RGB pixel analysis of fingertip video image captured from sickle cell patient with low and high level of hemoglobin

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RGB Pixel Analysis of Fingertip Video Image Captured From Sickle Cell Patient With Low and High Level of Hemoglobin

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Abstract— **The demand for medical image processing is ever growing, especially for medical device manufacturers, researchers, and innovators. In this article, we present the image processing of a fingertip video to investigate the relationship between image pixel information and different hemoglobin (Hb) levels. We use the smartphone camera to record the fingertip videos of different sickle cell patients. We also collect their clinical Hb records. We extract the red, green and blue (RGB) pixel of the video image and make the histogram of selected frames for each video. The averaged histogram values of those selected frames are used as an input feature matrix in the regression analysis. Linear regression as well as the partial least squares (PLS) algorithm is applied to the input feature matrix. We consider five sickle cell patients who received the blood transfusion. We analyze the thirty fingertip videos from five patients where each patient gave three videos at the same time. Fifteen fingertip videos are recorded before blood transfusion, and rest of the videos are captured after two weeks of their blood transfusion. Matlab tool is used for the data analysis and visual image presentation of the RGB image histogram values, masked RGB image, and the confusion matrix of this paper. The result generated from linear regression and the goodness of fit of PLS model shows the reliable performance of this research work.**

I. INTRODUCTION

At present, Hemoglobin (Hb) is one of the prognostic factors for some diseases including cancer and anemia- is measured using invasive approaches around the world [4]. Albeit the satisfactory measurement accuracy of 95-98%, the conventional invasive approaches have several drawbacks. From the patients aspect, the invasive methods are not applicable for all sorts of people. In particular, invasive techniques are not always recommended for premature infants, aging population, pregnant women, sickle cell and anemia patients. Besides that, some people hesitate to go through any invasive diagnosis process regardless of age, gender, and race. From the health-care providers point of view, in the emergency department, it is cumbersome to provide efficient patient management in the case of Hb level measurement every day. In addition, the setup cost for invasive Hb level measurement is sometimes a challenge for the small health-care providers. Apart from that, the patients' daily travel cost will aggravate the price statistics regarding the invasive measurement.

For this reason, researchers are interested in adopting noninvasive approaches to measure Hb level. Noninvasive techniques are also applicable to smartphones since it offers many advantages as a noninvasive point-of-care (POC) tools. Smartphone provides benefits like mobility, high-resolution-camera, smart application, network connectivity to health-care providers and so on. Nowadays smartphones are not only ubiquitous in the developed countries but also commonly used in the developing and underdeveloped countries because of its easy-to-use features and availability at reasonable prices.

In the recent past, several researchers have presented their work on advancements in medical image processing. Various imaging techniques are used in the automatic diagnosis of early detection of leukemia from blood microscopic images [1], White Blood Cells (WBCs) segmentation [2], signal and image Processing [3] in medical applications. Again, smartphone-based noninvasive approaches have already proved their capabilities in health monitoring such as heart-rate monitoring, sleep-monitoring, pulmonology, gait detection [5], symptom monitoring system [6], cancer care [7], palliative care [8], eESAS [9] and point-of-care diagnostics. From the outcomes of these systems, it is evident that smartphones can be an excellent candidate for both clinical and remote-health-care platforms.

Based on the insights from these articles, we aim to analyze the fingertip video image for the development of noninvasive hemoglobin measurement. The main contribution of this paper is as follows.

1) Record the fingertip video data as well as clinical Hb level from sickle cell patients who received the blood transfusion.
2) Analysis of the captured fingertip video and correlate the pixel information with the different level of Hb.
3) Data analysis and comparison of the histogram values, masked RGB image, and regression results based on input feature matrix of red, green and blue pixels.

II. MOTIVATION

The commonly adopted invasive Hb measurement techniques are limited to blood sample tests. It takes 3mL of blood for a complete blood count (CBC) which offers information regarding red blood cells(RBC), white blood cells (WBC), and platelets. The mixture of blood and chemical agent changes solutions density proportionally to the Hb concentration. After that, it is optically measured to obtain the required Hb level assessment. Nowadays, invasive POC tools are used rather than the time-consuming CBC tests. The hemocue device, a commonly used POC tool, requires a small drop of blood. Then, blood sample and chemical reagents are mixed on a test panel to determine the Hb level within a minute. This method exhibits a rank order of 0.89 at

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a mean accuracy of 0.5 g/dL while compared to the results from the CBC test [15], [16].

Conventionally, hyperspectral cameras are also used to measure Hb level in a noninvasive way. Though it is evident from several research articles, hyperspectral camera-based measurement shows significant accuracy; the hyperspectral cameras are costly to adopt in the local health-care centers even in the developed countries. In resource-poor and developing countries, it is quite impossible to take this noninvasive tool because of the expense of the hyperspectral camera. Besides, they are not handy-to-use. Hence they cannot be applied in the remote-health-care-setup. Spectrometers are also used by the researchers and health-care professionals to measure the Hb level noninvasively. Although these research approaches cut the tool-cost of the noninvasive measurement, the cutback is not significant, and its still expensive for the resource-poor settings.

To overcome the challenges of expense and mobility, in this paper, we analyze the RGB pixel intensities of fingertip video image to correlate clinical Hb level to develop a noninvasive Hb measurement system. Since the smartphones are ubiquitous around the world including the resource-limited countries and these are mobile, per se, this smartphone-based device can meet the challenges mentioned above. The tool can be adopted at a reasonable cost and can be applicable in remote-setups. Besides that, like other smartphone apps, this tool is easy-to-use and can be used in person. In addition, it offers network connectivity that assures necessary analysis as well as measurement results. Many health care centers, as well as different individuals, use this tool as a POC tool.

Some approaches have been adopted around the world to implement the noninvasive technique in the case of measurement and diagnosis. External LED light was used as supplemental hardware in addition to the smartphone for hemoglobin level measurement [17]. In [18], Jeff Thomson proposed an attachment that mechanically couples a stethoscope. These tools are headed to a 3D printed attachment which leads the regarding sound to the smartphones microphone. In [19], Hongying Zhu, and Aydogan Ozcan proposed an optics system that initially illuminates a flow cytometer test strip. Then, to conduct point-of-care blood tests, it can be attached to a smartphone camera. Here, the optics system is dedicated to light up the strip with the required wavelength, then the necessary chemical reaction to tie up the proteins and the compounds of interest in the blood specimen comes out from the test strip. In this occasion, the smartphone-camera functions as a sensor. One of the advantages of this system involves using attachments that can be tailored to specific tasks such as mechanical amplification, illumination, chemical reaction.

In all of these approaches, the proposed models face several limitations. For example, LED lights might be misplaced from patients finger. Test strips have an expiration date, and the optical system can show aberrant behavior after a couple of months. In this situation, smartphone-based non-invasive techniques is an appreciable alternative.

The organization of the paper is as follows. There are a couple of noninvasive hemoglobin measurement techniques illustrated in Section III. RGB histogram, patient information, data collection system, video processing, feature matrix creation, data analysis are described in Section IV. The result of the analyzed data is presented and discussed in Section V. Then, the conclusion is given finally in Section VI.

III. Related Works

Noninvasive hemoglobin measurement techniques are available in various ways. M. Rajendra Kumar et al. from IIT Kharagpur, India developed a useful method to predict hemoglobin levels for resource-poor setups in [27]. Here, the author captured an image of a blood drop using a filter strip under controlled conditions. Then, the Hb level is measured using image processing algorithm where a classification tree and correlation-based approach were used. They classify four levels of Hb (Class I-Hb above 12 g/dl, Class II-Hb between 10 and 12, Class III-Hb between 8 and 10, Class IV-Hb below 8) while analyzing the data. After that, the properties selected from the classification tree were used to train an artificial neural network. Here, they obtained a desirable confusion matrix on the testing set with an overall accuracy of 82%, sensitivity of 83%, and specificity of 82%.

In [28], Ali Madooei et al. presented a pilot study to detect and grade skin Erythema. In this paper, they conducted the experiment to demonstrate the efficiency of their approaches in reproducing clinical assessments as well as outperforming RGB imaging data. In [10], Jarrel Seah, and Jennifer Tang worked on a project named Eyenaemia.' Here, a color calibration card is set next to the eyelid of a particular patient. This card evaluates the redness of the underside of their eyelid when flipped over. However, though it can detect the risk of anemia, Eyenaemia cannot measure the actual concentration of hemoglobin. In [29], using color value of a video image, video-based bio-signal measurements, such as pulse rate, oxygen saturation, respiration rate, and blood pressure, have been proposed for the mobile-based health-care system by Hyo-Haeng Lee et al. This measurement method can estimate the information apropos of user's health status without any usage of sensor attachment. Then, in [30], Khalid M. Alabdulwahhab et al. developed an image processing-based tool for noninvasive measurement of bilirubin level. This tool is implemented by analyzing conjunctival images those imitate the blood level of bilirubin by calculating the intensity of yellow color. Besides that, machine learning techniques are applied here to develop the system capable of accurately predicting the bilirubin level of the patients. In [31], Vitoantonio Bevilacqua et al. proposed a novel non-invasive approach to estimate hemoglobin level majorly based on image analysis of a particular conjunctival region. Besides the illustration of the prototype of this tool, it includes the test result on 77 anemic and healthy patients that show significant correlation between the hemoglobin value from invasive samplings and the value predicted by their algorithm. In [20], Mathew J. Gregoski et al. developed an android application and compared the heart-rates acquired from a Motorola-Droid to ECG and Nonin 9560BT pulse

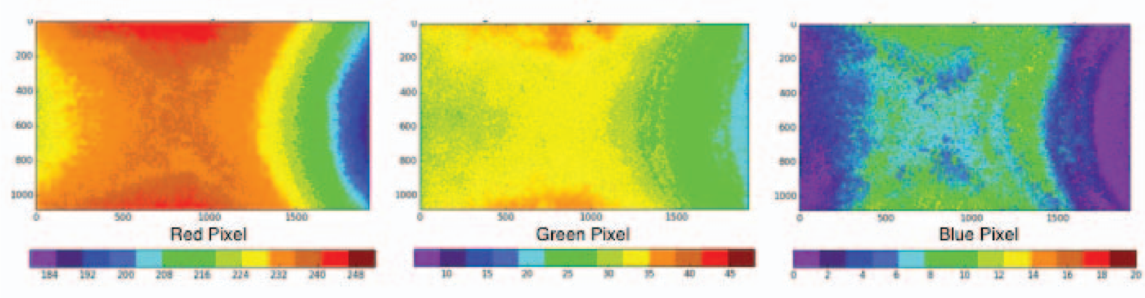

Fig. 1. Red, green and blue pixel intensity of a single frame are presented separately.

oximeter readings for the occasion of various movement-free tasks. Then, in [21], [22], Walter Karlen et al. from the University of British Columbia-Vancouver delineated a novel technique to automatically detect the optimal ROI (Region of Interest) for the image captured by phone-camera to extract a pulse waveform. Here, from an extensive study, this paper suggested an optimal camera settings. From their experiments, it is evident that the incandescent white balance mode is the preferable setting for camera-oximetry-applications on the tested mobile phone such as Samsung Galaxy Ace.

Besides that, several research projects have also explored the implementation of smartphone-cameras. In [11], Christopher G. Scully et al. stated that a mobile phone could serve as an accurate monitor for several physiological variables, based on its ability to record and analyze the varying color signals of a fingertip placed in contact with its optical sensor. In this course, they validated the accuracy of the regarding measurements of breathing-rate, cardiac R-R intervals, and blood oxygen saturation by comparisons to standard methods for making such measurements such as ECGs, respiration belts, and pulse-oximeters. In 2010-2011, Alam et al. have- through optical measurement of the blood at fingertip- developed a finger probe with 6 LEDs for noninvasive measurement of the hemoglobin concentration [12], [13]. It covers multiple wavelengths in the red to IR spectrum (630, 660, 680, 770, 880, and 1300 nm) to measure hemoglobin to water ratio (H/W) in blood plasma. In [14], using three LED (670, 810, 1300 nm) finger probe, Kraitl et al. found similar results after conducting an extensive study on 41 subjects.

Since the existing methods have cost issue due to external devices like LED, optical instruments, and additional sensing devices, in this paper, we aim to analyze the fingertip image data and make a relationship with the clinical Hb value as an alternative approach to mitigate those issues.

IV. System Architecture

Every image has three basic color components named as red, green and blue (RGB). Among all other color spaces, RGB is the most frequently used color space by the researchers due to its simplicity and easy-to-implement approaches. But, it is nonlinear with visual perception and device dependent. Besides that, its color specification is semi-intuitive. A sample fingertip image is presented by its red, green and blue pixels' color map in Figure 1. Here, we observe that red pixel intensity with value 232 is more in the first image. Again, the green pixel intensity from 25 to 35 is mostly available in the second image. In the third picture, we can see that the blue pixel intensities from 6 to 10 are highly spread over it.

A. Histogram based on RGB pixel

To get the internal pixel intensity distribution, the pixel information of an image can be presented as a histogram. We present a fingertip video recording process in Figure 2. The index finger is put on the smartphone camera where the flash light is on, and the reddish fingertip is visible on the smartphone screen in Figure 2. We consider sickle cell patients who have the low level of Hb before the blood transfusion and high level of hemoglobin after the blood transfusion. In Figure 3, we have shown RGB intensity histogram for two different (before and after blood transfusion) fingertip image of the same person. In Figure 3, the bottom image is collected when the patient has a low level of hemoglobin, and the top image is recorded when the same person has the high level of hemoglobin.

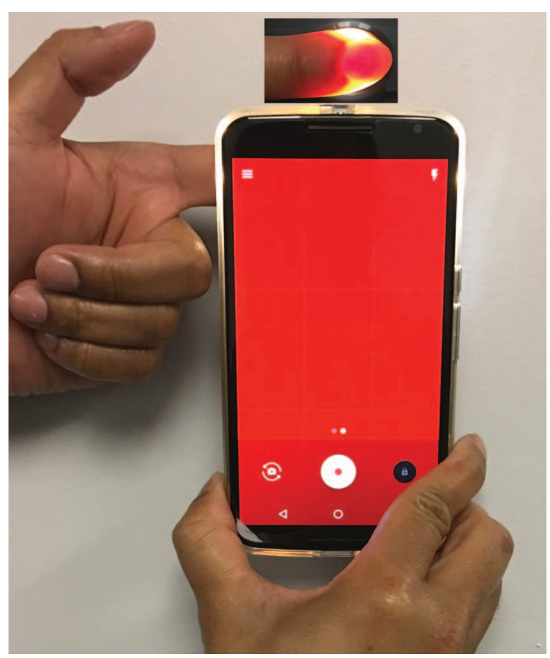

Fig. 2. Fingertip video recording system.

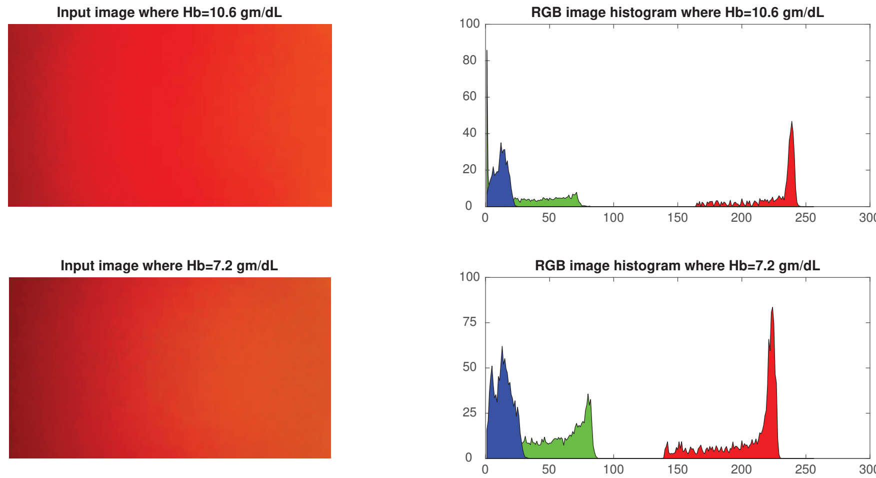

Fig. 3. Different level of hemoglobin shows RGB variations for the same person's fingertip image.

B. Patient information

We have considered five sickle cell patients of the Medical College of Wisconsin (MCW). They needed blood transfusion due to their physical conditions. A research coordinator (RC) in the MCW helped us to collect the fingertip video and clinical Hb report of those patients. These five patients provided fingertip video data before their blood sample collection. Afterwards, the blood transfusion was done. Similarly, these same patients came to the MCW after two weeks of blood transfusion. Then the RC recorded the fingertip video as well as clinical Hb report of those patients. Since this is the first data collection to figure out the relationship between RGB pixel intensity and the hemoglobin level, we didn't record the age, gender and other information of this patient. We recommended collecting three fingertip video of each subject by the same smartphone before their blood sample collection because there was a possibility of getting faulty video. Since five subjects were used, 30 fingertip videos were recorded. Out of the 30 videos, 15 videos were recorded before the blood transfusion, and rest of the videos were collected after the blood transfusion. The clinically measured hemoglobin level is mentioned as gold standard hemoglobin level in the following sections. We have treated thirty received sample fingertip video and respective hemoglobin level as thirty observations in our data analysis.

C. Video capturing procedures

The steps of smartphone-based fingertip video recording and frame extraction techniques are presented in Figure 4. There are a couple of steps to collect the sample data and calculate the correlation level with clinical Hb. The first step is video data collection from the patient. Having the IRB of Blood Center of Wisconsin, the patient's consent was taken. Later, the fingertip videos and blood samples were collected one after another.

The fingertip video samples were collected by Google Nexus 4 smartphone. We recommended a couple of directions while recording the fingertip video. First, we suggest to record the fingertip video before blood sample collection and to use the index finger for video recording. Second, we ask to cover the smartphone camera as well as flash properly so that no ambient light can penetrate as shown in Figure 2. Third, we recommend to turn on the smartphone camera flash while video recording as illustrated in Figure 2 and record a 10-second video. Fourth, keep a record of the name of video file against the clinical Hb report. And finally, collect blood sample with in one hour of video recording.

D. Fingertip video processing

In general, a smartphone captures 30 frames per second (fps) of a video. Thus a 10-second video consists of 300 frames are considered as the main data source in this research. Before color intensity analysis, we checked each video playing one by one. We observed that nearly the first 50 frames contained mostly noise (black/very dark area) for 35% of the total number of videos. We found this type of issue not only in the first image sequence of the video but also in the last section of the frame sequence. To overcome this scenario, we decided to consider frames from 101-200 to create our feature matrix. So we calculated histogram values of each frame having the frame number from 101 to 200. We averaged them to make one observation which defined as input feature vector. Since we created red, green and blue color histogram values, we generated three feature vectors from one video. The video and images are processed in Python OpenCV, Matlab, and R.

E. Creating input feature matrix

We found three feature vectors R, G, and B per fingertip video data. Each feature vector contains 256 histogram values since the pixel intensities are from 0 to 255. Note that, the input feature vector is the average of 100 histogram

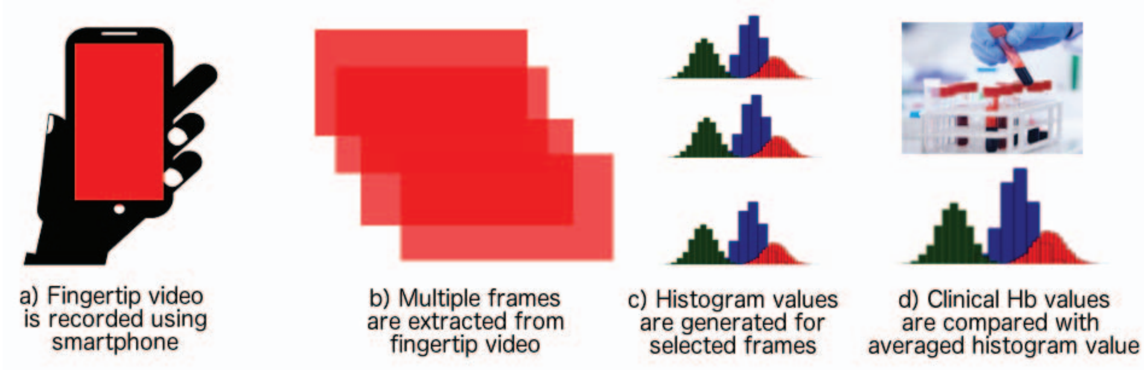

Fig. 4. Flowchart of data collection, feature extraction and analysis.

values of three R, G, and B colors. Here, the dimension of each R, G, and B color pixel vector is 1×256. If we consider all three R, G, and B colors, then the length of the input feature vector of one video will be $3 \times 256 = 768$. Therefore, we get an input feature vector of size 1×768 combining the three histogram values of R, G, and B. We generate a feature matrix with the dimension of 30×768 from 30 observations of the MCW.

Here we present the data extraction and analysis flow for each video step by step. First, we extract the red, green, and blue (RGB) pixel intensities of 100 image frame. Then, we generate 100 histogram values for each R, G, and B color for each video. Later, we make the average of 100 R, G, and B color frequencies. Second, we consider averaged R, G, and B histogram values of videos as a feature vector. Since we have 30 observation videos, we create one input feature matrix with the dimension of 30×768 from the MCW data. Third, we name the input feature matrix as X (later mentioned as predictor matrix X). The clinical hemoglobin levels are stored in Y matrix is also known as response matrix Y. This clinical hemoglobin data are considered as gold standard Hb data, and the matrix has the dimension of 30×1.

We standardize each input matrix before data analysis. In this case, each column of X is centered on having mean 0 and scaled to have the standard deviation of 1. Then, we apply linear regression, and PLS algorithm on the input feature matrices are generated. We apply 10-fold cross validation and 2 PLS components in the data set.

F. Relation between fingertip video image and hemoglobin level

In this research, we explored the video image captured by smartphone to identify a relationship with an important biomarker of human body called hemoglobin. Here we present the basic relationship between the level of hemoglobin and the pixel intensity of fingertip video image captured by the smartphone.

We have mentioned already that we investigate the hemoglobin level as well as fingertip video of a special group of sickle cell patients who received the blood transfusion. We consider one subject from this group named as Sub-A with Hb level 7.2 gm/dL before blood transfusion. The Hb quantity of this Sub-A raised to 10.5 gm/dL after blood transfusion. The RGB image histogram of these both periods are presented in Figure 3. In Figure 3, the fingertip image and respective frequency of red, green and blue pixel intensities are illustrated. The RGB color intensity of fingertip video image for the lower level of hemoglobin has more frequency than that of the higher level of Hb as shown in Figure 3. From the change of pixel frequency, we can understand that there is a good relationship between hemoglobin level and a number of RGB pixels in the fingertip image.

We have analyzed the same video image of Sub-A using image mask. We have used a mask based on the green threshold. In Figure 5, the regular fingertip image, respective mask and masked RGB images are shown. Here we observe that mask image (mid column) has a black pixel for the lower level of Hb than that of a higher level of Hb. The similar effect is also presented in the third column of an image set in Figure 5. In Figure 3 and Figure 5, we notice that the pixel frequency is nearly double for lower level Hb with respect to higher level of Hb. In light of the evidence from the color difference of these two frames, we can presume a strong intuitive relationship between hemoglobin level and video image pixels. This strong relationship motivates us to go forward for noninvasive hemoglobin level prediction using smartphone camera video image.

We create two classes of hemoglobin level named as low (L) group and high (H) group. We include the Hb level of 7.2, 7.5, 8.7 and 9.5 gm/dL in L-group and 10.0, 10.1, 10.3, 10.4, 10.6 and 11.6 gm/dL in H-group. We have used linear regression on the input feature matrix created by the RGB histogram of fingertip image. Again we have also applied the partial least squares (PLS) algorithm on the same input feature matrix created by 30 observations.

V. Result and Analysis

We have applied linear regression using Matlab command `fitlm` on the feature matrix. Due to the small data set, we use 30 observations for training the model [25]. 30% random observations of total data set are treated as a testing set. We choose three random observations out of 30 subjects' data and test 10 times using the model. Based on our classification, 30 random test data are presented as a confusion matrix.

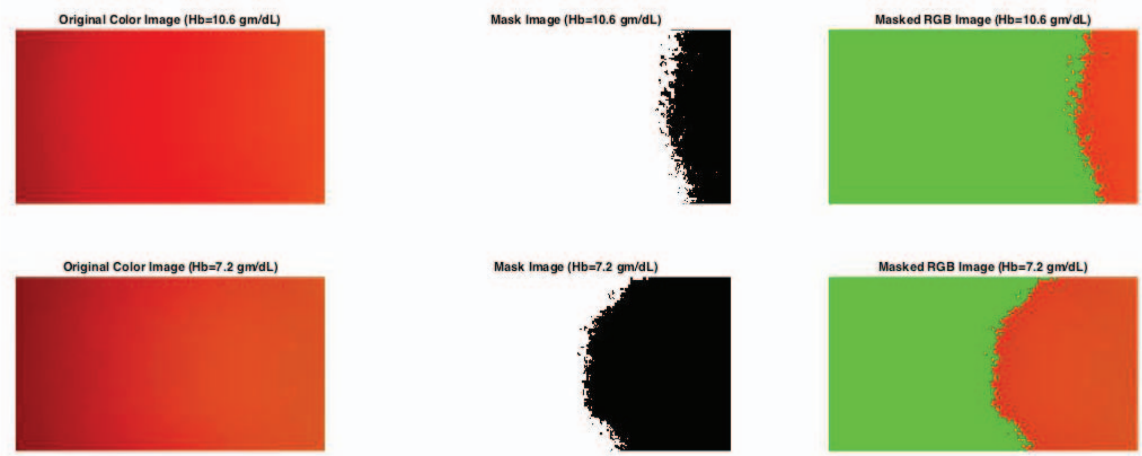

Fig. 5. Masked image of fingertip video for the same person's different level of hemglobin.

The confusion matrix is given below where 11 observations are perfectly identified as L-group subjects. Again, 19 sample data are recognized as H-group observations accurately as shown in the confusion matrix.

	L-group	H-group
L-group	11	0
H-group	0	19

Furthermore, we use PLS algorithm using the Matlab command `plsregress` to test the relationship between image RGB pixels and Hb level using the PLS model. We use only 2 PLS components to generate the prediction model. Since cross-validation (CV) evaluates the predictive ability of potential models, we use 10-fold CV for our predictive model. We have used the input feature matrix X with 30 observations to train the model. We take 30% random subjects randomly as a test set from this total data set. We apply the PLS regression ten times on the 30% random subjects. We store those ten results and average finally.

In PLS regression, the R^2 test is accomplished to identify how well the PLS regression model can predict an experimental data. Besides, it represents the proportion of variation in the responses which can be predicted by the original model. Since we are predicting only hemoglobin component, a higher R^2 value is significant. We found ten R^2 value as follows: 0.94, 0.84, 0.89, 0.82, 0.90, 0.89, 0.87, 0.87, 0.84, and 0.81. We got average R^2= 0.87 for 5 users' 30 observations with 2 PLS components.

The main goal of this research is to validate the relationship between the RGB image and hemoglobin level of the respective finger. Since the sickle cell patients came to the MCW with the lower level of Hb, they received the blood transfusion. This patient group has been very significant in meeting our research objectives in spite of the small size. Since we get two different level of Hb, these fingertip image data have potential information to correlate with Hb. For example, the frequency of RGB pixel of a finger image shown as a histogram in Figure 3 gives an important hint about the linear relationship. As shown in Figure 5, the visual information reveal the unique distribution of pixels, which are not obvious from the RGB image (first column). Both illustrations presented in Figure 3 and Figure 5 shows the linear regression between Hb level and fingertip image pixel distribution.

With this in mind, we apply linear regression on 30 observations where the training and testing sets are defined. We observe reliable performance from the confusion matrix where the test data set are selected randomly. Furthermore, R^2 value is found 0.87 which is also a significant statistical measure using only 2 PLS components.This numerical evaluation supports the feasibility that there is a strong correlation between the fingertip image pixels and the Hb level.

VI. CONCLUSIONS

In this article, we aim to present our research findings by comparing clinical Hb measurement data with the pixels information of fingertip image. We use the smartphone camera as our primary tool to record finger images. We correlate the image pixels to the clinical Hb data. In the process, we demonstrate that the pixel information of the image is changing with the variation in a patient's hemoglobin level. We analyze the data using both linear regression and PLS applying on the input feature matrix. We found that the output of confusion matrix and goodness-of-fit method show a significant correlation between image pixels and Hb level, which is very promising result for our research. Our current data set is small and comprised of only five sickle cell patients. However, we intend to add more subjects as well as explore a few other techniques concerning fingertip video image analysis and generation to strengthen our research findings. For example, analysis the RGB image in different color space and make a robust model for human Hb measurement. Our primary aim is to make our method user-friendly, cost-effective, accurate; and eventually smarter. We anticipate that the smartphone camera will be used as the tool of data collection and the mobile app will be chosen for result presentation.

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