Automatic Bleeding Detection in Wireless Capsule Endoscopy Based on RGB Pixel Intensity Ratio

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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 the variation of pixel intensities in RGB color planes. Based on statistical behavior of bleeding and non-bleeding pixel intensities in terms of pixel intensity ratio in different planes, distinguishing color texture feature of an image is developed. Support vector machine (SVM) classifier is employed to detect bleeding and non-bleeding images from WCE videos. From extensive experiment-tation 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, pixel intensity ratio, RGB color space, 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 proven to be the best choice of investigation for visualizing the entire small bowel [2], [3]. It can directly view 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 invented by Given Imaging Company in 2000 and first clinical experiment was implemented in 2001 [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 symptom 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 clinic. 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 the pixel intensity ratio in different RGB planes is investigated for bleeding and non-bleeding video frames. Apart from average intensities in different RGB planes, particular ratio 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 uses to measure the electromagnetic spectrum. There are a lot of

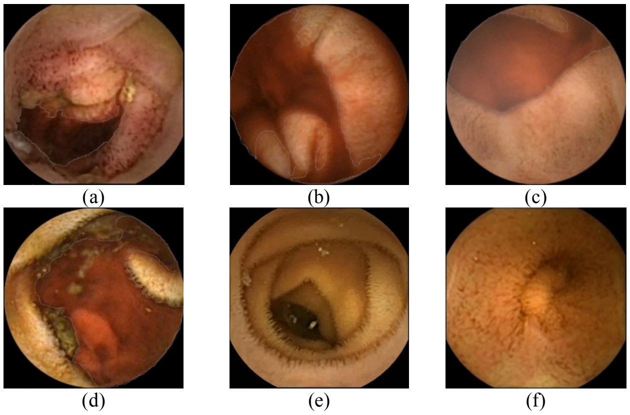


Fig. 1. Bleeding and non-bleeding WCE images. (a),(b),(c),(d) Bleeding images (the region in the grey boundary denotes bleeding region); (e),(f) non-bleeding image.

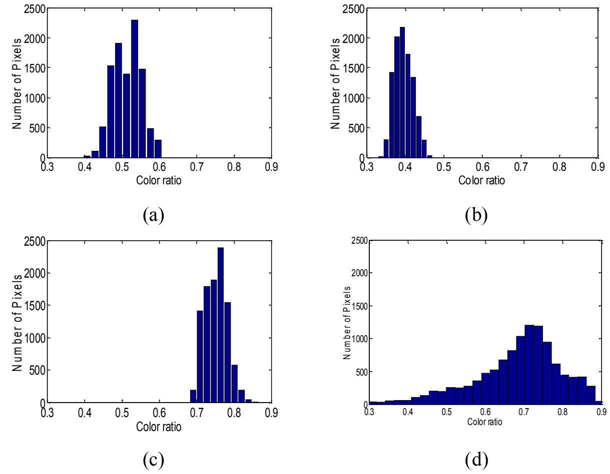


Fig. 2. Statistical characteristics of pixel intensity ratio between different color planes (R, G, and B) shown with the help of histograms for bleeding and non-bleeding WCE images. (a) G/R pixel intensity ratio in WCE bleeding image, (b) B/R pixel intensity ratio in WCE bleeding image, (c) G/R pixel intensity ratio in WCE non-bleeding image, and (d) B/R pixel intensity ratio in WCE non-bleeding image.

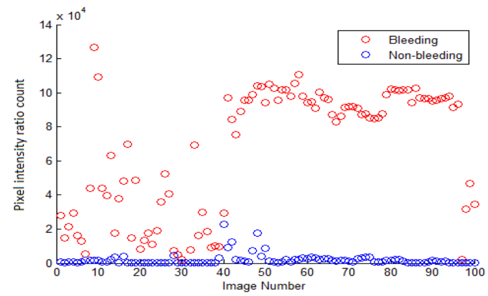


Fig. 3. Color ratio distribution of 200 WCE images

color spaces to demonstrate a color image and different researchers in various applications employ their own suitable color space. A common problem of WCE images are that the illumination changes due to the battery weaken of the capsule over time. So the color space and features are selected on the basis of less sensitive to illumination changes. In the proposed method, most widely acceptable RGB color space and in that space variation in pixel intensity ratio is capitalized to obtain potential features for bleeding detection in WCE images. The typical bleeding and non-bleeding WCE images are shown in Fig. 1 where (a), (b), (c), (d) are bleeding images and (e), (f) are non-bleeding images. The color images in Fig. 1 clearly show that the red bleeding zones differ from non-bleeding zone. Hence, the color features are always important in bleeding detection.

A. Pixel Intensity Ratio Based Proposed Feature

In RGB color space the distribution of color pixels in typical bleeding zone is different from that of the non-bleeding zone. Bleeding zone is typically red or dark red color which is shown in Fig. 1. It is observed that the ratio of green to red (G/R) gives significant pattern and it is always noticeable to detect bleeding images. In order to demonstrate the statistical behavior of pixel intensity ratio between different color planes (R, G, and B), sample bleeding and non-bleeding images are taken and pixel intensity ratio for all pixels are computed. Next histogram plot is used to present distribution of pixel intensity ratio of different pixels. It is to be noted that red is the most dominating color that naturally helps in identifying bleeding. Hence, the level of pixel intensity values of other two colors with respect to red pixel intensity may help in extracting bleeding characteristics. In Fig. 2, distribution of pixel intensity ratio in bleeding and non-bleeding images is shown using histograms. In this case green to red (G/R) and blue to red (B/R) intensity ratios are considered. In Fig. 2 (a) and (b), respectively G/R and B/R intensity ratios for bleeding images are shown. From Fig. 2 it is observed that G/R pixel intensity ratio follows a specific pattern in bleeding zone which is different from non-bleeding zone. Bleeding zone pixels possess ratio value greater than 0.6. It is observed that to avoid pink and blue color pixels, further second condition can be added depending on B/R pixel intensity ratio which must be kept below 0.6 to declare as bleeding. From these observations, in the proposed method, the number of pixels in an image that satisfies both conditions i.e., G/R $\leq T_{G/R}$ and B/R $\leq T_{B/R}$ is counted. The thresholds are chosen based on statistical analysis of several bleeding and non-bleeding images. This pixel intensity ratio count is used as a feature and called pixel intensity ratio count feature. In Fig. 3, pixel intensity ratio count feature is plotted for 200 WCE images (100 bleeding images and 100 non-bleeding images). In the figure red dot represents bleeding image and green dot represents non-bleeding image. It also shows that color ratio count feature is highly separable for bleeding detection in WCE images.

B. Average Intensity in Different Color Planes

Color texture statistical feature in terms of average pixel intensity of R, G, and B color planes is also incorporated in the overall feature vector in order to enhance the feature quality. The mean pixel intensity E_i of i-th color plane can be calculated using the following equation

$$E_i = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} I_i(x, y) \quad (1)$$

Hence, the overall dimension of the proposed feature vector will be 4, as along with pixel intensity ratio count, three mean intensities are included.

C. SVM Based Classification

Support vector machine (SVM) is used for classification. Bleeding detection is a two class problem and SVM works well for two class problems. Accuracy, sensitivity, and specificity for different kernel function, as linear, polynomial, and Gaussian Radial Basis function are calculated. Extensive experimentation is carried training and test based technique to classify a given WCE image into one of the two classes, namely bleeding or non-bleeding. The classifier classifies the data into different groups generally, depending on the significant characteristics of the group members. The quality of a classifier depends on its ability to provide the compactness among the member within a cluster and the separation between the members of different clusters in terms of feature characteristics. The task of recognizer is to identify the class label of a test sample utilizing the classified data.

In the proposed method, the support vector machine (SVM) is used to classify the test WCE image. 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, which need to lie right on the marginal hyper-planes.

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 $\boldsymbol{w} = [w_1 \; w_2 \; \ldots \; w_M]^T$ 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 with teacher values +1 and −1, in the basic SVM, all the training vectors $\boldsymbol{x}_i$ satisfy the following inequalities:

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

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

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

A nonlinear kernel function can also be adopted as the inner product and in some cases becomes more effective for supervised classification.

TABLE I

PERFORMANCE MEASURES OBTAINED BY THE PROPOSED METHOD

Classifier	SVM linear	SVM polynomial	SVM Gaussian Radial Basis Function
Accuracy	92.40%	92.95%	95.80%
Sensitivity	97.25%	97.00%	96.50%
Specificity	91.19%	91.94%	95.63%

TABLE II

EFFECT OF VARIATION OF COLOR RATIO ON PERFORMANCE MEASURES

Classifier	Pixel intensity ratio <=0.5	Pixel intensity ratio <=0.6 (proposed)	Pixel intensity ratio <=0.7
Accuracy	92.30%	95.80%	90.50%
Sensitivity	94.50%	96.50%	87.00%
Specificity	91.75%	95.63%	91.38%

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 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], the thresholds for pixel intensity ratio are kept same for both $T_{G/R}$ and $T_{B/R}$ and it is $T_{G/R} = T_{B/R} = 0.6$.

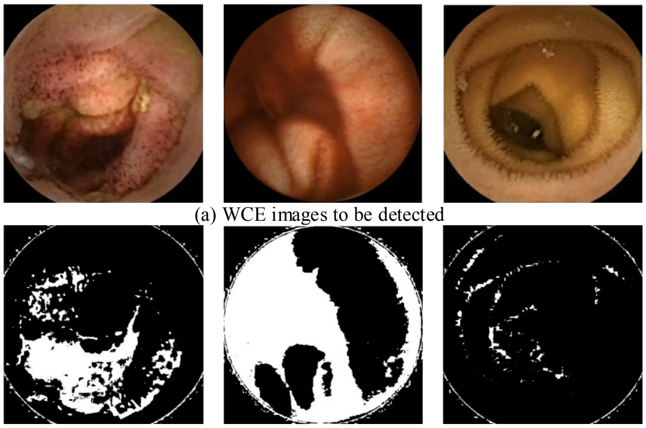
There are four cases about the detection result of bleeding and non-bleeding images. The bleeding image will be possibly detected as non-bleeding image, which is called false non-bleeding recognition (Fnb). In a similar way, when the non-bleeding images are detected as bleeding images, it is called false 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]

$$Sensitivity = \frac{\sum Tb}{\sum Tb + \sum Fnb} \quad (4)$$

$$Specificity = \frac{\sum Tnb}{\sum Tnb + \sum Fb} \quad (5)$$

$$Accuracy = \frac{\sum Tb + \sum Tnb}{\sum Tb + \sum Fnb + \sum Tnb + \sum Fb} \quad (6)$$

In Table I, different performance measures obtained by the proposed method are presented considering three different types of kernel functions in SVM classifier, namely linear, polynomial, Gaussian radial basis function (RBF). Among these three kernels, it is observed that the RBF kernel exhibits the best performance. Fig. 4 shows the accuracy, sensitivity and specificity of different SVM classification. The performance of the proposed scheme is also investigated with



(a) WCE images to be detected

(b) Detection result

Fig. 5. The detection result of bleeding pixels of WCE images using proposed criterion.

TABLE III

PERFORMANCE COMPARISON AMONG DIFFERENT METHODS

Method	Uniform LBP [5]	Method in [11]	Proposed method
Accuracy	91.50%	77.15%	95.80%
Sensitivity	79.25%	83.00%	96.50%
Specificity	94.56%	75.69%	95.63%

the variation of the threshold value ($T_{G/R}$ = $T_{B/R}$). In Table II, performance variations using the RBF kernel in SVM is shown. It is observed that the performance is very satisfactory in the neighborhood of chosen threshold, which is also expected from Fig. 2. Fig. 5 illustrates the detection result of bleeding pixels of WCE images using pixel intensity ratio. It shows that the proposed pixel intensity ratio based criterion successfully detects bleeding zone in bleeding images and almost does not detect any bleeding zone in non-bleeding images. For the purpose of comparison, the result obtained by the proposed method is compared with those obtained by the methods proposed in [11] and the uniform local binary pattern (LBP) feature proposed in [5]. It is to be mentioned that the LBP features are extracted independently from HSI color space. Here, uniform LBP acquired from plane I (intensity) of HSI color space and histogram values of uniform LBP are used as feature. In the implementation of the method proposed in [11], best feature combination, which are histogram probability, mean and energy of R, G, and B color plane are used. 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 III. 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, and 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. Each pixel ratio between different planes is considered instead of directly considering pixel intensity values in three planes. Proposed ratio count feature along with the average intensity of different color planes is found sufficient to construct a robust color texture feature vector. Finally for classification purpose the SVM classifier is tested with different kernels and it is found that the Gaussian radial basis function provides better performance. 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.

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