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Automated ABO Rh-D Blood Type Detection using Smartphone Imaging for Point-of-Care Medical Diagnostics

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Abstract— We present a novel methodology for automated ABO Rh-D blood typing using simple morphological image processing algorithms to be used in conjunction with a fabric strip based rapid diagnostic test. Images of the fabric strip post testing are acquired using low cost mobile phones and the proposed algorithm proceeds to automatically identify the blood type by processing the images using steps comprising of noise reduction, range filtering and empirically derived heuristics. The ultimate goal is to provide a simple mobile phone application to enable automated, rapid and accessible blood type detection at the point-of-care.

I. INTRODUCTION

Blood typing is crucial before a blood transfusion to prevent the risk of receiving incompatible blood. It is also important for correct classification and banking of blood from donors as well as to determine compatibility between a pregnant woman and her developing baby. Blood typing is typically done in a laboratory by trained technicians who test for red blood cell agglutination against A, B and Rh antibodies. There are also several use cases where blood typing may be needed at the point-of-care (PoC) such as public health centers, battle field, schools, veterinary care centers and forensic sites. Perhaps, the most telling need is in rural areas of developing countries where access to labs and trained technicians is simply not present. While there exist PoC solutions from companies such as Micronics, Eldon Biologics and a few others, these are prohibitively expensive (ranging from \$10-20 per test) for large scale use in developing countries. Notable new solutions that may cost a dollar or less are being developed by Haemokinesis Pty. Ltd. [1],[2] and Achira Labs [3].

The gap between blood donation and need is massive in developing countries. For example, by some estimates, in India, 50 Million units of blood are needed yearly as against only 0.8 Million units being donated [4]. Companies such as SocialBlood (www.socialblood.com) are leveraging the power of Facebook for recipients to quickly find blood donors in local neighborhoods, create an accessible bank of donors and ease the process of donation. However, with a large percentage of people not knowing their blood types, the inertia to first go to a lab to determine blood type significantly reduces the number of people who come forward to donate blood. Low cost, rapid, at-home PoC blood

type testing can become a significant catalyst to overcome this hurdle and convert more people into blood donors.

In this paper, we present a solution based on simple morphological image processing to be used in conjunction with the low-cost silk yarn based fabric test strips developed by Achira Labs [3] for blood type testing. With our ultimate goal being to develop this into a mobile application, at-home and rural PoC blood type testing can be enabled at low cost and scale.

II. METHODS & MEASUREMENTS

A. The Fabric Strip Based Diagnostic Tester

Silk fabric is spotted with reagents for A, B and Rh antibodies and blocked. Wax-printed circles of 25 mm outer diameter and 20 mm inner diameter are printed such that the reagents are restricted to the inner zone of the circles. The fabric is backed on medical-grade adhesive and cut into individual strips for use (see Figure 1) [3].

B. Testing of whole blood samples

At the point-of-care, a droplet of water is placed on the colored part at the center of each circle and then a drop of 2-3 μL blood from the finger of the patient is added to the water and mixed for 10 seconds. Depending on the blood type, agglutination occurs within the circle if that specific antibody is present in the patient's blood (see Figure 2). If agglutination occurs in the Control circle, then the strip is faulty and testing needs to be repeated.

C. Test Samples & Image Acquisition

Four test participants T1, T2, T3 and T4 with blood types O+, O-, AB+ and B+ respectively volunteered for the test. Images were captured for each with ten different Android phones (Table I) representative of phones in use in emerging markets. The images were acquired by taking photographs of the strips such that all 4 circles of each strip were in one field-of-view. The experimental procedure involving these four human subjects was done in accordance with the Helsinki Declaration of 1975, as revised in 2000 [5]. Informed consent has been obtained from all of them.

D. Image Processing

The acquired image strip was further processed to extract the inscribed squares (A*, B*, Rh* and C* – see Figure 2) within each circle to exclude fabric strip without any tested blood in it. This extraction was done manually using Matlab Student version R2015b. The image processing tool box was also used for developing and testing the algorithms. A combination of median filtering and range order filtering along with empirical heuristics are used for the blood type detection as described in detail in Section IV.

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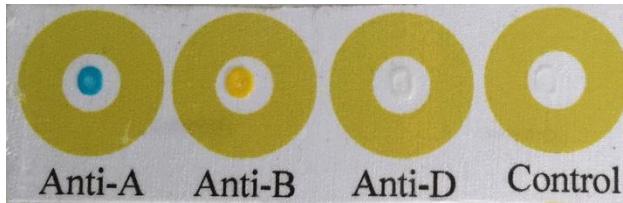


Figure 1: Fabric based test strips. At the center of each yellow circle, silk yarn coated with antibodies corresponding to A, B and Rh are present. The Control circle does not have any antibodies present at its center.



Figure 2: Fabric test strip showing agglutination of blood for participant T3 with blood type AB+. Note that agglutination is present in the first three circles while the control remains un-agglutinated. Also shown is the inscribed square image A^* described in Section II.D.

Table I: Phone models & respective camera resolutions used in imaging

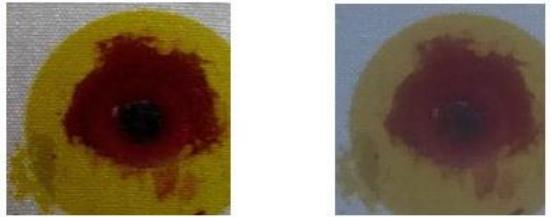
Phone Model	Camera
Lenovo S 660	8 MP
Nexus 6	13 MP
LGE LS 980	13 MP
Xiaomi Redmi 1S	8 MP
Lava iris 504Q	8 MP
HTC One E8	13 MP
Xolo Q1000 Opus	5 MP
Samsung Galaxy S 4	13 MP
Moto G	5 MP
Sony Xperia T2 Ultra Dual	13 MP

III. PROBLEM FORMULATION

The primary problem considered in this paper is the use of image processing techniques to determine the ABO Rh-D blood group of a patient from images of fabric based blood typing test strips captured on low cost mobile phones. The goal of the algorithms is to detect agglutination or lack thereof and identify the blood type of the person being tested. For example, with reference to Figure 2, the goal is to identify that agglutination has occurred in the circles corresponding to antibodies A, B and Rh in the tested strip and output the correct blood type as AB+.

Automated detection is complicated by field conditions of image capture - from the type of mobile phone and its associated camera quality, to lighting conditions, manufacturing variations of the fabric strip and whether the testing personnel use the strip in the proper manner. Figure 3 shows some variations for capture of the same portion of image using two different phone models under different lighting conditions.

Additional complications arise if the personnel do not capture the image with the phone camera being parallel to the tested strip without any pan and tilt. These latter issues are



(a)

(b)

Figure 3: Differences in texture and color of the tested fabric strips arising from capture using different mobile devices and lighting conditions. Note that image in (a) has much higher texture “noise” than the one in (b). Also note the variability in manufacturing quality with bleed of yellow wax as seen in the bottom left of both images.

not considered in this paper; we will be addressing this in the future by providing automated guidance to the field personnel when capturing the images (by having circular markers on the home screen of the mobile phone application and guiding the personnel to align these markers with the circles on the strip thereby avoiding any skewing in the capture).

IV. PROPOSED ALGORITHM

In designing the algorithm, our basic principle was to use the simplest techniques that could solve the problem with as low a computational complexity as possible. We fine-tuned the algorithms using a total of 10 samples (images captured using 5 phone models for each of 2 of the test participants T1 and T3) and tested the accuracy on the remaining 30 samples.

The proposed algorithm involves the stages described below:

A. Median Filter to remove noise:

As the captured images contain varying levels of fabric texture noise (see Figure 3), it is necessary to pre-process the images to reduce this noise. Given that the fabric texture noise has “granular” characteristics, we found that a 2 dimensional median filter provides adequate noise reduction [6]. This filter serves the purpose of removing a majority of fabric noise, while largely preserving features (see Figure 4). The size of the window used for the median filter was empirically determined to be a 7-by-7-pixel neighborhood. Let us denote the median filtered images as A^{mf} , B^{mf} , Rh^{mf} and C^{mf} .

B. Application of Range Filter and Choosing a Color Channel for further processing:

Since agglutination exhibits as “clumping” as compared to a “smoother” spread of blood when non-agglutinated, we investigated morphological filters to determine if agglutinated images appear “busier”. We experimented with morphological top hat filtering and range order filtering [6][7][8]. For our specific case, range filtering yielded better results by being able to enhance and extract features in agglutinated images as compared to non-agglutinated ones with more precision than top hat filtering.

Each color channel red (α), green (γ) and blue (β) across each of the four A^{mf} , B^{mf} , Rh^{mf} and C^{mf} images were range filtered with a flat structuring element of a 5×5 pixel



(a)



(b)

Figure 4: Top left portion of unfiltered image from test subject T1 in (a) versus 7 x 7 neighborhood median filtered image in (b) captured using Lava phone in Table I.

neighborhood. The filter output for every pixel is therefore the difference between the maximum and minimum values within its 5 x 5 neighborhood. Figure 5 shows the blue color channel of the range filtered images for test subject T1 with blood type O+. Range filtered images are referred in this paper by a notation of $Rf(A^{mf}(\alpha))$ - which denotes the range filtered image of the red channel of the A^{mf} image. Post range filtering, the standard deviation of each color channel across all four filtered images is found. The standard deviations are denoted as $\sigma_{Rf(A^{mf}(\alpha))}$ which is the standard deviation of the range filtered red channel of the median filtered A^* image. For simplification of notation, we shall denote this as $\sigma_{a(\alpha)}$. Reiterating, the notation is:

$\sigma_{i(\lambda)}$ = the standard deviation of λ color channel of image i where $\lambda = \alpha$ (red), γ (green) or β (blue) and i = a,b, rh or c denoting one of range filtered A^{mf} , B^{mf} , Rh^{mf} and C^{mf} images respectively

For the final step of determining the agglutination (and therefore the blood type), we use information from only one color channel of each image. The choice of color channel (λ) is chosen as the color channel in the range filtered Control image $Rf(C^{mf})$ with the minimum standard deviation (since the C^* image should not be agglutinated we choose the color channel in this image with the maximum amount of “smoothness”). In this paper, we do not check for whether the strip is faulty by checking for agglutination in the Control image – this is a topic of future research. The choice of color channel therefore is:

$$\lambda \equiv j \text{ for } j \text{ such that } \sigma_{c(j)} = \min(\sigma_{c(\alpha)}, \sigma_{c(\gamma)}, \sigma_{c(\beta)}) \quad (1)$$

C. Final Blood Type Determination:

To arrive at the blood type, we compare the four standard deviations $\sigma_{a(\lambda)}$, $\sigma_{b(\lambda)}$, $\sigma_{rh(\lambda)}$, and $\sigma_{c(\lambda)}$ (λ obtained from Equation (1)) and make a determination using empirically derived heuristics. Let:

$$\delta_{\{a,b,rh\}} = |(\sigma_{\{a,b,rh\}(\lambda)} - \sigma_{c(\lambda)})| / \sigma_{c(\lambda)} \times 100 \quad (2)$$

Table II: Percentage deviation of the $\sigma_{a(\lambda)}$, $\sigma_{b(\lambda)}$, $\sigma_{rh(\lambda)}$ against $\sigma_{c(\lambda)}$ for Test Subjects T1 and T3 with blood types O+ and AB+ respectively

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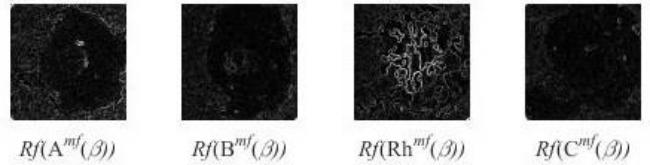


Figure 5: Range filtered images of test subject T1 for blue color channel. Original image was captured using an HTC phone (see Table I). Notice how the Rh image is busy while the A and B are much less so clearly indicating blood type O+.

i.e., each of the δ s is the % deviation of the respective $\sigma_{a(\lambda)}$, $\sigma_{b(\lambda)}$, $\sigma_{rh(\lambda)}$ from that of the control $\sigma_{c(\lambda)}$). Table II shows the δ s for test subjects T1 and T3 for images captured with five phone models each.

Based on some testing, we have come up with the following empirical heuristics:

1. If $\max(\delta_a, \delta_b, \delta_{rh}) < 40\%$, then blood type is O-.
2. Else, let $\delta_{\max} = \max(\delta_a, \delta_b, \delta_{rh})$. If $\delta_{\{a, b, rh\}} > 0.33 * \delta_{\max}$ then the patient's blood contains that particular antigen and the result is accordingly given as output.

V. RESULTS AND DISCUSSION

The blood type could potentially be manually read based on the agglutination or absence thereof within each circle of the tested strip. However, given that in rural areas of emerging markets, untrained personnel could be supporting physicians and technicians, the aim of this research is to provide a simple mobile phone application to enable rapid blood type detection. This would also be beneficial for in-home use. To this end, this paper focusses on simple morphological image processing techniques to detect the blood type automatically. Table III shows the results from the algorithms developed in this paper. An analysis of the 40 images reveals a significant amount of variations across the captured images – color contrasts, image focus, fabric noise and inherent “bleed” in Table III: Results from the algorithms across 40 samples. 10 samples were used to derive empirical heuristics to determine the algorithms while the remaining were used for testing the heuristics

Subject	T1	T2	T3	T4
Blood Type (Lab Test)	O+	B+	O-	AB+
Phone Model	Blood Type Determined Via Our Algorithms			
Lenovo S 660	O+	B+	O-	AB+
Nexus 6	O+	B+	O-	AB+
LGE LS 980	O+	B+	O-	AB+
Xiaomi Redmi 1S	O+	B+	O-	AB+
Lava iris 504Q	O+	B+	O-	AB-
HTC One E8	O+	B+	O-	AB+
Xolo Q1000 Opus	O+	B+	O-	AB+
Samsung Galaxy S 4	O+	B+	O-	AB+
Moto G	O+	B+	O-	AB-

Sony Xperia T2 Ultra Dual	O+	B+	O-	O-
% Correct Detection	100%	100%	100%	70%
Aggregate Correct Detection	93%			



Figure 6: “Ridges” in Control image leading to high standard deviation of range filtered image and consequent mis-classification

the test strips due to manufacturing inefficiencies. Nevertheless, the algorithms outlined in this paper were able to classify the blood type with reasonable accuracy. 37 of the 40 samples were correctly detected (an aggregate correct detection percentage of 93%).

In 2 of the 3 cases where the proposed algorithms incorrectly classified the blood type, the key factor turned out to be that the Control image C* had a significant number of “ridges” (see Figure 6) caused due to the coagulation of blood in the control portion of the test strip. The former led to the standard deviation $\sigma_{c(\lambda)}$ being high and throwing the rest of the detection algorithm into misclassification. In the 3rd case, the images were well defined, however the algorithms misclassified the AB+ to AB- leading us to conclude that a further fine tuning of the heuristics is required. While the results are encouraging with a high degree of correct classification, a misreading of blood typing can cause significant harm to a patient. We are therefore led to conclude that the proposed methodology needs to be enhanced to throw up an error “when in doubt”, to prevent any serious mishaps in the field, and to encourage the field personnel to repeat the test or perform a manual reading.

Future research will focus on three key areas:

1. Methodology to throw up an error when either the Control strip shows any agglutination or when “in doubt” to ensure zero error in classification.
2. Automatic detection of the optimal neighborhood for median and range filtering as well as for the thresholds for detection described in Section IV.C. For instance, the size of the median filter could be a function of the area of detected yellow circles for each phone model. This would be to calibrate against pixel number differences in sensors. Similarly, the parameters of 40% and 0.33 in Sections IV.C.1 and IV.C.2 can be fine-tuned using a large number of training samples to minimize false detections.

3. Converting the algorithms into an Android application for real world use.

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