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A Novel Real-Time Non-invasive Hemoglobin Level Detection Using Video Images from Smartphone Camera

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Abstract:
Hemoglobin level detection is necessary for evaluating health condition in the human. In the laboratory setting, it is detected by shining light through a small volume of blood and using a colorimetric electronic particle counting algorithm. This invasive process requires time, blood specimens, laboratory equipment, and facilities. There are also many studies on non-invasive hemoglobin level detection. Existing solutions are expensive and require buying additional devices. In this paper, we present a smartphone-based non-invasive hemoglobin detection method. It uses the video images collected from the fingertip of a person. We hypothesized that there is a significant relation between the fingertip mini-video images and the hemoglobin level by laboratory "gold standard." We also discussed other non-invasive methods and compared with our model. Finally, we described our findings and discussed future works.

SECTION 1.
Introduction

Hemoglobin is the iron-containing protein in red blood cells which carries oxygen from human lungs to the tissues of rest of the body. Hemoglobin level detection is necessary for diagnosis and triage of multiple medical conditions including sickle cell anemia and chronic anemia. The hemoglobin (Hb or Hgb) level measurement test ranks as one of the most common laboratory tests ordered [15]. Early detection of hemoglobin level can be useful for diagnosis. Sometimes the test may take some time, and the result is not instantly available at the point-of-care. It produces a delay in diagnosis which influences the treatment and outcome [5].

Scenario 1

Sickle Cell Disease (SCD) is a chronic condition related to the deformed shape of red blood cell in human. In the US about a hundred thousand people suffer from SCD. When hemoglobin level decreases, due to the deformed shape of red blood cells, the patients feel severe pain. An average adult suffering from SCD is admitted to emergency department (ED) about four times a year, and about

10 percent of the patients are admitted to the ED once per month. This amounts to an estimated cost of 1.1 billion dollars.

The difference in high-risk and low-risk patients can be determined by the hemoglobin level and vital signs. If information about hemoglobin levels could be obtained earlier in the communication between the patient and ED, that information could be used to triage the patients and reduce the cost for low-risk patients. A smartphone-based system that calculates the hemoglobin level fast will be useful for quick detection and classification of different risk groups.

Scenario 2

Anemia is the lack of red blood cell or hemoglobin in the blood. Iron deficiency anemia can be found in various age-groups of Bangladesh. It is essential for diagnosing different types of anemia by measurement of hemoglobin. But in a rural area of Bangladesh, the availability of a good hemoglobin detection method is not much. Also, a study among the garment workers in Bangladesh has shown that about 77% of the female worker suffer from different degrees of anemia [13]. Therefore, it is important to have a portable method of hemoglobin detection. Analyzing the above scenarios, we propose a system and mathematical model for hemoglobin detection. We propose the following model:

- Non-invasive hemoglobin level measurement using Smartphones camera.
- Continuous noninvasive measurement of hemoglobin by patient and caregiver.
- Development of a cost-effective and widely available means to measure hemoglobin level.

In our solution, we have the following challenges:

- Data collection from a wide range of population to validate the study.
- Determine the important features to correlate hemoglobin level and captured image/video.
- Develop a mathematical model to determine hemoglobin level from the extracted features.

In short, our main contribution in this paper is to explore a non-invasive method to detect hemoglobin by using a smartphone camera.

In section 2, we discuss the related studies in this topic. We discuss different noninvasive methods and how they can be compared to our system. In section 3, we describe our system in details. We discuss data collection, functionality and system flows. In section 4 of this paper, we discuss the results of this elaborate study. In section 5 we conclude this paper and present a future research direction.

Blood transfusion of the patients showed us that there were noticeable changes in the collected data before and after transfusion. But data collected from different participants did not give us a good correlation. We also think that smartphone might have done some preprocessing to video files captured from smartphone camera app that has led to change in the data. It might be helpful to develop a separate application which helps to capture the video images without any preprocessing.

SECTION 2.

Related Works

In the laboratory setting, hemoglobin level is calculated with a colorimetric method [1] [2]. Usually, this is an invasive method where blood is obtained by venipuncture. Then after adding different chemicals to make a solution, the chromatic property is calculated. In modern days, this is done by high-end machines in laboratories. This is an invasive method because for this analysis, blood needs to be taken from the vein and it requires safety procedures to protect the patients.

We will now discuss some non-invasive methods developed and described by different authors. Patil et al. [16] did a review on different non-invasive methods and devices to determine hemoglobin. They discussed that these methods could be classified into pulse oximetry, optoacoustic method, diffuse reflectance spectroscopy, photoplethysmography (PPG) and imaging-based technique. From our survey, we deduced that pulse oximetry uses PPG as an important component. Thus, we discussed in this section, the four different general methods for non-invasive hemoglobin detection as shown in Figure 1.

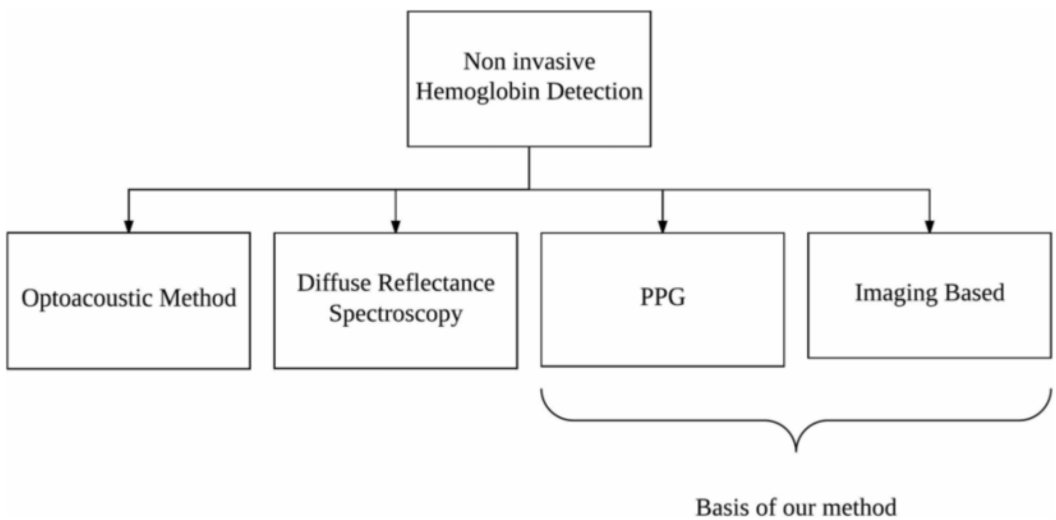


Figure 1. Non-invasive methods for hemoglobin detection

Barker et al. [7] discussed the uses of multiwavelength pulse oximeters to detect hemoglobin level. Macknet et al. [9] conducted a study with 20 healthy volunteer subjects undergoing hemodilution to compare the simultaneous measurement of hemoglobin using a noninvasive pulse COOximeter (Masimo Radical-7) and an invasive laboratory CO-Oximeter.

Frasca et al. [10] compared laboratory reference values to Pulse CO-Oximeter and concluded that there was absolute and trending accuracy. Linder et al. [15] reviewed the advantages of using Pulse CO-Oximetry by analyzing several other evaluation studies and commented that this method is very promising and potential to improve.

There were also some studies where the result was not in favor of this method. In one study to compare the accuracy of Masimo Radical-7 device with results obtained in the laboratory of 300 patients, Gayat et al. [11] concluded that the device was systematically biased and could lead to misestimation of the need of blood transfusion. Knutson et al. [14] analyzed the degree of variation of hemoglobin data between using a noninvasive device (Masimo Radical-7 Pulse) and actual venous blood draw. They concluded that such noninvasive method was not sufficiently accurate for emergency department use as the relation is not statistically significant.

Suner et al. [6] used images of the palpebral conjunctiva to detect hemoglobin level. They took 117 digital pictures of 63 patients. From the grayscale photograph, they matched with a gray standard photo and found a correlation of 0.634. Collings et al. [17] also used the method of digital photographs to detect anemia in patients. In this study erythema index of the palpebral conjunctiva was calculated from images taken with a compact camera or mobile phone. They found the screening method very useful with significant sensitivity and specificity.

Bender et al. [8] described a system using diffuse reflectance spectroscopy (DRS) to monitor hemoglobin during surgery. They used fiber-probe-based spectra to calculate the diffusion and absorption of light in tissues. McMurdy et al. [5] used diffuse reflectance spectroscopy on the conjunctiva and found that it improves the diagnosis over observational studies. This leads to an improvement in the methods of non-invasive hemoglobin detection.

Esenaliev et al. [3] [4] showed that optoacoustic methods have the potential for non-invasive and real-time measurement of hemoglobin. They found a very good result for in vitro experiments but results from in vivo experiments were not available.

Scully et al. [12] have shown that mobile phone camera has the potential to capture reflection PPG imaging with the help of a white LED phone flash. In their study, they have also shown how this feature can be used to monitor several physiological parameters such as heart rate, heart rate variability, respiration rate and oxygen saturation of blood.

From our surveys, we deduced that using Pulse COOximetry or optoacoustic method will require a complex setup and also will be costly. One of our goals is to design a system which is simple and easily available. We figured out, if we have a system which uses the imaging capability of a smartphone and utilize the flash of the camera to illuminate and capture the image while holding it to a body part, we can have image data similar to a PPG. On that basic idea, we designed our methodology.

Figure 2. Video image capture

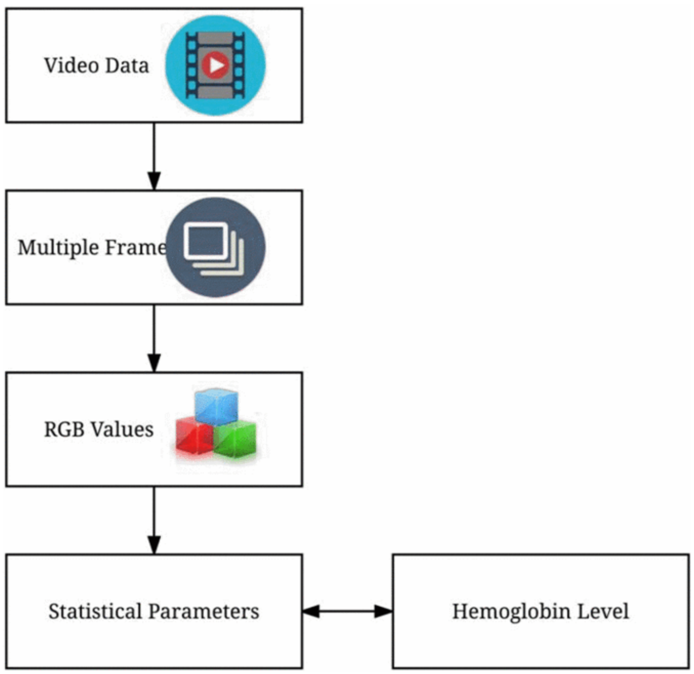


Figure 3. Flow diagram

Table 1. Comparison of different methods of hemoglobin detection

Method	Reference	Process	Invasive	Discussion
Lab Gold Standard	[1], [2]	Blood from vein, chemical agents, compare color	Yes	Lab environment, time-consuming, not mobile
Opto-acoustic	[3], [4]	Laser IR range, detect optoacoustic signals	No	Oxygen saturation in Hemoglobin
DRS	[8], [5]	Fiber probe, Tissue absorption, and scattering	No	
PPG	[12]	Pulse Oximeter	No	costly, partly portable
Imaging	[17],[6]	Image from conjunctiva	No	Few studies performed, mostly positive output
Our Approach		Combination of PPG and Imaging	No	PPG, Imaging methods, portable, cost-effective

SECTION 3.

Our Approach

3.1. Data Collection

We use a smartphone camera to collect video images of fingertips. Using the camera app, we turn on the flash of the phone which is just beside the camera sensor of the phone. The fingertip is then placed in such a way that it covers both the flash and the camera sensor. The finger is pressed to the camera neither too tight nor too loosely, and it is made sure that no outside light is not allowed to enter the camera. The flash of the camera works as a light source to illuminate the finger. The hand is put in a resting place so that there are no shakes. In Figure 2, the setup of the fingertip on the camera of the smartphone is shown. The video is captured for about 30 seconds. Parallel to this process, we also take blood samples from the participant with the help of medical professionals to measure the gold standard hemoglobin level from laboratory measurements. From the exact hemoglobin value, we also assign a level of hemoglobin as high, medium or low. The video is stored in the mobile phone internal memory for initial storage. Later, we transferred the recorded video from the phone memory to the computer for analysis using Matlab tool.

3.1.1. Frame Extraction

Using the Matlab tool we have extracted the nearly 900 frames (30 frames per second) from the 30 seconds video. Each frame's red, green and blue pixel values are stored in three two-dimensional matrices which have values from 0 to 255. We calculate the mean, median, mode, maximum, minimum and standard deviation. Also, we implement the singular value decomposition(SVD) and calculate the 10 most significant value for these pixel values. In Figure 3, the frame extraction system is shown step by step.

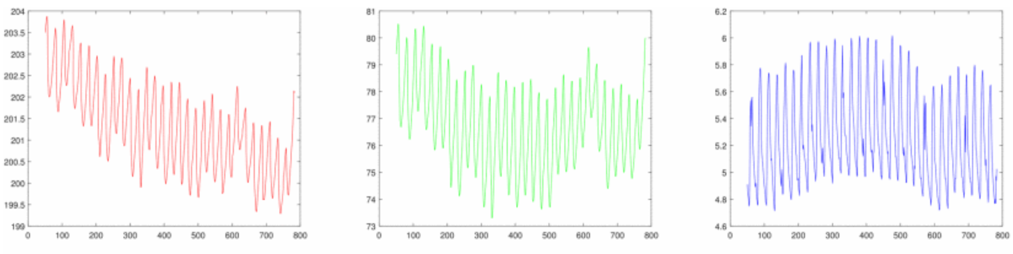
1. Frames are extracted from video data.
2. Red, green and blue pixels are separated from each frame. Two-dimensional arrays are storing the pixel values.
3. From the **RGB** values, different statistical parameters and feature variables are calculated
4. Feature variables are matched with hemoglobin values to create a mathematical model for future detection.

3.1.2. Outlier Removal

We observed some unexpected/irregular spike/pattern in the extracted data on the graph. To remove the outliers, we have removed five percentile of data from the top and bottom of the curve for each frame. In addition, we have used Singular Value Decomposition (SVD) to remove the insignificant data for each frame.

3.2. Data Analysis

For data analysis, we use regression (for exact Hb value) and classification (for hemoglobin level in a range). Linear regression with individual feature values and multivariable linear regression is modeled to calculate the correlation coefficients. As a classification method, we used different Decision Tree algorithms, SVM, naive Bayes etc. methods. All these analyses can be grouped under two different types of studies.



(a) Red Pixel Intensities (b) Green Pixel Intensities (c) Blue Pixel Intensities

Figure 4. Different color intensities collected from the same video image

3.2.1. Analysis of Blood Transfusion

In this part, we analyze how blood transfusion to individual participants change their hemoglobin level and the changes it causes to the video images. The data was collected at the BloodCenter of Wisconsin (BCW) from eight patients. These participants came to BCW for a blood transfusion as they had a low hemoglobin count due to Sickle Cell Disease. After transfusion, the hemoglobin level becomes much higher than it was before. For each patient, data was collected thrice before and after transfusion. We calculated the feature vectors for before transfusion and after transfusion. We took the average of before values and after values. From these values, we calculated the differences and their relation with respect to the hemoglobin values.

3.2.2. Analysis of Multiple Subjects

In this study, we tried to come up with a general model for detecting hemoglobin level. Here we collected video images 3 times from each patient for 30 seconds. Data was collected from these following sites.

1. Emergency Room, Froedtert Hospital
2. Amader Gram, Bangladesh
3. BloodCenter of Wisconsin

From Amader Gram, Bangladesh, data of 94 patients were collected totally. 5 of the videos were not correctly uploaded and hemoglobin values were not collected for 5 other participants. So, we found 84 sets of fingertip video and hemoglobin values. From The emergency room of Froedtert Hospital, about 17 sets of data were collected. Hemoglobin levels ranged from 7.5 to 15.9. From BCW (BloodCenter of Wisconsin) data was collected in two phases. Initially, data was collected from 20 people. Among the

20 data, one hemoglobin value was missing. In the second phase, data was collected from Sickle Cell patients. There were 29 participants in that phase.

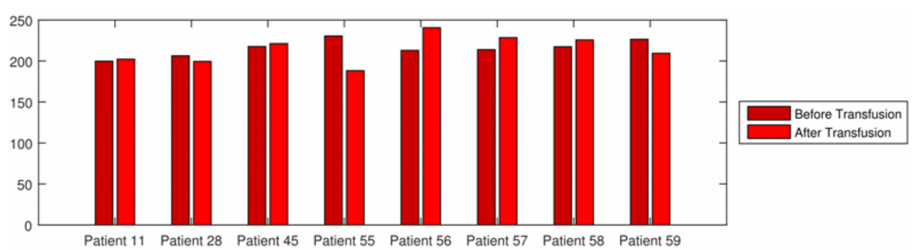
For all these sets, we tried different regression and classification method to come up with mathematical models. In the next section, we will discuss our findings.

SECTION 4.

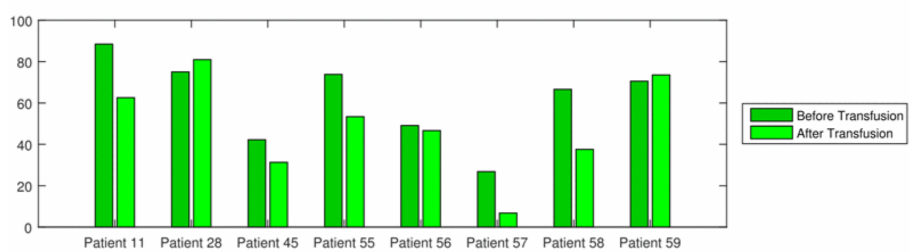
Results Analysis

4.1. Feature Changes for Transfusion Patients

From our transfusion study, we find the following results. Red and Green pixel intensities are shown in Figure 5. Here we notice that either red values are increasing or green values are decreasing after transfusion in most cases, which is in align with our hypothesis. But in some cases, it did not work accordingly. One of the reasons we found from looking at the videos is that in some cases the patients became tired afterward and could not hold the phone properly and the video was not captured correctly for those patients.



(a) Changes in Red pixel intensities



(b) Changes in Green pixel intensities

Figure 5. Changes in pixel values before and after blood transfusion

Table 2. Correlation coefficient from froedtert hospital

	Average	Mode	Maximum	Minimum
Red	0.3834	NA	NA	0.4069
Green	-0.5021	-0.5355	-0.4752	-0.4694
Blue	-0.2283	-0.2283	-0.1066	NA

4.2. Features from Individual Patients

Next, we look at the results from individual studies. There were three sites where we collected data from. In the following subsections, we will look at the data from different sites.

Table 3. Correlation coefficient from amader gram data

	Average	Mode	Max	Min	Std Dev	Median
Red	-0.22	-0.07	-0.18	-0.24	0.27	-0.13
Green	0.11	-0.00	0.23	0.2	0.17	0.07
Blue	0.02	-0.1	0.06	NaN	0.06	0.02

Table 4. Correlation coefficient from BCW data (first study)

	Average	Mode	Maximum	Minimum
Red	0.3917	NA	NA	0.347
Green	-0.0839	-0.0585	-0.1106	-0.0867
Blue	-0.205	-0.2346	-0.1205	-0.2573

4.2.1. Emergency Room, Froedtert Hospital

We calculated the linear regression for these data and found the correlation coefficients. The coefficients are shown in table 2. Here we see that the red intensities are positively correlated and green intensities are negatively correlated.

4.2.2. Amader Gram, Bangladesh

We look at the correlation coefficients of different features collected from video images (average, median, mode, maximum, minimum, standard deviation) with hemoglobin values and find that the correlation coefficient is very low for all the values (Table 3).

We also calculated the multivariate linear regression from this data. We found that if we took all the RGB variables the correlation coefficient is 0.56 and if we only take the average and standard deviations, we get a correlation coefficient of 0.59. Both of them are low to be of any significance. We calculated for SVD values too, and the results were similar.

We also applied some classification algorithms on this dataset. For classification, we used J48 method, and we classified the hemoglobin values into three groups. For Hb values greater than 11.5, we used “High”, for values between 10 to 11.5 we assigned “Medium” and for values less than 10 we assigned “Low”. We took different subsets from the dataset (all pixel values with age and sex, only the average pixel values with standard deviations, using all the SVD values, only the first 3 SVD values for each pixel etc.). We analyzed the confusion matrices and we looked at the ROC curves. From these analyses, we found that the biggest area under ROC was 0.64 and it was when we took only average pixel values with standard deviation, age, and sex of the patients.

We also analyzed the SVD values we calculated earlier using some learning algorithms. We used 10 fold verification for these training and test sets. The result can be seen in Table 6. Note that here we are representing the accuracy of each method in percentage. That means with the simple tree and all values, the accuracy was 48.8%.

Table 5. Correlation coefficient from BCW data (second study)

	Average	Mode	Maximum	Minimum
Red	-0.0533	0.0279	0.0301	-0.1068
Green	-0.0895	-0.163	-0.0638	0.0141
Blue	0.1611	0.0826	0.1359	NA

4.2.3. BloodCenter of Wisconsin

The correlation coefficient of different feature values with the hemoglobin value of the first phase can be seen in Table 4. The coefficients of the individual variables for the second phase, which can be seen here in table 5. Here we see that the values are very low to have any kind of significance, unlike the previous study. We also had low values for multi-variable linear regression.

We also did classification analysis for this data. One major difference of data from Sickle Cell patients is that the values are much lower than Amader Gram patients. So for classification, we have new sets of range for this data. We applied two classification methods, ADTree and J48. ADTree is only used for binary classification. For ADTree we assigned “High” for hemoglobin values more than or equal to 8 and “Low” for hemoglobin values less than 8. For J48, hemoglobin values less than 6 were marked “Low”, values from 6 to 8 were marked “Medium” and values more than 8 were marked “High”. The results from J48 showed that it was not able to detect low values. While we were classifying with ADTree, we tried changing the value of cut-off at 7 instead of 8 and found that the classification was better for the previous cut-off point.

SECTION 5.

Conclusion

In this paper, we have shown our data collection and analysis towards having a hemoglobin detection method from smartphone video images. This ensures a non-invasive method which is our systems first characteristic. Our system can be running continuously with a feedback which will be useful for personal and clinical scenarios. The solution is cost effective as it only utilizes the smartphone's camera and no extra devices are needed. We were able to detect the feature variables from the data from a variety of population.

We have seen that the basic hypothesis works but there needs to have a more accurate method if we want to use it in a clinical setup. We propose to implement the following upgrades to our system so that we can have better results. During the experiment of blood with different dilution, we notice that the average green pixel values are very highly correlated with the hemoglobin values in the different dilution. We also notice that the red pixel values were very low for these test cases. If we took other different dilution of the same blood samples, we would see the relationship of hemoglobin with red pixels more clearly. In our study, we have collected data from different demographics. We are extending the demographics by collecting data from Taiwan.

In our experiments, we have used the phone camera apps to collect video. But generally, these camera apps enhances the image for beautification. We might need to develop a camera app to get the raw image in our desired exposure. For the diluted blood study, we require a more detailed data set in an extended range. Also, we can use a filter with a gradient to have more feature variables to analyze.

Table 6. Using different machine learning algorithms

Classifiers	All (with 10 significant values)	5 most significant values	No Age or Sex	2 values only	Female	RGB Values
Simple Tree	48.8	44.0	38.1	39.3	36.9	35.7
Complex Tree	40.5	35.7	36.9	46.4	39.3	44.0
Weighted kNN	41.7	42.9	40.5	41.7	52.4	41.7
Cosine kNN	41.7	39.3	36.9	46.4	44.0	32.1
Boosted Trees	45.2	46.4	36.9	36.9	41.7	35.7
Linear SVM	39.3	52.4	34.5	40.5	40.5	32.1
Quadratic SVM	42.9	41.7	45.2	45.2	40.5	38.1
Cubic SVM	35.7	34.5	35.7	40.5	33.3	44.0

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