IMAGE PROCESSING BASED ABNORMAL BLOOD ELLS DETECTION

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ABSTRACT:
This paper is concerned with the detection of abnormal blood cell with a technique of image processing. For some high risk disease like cancer and hepatitis B, the result of the test report must be known to the patient as soon as possible. There are either techniques like MRI but for generating the result of these techniques takes time for some 1-10days. It is costly and consumes more time. This paper deals with a quick detection of the abnormal blood cell. Here we take a microscopic image of blood cell and convert it into binary and clean the image. The diameters of the blood cell are examined for the determination of abnormally in the blood cell.

Keywords: Abnormal blood cells, form factor, image processing, MATLAB etc.

[1] INTRODUCTION
In this paper image processing techniques are used to detect the abnormal blood cells. The blood consists of special cells in liquid called plasma. The Blood consists of 55% plasma, and 45% by cells called formed elements. Various important functions of our body is performed by blood. Erythrocytes, contains hemoglobin which carries oxygen to the tissues and collects the carbon dioxide (CO2). Due to the mutation the genes in our body get affected resulting in DNA injuries. In human body %age of blood cell is pre-determined so any variation in this count indicates the abnormality in blood cell. Counting this blood cell manually is a very tough and time consuming job. BY means of image processing we can easily determine the number of blood cell count. Blood is also responsible for passing nutritive substances (e.g. amino acids, sugars, Mineral salts) to the tissues. Mostly in case of high severity diseases where the mortality rates are more, the waiting time of patients for their reports such as blood test, MRI is more. The time taken for generation of any of the test is from 2-8 days. In high risk diseases like Hepatitis B, it is recommended that the patient’s waiting time should be as less as possible and the treatment should be started immediately. The current system used by the pathologists for identification of blood parameters is costly and the time involved in generation of the reports is also more sometimes leading to loss of patient’s life. Also the pathological tests are expensive, which are sometimes not affordable by the patient. Hence, there should be an automated system where the blood reports should be generated in a very less time with as minimum cost as possible. The time for generating blood test report and cost efficiency using image processing gives a better
performance than today used processes by the pathology lab. Pathologist takes 2-8 days to give the result using current based technologies. The process of determining the report in this paper does not need any chemical treatment with the blood as in today’s process, which is costly and time consuming as the instruments used for identification of the blood parameters are costly. Due to this reason the patient suffers both physically as well as mentally. In detection process several methods are used for the segmentation of red blood cell from white blood cell Using color space model with the help of MATLAB software where we can get the accuracy of up to 87%.

Various types of blood will be discussed in Section II. Section III gives a block diagram of the proposed technique. The form factor calculation used for segregating the various types of abnormal blood cells is discussed in Section IV. Section V discusses the results obtained. Concluding remarks are given in section VI.

[2] TYPES OF BLOOD CELLS

There are two types of blood cells: (A) Normal blood cells and (B) Abnormal blood cells.

[2.1] NORMAL BLOOD CELLS

The various normal blood cells are: Erythrocytes, Leucocytes and Thrombocytes

i) Erythrocytes
The most widely available blood cells in our body is Erythrocytes i.e. about 4-6 millions/mm3. They are also called red cells. Both in humans and in all mammals, erythrocytes are devoid of a nucleus and have the shape of a biconcave lens but in the mother vertebrates (e.g. fishes, amphibians, reptilians and birds), they have a nucleus. These cells are rich in hemoglobin, a protein able to bind in a faint manner to oxygen. Hence, these cells are responsible for providing oxygen to tissues and partly for recovering carbon dioxide produced as waste but most CO2 is carried by plasma, which are in form of soluble carbonates.

ii) Leucocytes
Leukocytes are also known as white cells. Leucocytes are responsible for the defense of the organism. In our blood, they are much less numerous than red cells. The density of the leukocytes in the blood is 5000-7000 /mm. Leukocytes are divided into two categories: granulocytes and lymphoid cells or agranulocytes. The term granulocyte is due to the presence of granules in the cytoplasm of these cells. In the different types of granulocytes, the granules are different and help us to distinguish them. In fact, these granules have a different affinity towards neutral, acid or basic stains and are responsible for giving the cytoplasms different colors.

iii) Thrombocytes
Thrombocytes are also known as platelets. Thrombocytes stops the loss of blood from wounds. To this purpose, they aggregate and release factors which promote the blood coagulation (blood are turned in a semisolid mass). Among them, there are the serotonin which reduces the diameter of lessened vessels and slows down the hematic flux, the fibrin which trap cells and forms the clotting. Even if platelets appear roundish in shape, they are not red cells. In the smears stained by Giemsa, they have an intense purple color.
[2.2] AB NORMAL BLOOD CELLS

The various abnormal blood cells are: Elliptocyte, Echinocyte, Dacrocyte, and Sickle cells.

i) Elliptocyte
Elliptocytes are red blood cells and have an oval or cigar shape which can be seen from [Figure-1]. They may be found in various anemias, but are found in large amounts in hereditary elliptocytosis.

![Figure: 1. Elliptocyte Cells](image)

ii) Echinocyte (Crenated Red Blood Cells)
Echinocytes shown in [Figure-2] are red blood cells with many blunt spicules. These are due to faulty drying of the blood smear or from exposure to hyperosmotic solutions. Echinocytes contain adequate hemoglobin and the spiny knobs are regularly dispersed over the cell surface, unlike those of acanthocytes.

![Figure: 2. Echinocyte Cells](image)

iii) Dacrocyte (Tear Drop Cells)
Teardrop shaped red blood cells are shown in [Figure-3]. These blood cells are found in myelofibrosis and other myeloproliferative disorders, pernicious anemia, thalassemia, myeloid metaplasia, and some hemolytic anemias.
b) Sickle Cells

Sickle cells shown in [Figure-4] are red blood cells that have become crescent shaped. When a person with sickle cell anemia is exposed to dehydration, infection, or low oxygen supply, their fragile red blood cells form liquid crystals and assume a crescent shape causing red cell destruction and thickening of the blood. Since the life span of the red blood cell is shortened.

The paper aims to detect the abnormal blood cells by image processing technique. Here, the abnormality off the blood cells will be detected by determining the form factor of the cells. The form factor will be calculated by calculating the area and perimeter of the cells with the help of edge detection algorithm and finally the number of abnormal blood cells will be counted. The proposed technique will help in reducing the cost as well as waiting time of the patients for availing the pathological reports.

[3] BASIC BLOCK DIAGRAM

The system will be working as follows:- Once the patient’s blood sample is collected, it will be processed immediately and using an high end camera’s in microscope, the images can be captured and using the image processing techniques, the different values of the desired parameters can be calculated immediately [1]. Use of parameter dependent image processing technique will definitely reduce the cost involved and also will save the time of generating the reports. This will definitely help to reduce the mortality rate in high risk diseases [2]. [Figure-5] shows the basic block diagram for detecting the abnormal blood cells.
i) IMAGE ACQUISITION
The digital microscope is interfaced to a computer and the microscopic images are obtained as digital images. The resolution of the digital image depends on the type of digital microscope used.

ii) IMAGE ENHANCEMENT:
For better segmentation of the blood cells, the imported image has to be enhanced. This improves the quality of the image in terms of details.

(a) Green Plane Extraction:
The green plane is extracted from the imported blood cell image. The other planes such as red and blue are not considered because they contain less information about the image.

(b) Contrast Adjustment:
To enhance the image, its contrast is adjusted by altering its histogram. The image’s histogram is equalized.

iii) IMAGE SEGMENTATION
This involves selecting only the area of interest in the image. Here only the blood cells are selected, because they are the areas of interest. A segmentation can be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression, image editing or image database look up.

Figure: 5. Block diagram for detecting abnormal blood cell
**[4] DETECTION AND COUNTING OF ABNORMAL BLOOD CELLS USING FORM FACTOR CALCULATION [4]**

Form factor threshold is fixed for different abnormal cells. All the cells having the form factor value less than 0.6 are considered abnormal and the cells having the form factor range between 0.6-1 are considered as normal cells. Based on these criteria the abnormal cells are detected. The flow chart for detection and counting the blood cells is given in Fig. 6. By incrementing a counter value within for loop, the number of normal cells and abnormal cells can be calculated. Form factor is calculated for the labeled cells. So the basic aim is to calculate the area and perimeter [9], [10].

Calculation of an area:
Number of pixels in one cell makes its area. So the number of pixels having same label constitute the area of the labeled cells.

Calculation of the perimeter:
Any pixel whose four neighborhoods are white is surely not a boundary pixel as it lies interior of the cell. So we get number of those pixels whose four of the neighborhoods are white. And if we subtract this value from the total area of the Image then this will give area outside the cell along the perimeter of the cell.
Hence the form factor can be calculated easily using eqn. (1).

Form factor=$4* \pi * \text{area} / (\text{perimeter} * \text{perimeter})$ (1)

This form factor varies as the shape of an object varies. For a perfect circle, the form factor value is equal to 1, for objects other than circle, this form factor varies. The form factor ranges for different abnormal cells
Acanthocyte: 0.31-0.5
Echinocyte: 0.7-0.8
Elliptocyte: 0.6-0.7
Dacrocyte: 0.4-0.6
Sickle cell: less than 0.5

Nucleated erytrocyte: 0.6-0.65.

Based on this criteria, different objects in an image can be detected and classified.
The Steps involved in the algorithm are explained below:
- Read Image
- Get the x and y corner coordinates as integers
- Index into the original image to create the new image
- Extract the cytoplasms
- Solidifying the cytoplasms
- Use the Gradient Magnitude as the Segmentation Function
- Use the Sobel edge masks, \texttt{imfilter}, and some simple arithmetic to compute the gradient magnitude. The gradient is high at the borders of the objects and low (mostly) inside the objects.
- Mark the Foreground Objects
- A variety of procedures could be applied here to find the foreground markers, which must be connected blobs of pixels inside each of the foreground objects. In this example you'll use morphological techniques called "opening-by-reconstruction" and "closing-by-reconstruction" to "clean" up the image. These operations will create flat maxima inside each object that can be located using \texttt{imregionalmax}.

- Opening is erosion followed by a dilation, while opening-by-reconstruction is an erosion followed by a morphological reconstruction. Let's compare the two. First, compute the opening using \texttt{imopen}.
- Compute the opening-by-reconstruction using \texttt{imerode} and \texttt{imreconstruct}.

Following the opening with a closing can remove the dark spots and stem marks. Compare a regular morphological closing with a closing-by-reconstruction. First try \texttt{imclose}. Now use \texttt{imdilate} followed by \texttt{imreconstruct}. Notice you must complement the image inputs and output of \texttt{imreconstruct}.

Figure: 6. Flowchart for detection of abnormal
As can be seen by comparing |io| with |io|, reconstruction-based opening and closing are more effective than standard opening and closing at removing small blemishes without affecting the overall shapes of the objects. Calculate the regional maxima of |io| to obtain good foreground markers.

To help interpret the result, superimpose the foreground marker image on the original image. Notice that some of the mostly-occluded and shadowed objects are not marked, which means that these objects will not be segmented properly in the end result. Also, the foreground markers in some objects go right up to the objects’ edge. That means you should clean the edges of the marker blobs and then shrink them a bit. You can do this by a closing followed by erosion.

This procedure tends to leave some stray isolated pixels that must be removed. You can do this using “bwareaopen”, which removes all blobs that have less than a certain number of pixels.

Compute Background Markers. Now you need to mark the background. In the cleaned-up image, |io|, the dark pixels belong to the background, so you could start with a thresholding operation.

The background pixels are in black, but ideally we don't want the background markers to be too close to the edges of the objects we are trying to segment. We'll “thin” the background by computing the “skeleton by influence zones”, or SKIZ, of the foreground of |bw|. This can be done by computing the watershed transform of the distance transform of |bw|, and then looking for the watershed ridge lines (|DL == 0|) of the result.

Compute the Watershed Transform of the Segmentation Function. The function |imimposemin| can be used to modify an image so that it has regional minima only in certain desired locations. Here you can use |imimposemin| to modify the gradient magnitude image so that its only (a)regional minima occur at foreground and background marker pixels.

Finally compute the watershed-based segmentation.

Visualize the Result: One visualization technique is to superimpose the foreground markers, background markers, and segmented object boundaries on the original image. You can use dilation as needed to make certain aspects, such as the object boundaries, more visible. Object boundaries are located where |L == 0|. This visualization illustrates how the locations of the foreground and background markers affect the result. In a couple of locations, partially occluded darker objects were merged with their brighter neighbor objects because the occluded objects did not have foreground markers.

Another useful visualization technique is to display the label matrix as a color image. Label matrices, such as those produced by |watershed| and |bwlabel|, can be converted to truecolor images for visualization purposes by using |label2rgb|. One can use transparency to superimpose this pseudo-color label matrix on top of the original intensity image.

Separate all solo-connected shapes.
Calculate form factor F.
[5] RESULTS AND DISCUSSION

The proposed algorithm is tested on the blood cell images as shown in Fig. 7. The total number of blood cells present in the image is counted using the proposed algorithm (implemented using MATLAB). The algorithm shows the form factor for the blood cells which are more or less in circular shapes is in the range of .8 to 1 and that for others in the range of 0.4 to 0.6. Also, the total number of cells is estimated and it matches with the actual count.
Figure 7. (a) Blood cell image (b) Gray scale image (c) contrast adjustment (d) Binary image (e) Holes filled in the image (f) Clearing the borders in the image

![Image of blood cells](image)

Figure 8. Blood cell image for testing purpose

<table>
<thead>
<tr>
<th>Number of cells</th>
<th>Form Factor</th>
<th>remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total cells:</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>Detected Cells</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Normal Blood Cells</td>
<td>09</td>
<td>Between 0.94 to 1.12</td>
</tr>
<tr>
<td>Abnormal Blood Cells</td>
<td>01</td>
<td>0.4</td>
</tr>
<tr>
<td>Valance of Observed Response</td>
<td>0.06416</td>
<td></td>
</tr>
<tr>
<td>Sum of Squares of Error</td>
<td>0.5775</td>
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</tr>
<tr>
<td>Total Sum of Squares(SSE)</td>
<td>0.81913</td>
<td></td>
</tr>
<tr>
<td>Coefficient of Determination($R^2$)</td>
<td>0.29498</td>
<td></td>
</tr>
</tbody>
</table>

Figure 9. Statistical analysis of the blood cells shown in Figure 8

[6] RESULT AND DISCUSSION

The proposed algorithm is tested on the blood cell images as shown in [Figure-]. The total number of blood cells present in the image is counted using proposed algorithm (implemented using MATLAB). The algorithm shows the form factor for the blood cells which are more or less in circular shapes is in the range of .8 to 1 and that for others in the range of 0.4 to 0.6. Also, the total number of cells is estimated and it matches with the actual count. In the cell image we have total 12 cells. Where 10 cells are normal and 1 cell is abnormal. Calculated form factor is as follows: 1.05, 1.04, 0.90, 1.12, 1.00, 0.98, 0.96, 0.94,
0.40, and 1.05. So here range of form factor is in between 0.94 to 1.12. So there are the normal cells. But the cell which have a value of form factor is less than 0.8 is considered as an abnormal cell. Here the only one cell which has a value is 0.40, considered as abnormal blood cell. The statistical analysis is given in [Figure-8].

I. The R² value indicates there is 29% variation in observed values. Analysis of the blood cells shown in [Figure-8].

[6] CONCLUSION

The paper proposes an image processing technique for detecting and counting the abnormal blood cells. The proposed method detects the abnormalities in blood cell in very less time and efficiently. The 83% accuracy is achieved in counting the number of blood cells and 29% variation in observed values of detected abnormalities. The abnormalities of the blood cells are getting segregated based on form factors.