Automatic Detection of Intestinal Bleeding using an Optical Sensor for Wireless Capsule Endoscopy

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Abstract— **Wireless capsule endoscopy (WCE) has been an effective and safe way to diagnose gastrointestinal (GI) disorders, such as, colon cancers, polyps and bleeding. The detection of bleeding and other anomalies is currently determined through conventional visual inspection of the WCE images by the physicians. An on-chip bleeding sensor is thus required, that can perform an automatic prescreening of the bleeding areas in real-time using blood's optical properties to assist the diagnosis. In this study, a spectrophotometer was initially used to evaluate the chromatic properties of blood. It is found that the reflection ratio pairs of 700 nm to 630 nm and 480 nm to 530 nm provide important statistics to separate blood from non-blood samples. It has been implemented hardware using small LEDs and photodiodes to validate the results. Therefore, the proposed sensor system works as a good candidate to be integrated in a WCE device to detect GI bleeding quickly and in real-time.**

Keywords—endoscopy; capsule; blood detection; Spectrophotometer; gastrointestinal bleeding

I. INTRODUCTION

Bleeding is a common sign of many gastrointestinal diseases; therefore, monitoring GI bleeding is the key to the diagnosis of relevant diseases [1]. Traditional endoscopy is useful in monitoring stomach and esophagus, but causes patient's pain and discomfort. Therefore, wireless capsule endoscopy (WCE) is becoming a reasonable alternative to the current invasive endoscopy [2, 3]. Bleeding in the small intestine along with other abnormalities, including tumors, ulcers are usually identified by examining endoscopic images. The analyses may be difficult and time consuming task, if it is performed manually by the physicians [3]. Therefore, an automated diagnostic approach is very helpful in this scenario.

A recent study by Alam *et al.* [4] has shown that feature selection from optical properties could be an alternative way to distinguish normal cells versus cancer cells. Similarly, a number of methods were proposed to detect GI bleeding in the literature, where researchers have been able to successfully distinguish blood from non-blood samples using the characteristics of blood [5, 6]. Few studies are available that describe the characteristics of blood by using spectrophotometer or color sensors [3, 6]. The study by Liu *et al*. [6] is based on TCS230D sensor, which converts the light wave into a corresponding frequency square pulse train. Ovesco Endoscopy AG (European VECTOR project) designed HemoCop Telemetric Sensor System [7]. They performed an in-vivo assessment with a sensor implant anchored to the stomach wall, where they applied different liquids such as water, milk, tea, red wine, orange juice, and a few more items into the sensor through an endoscopic channel. The ratio of transmitted intensities of red light (720 nm) and violet light (415 nm) had been used as a single parameter to distinguish blood from other substances [7]. Acute upper GI bleeding is detected by using a telemetric real-time sensor in [5]. The red and violet wavelengths of the spectrophotometer were used in their experiment to determine the optical characteristics of the blood. In the next step, two light emitting diodes (LEDs) with red and violet wavelengths are utilized to compare the results with the spectrophotometer study.

The goal of this research is to develop a low power sensor array that can be used to distinguish GI blood from other GI fluids and substances which can be integrated with the conventional wired endoscopy or WCE. In this regard, various spectrum of wavelengths for blood and non-blood samples have been investigated. Then, logistic regression is applied for classifying the recorded data. For validation, optical sensors are used in the experiment.

II. MATERIALS AND METHODS

The spectrophotometer is a device that measures the intensity of an object's emitted or reflected light, and transmitted light through any substance [8]. A Spectrophotometer (CM-600d) from Konica Minolta has been used in our experiments. It works at a range of 400 nm to 700 nm with a pitch of 10 nm.

A. Data collection

Two different datasets were used that contain both blood samples (BS) and non-blood samples (NBS). The first dataset used to develop a separation model between the two samples contained 22 BS and 13 NBS. The second dataset was used to verify the model's performance using the first dataset. Both datasets, therefore, contained a total of 43 blood samples with 23 non-blood samples. The blood samples included different types of blood samples, such as horse blood, swine blood and bovine hemoglobin. Table 1 shows the concentration range and Figure 1 shows some of the blood samples with various dilution that were used in the experiment. Due to the safety regulations and lack of facilities, experiments have been done on non-human blood samples. Since, the selected blood samples have many similarities to human blood, such as, the presence of hemoglobin and other components of the blood, the results of this work are expected to be similar to that of using human blood.

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Fig. 1. Blood solutions with various concentration

TABLE I. BLOOD SAMPLES AND CONCENTRATION RANGES

Blood Type	Datasets	
	First dataset	*Second dataset*
Horse blood	8% to 58%	4% to 75%
Swine blood	6% to 100%	0.1% to 100%
Hemoglobin	19.4g/L to 70.2 g/L	3 g/L to 39g/L

B. *Proposed method*

The operating principle of the sensor for the detection of blood is based on the optical properties of blood. Two sets of wavelengths were selected after the initial experiments with the spectrophotometer. The first set contains LEDs of 730 nm and 625 nm wavelength, and the second set contains 475 nm and 530 nm of wavelength. To validate proper functioning of the sensor, the prototype was developed using a photodiode, a specific set of LEDs, a microcontroller module and associated peripheral circuit.

The prototype was designed with a microcontroller and a high-speed epitaxy photodiode and 3 mm through-hole LEDs. The developed sensor and its components are shown in Figure 2. Two set of LEDs were individually tested to separate the blood samples from the non-blood samples. The first set contains LEDs with wavelengths of 700 nm and 625 nm, and the second set contains wavelengths of 475 nm and 530 nm. The LEDs emit the light to the surface and the reflected light from the sample surface is then measured using the photodiode. The experiments were conducted in a dark container to avoid environment light interferences. The logistic regression model used the sample average and ratio as features of the model to train the blood detection model, and calculated the probabilities using the sigmoid functions. Mathematically, the logistic model is a linear combination of independent variables, as follow [9]:

$$Logit = log\frac{P(x)}{1-P(x)} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \quad (1)$$

The estimation in logistic regression chooses parameters that maximize the likelihood of observing the sample values, instead of choosing parameters that minimize the sum of squared errors. In order to achieve the best features, the model is trained and analyzed separately for both sets, i.e., for the first set (700 nm and 625 nm wavelength) and the second set (475 nm and 530 nm wavelength) of sampled data.

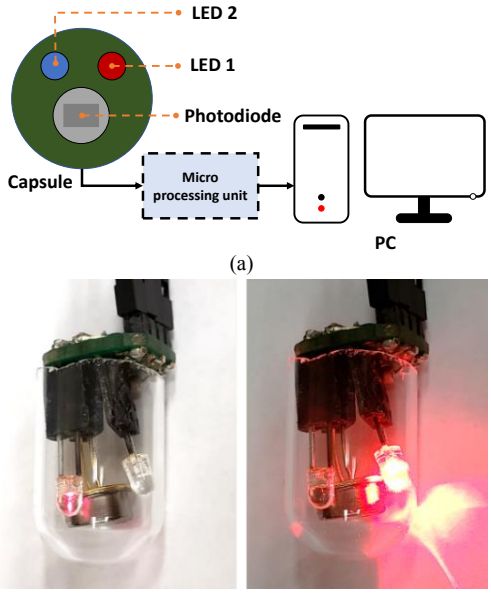

Fig. 2. a) Schematic design b) Developed prototype

III. RESULTS

In the first experiment using the spectrophotometer, three readings were taken for each sample and the average was used in the analysis. The amount of reflected light varied for different substances at different wavelengths. Figure 3 shows the spectral response to hemoglobin, blood, and all other solutions. In comparison with the water sample shown in the vertical axis, each sample was normalized. The figure indicates that the blood samples have a higher value in the region of 670 nm than in other wavelengths and a lower slope at approximately 630 nm. However, few blood solutions samples are very close to other non-blood solutions in spectral response. In this analysis using spectrophotometer, two different datasets were used to investigate the spectrum of light which could be used to separate blood samples and non-blood samples.

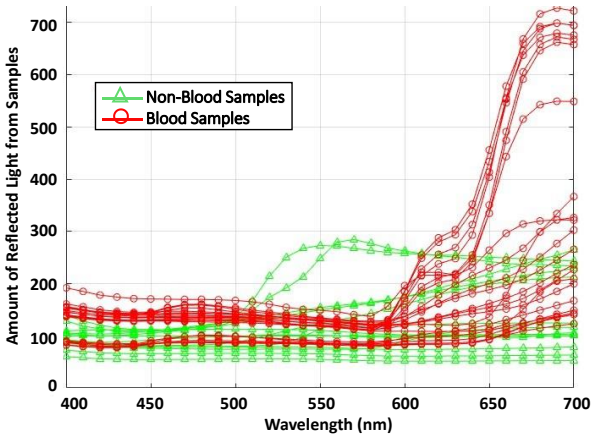

Fig. 3. The reflected intensity of different samples

Figure 3 suggests that the ratio of the amount of reflected light (ARL) at two different wavelengths could be used to distinguish the samples, and it was also proposed as a parameter to separate the samples according to some of the previous studies [5, 6]. The ratio of ARL at two wavelengths (λ_a, λ_b), for any sample *n*, can be expressed as:

$$R_n(\lambda_a, \lambda_b) = \frac{\text{ARL at } \lambda_a \text{ for sample n}}{\text{ARL at } \lambda_b \text{ for sample n}} \quad (2)$$

Figure 4 shows two different areas with maximum separation. The vertical axis shows the BS and NBS separation. Two horizontal axes show the wavelengths (λ_a, λ_b) in equation (1). The first region is around (700 nm, 630 nm), while the second is about (480 nm, 530 nm). In order to separate blood samples (RBS) from non-blood samples (RNBS), a cut-off point (CP) of the ratio was determined. The normalized ratio is calculated from the ratio by subtracting the cut-off point. Conditions for "i" sample to be a sample of blood or non-blood could be written as Blood samples : R_{BS_i} > = CP and Non-blood samples : R_{NBS_i} < CP.

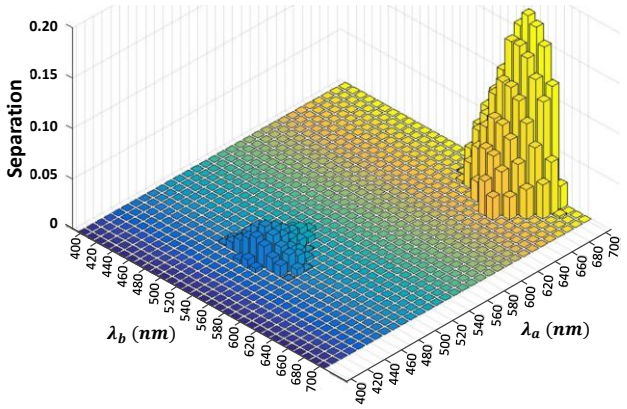

Fig. 4. The separation between the ratio of ARL at two different wavelengths

For both datasets, the ratio at (700 nm, 630 nm) and the ratio at (480 nm, 530 nm) show better separation. In the first datasets, the cut-off point was determined to be 1.3664, which means that if the ratio is greater than or equal to 1.3664, the sample is very likely to be a sample of blood; otherwise, the sample would be a non-blood sample. The cut-off point for the second data set was found as 1.2093, which is very close to the cut-off point found in the first data set analysis. Table 2 shows the values of the cut-off points. The accuracy of the algorithm for the datasets at different pairs of wavelengths is shown in Table 3.

TABLE II. THE VALUE OF THE SEPARATING POINT AT DIFFERENT PAIRS OF WAVELENGTHS RANGE OF THE CONCENTRATION OF BLOOD SAMPLES

Pair of wavelengths	Datasets	
	First dataset	*Second dataset*
(700 nm, 630 nm)	1.3664	1.2093
(480 nm, 530 nm)	1.0095	0.9189

TABLE III. ACCURACY OF THE ALGORITHM AT DIFFERENT PAIRS OF WAVELENGTHS

Pair of wavelengths	Datasets	
	First dataset	*Second dataset*
(700 nm, 630 nm)	100%	98.48%
(480 nm, 530 nm)	100%	84.00%

IV. DISCUSSION

All samples have been correctly identified by the algorithm for the first dataset. The ratio at (700 nm, 630 nm) shows better performance for the second dataset than the ratio at (480 nm, 530 nm). After comparing the results with the samples properly, we found that the blood samples that are not properly identified are mainly with low dilution samples. The first set of LEDs performed well. The loss of the model is gradually reduced for 2000 training iterations, and the overall accuracy of around 99.88 percent is obtained. The second set of LEDs, however, does not perform as well as the first LED sets. The training loss is still higher than the loss of the first set of LEDs for the same number of training iterations. The first set of LEDs can easily separate blood and non-blood samples using the model decision boundary. On the other hand, for the second set of LEDs, the model seems to be struggling with the separation of the blood and non-blood samples which can be seen from Figure 5. The overall accuracy for the second set of LEDs is 90.22%, which is lower compared to the first one. As a result, the first set of LEDs with the 700 nm and 625 nm wavelength is the perfect selection for separating the blood samples from the non-blood samples.

The proposed system is capable of distinguishing blood and non-blood samples with higher accuracy compared to the other existing system. Unlike the work performed by H. Liu *et al* [10], the proposed system is not limited to detecting blood for concentration of Hb above 0.05 g/ml. In [9], the blood was detected based on the HSL color space which may fail to differentiate the blood and non-blood in different light conditions, or when blood is mixed with other food substances. On the other hand, the proposed system provides better results even if the light condition is consistent or the food substances are mixed with blood. The work proposed in [5] using LEDs (415 nm, 720 nm) failed to provide better results at lower blood concentrations of 0.1% to 10%. Moreover, the sensor had to positioned properly to receive the transmitted light from the blood. Otherwise, it will not be able to provide the indicated results. The use of spectrophotometer is not feasible due to its enormous size compared to the tiny WCE system.

Table 4 shows a comparison between different methods. The proposed system has been tested with different concentrations of blood samples and various non-blood samples. It is able to distinguish the blood and non-blood samples with an accuracy of 99.88% using the ARL average and ARL ratio of the samples.

V. CONCLUSION

In this article, we have developed a proof of concept of a detection device that can separate bleeding from non-bleeding samples. Based on the accuracy of the machine learning model and spectrum analysis suggests only two different regions, where the samples could be easily separated. It can be observed that the first set of wavelengths of 700 nm and 625 nm provides a better result than the second set of wavelengths of 475 nm and 530 nm. The average and ratio of ARL at the first set of LEDs seem to be very informative in separating blood and non-blood samples according to our logistic regression model with

binary classification algorithms. It can be concluded that, based on the study data and defined algorithms, the optical sensor can reliably detect GI bleeding. Therefore, it is an excellent option for integration with the WCE system.

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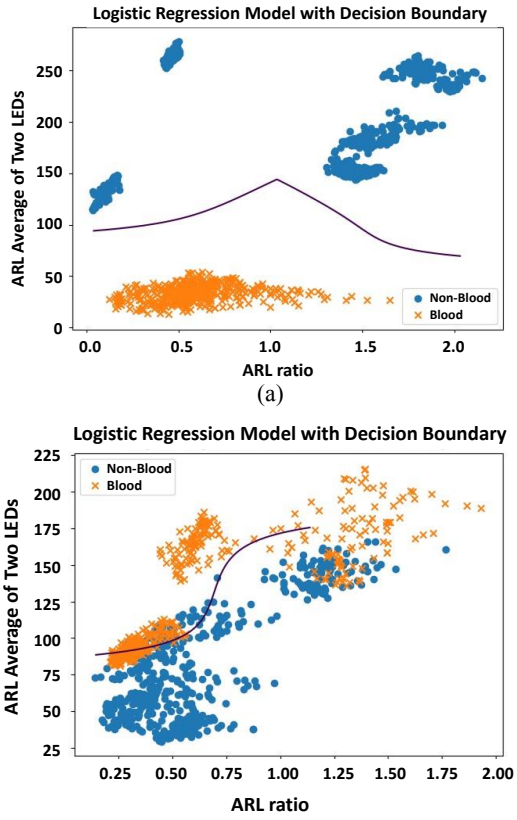

Fig. 5. Logistic regression Model's with decision boundary for a) 700 nm and 625 nm wavelength, and for b) 475 nm and 530 nm wavelength

TABLE IV. COMPARISONS BETWEEN EXISTING SYSTEMS

Ref	Sensor used	Principle	Parameter	BS	NBS	Limitations
[10]	TCS230D	Internal reflection	Two factors	13 Hemoglobin	0	It fails to detect blood for Hb concentration below 0.05g/ml
[6]	TCS3200	Internal reflection	HSL	8 Normal human blood	2 Intestinal juice	Fails in low concentration Max/ (128, 256, 512). It may fail to detect if blood is mixed with other food substances.
[11]	The LED (415 nm, 720 nm)	Transmission Anchored in the GI wall	Ratio	1	5	The implant must be positioned in a way that blood from a bleeding lesion can reach the sensor's recess.
[5]	LED (415nm, 720nm)	Transmission	Ratio	Human blood 0.1%, 1%, 5%, 10%, 50%	19	Unable to distinguish red light values at low blood concentrations (0.1% up to 10%).
[5]	Spectrophotometer	Transmission	Ratio	Human blood 0.1%, 1%, 5%, 10%, 50%	19	Unable to properly differentiate the low transmission values of violet light at high blood concentrations of 5% or more.
[7]	The LED (415nm, 720nm)	Transmission	Ratio	Human blood 5%, 7.7%, 13.3%, 15.4%, 33%, 40%	Water	The role of a time delay between a detected bleeding and capsule ingestion remains unclear in the study.
Proposed method	The LED (700nm, 625nm)	Reflection	ARL	4 Bovine Hemoglobin (Sigma H2625)	5	It finds it difficult to distinguish blood at low dilutions of blood samples less than 1%