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A Survey Of White Blood Cells Segmentation In Medical Image Analysis

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Abstract— The primary level for the preliminary diagnosis of disease like cancer is the biomedical analysis of microscopic blood sample images. In medical microscopic image analysis, a single image can be evaluated for different types of cells in different phases of maturation. For each cell, the nucleus and cytoplasm might differ in shape, texture, color and density. So it is a challenging problem to automatically segment the cell. In this paper, the various types of white blood segmentation techniques are discussed and the limitations of these methods are also investigated.

Keywords— Medical image analysis, White blood cell image segmentation

I. Introduction

The defence systemof the human body, which is the immune system thatprotects the body from infections. This natural defence system identifies and eliminates abnormal infected cells. The principal components of immune system is White blood cells (WBCs). WBCs play a vital role in immunity. WBCs normally have a constant amount in the human blood.If the amount of WBC exceeds the range, then health issues may occur. The morphological analysis of WBCs is one of the basic steps of blood analysis. Morphological analysis of blood done manually, hence this is a time consuming task, even for an expert. Furthermore, morphological analysis is limited to the skills, professional knowledgeof a pathologist.

In the diagnosis of variety of diseases leukocytes play an important role and for hematologists the extracting information about that is significant. In the past years,analyze the infected cells using digital image processing technologies lead to more accurate and remote disease diagnosis systems. However, due to large variation of cells in shape, edge, size, and position there are a few difficulties in extracting the information from WBC.Since illumination is imbalanced, depending on the condition during the capturing the image contrast between background and the cell boundaries varies.In the field of segmentation methodsMany works have been conducted.

The rest of the paper is organized as follows. Section II presents different WBCs segmentation Techniquesand we conclude the paper with discussions in Section III.

II. WBC (White Blood Cells) Segmentation Techniques

A. Thresholding Method:

The most popular and commonly used method for image segmentation is Thresholding methods. In this method, image pixels are divided with the help of intensity level of an image. This method is mainly used to distinguish the foreground objects from background images. In this objects are lighter than its background. Selection of this method depends upon our prior knowledge. The thresholding method is broadly classified into three categories.

1) Global Thresholding: Global Thresholding is based on selecting an appropriate threshold value i.e. T. This T is a constant and output image pixel depends upon this T value.

$$q_{(x,y)}=\begin{Bmatrix}1, if\ p_{(x,y)}>T \\ 0, if\ p_{(x,y)}<=T\end{Bmatrix} \quad (1)$$

2) Variable Thresholding: Another type of thresholding method is Variable thresholding. In this method, the value of T varies over an image. It is further divided into two categories:

- Local Threshold: In this the value of T depends upon the neighborhood of x and y.
- Adaptive Threshold: The value of T is a function of x and y.

Blood cells have different intensity levels, so it can be easily extracted using thresholding. Yazan M. et al. [1] used Otsu's thresholding to extract WBCs and RBCs from microscopic blood sample images.

B. Morphological Operations

Morphology is a wide set of image processing operation that process image base on shapes. Morphological operations apply a structuring element to an image and create output image of same size. In these operations[2], the value of pixel in the resultant image is based on a comparison of corresponding pixels in input image with its neighbors. Here the number of pixels added or removed from the objects in resultant image depends on the size and shape of structuring element used to process the image. Many researchers have applied morphological operation with the combination of other methods to segment and count blood cells. Erosion and Dilation are widely used operations to segment blood cells. P. Maziet al.in [3] used dilation and erosion for hole filling in cells. After that they have used erosion for smoothening the image before counting. Yazan M. et al. [1] have segmented blood cells using thresholding and used morphological operations as post processing steps before counting. Dilation can be used to fill holes while erosion can be useful for separating overlapped cells. J. Hari et al. in [4] have applied morphological operation opening to remove half-filled objects or cells that is the blood cells at the boundaries. After that closing operation is applied this enlarges the boundaries of foreground regions in an image. Hence morphological operations are widely used as a post or preprocessing step in segmentation and counting of blood cells.

C. Pixel-based Techniques:

In pixel-based image segmentation pixels [5]are clustered into two classes: foreground (cell) and background pixels. Pixels of the same class, that are connected, are grouped together to form a region. The classification of pixels into fore/background pixels has a significant impact on the final segmentation results. One key property of a pixel is its intensity. For color images the intensity is typically measured for each of three primary channels, red/blue/green, while for gray images only the gray-level is used. There are three drawbacks associated with a pixel-based segmentation. First, the absence of spatial information about the location of the pixel, which is particularly responsible for introducing errors in regions withblurred boundaries. Second, such an approach is sensitive to noise and causes over segmentation for noisy images. The third drawback relates to the fact that pixelbased segmentations are more sensitive to color and lighting variations than humans. For example, such a technique will not be able to produce semantic regions that can be used directly by humans. To address the first drawback, researchers have started to include spatial information as a part of pixel measurement. The problems of noise, the second drawback, may be circumvented by using the median or average of a block of proximate pixels. The (third) drawback related to semantics of a region isolated using region-based segmentation has not been addressed either systematically or exhaustively. The use of pixel properties, including color, texture, edge, spatial homogeneity and adaptability in the classification under constrains an image and does not quite facilitate a meaningful interpretation. Recall that cell images taken under different. The large background in these images is segmented into many regions even they have a very constant intensity that is close to black.

D. Boundary-based techniques:

In cell image analysis, and indeed in a number of biological/health care applications, it is important to detect various constituent objects in an image. There are two different ways to delineate boundaries of a constituent object: detection of edges and active contour model. The detection of ‘edges’ (of an object) relies on the fact that the changes in intensity of pixels across the edge of every two objects are more significant than that of the intensity within the confine of a simple object. There are two steps involved here. First, all edges are detected by the use of first and second derivative of intensity changes. Second, like the histogram based techniques [6], effective edges are located by detecting the most 'significant’ changes using a threshold value either manually or by using optimization techniques [7] for instance. The techniques mentioned above do not take into account the effect of noise on changes in the intensity across an image, and the consideration of noise is important for low contrast images where the rate of change of the intensity may not be well pronounced. Therefore, if a color image is available then it will perhaps be more worthwhile to use the color distribution or color moments for detection of boundaries. The problem of noise in detecting boundaries has been addressed through the use of statistical, wavelet techniques and neural computing techniques. The detection of edges can simplify the analysis of images by drastically reducing the amount of data to be processed, and the useful structural information about object boundaries is also preserved. However, typically a detected object boundary is discontinuous and the linking of a number of (discontinuous) edges remains an open challenge to researchers in the area. Therefore, researchers working on boundary-based segmentation are seeking for alternative methods for replacing the current detection of edge methods. Increasingly, attention is being focused on the so-called active contour models (ACM), also known as snakes. Essentially, an initial active contour is generated, either manually or automatically. The contour is then deformed as driven by two forces. One is the internal forces acting within the confines of a curve itself consisting of the continuity and the curvature of the contour curve, and the other is the external forces ‘exerted’ by the external environment, for instance, the visual features of the curve given that the curve is placed on an image. Deformation is terminated when the contour reaches the actual boundary of objects – the termination point is related to the minimization of an objective function generated from both internal and external forces. There are two major variants of the ACM proposed [8] in literatures: parametric models and evolving geometry models. Parametric models deform faster than the geometry models but the simulation of the model depends on the intrinsic properties of the contour and its parameterization. Also, parametric models cannot naturally handle changes in the topology of the evolving contour. The geometry model in contrast, can manage topology changes and allows multiple contours to be evolved simultaneously. However, geometry models are much slower in speed than parametric model. It appears that the snake has the flexibility (and its inherent straightforward numerical implementation) and the ability to achieve both image segmentation and smoothing by using a piecewise smooth representation of an image. It has been argued that a snake can generate a continuous contour, which is a much more precise representation of the object boundary than those produced though the conventional edge detection techniques

E. Region-based techniques:

Conventional region-based techniques [9] segment images in two different ways: growing and-merging and splitting and merging, as well as, more recently, region-based techniques rely on morphological operations. The growing-and-merging techniques involve the selection of seeds: pixels of an image with conspicuous features e.g. highest or lowest gray level. A selected seed (or segment) is grown by merging the neighboring pixels that are significant similar to the growing region. The procedure is repeated with another seed until no more seeds can be detected. For further analysis, it is required by cell biologist that the whole cell can be detected as a single region from which features used for further analysis can help to, for instance, make clinical decisions. The splitting and-merging techniques, in contrast to the growing/merging techniques, regard the whole image as a big region, and each region is iteratively divided into two until no more regions can be cut. At each stage of the division, a merger is performed to prevent over-segmentation. The growing-and-merging techniques are more widely used as they are object-focused thus producing better object segmentation than the splitting-and-merging. There are two important issues related to the growing-and merging techniques; seed selection, and the similarity measurements for region merging. The issues have been addressed by incorporating notions from fuzzy systems and from graph theory, but challenges still persistRegion-based techniques[10] use morphological operations that require the conversion of an image into its grayscale. The gray values are considered as topographic reliefs with each pixel being the elevation at the pixel. A relief is partitioned into regions called catchment basins, and the boundary of the basins is called a watershed. ‘Water’ that drops on the watershed lines has the equal probability of falling into the any one of the regions (called catchment basins) that are separated by the watershed. The search for a watershed is conducted using two different techniques: immersion approach and toboggan simulation. The former starts from the low altitude to high altitude, while the latter operates in the opposite direction. In the immersion approach, water floods from the catchment basins, and dams corresponding to the watersheds are built to prevent water from falling from one catchment to another. Thetoboggan simulation searches for a downstream path from every pixel with high altitude to the catchment basins, and pixels that can slide into more than one catchment basin are watersheds. Although the immersion approach is more popular than the toboggan approach, a recent comparison of the two algorithms suggests that the two algorithms produce exactly the same segmentation results and that the toboggan simulation algorithm performs more efficiently.

Watershed Transform: The watershed transform can be classified as a region-based segmentation technique. The instinctive idea underlying this method comes from geography: it is that of topographic relief which is flood by water, water shades being the divide lines of the domains of attraction of rain falling over the region. A clumped cell appears largely in blood smear images with various degree of overlapping. Watershed segmentation is an attractive method and tends to favor in the attempts to separate touched or overlapped objects which is one of the most difficult image processing operations . J. Hari et al. in [11] have segmented clumped cells using watershed with distance transform to pre-process the image to make it suitable for watershed segmentation. They have applied Euclidean, quasi-Euclidean, city block and chessboard distance transform and concluded that chess board distance with watershed segmentation gives the efficient counting result for blood cells. Hemant et al. used marker control watershed segmentation for counting of WBCs, RBCs and Platelets [12]. Although the blood cells were segmented the overlapped RBCs were not properly extracted. Pooja L. et al. [13] have presented automated approach for counting RBCs and Handled overlapping cell counting using modified marker controlled segmentation with the integration of morphological and distance mapping method. Overall accuracy of this method was 93.13% with the comparison of manual method. Hemant T. et al. [14] have also used marker based watershed segmentation to remove the problem of over segmentation. Although the watershed algorithm was originally proposed and used to analyze gray-level images, it makes more sense to apply the algorithm to the gradient image so that the catchment basins (partitioned regions) have lower altitude while the watershed (boundary that separates regions) has higher altitude. The watershed algorithm has a number of advantages; (a) The algorithm produces closed and connected boundaries for objects; (b) the algorithm helps to separate strongly overlapping objects; and (c) the algorithm helps to form the union of all the regions comprising the entire image. The three principal disadvantages of the algorithm are: (i) over segmentation; (ii) sensitivity to noise, and (iii) ‘poor detection of significant areas with low contrast boundaries and thin structures'.

F. K-Mean Clustering:

The K-means is a clustering [15] method which is one of the most popular unsupervised learning algorithm due to its simplicity. The K-means clustering has been used for image segmentation. K-means clustering is based on minimizing the objective function, shown in equation 2

$$J = \sum \sum \left\| x_i - c_j \right\|^2 \quad (2)$$

x_i is the i-th sample, c_j is the j-th centre of the cluster. Each data will be clustered into 3 groups for all analyses[4].Classify the colours of Luv system into three classes which can be done by applying simple K-means clustering method [13] on Luv colour system and mapping this cluster again to RGB colour system. The algorithm is composed of the following steps:

1)Select randomly k points into the space represented by the pixels that are being clustered. These points represent the initialcluster centre, c_j.

2) Assign each data to the nearest centre.

3) When all data have been assigned recalculatethe new centre position.

4) Repeat step 2 and 3 until the centres are nolonger move. This will produce a separation ofthe object into group from which the metric tobe minimized can be calculated.

Extract candidate zone for nucleoli, the curve let transform is applied on extracted nucleus. Curve let transform is an appropriate transform for detecting detailed information in images due to its optimality for extraction of 2D singularity based features shown in equation 2. The main image is decomposed to different sub bands with different resolution. To apply curve let transform shown in equation 2, the proposed algorithm in is used, decomposes an N×N Image as follows:

$$f(x, y) = c_j(x, y) + \sum_{j=1}^{J} w_j(x, y) \quad (3)$$

III. CONCLUSION

This paper presented a comprehensive survey of various WBC segmentation techniques. Several segmentation processes have been investigated and their limitations have also been dealt with. This work deals with the analysis of widely and popularly used WBC image segmentation methods such as thresholding method, region based segmentation, watershed segmentation, pixel based segmentation, morphological operation and K-mean clustering method.

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