Robust and Efficient Approach to Diagnose Sickle Cell Anemia in Blood

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Robust and Efficient Approach to Diagnose Sickle Cell Anemia in Blood

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Abstract. Red Blood Corpuscles (RBCs) form the main cellular component of human blood. RBCs in common physiological status has a circular form in the front view and bi-concave form in side view. In case of a person is infected with anemia RBCs form as sickle-shaped cells which drive to blood vessel obstruction joined by painful episodes and even death. Precise and robust cells classification and counting are essential in evaluating the level of anemia disease danger. The classification and counting of red blood cells (normal and abnormal RBC cells) are challenging due to the complex and heterogeneous shapes and overlapped cells. In this paper, we propose a new robust approach to classify red blood cells to two groups: Normal and Abnormal RBC cells based on area and Eccentricity of each cell, then count the total number of normal and abnormal RBC cells individually. For the sake of comparison, we also implement the latest Sickle cell research, which uses circular Hough transform. We compare our approach to circular Hough transform in the same execution environment. Our new approach sets the state-of-the-art performance in term of effectiveness (cell counting) and efficiency (execution time).

Keywords: Cell counting, Sickle Cell Anemia (SCA), Circular Hough Transform, Eccentricity, Area, Classification.

1 Introduction

Sickle cell anemia is a type of blood disorder. In 2015, there are about 4.4 million people infected with sickle cell disease while an additional 43 million have sickle cell trait (also known as transporter) [1]. It is a genetic disease including an abnormity in the oxygen-carrying protein, hemoglobin, found in red blood cells. This leads to a rigid, sickle-shape cells [1]. Different health problems may develop, such as attacks of pain, anemia, swelling in the hands and feet, bacterial infections and stroke Long-term pain may develop as people get older[2].

Red Blood Corpuscles, also known as Erythrocytes, are the most common in the bloodstream. These scattered cells function as oxygen transporters in our body. Depending on gender and age of the person, the medium volume of red blood cells is approximately 4.8-7.2 million/mm3 for baby, about 3.8–5.5 for child, approx. 4.2-5.0 for woman and approx. 4.6-6.0 for man. The hemoglobin volume is a measurement of RBC in the bloodstream. The major signs of Sickle Cell Anemia (SCA), including tiredness and shortness of breathing, would manifest when the hemoglobin level is very low because insufficient oxygen is provided to tissues of human body [3]. The children are said to be homozygous and will hurt from SCA if their father and mother hold the faulty gene. The baby will get the feature of sickle cell. In case of one parent infected with SCA, the babies will not be the sufferer, but only a transporter.SCA formed as a new crescent and these causes the decrease of the life expectancy to around 42 years old for men and 48 years old for the women [4]. Accurate counting is practically significant in setting the grade of sickle disease risk.Image processing takes the main role in the biomedical studies and analyses of red blood cells. Both image processing and machine learning methods used in variety of biomedical applications such as cells detections, counting, etc [5]. Researchers have used different digital image processing techniques such as edge detection, segmentation, and classification for sickle detection leading to successful outcome [6]. Blood faults may be grouped depending on the characteristics of the cells concerned including the area, shape, area proportion, perimeter, deviation, diameter, central pallor etc [7]. The classification of red blood cells is carried out based on image properties such as colour, shape, and texture. Segmentation technique, features extraction, and detection techniques were implemented to perform a classification of red blood cells and computed number of sickle cells anemia [8]. 12 types of Red blood cells were classified based on feature extraction with the help of decision logic [9]. Back propagation neural network has been applied on extracted features to classify Red blood cells [10]. Sickle cells have been identified by locating the highest, the lowest and average radius of every type of cell by matching it with cell size then cells are labeled by a red circle for recognition. Furthermore, both incomplete and overlapped blood cells on the border are first removed. Then edge detection algorithm extracted only single blood cells [11, 12]. In the recent year, Machine learning algorithms and deep learning approaches have been used to classify red blood cells diseases [15, 16]. These approaches required large amount of data for training while our proposed approach does not required training data which makes it robust.

In this paper, we present the following: (i) we propose a new approach to count the number of normal and abnormal RBC cells based on area and Eccentricity (ii) we implement circular Hough transform segmentation (iii) we compare our proposed approach to circular Hough transform.

2 Methodology

In this section, we first present our new proposed approach based on the computation of area and Eccentricity then the circular Hough transform method has been implemented to count the number of cells.

2.1 The Proposed Approach

We calculate area and eccentricity for every single cell to study their behavior. Based on these measures we can classify between normal and abnormal cells. Fig.1 shows the stages of our new approach.

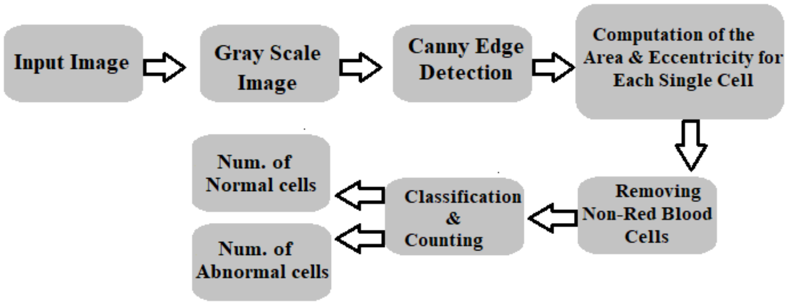

Fig. 1. Stages of the proposed approach

Input image:
The taken images in Fig.2 can be acquired by employing microscopes and glass slides. Image slides of blood are examined under oil immersion. The taken image is formatted to JPEG with excellent resolution. Input image has been adopted from [14] and all other images with ground truth to use them for testing.

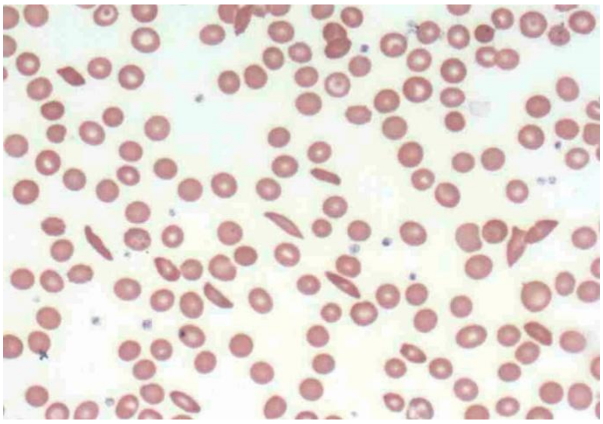

Fig. 2. RGB image of a blood smear

Grayscale:
Converting the color input image to grayscale image in order to have 2-channels image to be handled by the system.
Canny Edge detection:
This Edge detection method has been applied on the grayscale image. It has multi-steps. Starting by smoothing image with a Gaussian then computing the gradient

magnitude using approximations of partial derivatives. Next, non-maxima suppression is applied to the gradient magnitude to thin edges. Lastly, double thresholding has been applied to detect edges.

Computation of the area & Eccentricity:

An accurate cell counting is significant in evaluating the grade of anemia disease risk. Area and Eccentricity have been calculated for every single cell in the smear. The area has been calculated for all objects in the smear. Eccentricity is a measure of how much the cell deviates from being circular, For example, the circular shape is 0, and the parabola is 1 as shown in Fig.3.

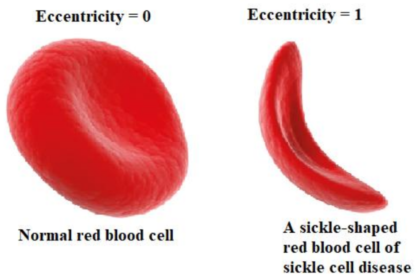

Fig. 3. The difference in eccentricity for normal red blood cell and sickle-shaped red blood cells.

The output values of both area and eccentricity have been prepared for removing small objects and classification processes.

Remove non-red blood cells.

Blood smear has many objects not only red blood cells which lead to false counting results as shown in Fig. 4.

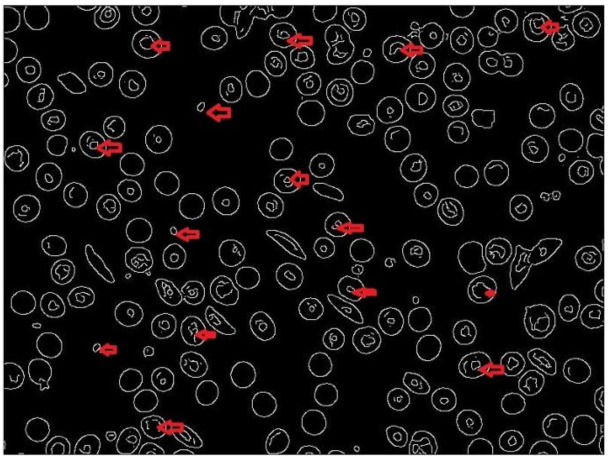

Fig. 4. Blood smear with different objects after Canny edge detection process

Since areas for all objects have been calculated, we found that the values of the area of red blood cells are above 80mm^2 by testing 10 red blood cells images. Therefore, we have applied a threshold (=80mm^2)to remove the small objects which include non-red blood cells as well as make red blood cell smoother by removing inner-radius. All removed objects have an area less than 80 without losing any red blood cell as illustrated in Fig.5.

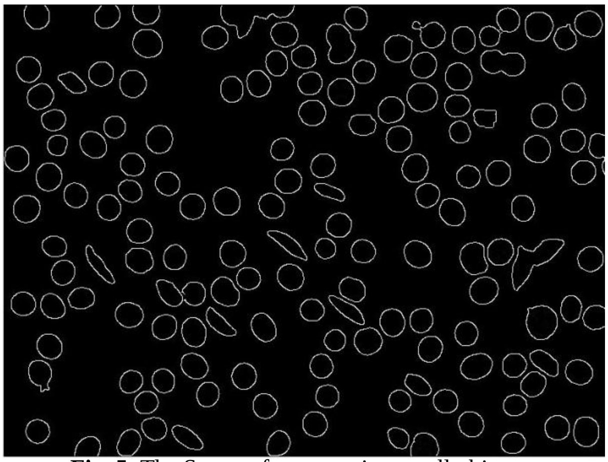

Fig. 5. The Smear after removing small objects.

Counting process.

In order to calculate a number of normal cells and abnormal cells (sickle-shaped cells), a threshold has been applied to the Eccentricity values to classify between them. Cells start to be in sickle shape when the value of Eccentricity is 0.7 and above. The value of Eccentricity is less than 0.7 for normal cells. We have applied the threshold (0.7) to the smear eccentricity values.Table 1 illustrates the difference of eccentricity values. Normal cells have less than 0.7 eccentricities while sickle-shaped cells have (>=0.7).

Table 1. The Difference in eccentricity Values of Normal and Abnormal Cells:

Area	Eccentricity	Type	cells
124	0.2787	Normal	
162	0.9448	Abnormal	
134	0.1948	Normal	

172	0.8760	Abnormal	

As clarified in Table 1, it is clear that normal cells are less than 0.7 and abnormal cells are equal to or more than 0.7.

2.2 Circle Hough Transform (CHT)

CHT is an image processing method used for identifying circular objects in numerous applications. CHT concept is to extract features to identify circular objects. Detecting circular objects in deficient images is the main purpose of CHF. This technique has three main steps listed as follows:

Accumulator Array calculation.
Pixels, which are maximum gradient foreground, are proposed as nominee pixels. They are passed to falling "votes" in the accumulator array. In the execution procedure of circle Hough, the nominee pixels shall vote in a shape around them. This will lead to composing a complete circle of fixed radius.

Center Estimation.
The accumulator array holder accumulates the votes of nominee pixels that be owned by a circle and matches to circle center. Therefore, the centers of the circle are guessed by identifying the peaks in the accumulator array.

Radius Estimation.
The accumulator array has been utilized as a voting container for radius values. The radius values of detected circles must be specified as a separated step [7]. Fig.6 illustrates the process of segmentation for sickle cells anemia using circle Hough, as listed in the following stages:

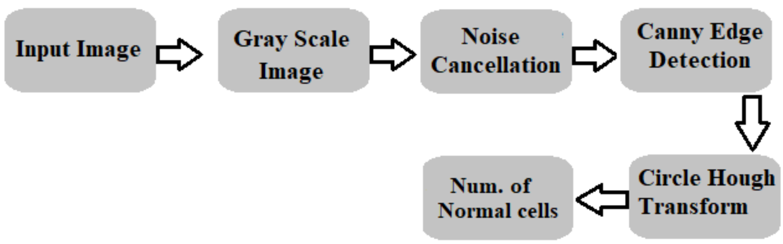

Fig. 6. Stages of counting Process using CHT

Input image, grayscale and canny edge steps are explained as in our new approach above. Noise Cancellation: this step considers as a preprocessing step, which intends to remove unwanted effects such as a non-red blood cells and prepare the image for edge detection process. The gradient calculated by the next equations:

$$g(m,n) = G_\sigma(m,n) * f(m,n) \tag{1}$$

where,

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(- \frac{m^2+n^2}{2\sigma^2} \tag{2}$$

The gradient of G(m,n) is calculated by applying any gradient operators such as Roberts, Sobel, Prewitt or other method to get:

$$M(n,n) = \sqrt{g_m^2(m.n) + g_n^2(m.n)} \tag{3}$$

3 EXPERIMENTAL RESULTS.

This section is presented as follows: (i) results of our proposed approach. (ii) Results of circle Hough Transform. (iii) We compare the results of our proposed approach to that of circle Hough Transform. We have implemented our approach and the Circle Hough Transform using MATLAB R2018a. The Laptop specifications used in this experiment are RAM 16 gigabyte and processor core i7. MATLAB script is utilized to diagnose sickle cell anemia in the bloodstream.

3.1 Results of the Proposed Approach.

We have tested our new approach on one smear by counting a total number of the red blood cell (normal and abnormal). A number of the normal cell has been counted which equals to (=131) as shown in Fig.7 and number of abnormal (sickle-shaped cells) equals to (=13) as displayed in Fig.8. Table 2 reported a concise report of the results of our proposed approach. In addition, the implementation time has been computed based on tic-toc. It is worth to mention that we tested our approach on 20 different images.

Table 2. Number of RBC Using Our Proposed Approach

Total number of cells	Normal cells	Abnormal cells	implementation time in Sec.
144	131	13	0.205836.

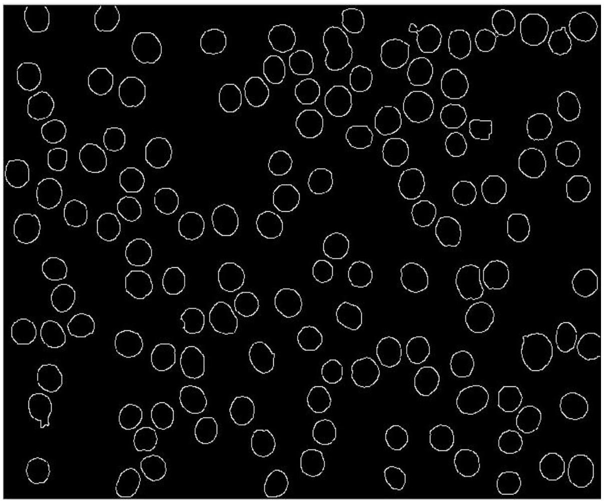

Fig. 7. Proposed approach results of normal cell anemia

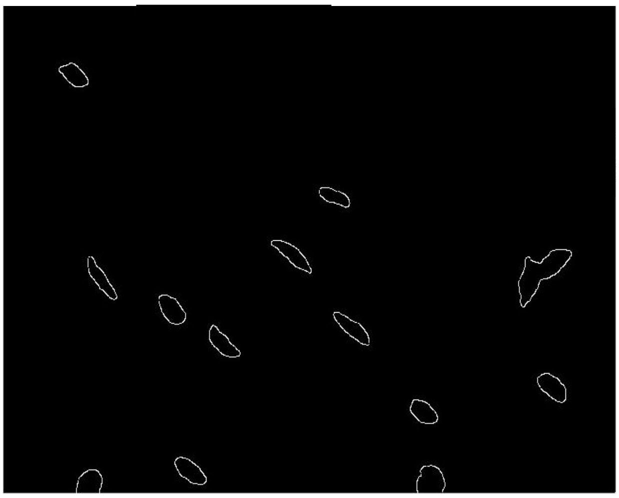

Fig. 8. Proposed approach results in sickle cell anemia slide

We can use Eccentricity of cells to distinguish between red blood cells further to have an accurate cell counting application. For example for, when Eccentricity values of cells are less than 0.3 are normal red blood cells since they are circular. Eccentricity values are larger than 0.3 and less than 0.7 are miscellaneous cells. Eccentricity values are larger than 0.7 then cells are sickle cells anemia.

3.2 Circle Hough Transform

The stages of the CHT for counting the total number of the abnormal cells are identical to those reported in [13] and are conceptually listed as follows: (i) Apply the CHT on the normal slide of red blood cells which is in same size of abnormal RBC smear as shown in Fig.9 then count the total number of the cells which equals to (247).

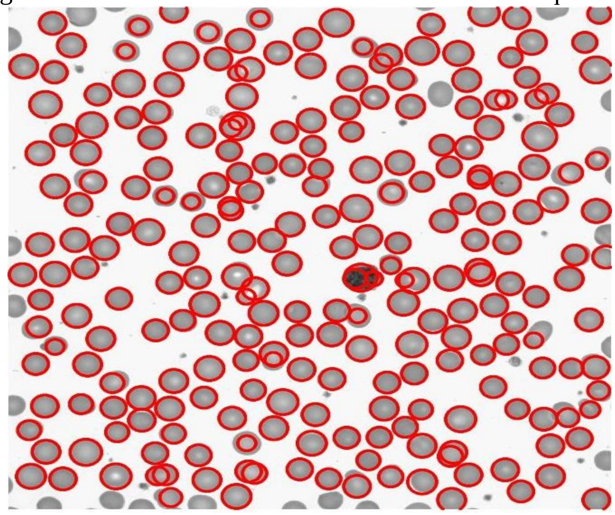

Fig. 9. Results of CHT for normal RBC slide

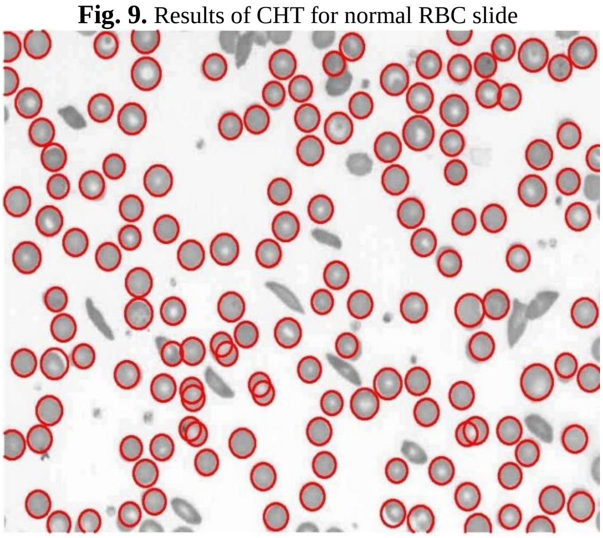

Fig. 10. Results of CHT for sickle cell anemia slide

(ii)Apply the CHT on sickle anemia slide as shown in Fig.10 then count the number of the normal cells, which equals to (139).

(iii) Subtract the total number of normal cells of Sickle cells anemia slide from a total number of normal cells of normal RBC slide. The rest number of total number of normal slide is an approximate total number of abnormal cells, which equals to (108) as reported in Table 3.

Table 3. : Number of RBC Using CHT

Total number of cells	Normal cells	Abnormal cells	implementation time in Sec.
247	139	108	10.810206

Comparison of our new approach to Circle Hough Transform

The Circle Hough Transform has weaknesses listed as follows: (i) The CHT is not functional enough to count abnormal cells in sickle anemia slide. The CHT process is to consider the total number of cells from normal smear slide instead of considering it from sickle anemia smear slide, which produces the approximate number of the abnormal cell, which is far from real number as reported in Table 3. While our proposed approach used sickle anemia smear slide only that means it shows the exact total number of abnormal cells. (ii) CHT detects only circular cells, which lead to losing some cells that are not exactly circular and cells that are sickle shaped cells. In addition, CHT detects circular small objects and count them as normal cells. On the other hand, our approach works based on area and eccentricity means error rate is zero. Furthermore, our approach removes small objects based on the area since the normal and abnormal cells have a larger area than other objects in the smear, which lead to avoid non-red blood cells in counting process. (iii) The elapsed time of the CHT is 10 times longer than our new approach. As result, our new approach is robust and efficient in term of counting of abnormal cells.

4 CONCLUSION

In this paper, Red blood cells (RBC) have been classified into two groups: Normal and Abnormal RBC cells using our new approach based on area and Eccentricity of each cell then counted the total number of normal and abnormal RBC cells. We also implemented circular Hough transform method. We compared our new approach to circular Hough transform in the same running environment.

The results have shown that our proposed approach counting is efficient and robust superior to CHT. Our proposed approach accomplished an accurate total number of normal and sickle shaped cells anemia than other approaches. In addition, our approach showed the state-of-the-art performance in term of cell counting and execution time.

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