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RESEARCH ARTICLE

RESULT ANALYSIS OF BLOOD CELLS BLAST DETECTION BY USING LPG PCA LPG 2DPCA AND FAST NONLOCAL FILTERING ALONG WITH OTSU'S THRESHOLDING TECHNIQUE

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Abstract:- The paper focuses on white blood cells disease, Leukemia. The system will use features in microscopic images and examine changes on texture, geometry, color and statistical analysis. Changes in these features will be used as a classifier input. The presented method shows the effectiveness of an automatic morphological method to identify the Acute Lymphocytic Leukemia by peripheral blood microscope images. The proposed system firstly individuates in the blood image the leucocytes from the others blood cells, then it select the lymphocyte cells (the ones interested by acute leukemia), it evaluates morphological indexes from those cells and finally it classifies the presence of the leukemia. This also includes Local Pixel Grouping based Principal Component Analysis (LPG-PCA), 2 Dimensional PCA, Fast Nonlocal Filtering for image de-noising. Then Otsu's Thresholding method for image enhancement is used. Morphological Operations are also carried out to count number of blast cells.

Keywords:- Acute Lymphoblastic Leukemia(ALL), Acute Myloid Leukemia(AML), Principal Component Analysis(PCA),Local Pixel Grouping(LPG), Otsu's Thresholding, Lymphoblast, Leucocytes

I. Introduction

Image processing and segmentation are very important sectors in terms of detecting features from blood cell images. Manual detection and counting of abnormal blast cells from microscopic cell images are prone to have errors due to lack of efficiency, difficulties in cell nature and problems related to preparation and problems related to preparation and staining of

blood cell slides[1]. Leukemia is a type of blood cancer involving white blood cells. It is a bone marrow disorder that arises when abnormal white blood cell begins to continuously replicate itself [1]. Acute leukemia is a rapidly progressing disease that affects mostly cells that are unformed (not yet fully developed or differentiated) [2]. ALL is most common in children while AML mainly affects adults but can occur in children and youngsters. In 2009, it is estimated that approximately 31,490 individuals will be diagnosed with leukemia and 44,510 individuals will die of the disease in the United States [3]. The early and fast identification of the leukemia type, greatly aids in providing the appropriate treatment for the particular type. Its detection starts with a complete blood count (CBC). The patient should perform bone marrow biopsy if there are abnormalities in this count. Therefore, to confirm the presence of leukemic cells, a study of morphological bone marrow and peripheral blood slide analysis is done. In order to classify the abnormal cells in their particular types and subtype of leukemia, a hematologist will observed some cells under a light microscopy looking for the abnormalities presented in the nucleus or cytoplasm of the cells. This classification is very important in predicting the clinical behavior of the disease and the prognosis in order to determine which treatment should be given to the patient [5].

A typical blood microscope image is plotted in Fig. 1. The principal cells present in the peripheral blood are red blood cells, and the white cells (leucocytes). Leucocyte cells containing granules are called granulocytes (composed by neutrophil, basophil, eosinophil). Cells without granules are called agranulocytes (lymphocyte and monocyte). The percentage of leucocytes in human blood typically ranges between the following values: neutrophils 50-70%. Eosinophils 1-5%. basophils 0-1%. monocytes 2-10%, lymphocytes 20.45% [6].

Conventionally, manual counting done under the microscope was performed in order to count the white blood cells in leukemia slides. This way is troublesome and time consuming if the counting process is interrupted; it has to be started all over again. Thus, the traditional method of manual counting under the microscope affords susceptible to error procedure and put an intolerable amount of stress on the medical laboratory technicians. Although there are hardware solutions such as the Automated Hematology Counter to perform counting, certain developing countries are not capable to deploy such an expensive machine in every hospital laboratory in the country [7]. Furthermore, hematologists still carry out the manual counting based on slide of blood and bone marrow samples to confirm the case. Therefore, here we propose to provide an alternative solution to the problem where white blood cell counting can be carried out automatically at low cost by designing an automated system to count white blood cells in leukemia slides.

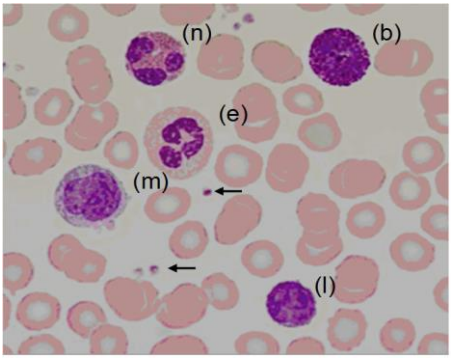


Figure1. Blood's white cells marked with colorant: basophil (b), eosinophil (e), lymphocyte (l), monocyte (m), and neutrophil (n). Arrows indicate platelet Others elements are red cells.

II. LITERATURE SURVEY

Paper [13] using a filter bank of a' trous wavelet filters, curvelet transform implements curvelet subbands and uses a ridgelet transform as a component step, and idea throughout is that transforms should be over complete, more willingly than critically sampled. In this digital transforms are applied for de-noising of some standard images rooted in white noise.

For image de-noising [17] uses a wavelet-based multiscale linear minimum mean square-error estimation (LMMSE) scheme and the way to determine the optimal wavelet basis with respect to the proposed scheme is also specified. The over

complete wavelet expansion (OWE) which is better as compared to orthogonal wavelet transform (OWT) in noise reduction is also included in this methodology. To walk around the strong interscale dependencies of OWE, the pixels at the same spatial location are combined and supposed to be a vector and LMMSE is applied to the vector.

Local Pixel Grouping based on Principal Component Analysis is presented in [28] for improving vast performance in image de-noising and also for local structures preservation.

A combination of geometric distance and an enhanced distance transform combining intensity gradients is used for the watershed step in [14].An explicit mathematical model for characteristics of cell nuclei like size and shape measures is included. For each detected nucleus, a confidence score is computed by measuring suitability of nucleus in the model.

Paper [15] shows the usefulness of an automatic morphological method to recognize the Acute Lymphocytic Leukemia(ALL) with the help of images of peripheral blood microscope. The presented methodology individuates the leucocytes from the others blood cells, after that it selects the lymphocyte cells (the cells causes acute leukemia), morphological indexes from those cells are evaluated then after and at last classification is performed whether the presence of the leukemia is there or not.

A method based on software is cost effective and an efficient for recognizing and analyzing blood cell is used in paper[20].In this performance evaluation is done at last by analyzing manual counting verses interactive counting on both WBC and RBC. Results shows that interactive method reduces error rate from 0.054% to 0.009%.

In paper[21] for the leukocyte segmentation an iterative Otsu's approach is used which is based on circular histogram.

[32] discusses an automated method to detect Acute Leukemia blast cells from human microscopic blood images. It comprises four basic modules ,1]de-noising module performs two staged noise reduction by 2D PCA and LPG.2]The contrast enhancement section includes color space conversion and morphological filtering based on pixel intensities.3]In threshold selection module, threshold value is determined using two methods namely, Edge Sensitive Variational Thresholding and Otsu's Thresholding.4]Blast cells are segmented based on threshold value obtained from these two methods. Morphological operations and Connected Component Analysis are used to count the number of blast cells present in the images.

III. Research Methodology

The system we propose is an automated method to detect Acute Leukemia blast cells from human microscopic blood images. It comprises four basic modules.

1]The de-noising module performs two staged noise reduction using 2D Principal Component analysis (2DPCA)and local pixel grouping(LPG),LPG-PCA and Fast Nonlocal Filtering. LPG-PCA works as shown in figure 2.

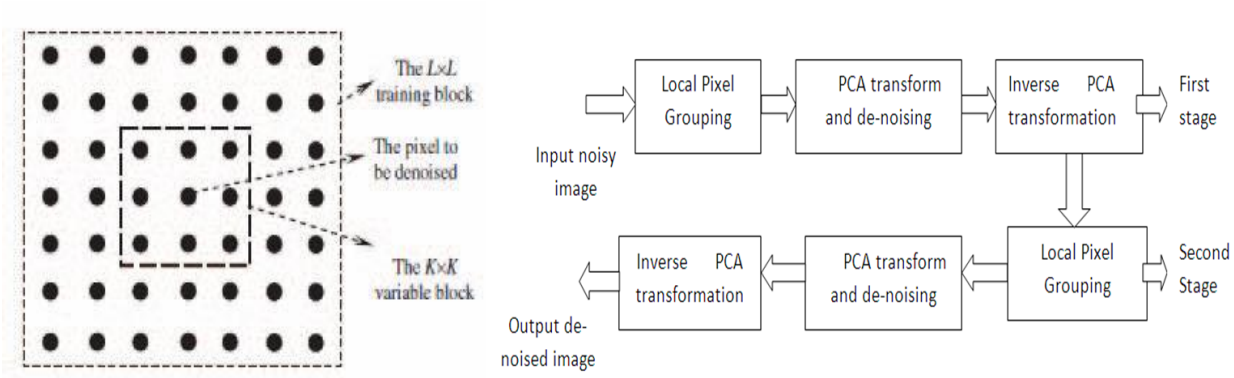


Figure 2.LPG-PCA Based de-noising

Similarly 2D PCA works same as LPG-PCA instead it uses 2 dimensional vector matrix. Fast Non Local Filtering builds on the separable property of neighborhood filtering. It offers a fast parallel and vectorized implementation by reducing the theoretical computational complexity of the original filter. Fast NLF works as follows:-

Terms in algorithm:-

V = Original noisy image

d = Dimension

s = Image site

Z(s) = Normalization constant

N(s) = Set of neighborhood pixels

w(s , t) = Square average values of pixels that are centered

K = Window size

h = Sigma value

P = Patch size

This algorithm works as shown in figure 3

Calculation of restored value:-

$$u(s) = \frac{1}{Z(s)} \sum_{t \in \mathcal{N}(s)} w(s,t) v(t) \quad , \qquad (1)$$

Calculation of average weights:-

$$w(s,t) = g_h \left(\sum_{\delta \in \Delta} G_\sigma(\delta) \left(v(s+\delta) - v(t+\delta) \right)^2 \right) \quad , \qquad (2)$$

Obtaining new image:-

$$S_{d_x}(p) = \sum_{k=0}^{p} \left(v(k) - v(k+d_x) \right)^2 , \quad p \in \Omega. \qquad (3)$$

Re parametrization:-

$$w(s,t) = g_h \left(S_{d_x}(s+P) - S_{d_x}(s-P) \right) \qquad (4)$$

Figure 3.Fast NLF

2]Secondly, the *Contrast Enhancement Module* includes linear contrast stretching for adjusting image intensities and histogram equalization for enhancing contrast of image and morphological filtering based on pixel intensities.

3] In Threshold module we use *Otsu's Global Thresholding*

Otsu's thresholding method which is given below includes iteration throughout all the possible threshold values. At the same time for the pixel levels, calculation of a measure of spread at all surface of the threshold, i.e. the pixels that moreover fall in foreground or background is performed. The intent is to find out the threshold value where the summation of forefront and background is its minimum. Otsu's method computes the threshold value automatically for conversion of a gray scale image into a binary image in image processing. The algorithm considers that the image which is to be thresholded includes two divisions of pixels. We can calculate the within-class variance as the weighted summation of the variances of every cluster object (O) and background (B):

$$\sigma^2_{Within}(\mathrm{T}) = n_B(\mathrm{T})\,\sigma^2_B(\mathrm{T}) + n_O(\mathrm{T})\,\sigma^2_O(\mathrm{T}) \qquad (1)$$

where,
$n_B(T) = \sum_{i=0}^{T-1} p(i)$,
$n_O(T) = \sum_{i=T}^{N-1} p(i)$.

σ^2_B (T) is the background pixels variance, and σ^2_O (T) is the foreground pixels variance, p_i is the pixel probability value x_i. that occurs.

Computation of this within-class variance for all of the two divisions for every possible threshold includes lots of computation, however this computation can be minimized by changing eqn. (1). If we remove the in class variance in eqn. (1) from the total variance of the distribution which is combined, the obtaining between-class variance is shown as:

$$\begin{aligned}\sigma^2_{Between}(\mathrm{T}) &= \sigma^2 - \sigma^2_{Within}(\mathrm{T}) \\ &= n_B(\mathrm{T})\,[\mu_B(\mathrm{T})-\mu]^2 + n_O(\mathrm{T})[\mu_O(\mathrm{T})-\mu]^2 \end{aligned} \qquad (2)$$

where, σ^2 and μ is the combined variance and the combined mean of the pixels x_i respectively. Note that the between-class variance is basically the weighted variance means of the cluster themselves in the region of the overall mean. Substituting

$\mu = n_B(\mathrm{T})\,\mu_B(\mathrm{T}) + n_O(\mathrm{T})\,\mu_O(\mathrm{T})$ in equation 2 and simplifying we get,

$$\sigma^2_{Between}(\mathrm{T}) = n_B(\mathrm{T})\,n_O(\mathrm{T})\,[\mu_B(\mathrm{T}) - \mu_O(\mathrm{T})]^2 \qquad (3)$$

Rather than using mean value which is shown in above eqn. (3) we employ the standard deviation of background pixels, which is subtracted from the standard deviation of object pixels. For any region ,the standard deviation with N pixels of intensity X_i, $i = 1, 2\ldots\ldots N$, is given as:

$$\mathrm{S} = \sqrt{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2 / N} \qquad (4)$$

Here $\bar{x}$ is the mean of xi. By substituting eqn. (4) in eqn. (3) we get:

$$\sigma^2_{Between}(T) = n_B(T)n_o(T)[S_B(T) - S_o(T)]^2 \qquad (5)$$

Here,

S_B = The standard deviation for the background pixels

S_O = The object pixels.

For getting an optimum threshold value, eqn. (5) is calculated by changeable T and finding the smallest value for $\sigma 2_{Between.}$ The pixel value xi at which the minimum $\sigma 2_{Between}$ obtained is the threshold value T. Making use of the threshold value T, the given input image f (x , y) is transformed into a binary image g and it is given as:

G (x , y) = 1 if f (x , y) >= T

= 0 otherwise. (6)

4]Blast cells are segmented based on threshold value obtained from *Morphological closing and Connected Component Analysis* is used. White Blood Cells are retained and all other objects are removed based on area of each cell then counting of objects in image is done.

5]Finally *Performance Evaluation* is carried out in terms of accuracy based on a comparison of number of blast cells detected by manual count and those detected by automated method.

The system we propose in this paper is the sub-system which has to recognize if a lymphocyte is blast or normal, and these blast cells are counted by automated method that we proposed in above modules. Figure 4shows working of methodology.

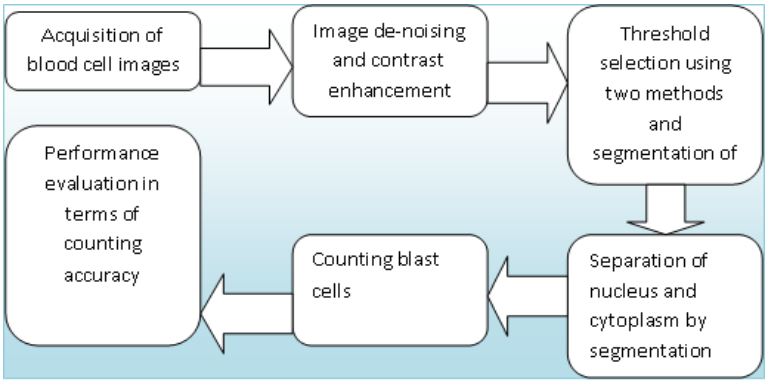
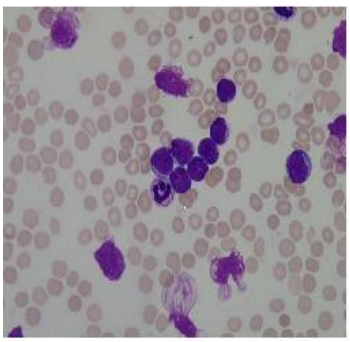


Figure 4. Process Methodology

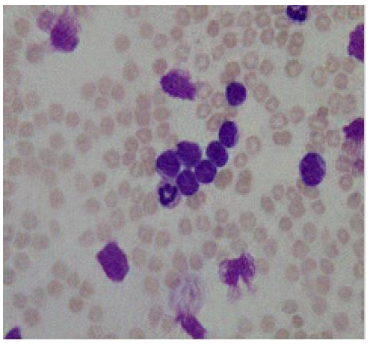
IV. RESULTS AND ANALYSIS

A. For de-noising module results shown are as follows:-

A.1For LPG PCA de-noised image is shown in figure 5



Original Noise Image



De-Noised Image

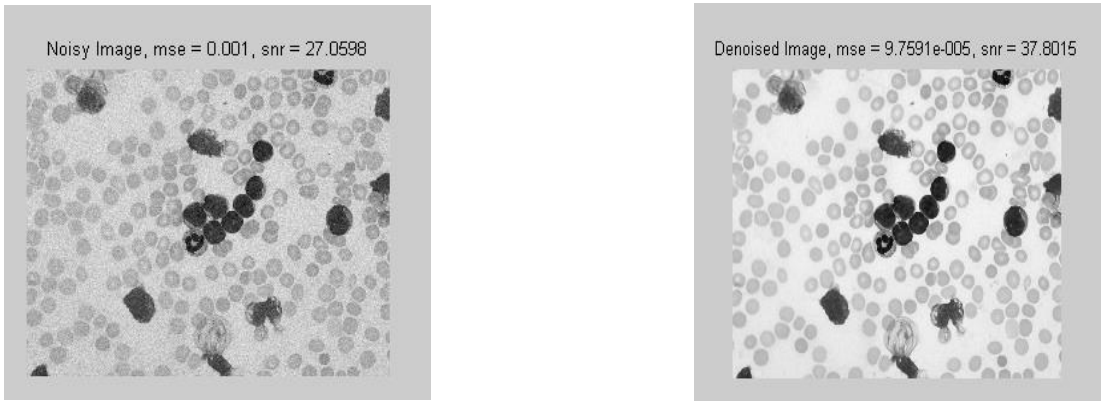
Figure 5

A.2For LPG 2D-PCA de-noised image is shown in figure 6

Original Image De-Noised Image

Figure 6

A.3For Fast NLM de-noised image is shown in figure 7



Original Noisy image De-Noise image

Figure 7

B. For WBC segmentation output is as follows in figure 8

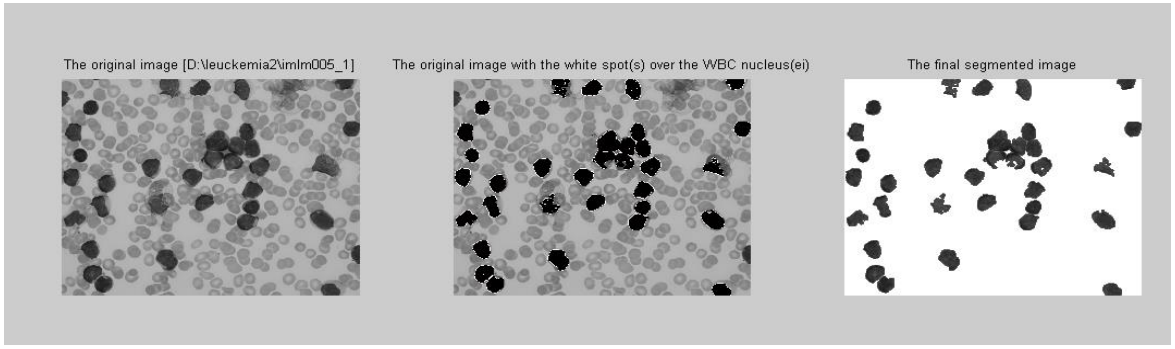


Figure 8

C. Final segmented image is shown in figure 9

Figure 9

Results shows that along all de-noising methods Fast NLF works better as compared to other methods i.e LPG PCA and LPG-2DPCA.The proposed 2DPCA does not work better in all aspects i.e. Time complexity and image de-noising quality of LPG -2DPCA algorithm has very poor peak signal to noise ratio(psnr) as compared to LPG-PCA and Fast NLF.

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