Improvement of Blood Detection Accuracy using Image Processing Techniques suitable for Capsule Endoscopy

Yong-Gyu Lee and Gilwon Yoon*

Abstract—Bleeding in the digestive duct is an important diagnostic parameter for patients. Blood in the endoscopic image can be determined by investigating the color tone of blood due to the degree of oxygenation, under- or over- illumination, food debris and secretions, etc. However, we found that how to pre-process raw images obtained from the capsule detectors was very important. We applied various image process methods suitable for the capsule endoscopic image in order to remove noises and unbalanced sensitivities for the image pixels. The results showed that much improvement was achieved by additional pre-processing techniques on the algorithm of determining bleeding areas.

Keywords— blood detection, capsule endoscopy, image processing.

I. INTRODUCTION

CAPSULE endoscopy is one of the most useful endoscopic applications in diagnosing the digestive duct where a patient simply swallows a small pill [1]. Above all, the best merit of the capsule endoscopy is to examine all the digestive tracks. It is possible to view the status of organ and biological tissues in the digestive duct [2]. The main purpose is to provide with appropriate measures on potential diseases found along the duct. Detection of bleeding regions is of the primary interest since bleeding is associated with detrimental diseases. For examples, ulcers, tumors, Crohn's disease and cancer are closely linked with bleeding or abnormal blood vessels. Bleeding itself causes complications such as cacochylia and anemia. Therefore the importance of bleeding detection is more increasing [3].

Unfortunately, there are several difficulties for an automatic detection of bleeding. There are a prohibitively large number of image frames and the resolution of the frames is low. A typical image resolution is about 320 x 320. The number of frames is also very few (~ 3 frames/second) and the images between the previous and current frames are less correlated due to the time interval. We may say that each frame contains more or less independent information [4]. Therefore, there is no room for neglecting any single frame. One has to examine a number of frames during a time period of many hours and there can be inevitably a potential of misjudgment.

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We have reported the algorithms of bleeding detection based on various characteristics of bleeding [5,6]. These characteristics were extracted through statistical analysis of the actual frames with bleeding regions in them. What we have found was that the images obtained by the receiver of capsule endoscopic system were relatively of poor quality. The images taken in the digestive duct are transmitted through human body communication to a data receiver attached to the outside of the body. There can be erroneous reception or loss of data due to communication errors, the power instability and poor contacts of the electrodes in human body communication [7]. These errors can distort the actual images and will results in poor diagnosis. In this study, we applied various image preprocessing techniques suitable for the capsule endoscopic images and increased the accuracy of predicting bleeding regions.

II. IMAGE PRE-PROCESSING

A. Image Processing suitable for Capsule Endoscopy

We studied preprocessing routines to convert raw image data to more appropriate ones before they were put through blood detection algorithms. Noise removal, amplification and the normalizations of color bands were performed for this purpose. One of the typical noise types in the capsule image was due to data communication errors shown in Fig. 1. It was a pepper and salt type error and showed a substantial difference in intensity compared to the adjacent pixels, mostly with low intensity.
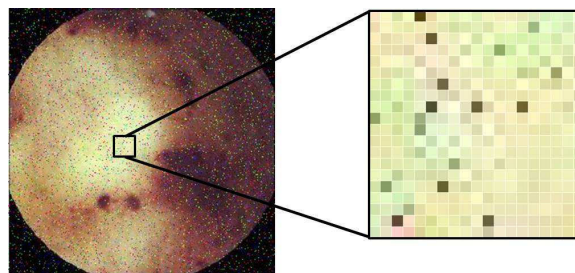

Fig. 1 An example of noise in the capsule endoscopic image

The median filter is reported to show an excellent performance to this type of noise. However, to the contrary, what we observed was that there was also a negative aspect of producing blurring. Outline of bleeding regions could not be

well defined. In order to remove noises and to prevent outline blurring at the same time, we applied a filtering method based on variance. First, we calculated the variance on a particular pixel using Eq. (1). Once the variance of the pixel was abnormally high, we chose the intermediate value among the pixels of high correlations. By doing this, we could minimize the image blurring and noises at the same time.

$$Var(i, j) = \frac{1}{m \times n} \sum_{k=-n/2}^{n/2} \sum_{l=-m/2}^{m/2} (x(i+l, j+k) - \mu)^2$$

$$\mu = \frac{1}{m \times n} \sum_{k=-n/2}^{n/2} \sum_{l=-m/2}^{m/2} x(i+l, j+k)^2 \qquad (1)$$

where i is horizontal index, j is vertical index

The images became dim or an overall intensity distribution was low when there was low illumination or lower sensitivity of a particular color band. This brought some changes in the optical properties of blood and it made difficult to determine the region of blood. Therefore, we enhanced dark or low-intensity images and sharper images were produced. As results, the features used as parameters to predict blood or non-blood became more distinct in their distributions. For this purpose, we amplified DC and AC levels for each color band.

Spectral analysis was our approach where we treated R, G and B color bands as discrete spectral responses. Spectral compensation with a known reference material is a well practiced method in spectroscopy analysis. We also performed a compensation of non-uniform spectral sensitivities of the detector although spectral calibration is an alien concept to RGB images since they are natural to the naked eye. In our study, the intensity of each color band was normalized and this normalization process was effective to enhance low-intensity color band. Our method increased the accuracy of blood prediction especially for the images of poor quality.

B. Optical Parameters that Characterize Blood

Fig. 2 shows a one dimensional presentation of an image that included a bleeding spot. Each pixel (x-axis) has the intensities of R, G and B. Blood pixels show lower values of G and B than R. This characteristic was defined as one of the parameters (F_1) which we called as feature. We defined other features where F_2 was the difference between G and B. In a similar manner, the average amplitude of G and B was defined as F_3. F_4 was the difference between the maximum and minimum values among R, G and B. Equations of F_1, F_2, F_3 and F_4 are given in Eq. (2).

We found that apparent blood pixels had large values of F_1 and F_4 and small amplitudes of F_2 and F_3. However, these alone were not sufficient for predicting blood pixels. The effect of brightness should be taken into account before the prediction of bleeding region was announced. Bright images had distributions of the features that were distinct and separable one another. Images that were not bright enough did not have distinct features. The reason was due to the fact that there were higher quantization errors in dim images compared to bright images.

This would result in less reliable determination of bleeding spots. Therefore, for blood detection of minimizing the effect of brightness, weighting factors were computed based on the features and we applied them to the original image. This modification could generate more clear separation between blood and normal tissue.

$$F_1(i, j) = \frac{2R(i, j)}{G(i, j) + B(i, j)}$$

$$F_2(i, j) = \left| G(i, j) - B(i, j) \right|$$

$$F_3(i, j) = \frac{G(i, j) + B(i, j)}{2} \qquad (2)$$

$$F_4(i, j) = R(i, j) - \min(G(i, j), B(i, j))$$

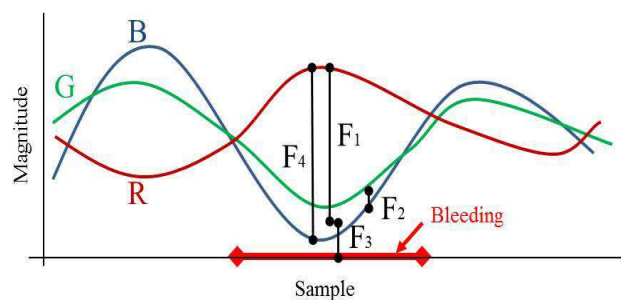

Fig. 2 An example of the capsule image with blood that was converted into one dimensional graph where values of R, G and B are shown at each pixel

C. Blood detection algorithm

Our proposed method to detect bleeding was based on the features that were introduced in the previous section. Fig. 3 shows a flow chart for our program. There were three parts in the program. They are statistical analysis, verification and prediction. We already extracted the averages and standard deviations of all the features, $F_1 \sim F_4$, from 30 images with blood. Using these values, we produced weightings given in Eq. (3). The estimation of the standard deviation before deciding the weighting factor was the important step. In other words, classification of bleeding or normal tissue was interdependent in terms of the amplitude of the standard deviation and the accuracy of determining one type of tissue would induce the inaccuracy for the other type. We chose a parameter of k that reflected the increase of the standard deviation by analyzing experimental data. We found that a value of 5 for k produced the best results. Along with k, a weighting factor was assigned as shown in Eq. (3). When the weighting factor was used, bleeding became strong red color and normal tissue became more contrasting color against red. We selected the candidates of bleeding spots by categorizing colors.

During statistical analysis, we computed the features of a pixel and compared those with our previous database. If this pixel belonged to blood, the verification step was followed. Verification was done by examining its morphological characteristics.

Bleeding tended to be clustered to some degree in terms of a pixel size. A candidate for blood pixel was finally determined as blood pixel when it was surrounded by other blood pixels. Otherwise, it was regarded as normal pixel.
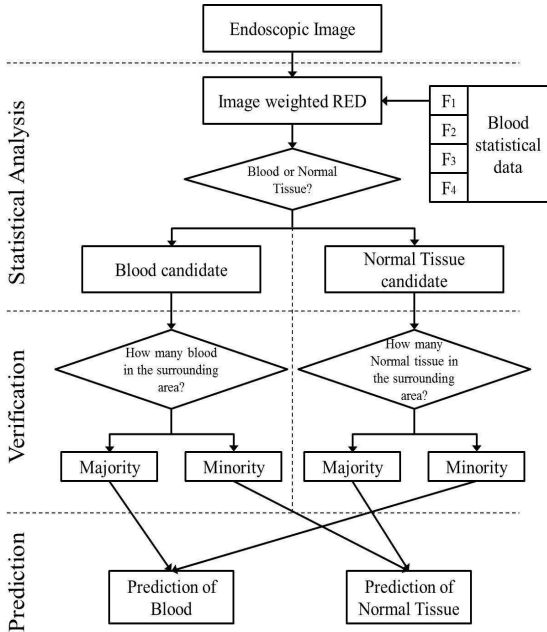

Fig. 3 a flowchart of the blood detection algorithm

$$W_1(i,j) = \begin{cases} \dfrac{N}{\sqrt{2\pi}k\sigma_1} e^{-\frac{F_1(i,j)-\mu_1}{2\sigma_1^2}} & , F_1(i,j) \le \mu_1 \\ \alpha_1 F_1(i,j) - \mu_1 & , F_1(i,j) > \mu_1 \end{cases}$$

$$W_2(i,j) = \begin{cases} \dfrac{N}{\sqrt{2\pi}k\sigma_2} e^{-\frac{F_2(i,j)-\mu_2}{2\sigma_2^2}} & , F_2(i,j) \le \mu_2 \\ \dfrac{N}{\sqrt{2\pi}k\sigma_2} e^{-\frac{F_2(i,j)-\mu_2}{2\sigma_2^2}} & F_2(i,j) > \mu_2 \end{cases} \qquad (3)$$

$$W_3(i,j) = \begin{cases} -\alpha_3 F_3(i,j) - \mu_3 & , F_3(i,j) \le \mu_3 \\ \dfrac{N}{\sqrt{2\pi}k\sigma_3} e^{-\frac{F_3(i,j)-\mu_3}{2\sigma_3^2}} & F_3(i,j) > \mu_3 \end{cases}$$

$$W_4(i,j) = \begin{cases} \dfrac{N}{\sqrt{2\pi}k\sigma_4} e^{-\frac{F_4(i,j)-\mu_4}{2\sigma_4^2}} & , F_4(i,j) \le \mu_4 \\ \alpha_4 F_4(i,j) - \mu_4 & , F_4(i,j) > \mu_4 \end{cases}$$

III. RESULTS

Fig. 4(a) is a capsule endoscopic image with bleeding region in the middle of the bottom part. Fig. 4(b) shows predicted bleeding area. Bleeding is in a pseudo color of white. There were two spots as bleeding areas predicted erroneously shown in the lower left corner. Moreover, along the boundary of bleeding region, there were additional pixels of misjudgment. We added the preprocessing method introduced in Section II and the result is shown in Fig. 4(c). Both error spots and errors

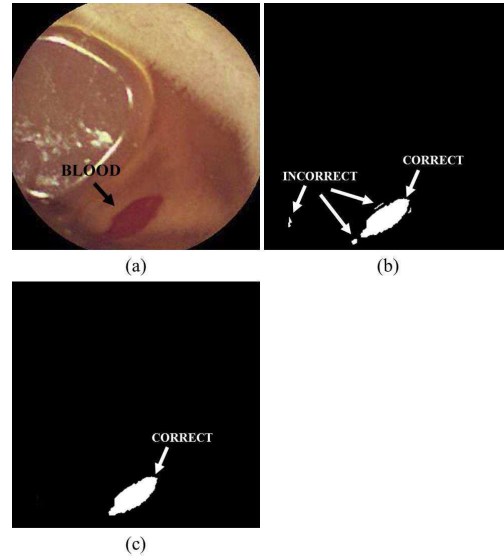along the interface between blood and normal tissue were clearly removed.

Fig. 4 Determination of blood; (a) the original capsule image, (b) bleeding spots predicted by the algorithm based on the features. Blood is shown in white. (c) Bleeding area predicted with additional pre-processing methods

We believe that this improvement, though it appears to be minute, will increase the performance of automatic bleeding detection for capsule endoscopy considerably.

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