SEMIAUTOMATIC WHITE BLOOD CELL SEGMENTATION IN MEDICAL IMAGE ANALYSIS USING NEURAL NETWORKS

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ABSTRACT— the complete blood count is a medical diagnostic test concerned with identifying and counting basic blood cells such as red blood cell, white blood cell and platelets. The computerized automation of CBC is the serious problem. Sub component of the CBC is perform the automatic classification white blood cell into one of the five WBC types in low resolution. Segmentation and feature extraction is performed by using k-means clustering using standard intensity and histogram features. PSO is used to select the particular feature, and evolving cascade neural network is used to classify the images.

Keywords:
WBC,RBC, Feature extraction, ECNN.

1. INTRODUCTION

Automatic cell segmentation remains a challenging problem, especially because in the same image, there exists a variety of cells in different stages of maturation, whose nucleus and cytoplasm might differ in shape, texture, color, granulites, and density. Our focus is the segmentation of white blood cells (WBC), also called leukocytes, into the morphological components nucleus and cytoplasm. WBC belongs to the immune system, and is found throughout the body, including bone marrow and blood. Since the number of WBC is often an indicator of some diseases, the count of different classes of WBC, named differential counting, plays a major role in the determination of the patient health in different stages: diagnosis, treatment, and follow up. Besides, being tedious and time consuming, the traditional manual method for differential counting is hard to reproduce and subjective, relying on the expert subjective assessment. This has motivated the development of automated or semi automated methods. Several WBC image segmentation methods have been proposed, and are usually based on region-finding or contour detection schemes. Mathematical morphology transformations are considered by several authors. An approach based on threshold segmentation followed by mathematical morphology and fuzzy cellular neural networks was proposed in for WBC detection, but the method presents problems when distinguishing nucleus from cytoplasm. A Teager energy operator is used to segment the nucleus boundary and a simple morphological based method is applied to extract the cytoplasm. Clustering-based techniques have been explored but typically present limitations when dealing with complex WBC images, requiring manual cropping in some cases. It helps in locating the WBC components by using a shape analysis step based on a roughly boundary detection obtained by image thresholding. On the other hand, such components were located with adaptive contour models. The color information for WBC segmentation was also considered by some authors. The hue, saturation, and value (HSV) color space model are used to build a 3-D histogram in order to extract the cytoplasm, and a scale-space filter to obtain the nucleus. It was argued that the HSV space is more appropriate than the red, green, and

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blue (RGB) space in WBC segmentation due to its low correlation. In an unsupervised automated WBC segmentation method based upon the mathematical morphology and scale space theories is proposed. In a first step, the cell nucleus is extracted using the watershed transform by image foresting transform (IFT). Then, based on the size distribution information of the red blood cells (RBC), the cytoplasm is segmented using basic operations such as thresholding and morphological opening. To avoid leaking, a common problem when dealing with cell images due to the low contrast between nucleus, cytoplasm, and background, a scale-space toggle operator is used with interesting simplification properties that conduce to a contour regularization. In this rest of the paper, Section 2 scale-space toggle operator for image simplification. Section 3 describes that proposed technique for WBC segmentation. Segmentation of nuclear related works are explained in Section 3.2. Classification and their related works, Sample Result will be discussed in Section 3.3 and 4. Performance Analysis and Accuracy of the classification and Conclusion in Section 5 and 6.

2. SCALE-SPACE TOGGLE OPERATOR FOR IMAGE SIMPLIFICATION:

The analysis of different representation levels has been largely used to handle the multistage nature of image data. One of the basic problems that arise when using multistage methods originates from the difficulty to relate meaningful information of the signal across scales. The author Witkin proposed a novel multiscale approach, named scale space, where the representation of an interest image feature describes a continuous path through the scales. In such a way, it is possible to relate information obtained in different representation levels, as well as to have a precise localization of the interest features in the original image. This representation also leads to a simplification of the image, reducing its information content by successively removing image structures while preserving the essential features. This constitutes the monotonicity property, which states that the number of features must necessarily be a monotonic decreasing function of scale.

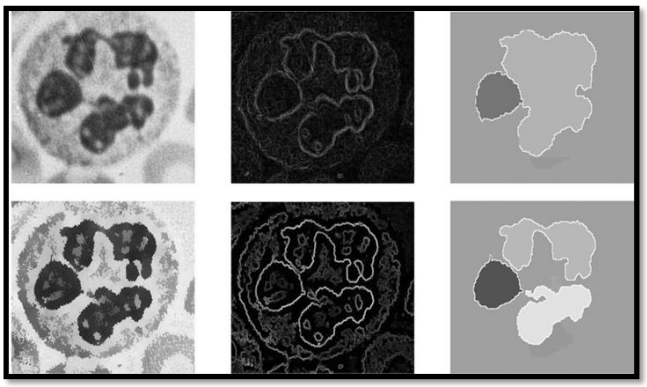

Fig 1.1 Improvement of the gradient image by applying the SMMT operator

3. PROPOSED TECHNIQUE FOR WBC SEGMENTATION:

Image segmentation is basically partitioning an image into a set of disjoint and homogeneous regions, which corresponds to image objects meaningful to a certain application. The main aim is to accurately segment the nucleus and cytoplasm components of blood-smear images, to further extract shape-based features for automated differential counting. To segment the nucleus components, two well-known approaches, namely, watershed transform and Level-Set methods are used. The cytoplasm is segmented by applying simple morphological transformations on images processed at different scales by the SMMT. In both cases, the preprocessing with the SMMT was essential to ensure satisfactory precision rates, thus showing the importance of the multiscale analysis, where it is possible to work on different representation levels to extract specific interest features.

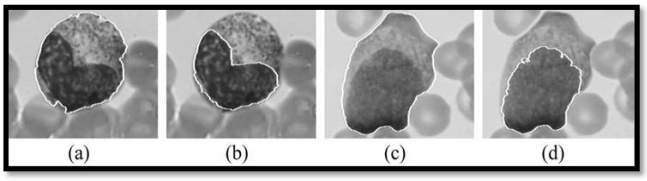

Fig. 1.2 Avoiding leaking on nucleus segmentation—watershed transform

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The following diagram shows the architecture of the system. It has Five modules (i.e)WBC Segmentation using k-means Clustering, Feature extraction using GLCM, Selection of the feature using PSO, Machine Learning and classification using ECNN and Performance Analysis using mse and ROC curve.

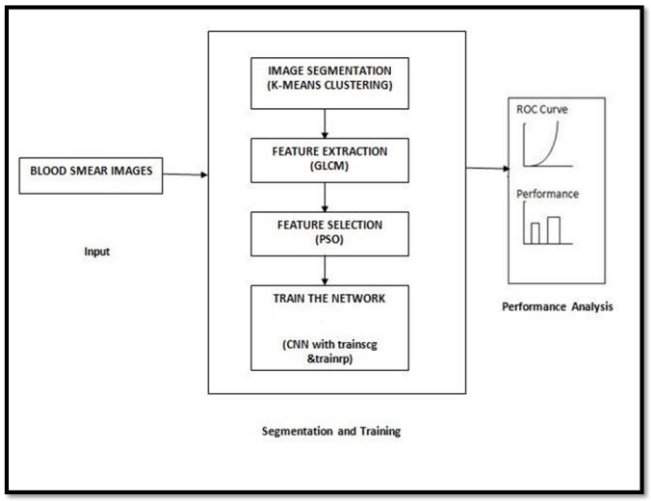

Fig 1.3: Proposed System Architecture

3.2 NUCLEUS SEGMENTATION:

Two different approaches were considered to segment the nucleus. First, the watershed transform by IFT is applied, a general tool for the design of image processing operators based on connectivity. Starting from defined internal and external seeds (markers), the IFT assigns a minimum-cost path to each pixel such that each seed becomes a root of an optimum-path tree composed by its most strongly connected pixels. The cost of a path in this graph is determined by a given cost function, which usually depends on local image properties along the path—such as color and gradient. The resulting optimum-path forest consists of two sub forests with distinct labels: object and background. The internal seeds must necessarily belong to the interest object, and the external ones are initialized as its edges (gradient image). Exploring the fact that the WBC nucleus is the darkest part of the image, we just apply a threshold to obtain (at least) one sample of each WBC nucleus to be considered as internal marker (we used 90 as a threshold value for all images).

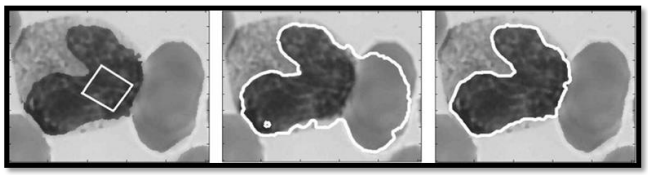

Fig. 1.4 avoiding leaking on nucleus segmentation

Image segmentation involves selecting only the area of interest in the image. It is a process of image partitioning into multiple segments or regions or structures of interest, so that the contents of each region have similar characteristics. It is a process of extracting and representing information from the image to group pixels together with region of similarity. Changing the image representation into a meaningful and easy-to-analyze one is the main goal of segmentation. In a given image, it assigns a label to each pixel, such that pixels with same labels share common visual characteristics. The algorithm follows,

1. *k* initial "means" (in this case *k*=3) are randomly generated within the data domain
2. *k* clusters are created by associating every observation with the nearest mean.
3. The centroid of each of the *k* clusters becomes the new mean.
4. Steps 2 and 3 are repeated until convergence has been reached.

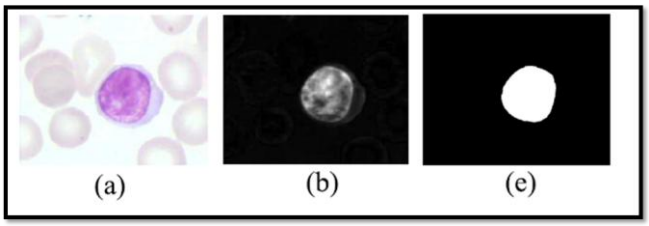

Fig 1.5Segmentation of the nucleus.

(a) An input cell image, (b) the combined image,

(c) The segmented wbc

3.3 FEATURE EXTRACTION:

Feature extraction also called description deals, Feature extraction is a sub-division of improved image into constituent parts or isolation of some aspects of an image for identifying or interpreting meaningful object forms, which includes finding

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lines, circles or specific shapes etc. that are basic for differentiating one class of objects from another. The texture based features are extracted using Gray Level Co-occurrence Matrix(GLCM). Level Coocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. GLCM represents the distance and angular spatial relationship over an image ,sub-region of size. It analyze the image as P_0, P_{45}, P_{90}, & P_{135}. (i.e) p(i,j) where i,j are gray level values in the image. The statistics of GLCM are,

Statistic	Description
Contrast	Measures the local variations in the gray-level co-occurrence matrix.
Correlation	Measures the joint probability occurrence of the specified pixel pairs.
Energy	Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.
Homogeneity	Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

Fig 1.6 GLCM PROPERTIES

3.4 CLASSIFICATION:

In a general way, the existing systems for automated differential counting do not have acceptable correct classification rates to be used in a hospital practice, which leads the process to be done manually by a human expert, becoming susceptible to a subjective assessment. The difference between the classifications performed by two independent specialists is approximately 15% and, thus, the accuracy of a human expert is estimated as 85%. Another factor that influences the results is that the maturation levels constitute a continuous variable, while the classification is discrete. In the experiments, we considered five classes (maturation levels) of WBC belonging to the granulocytic series. To characterize the different cells, we rely on features related to the geometrical shape of the nucleus and of the whole cell. We used the following parameters extracted from the nucleus component: (f1) area, (f2) solidity, (f3) eccentricity, (f4) the area of convex part of the nucleus and (f5) perimeter. The eccentricity consists on the ratio of the distance between the foci of the ellipse and its major axis length, assuming a value between 0 and 1. The solidity represents the proportion of the pixels in the convex hull that are also in the region. The (f6) computes ratio of the nucleus and cytoplasm areas. Two color space models, RGB (red-green-blue) and HSI (hue-saturation-intensity) are commonly used to describe the color characteristics of images. Human peripheral blood smear contains leukocyte, erythrocyte, platelets, various types of grunge and background, and the leukocyte contains the nucleus and cytoplasm. The nucleus has a strong physical adsorption and chemical affinity because it gathers highly dense nucleoprotein and nucleic acid; so the staining density of nucleus is much higher than that of cytoplasm and erythrocyte. That is, the intensity of the nucleus is the highest in the saturation channel image. Moreover, it has been discovered that the intensity of nucleus is the lowest in green channel image. To highlight the nucleus, in this paper a combined image SG is constructed where S is the saturation channel image and G is the green channel image. It is considered as a two-region image including the nucleus and other objects (cytoplasm, erythrocyte and background). It is known that global valley points of histogram are good thresholding values for segmentation; but many local valley points appear in original histogram of the combined image so the meaningful global valley point is not easy to determine. A smoothing procedure can remove these local valley points but at the same time move the positions of global valley points. Carlotto suggested filtering the histogram using a series of Gaussian filters with increasing variances, namely scale-space filtering, and drawing the valley points on each level in the same figure, namely "fingerprint figure". The fingerprint of histogram is where x-axis denotes the local valley points in histogram and y-axis the variance of Gaussian filters. It has been found that some fingerprint lines come into being while the global valley points are detected gradually. If a tracing back is taken from large to small variance, the accurate position of global valley points can be localized and regarded as the threshold for the nucleus segmentation. An ECNN starts to learn with one input node and then adding new inputs as well as new hidden neurons evolves it. The trained ECNN has a nearly minimal number of input and

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hidden neurons as well as connections**.** Cascade-forward networks consists of Nl layers using the weight function, net input function, and the specified transfer functions. The first layer has weights coming from the input. Each subsequent layer has weights coming from the input and all previous layers. All layers have biases. The last layer is the network output. Each layer's weights and biases are initialized. Adaption is done with training which updates weights with the specified learning function. Training is done with the specified training function. Performance is measured according to the specified performance function.

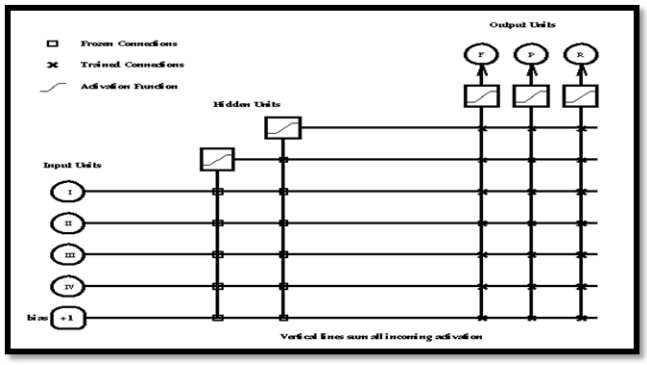

FIG 1.7 ARCHITECTURE OF ECNN

4. ANALYSIS ACCURACY AND PERFORMANCE:

The WBC are segmented from the blood smear image using the k-means clustering technique. The segmented WBC's are used for feature extraction using GLCM. The feature dimension is reduced based on the techniques like PSO. The Machine learning method ,ECNN is used for training and classification. The network is trained with three training algorithms along with the PSO with different number of epochs. Performance is evaluated based on the parameters like mse, Regression. The time taken by the algorithms are more or less similar. The graphs below show the plots of MSE and Regression analysis.

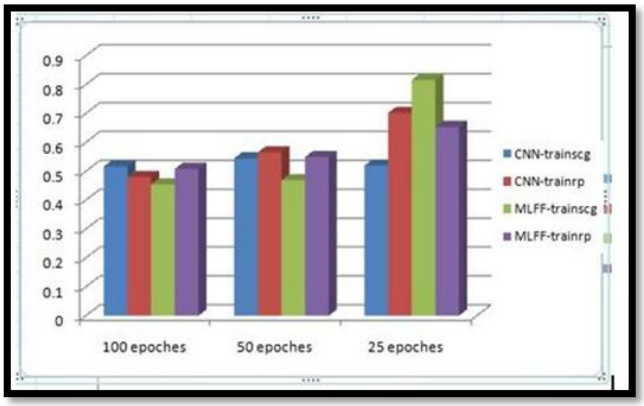

FIG 1.8 MSE PLOT

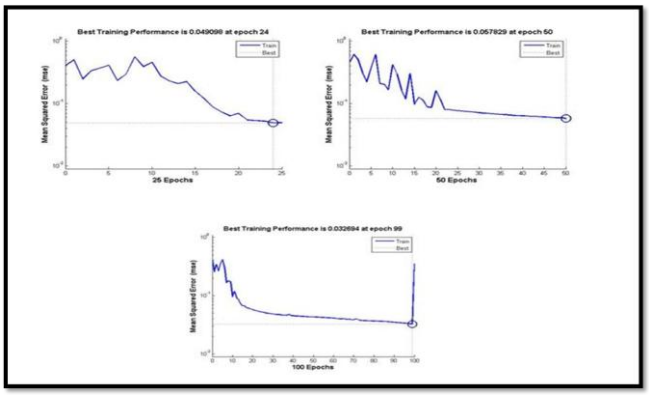

Fig 1.9: Best Performance Equation of ECNN in 25,50,100 epochs

5.CONCLUSION

Thus the wbc are segmented based on k-means clustering. When the dimensions are large for the image, clustering is the promising technique. The features are extracted from the segmented wbc image using GLCM. The reduced features are obtained by PSO. The network is trained based on ECNN and the cells are classified.The obtained result is compared against the algorithms like MLFFNN with trainscg and trainrp.

6. REFERENCE

[1] B. Alberts, A. Johnson, J. Lewis, M. Raff, K. Roberts, and P. Walter(2002), *Molecular Biology of the Cell*. New York: Garland, .

[2] N. Theera-Umpon and S. Dhompongsa(2007), 'Morphological granulometric features of nucleus in automatic bone marrow white blood cell classification', *IEEE Trans Inf. Technol. Biomed.*, vol. 11, no. 3, pp. 353–359.

[3] W. Shitong andW. Min(2006), 'A new detection algorithm (NDA) based on fuzzy cellular neural networks for white blood cell detection',

ISSN: 2278 – 7798

IEEE Trans. Inf.Technol. Biomed., vol. 10, no. 1, pp. 5–10.

[4] B. Kumar and T. Sreenivas(2002),'Teager energy based blood cell segmentation',in *Proc. Int.Conf.Digital Signal Process.*, vol. 2, pp. 619–622.

[5] K. Jiang, Q. Liao, and Y. Xiong(2006), 'A novel white blood cell segmentation scheme based on feature space clustering', *Soft Comput.*, vol. 10, pp. 12–19.

[6] S. Chinwaraphat, A. Sanpanich, C. Pintavirooj, M. Sangworasil, and P. Tosranon(2008), 'A modified fuzzy clustering for white blood cell segmentation',
in *Proc. Int. Symp. Biomed. Eng.*, pp. 356–359.

[7] Q. Liao and Y. Deng(2002),'An accurate segmentation method for white blood cell images', in *Proc. IEEE Int. Symp. Biomed. Imag.*, pp. 245–248.

[8] P. Yampri, C. Pintavirooj, S. Daochai, and S. Teartulakarn(2006),'White blood cell classification based on the combination of eigen cell and parametric feature detection', in *Proc. IEEE Conf. Ind. Electron. Appl.*,pp. 1–4.

[9] F. Sadeghian, Z. Seman, A. Ramli, B. Kahar, and M. Saripan(2009),'White blood cell segmentation in microscopic blood images using digital image processing', *Biol. Proced. Online*, vol. 11, pp. 196–206.

[10] L. B. Dorini, R. Minetto, and N. J. Leite(2007),'White blood cell segmentation using morphological operators and scale-space analysis', in *Proc. 20th Brazilian Symp. Comput. Graph. Image Process.*, pp. 100–107.

[11] A. X. Falc˜ao, J. Stolfi, and R. A. Lotufo(2004), 'The image foresting transform:Theory, algorithms, and applications', *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 1, pp. 19–29.

[12] A. P.Witkin(1984), 'Scale-space filtering: Anew approach to multiscale description',in *Image Understanding*. Norwood, NJ: Ablex, pp. 79–95

[13] P. T. Jackway and M. Deriche(1996), 'Scale-space properties of the multiscale morphological dilation-erosion', *IEEE Trans. Pattern Anal. Mach. Intell.*,vol. 18, no. 1, pp. 38–51.

[14] L. B. Dorini and N. J. Leite(2007), 'A scale-space toggle operator for morphological segmentation,' in *Proc. 8th Inform. Security Manage.Meas.*, pp. 101–112.

[15] J. Serra and L. Vicent(1992),'An overview of morphological filtering,' *Circuits,*
Syst. Signal Proc., vol. 11, no. 1, pp. 47–108.

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