is clearly observed that the proposed method exhibits the best performance in terms of all performance indices. Sensitivity is the most important performance index in bleeding detection, which represents the true bleeding image detection accuracy. It can easily be observed that the sensitivity obtained by the proposed method is extremely satisfactory.

IV. CONCLUSION

Considering the implementation aspect in real-life scenario, the computational burden involved in the proposed feature extraction scheme is kept very low, without sacrificing the overall accuracy as well as sensitivity. Moreover, for the purpose of supervised classification, most widely used SVM classifier is employed which is simple and easy to implement for clinical use. It is found that the proposed scheme can automatically detect the bleeding images of a WCE video, which will definitely assist physicians to reduce the labor involved in reviewing large amount of WCE images for a long duration. In view of reducing computations, there are methods that deal with only on a single color plane or on grayscale images, which definitely causes loss of necessary information. However, in the proposed method, all three color planes are utilized but for reducing the computational burden, efficient features are introduced. More significant bits form all three RGB color space form index image. Index image histogram values are found sufficient to construct a robust color texture feature vector. From detailed analysis on a large number of WCE images, it is observed that the proposed method offers high level of accurately, sensitivity, and specificity in classifying bleeding and non-bleeding images.

TABLE II. PERFORMANCE COMPARISON AMONG DIFFERENT METHODS

Method	Uniform LBP [4]	method in [11]	proposed method
Accuracy	91.50	77.15	94.5
Sensitivity	79.25	83.00	93.00
Specificity	94.56	75.69	94.88

REFERENCES

[1] National digestive diseases information clearing house. Bleeding in the digestive tract. Bethesda: National Institutes of Health, 7:1–6, 2004.

[2] D.G. Adler and C.J. Gostout, "Wireless Capsule Endoscopy," *Hospital Physician*, pp. 14-22, 2003.

[3] J. Liu and X. Yuan, "Obscure bleeding detection in endoscopy images using support vector machines," Optimization and Engineering, vol. 10, no. 2, pp. 289–299, 2008.

[4] G. Iddan, G. Meron, and A. Glukhovsky, "Wireless capsule endoscopy,"Nature, vol. 405, pp. 417–417, May 2000.

[5] L. Baopu and M. Q. H. Meng, "Computer-Aided Detection of Bleeding Regions for Capsule Endoscopy Images" IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 56, NO. 4, APRIL 2009.

[6] P. Guobing, Y. Guozheng, Q. Xiangling and C. Jiehao, "Bleeding Detection in Wireless Capsule Endoscopy Based on Probabilistic Neural Network" Springer Science Business Media, LLC 2010, DOI 10.1007/s10916-009-9424-0

[7] J. M. Buscaglia, S. A. Giday, S. V. Kantsevoy, J.O. Clarke, P. Magno, E. Yong, and G. E. Mullin, Performance characteristics of the suspected blood indicator feature in capsule endoscopy according to indication for study. Clin. Gastroenterol. Hepatol. 6(3):298–301, 2008.

[8] S. Liangpunsakul, L. Mays, and D. Rex, D. K., Performance of given suspected blood indicator. Am.J.Gastroenterol. 98 (12):2676–2678, 2003.

[9] M. Mackiewicz, M. Fisher, and C. Jamieson, "Bleeding detection in Wireless Capsule Endoscopy using adaptive colour histogram model and Support Vector Classification". Medical Imaging 2008 Conference, San Diego, CA, SPIE, 6914: R1–R12, 2008.

[10] G. Pan, G. Yan, X. Song, and X. Qiu, "BP neural network classification for bleeding detection in wireless capsule endoscopy". J. Med. Eng. Technol. 33(7):575–581, 2009.

[11] S. Sainju, F. M. Bui, K. Wahid, "Bleeding Detection in Wireless Capsule Endoscopy based on color features from histogram probability", 26th IEEE Canadian Conference Of Electrical And Computer Engineering (CCECE), 2013

[12] http://www.capsuleendoscopy.org

[13] R. C. Gonzalez, R. E. Woods, "Digital image processing", third edition, Prentice Hall, 2008