

March 2015 Issue

Classification of Acute Myelogenous Leukemia in Blood Microscopic Images Using Supervised Classifier

R.Renuka devi¹, C.V.Gnana Arivu² PG scholar¹, Assistant professor² Department of ECE Jerusalem College of Engineering, Pallikkaranai, Chennai renuka14.6@gmail.com¹, gnanavelappan@gmail.com²

Abstract:

Acute Myelogenous Leukemia (AML) is a subtype of acute leukemia that is prevalent among adults. The age of a person with AML is 64 years. The need for automation of leukemia detection arises since current methods involve manual examination of the blood smear as the first step toward diagnosis. It takes lot of time and its accuracy depends on the operator's ability. in proposed system a simple technique that automatically detects and segments AML in blood smears is presented. The proposed method differs from others in: 1) the simplicity of the developed approach; 2) classification of complete blood smear images as opposed to sub images; and 3) The nucleated cells are segmented and detected by the help of this algorithm. Computer simulation involved the following tests: comparing the impact of Hausdorff dimension on the system before and after the influence of local binary pattern digits and then comparing the performance of the proposed algorithms on sub images and full images, and then with some of the existing systems the result of the proposed system will be compared. Eighty microscopic blood images are detected, The current system will managed to obtain 98% accuracy for the localization of the lymphoblast cells and to separate it from the sub images and complete images.

Keywords: Acute Myelogenous Leukemia, Clustering, Supervised Classification.

I. INTRODUCTION

Leukemia is a set of hematological neoplasia which usually affects blood cells, bone marrow, and lymph nodes. Leukemia characterized by proliferation of abnormal white blood cells in the bone marrow without responding to cell growth inhibitors. For example, the Acute Lymphocytic Leukemia (ALL), and it's also known as acute lymphoblastic leukemia .This type of leukemia is a cancer of the white blood cells and it is classified by the overproduction and immature white blood cells by monitoring the peripheral blood film by expert operators is one of the diagnostic steps available to calculate the presence of the acute leukemia.

This result suffers from slowness and it provides a not standardized accuracy since it depends on the operator's capabilities. This morphological analysis just requires an image -not a blood sample and hence is suitable for low range of cost, standard-accurate result, and remote diagnostic systems. The cell composition of the blood reveals important

diagnosis detail about the patients as well as patient. The hematologist requires two different types of blood count for diagnosis and screening technique. The first one is called the Complete Blood Count (CBC) and the second one is called the Differential Blood Count (DBC) so on. The CBC could be done by device cytometer and could successfully be performed in automatic manner. Like that DBC is more reliable but recently it is a manual procedure to be done by hematology experts using microscope device. DBC, an expert counts 100 numbers of white blood cells on the smear at hand and calculates the percentage of occurrence of each type of cell calculated. The results reveal important information about patient's health details.

The leukaemia could be cured if it is detected and treated at the early stage of disease .In leukaemia diagnosis, specific morphological features such as size of abnormal white blood cell (blast) would be monitored by haematologists in order to differentiate the types of acute leukaemia present in the patient.

The Cytoplasm and nucleus regions contain important information to be observed by haematologists device. The computer vision tasks as it determines the structure of objects in image is given. So it can aid processes by substantially reducing the amount of information to be processed. In result, edge detection has served as a basis for many feature extraction technique, object detection and recognition, enhancement of the image , and segmentation algorithms, extensively used for remote sensing, security purpose systems, handwriting analysis, and biomedical application and so on.

II .PROPOSED METHODS

To detect and classify the acute myelogenous leukemia using support vector machine (svm) in blood microscopic images. The process of AML detection is done by k-means segmentation, feature extraction and neural network classifier.

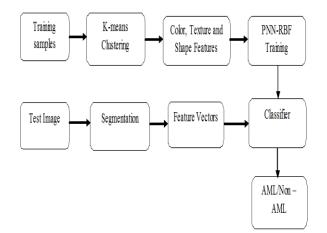


Fig 1 Block Diagram of Proposed System

A).k-Means Clustering Algorithm:

The k-means algorithm requires three user-specified parameters: k the number of clusters, cluster starting point, and distance metric. A k-means clustering procedure is used to assign every pixel to one of the clusters. In each pixel is assigned to one of these classes using the properties of the cluster center. In every pixel of an object is classified into k clusters based on the corresponding *a and*b values in the L*a*b color space. Therefore, each pixel in the L*a*b color space is classified into any of the k clusters by calculating the Euclidean distance between the pixel and each color indicator. These clusters correspond to nucleus (high saturation), background (high luminance and low saturation), and other cells . Each pixel of the entire image will be labeled to a particular color depending on the minimum distance from each indicator present in the system. We consider only the cluster that contains the blue nucleus in a particular cell, which is required for the feature extraction process. While performing k-means segmentation of complete images, it was observed that, in some of the segmented pictures, only the edges of the nuclei were obtained as opposed to the whole images of the nuclei of that cell. This shortcoming was overcome by employing morphological filtering [1]. An image is partitioned into several regions depending on the features to be extracted in the system. Employing morphological filtering ensures that perceptibility and visibility of these regions to be improve. The following actions performed to obtain the result.

The segmentation refers to the process of partitioning a digital image into multiple segments. The goal is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. The segmentation is performed by using spatial fuzzy C means clustering algorithm. This clustering algorithm is not supervised that classifies the input data points into multiple classes based on their inherent distance from each other. It includes the spatial function to modify membership function to get the accurate result by analyzing local neighborhood information. There are four steps present in k-means that are

Step 1: Place K points into the space represented by the objects that are being clustered. These points represent initial group centroid.

Step 2: Assign each object to the set that has the closest centroid.

Step 3: When all objects have been assigned to the image, recalculate the positions of the K centroid.

Step 4: Repeat Steps 2 and 3 until the centroid no longer MOVE. The pre processing includes the image resizing, Gray color space conversion and de-noising.

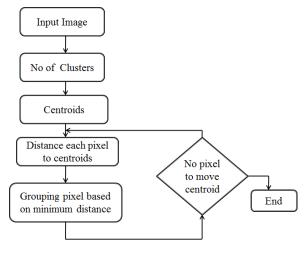


Fig 2 Flow Diagram of Process Flow

B).Pre-processing

The pre processing includes the image resizing, Gray color space conversion and de-noising. Before the segmentation process, we are going to resize the input image into fixed Row and Column size [256 256] using imresize command. Then the input image is converted into gray scale conversion for accurate segmentation. The conversion is done by RGB2GRAY Matlab commands. To reduce the effect of noise we apply the median filter for de-noising.

C).Segmentation process

The first step is to select the desired regions from input automatically based on identifying intensity variations. Here, grouping of similar region will be performed by K means clustering algorithm. It is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm take that the data signal features form a vector space and tries to find natural clustering in them. It is a well suited method for this process medical samples and it consumes less time and provides better result for better contrast image.

D).CIELAB Color Features and Color Correlation:

The images generated by digital microscopes are usually in RGB color space, is difficult to segment. The blood cells and image background varies greatly with respect to color and intensity which caused by multiple reasons such as camera setting process, varying illumination of images, and aging stain. To make the cell segmentation robust with respect to these variations, for this adaptive procedure is used: the RGB input image is converted into the CIELAB or, more correctly, the CIEL*a*b* color space.

The key reasons are reduce memory requirement and to improve the computational required time. Second, the perceptual difference between colors is proportional to the Cartesian distance in the CIELAB color space. Color differences between two samples can be calculated by using a Euclidean distance. The final is has only two color components (a and b), and it is designed to approximate human vision (the L component closely matches human perception of lightness or it can be used to adjust the lightness contrast using the L component. At last the a and b components can be used to make accurate color balance corrections. In other words, the L*a*b* color space with dimension L that represents the lightness of the color, dimension a* that represents its position between red/magenta and green, and dimension b* that represents its position between yellow and blue. Due to its perceptual uniformity, L*a*b produces a proportional change visually for a change of the same amount in color signal. This ensures that every minute difference in the color value is noticed visually. Independent device is an added advantage of the L*a*b color space. It presents the result of RGB to CIELAB color conversion and segmentation procedure.

E).Local Directional Pattern

LDP is a texture pattern of gray-scale which defined the spatial structure of a local image texture. A LDP operator process the edge response values in all eight directions at each pixel position and generates a code from the relative strength magnitude.LDP properties describes the local primitives including different types of curves, corners, and junctions, more stably and retains more information.

III. EXPERIMENTAL RESULTS

Experiments are done by using a real dataset of 160 classified images provided by the M. Tettamantibranch for Childhood Leukemias and Hematological DiseasesMonza. The signal set permitted to measure the accuracy of the tree main methods presented the background suppression and the estimation of the mean cell diameter and the white cells segmentation present in the images.

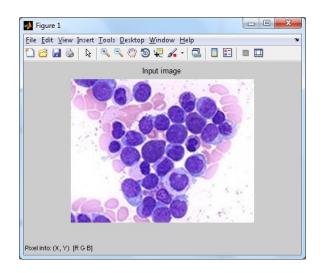


Fig 3 Input Test Sample

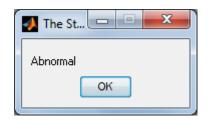


Fig 4 Stage of Test Sample

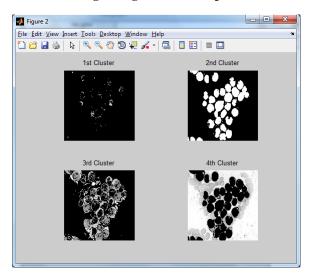


Fig 5 k-means Clustering

IV. CONCLUSION

In this Paper, Automatic Classification and segmentation method is experimented in order to find the Acute Myelogenous Leukemia present in blood cells. For effective classification, Probabilistic neural network is used. After classification, k means clustering method is used to segment the leukemia. These techniques produced very accurate results. It gives 98% accuracy.

V. REFERENCES

[1] F. Scotti, "Automatic morphological analysis for acute leukemia identification in peripheral blood microscope images," in Proc. CIMSA, 2005, pp. 96–101.

[2] V. Piuri and F. Scotti, "Morphological classification of blood leucocytes by microscope images," in Proc. CIMSA, 2004, pp. 103–108.

[3] M. Subrajeet, D. Patra, and S. Satpathy, "Automated leukemia detection in blood microscopic images using statistical texture analysis," in Proc. Int. Conf. Commun., Comput. Security, 2011, pp. 184–187.

[4] H. Ramoser, V. Laurain, H. Bischof, and R. Ecker, "Leukocyte segmentation and classification in blood-smear images," in Proc. IEEE EMBS,2006, pp. 3371–3374.

[5] C. Reta, L. Altamirano, J. A. Gonzalez, R. Diaz, and J. S. Guichard, "Segmentation of bone marrow cell images for morphological classification of a cute leukemia," in Proc. 23rd FLAIRS, 2010, pp. 86–91.

[6] G. Ongun, U. Halici, K. Leblebicioglu, V. Atalay, M. Beksac, and S. Beksac, "Feature extraction and classification of blood cells for an automated differential blood count system," in Proc. IJCNN, 2001, vol. 4, pp. 2461–2466.

[7] S. Mohapatra and D. Patra, "Automated leukemia detection using hausdorff dimension in blood microscopic images," in Proc. Int. Conf. Emerg. Trends Robot Commun. Technol., 2010, pp. 64–68.

[8] S. Mohapatra, S. Samanta, D. Patra, and S. Satpathi, "Fuzzy basedblood image segmentation for automated leukemia detection," in Proc.ICDeCom, 2011, pp. 1–5.

[9] S. Mohapatra, D. Patra, and S. Satpathi, "Image analysis of blood microscopic images for acute leukemia detection," in Proc. IECR, 2010, pp. 215–219.

[10] S. Mohapatra, D. Patra, and S. Satpathi, "Automated cell nucleus segmentation and acute leukemia detection in blood microscopic images," in Proc. ICSMB, 2010, pp. 49–54.

[11] MedlinePlus: Leukemia. National Institutes of Health. [Online].

Available:http://www.nlm.nih.gov/medlineplus/ency/article/0 01299.htm

[12] J. N. Jameson, L. K. Dennis, T. R. Harrison, E. Braunwald, A. S. Fauci, S. L. Hauser, and D. L. Longo, "Harrison's principles of internal medicine," JAMA, vol. 308, no. 17, pp. 1813–1814, Nov. 2012.

[13] S. Serbouti, A. Duhamel, H. Harms, U. Gunzer, J. Mary, and R. Beuscart, "Image segmentation and classification methods to detect leukemias," in Proc. Int. Conf. IEEE Eng. Med. Biol. Soc., 1991, pp. 260–261.

[14] D. Foran, D. Comaniciu, P. Meer, and L. A. Goodell, "Computer-assisted discrimination among malignant lymphomas and leukemia using immune phenotyping intelligent image repositories, and telemicroscopy, "IEEE Trans. Inf. Technol. Biomed., vol. 4, no. 4, pp. 265–273, Dec. 2000.

[15] K. S. Kim, P. K. Kim, J. J. Song, and Y. C. Park, "Analyzing blood cell image do distinguish its abnormalities," in Proc. ACM Int. Conf. Multim., 2002, pp. 395–397.

[16] Q. Liao and Y. Deng, "An accurate segmentation method for white blood cell images," in Proc. IEEE Int. Symp. Biomed. Imaging, Atlanta, GA, USA, 2002, pp. 245–248.

[17] S. Suri, S. Setarehdan, and S. Singh, Advanced Algorithmic Approaches to Medical Image Segmentation: State-of-the-Art Application in Cardiology, Neurology, Mammography and Pathology. Berlin, Germany: Springer-Verlag, 2001, pp. 541–558.

[18] N. Sinha and A. Ramakrishnan, "Automation of differential blood count, "in Proc. Conf. Convergent Technol. Asia-Pac. Region, 2003, vol. 2, pp. 547–551.

[19] W. Shitong, K. F. L. Chung, and F. Duan, "Applying the improved fuzzy cellular neural network IFCNN to white blood cell detection," Neurocomputing, vol. 70, no. 7–9, pp. 1348–1359, Mar. 2007.

[20] M. Oberholzer, M. Ostreicher, H. Christen, and M. Bruhlmann, "Methods in quantitative image analysis," Histochem. Cell Biol., vol. 105, no. 5,pp. 333–355, May 1996.