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WBC Segmentation in Blood Images for Medical Application

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ABSTRACT

In medical diagnosis blood cell count plays very important role. Increment or decrement in the count of blood cell causes many diseases to occur in the human body. There are different techniques of blood cell counting which involves conventional as well as automatic techniques. The conventional method of manual counting under microscope is time consuming and yields inaccurate results. Although there are hardware solutions such as the Automated Hematology Counter, developing countries are not capable of organizing such unaffordable expensive machines in every hospital laboratory in the country. As a solution to this problem, to provide a software-based cost effective and an efficient alternative in recognizing and analyzing blood cells, This paper presents the preliminary study of automatic blood cell counting based on digital image processing. The number of blood cell count that is WBC count is then may be use to diagnose the patient as well as detection of abnormalities like leukemia. For this purpose, few preprocessing and post-processing techniques have been implemented on blood cells image in order to provide a much clearer and cleaner image.

INDEX TERMS: Blood cell count , image processing technique, WBC, differential count, K-means clustering; segmentation; thresholding; watershed algorithm; white blood cells.

I. INTRODUCTION

to White blood cells (WBC) or leukocytes play a significant role in the diagnosis of different diseases, and therefore, extracting information about that is valuable for hematologists. In the past, digital image processing techniques have helped to analyze the cells that lead to more accurate, standard, and remotedisease diagnosis systems.

However, there are a few complications in extracting the data from WBC due to wide variation of cells in shape, size, edge, and position. Moreover, since illumination is imbalanced, the image contrast between cell boundaries and the background varies depending on the condition during the capturing process. This study is focusing on WBC segmentation using L2 microscopic images. Our goal is to segment the WBC nucleuses and cytoplasm using a K means clustering algorithm and Thresholding method and Watershed management that has been developed using digital image processing. The use of image processing techniques have developed rapidly in the last few years, to the point where hematologists can use blood images to automatically process blood slides for the first screening in detecting diseases. Many works have been conducted in the area of general segmentation methods. Among the common segmentation methods are edge and border detection, region growing, filtering, mathematical morphology, and watershed clustering. Ritter et al. presented a fully automatic method for segmentation and border identification of all objects that do not overlap the boundary in an image taken from a peripheral blood smear slide. In their work, pale tips of protuberances are lost.

Ongun et al. did segmentation by morphological preprocessing followed by the snake-balloon algorithm. Jiang et al. proposed a WBC segmentation scheme on color space images using feature space clustering techniques, scale- spacefiltering for nucleus extraction, and watershed clustering for cytoplasm extraction. Leyza et al. used morphological operators and examined the scale-space properties of toggle operator to improve segmentation accuracy. Scotti presented the automatic morphological method that is based on the morphological analysis of WBCs. Their proposed system extracts the morphological indexes(lymphocytes). Kumar et al. used teager energy operator for segmentation, nucleus based on the edges, which are detected effectively by teager energy operator but it required at least a weak edge to exist between red blood cell (RBC) and the background. For cytoplasm segmenting, the yuseda simple morphological method. C seke introduced multi-step segmentation scheme, which implements the automatic thresholding method proposed by Otsu.

II. LITERATURE SURVEY

Title : Automatic Blood Cell Analysis By Using Digital Image processing

Author : Prof. D.S.Patil, Miss. Madhuri G. Bhamare.

Year: 2013

Description:

In medical diagnosis blood cell count plays very important role.Increment or decrement in the count of blood cell causes many diseasesto occur in the human body. There are different techniques of blood cell counting which involves conventional as well as automatic techniques.The conventional method of manual counting under microscope is time consuming and yields inaccurate results. Although there are hardware solutions such as the Automated Hematology Counter, developingcountries are not capable of organizing such unaffordable expensive machines in every hospital laboratory in the country. As a solution tothis problem, to provide a software-based cost effective and an efficient alternative in recognizing and analyzing blood cells, This paper presentsthe preliminary study of automatic blood cell counting based on digitalimage processing. The number of blood cell count that is RBC & WBC count is then may be use to diagnose the patient as well as detection of abnormalities like leukemia. For this purpose, few preprocessing and post-processing techniques have been implemented on blood cells image

Title: Colour Space Transformation and Multi-Class Weighted Loss for Adhesive White Blood Cell Segmentation.

Author: Huiying Li, Xiaoqing Zhao, Anyang Su, Haitao Zhang,Jingxin Liu, and Guiying gu.

Year: 2020

Description:

White blood cells (WBCs) are the cells of immune system,protecting against infective diseases and invasion of viruses and bacteria. Their aberrant number, both abnormal increase and decrease, isa sign of an ongoing pathology, a precise evaluation of their number is of the utmost importance as the first step of assessing a potential disease. In blood cell microscopic images, since red blood cells and platelets are similar in color with WBCs, and WBCs are partially adhesive, WBC segmentation for counting is often not resulting in a good performance. Therefore, in this work, a color space transformation is proposed to filter out red blood cells and platelets, which is transforming he blood cell microscopic images of patients with acute lympho blasticl eukemia from RGB color space to HSV to detect and extract WBCs. For precisely segmenting adhesive WBCs in extraction results, we set cell border to the third class, in addition to foreground and background. A weighted cross-entropy loss function based on class weight and distance transformation weight enhanced U-Net to learn cell border features. Our results showed that the method proposed in this paper for WBC segmentation using the data set ALL_IDB1 could achieve an accuracy of 97.92%.

Title: Deep Transfer Learning Models for Medical Diabetic Retinopathy Detection
Author: Nour Eldeen M. Khalifa
Year: 2019
Description:
Diabetic retinopathy (DR) is the most common diabetic eye disease worldwide and a leading cause of blindness. The number of diabetic patients will increase to 552 million by 2034, as per the International Diabetes Federation (IDF). Aim: With advances in computer science techniques, such as artificial intelligence (AI) and deep learning (DL), opportunities for the detection of DR at the early stages have increased. This increase means that the chances of recovery will increase and the possibility of vision loss in patients will be reduced in the future. Methods: In this paper, deep transfer learning models for medical DR detection were investigated. The DL models were trained and tested over the Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 dataset. According to literature surveys, this research is considered one the first studies to use of the APTOS 2019 dataset, as it was freshly published in the second quarter of 2019. The selected deep transfer models in this research were AlexNet, Res-Net18, SqueezeNet, GoogleNet, VGG16, and VGG19. These models were selected, as they consist of a small number of layers when compared to larger models, such as DenseNet and InceptionResNet. Data augmentation techniques were used to render the models more robust and to overcome the over fitting problem.

III. METHODOLOGY

To provide a structured overview of the blood smear images and detection of wbc segmentation using image processing techniques, the proposed paper surveys the literature from the following perspectives:

1) Datasets available for segmentation.
2) Preprocessing techniques applied to detect images.
3) Otsu thresholding method is proposed for sub image separation of wbc .
4) Kmeans algorithm is proposed for nucleus segmentation.
5) Modified watershed transform method is proposed for separating touching nuclei.
6) Zack thresholding method is proposed for finding cytoplasm.

A. IMAGE PREPROCESSING TECHNIQUES

Images are subjected to numerous image preprocessing steps for visualization enhancement. Once the images are brighter and clearer, a network can extract more salient and unique features. The resizing of an image is a popular method of image preprocessing. The image is scaled down to a low resolution image according to the appropriate system. The resolution of an image is resized into the resolution required by the network in use.
Researchers often have to eradicate and mask the blood vessels and optical discs so that they are not classified as wrong lesions. Many blood datasets consist of images with a black border, with researchers generally preferring to segment the meaningless black border to focus on the region of interest . Image augmentation is applied when there is an image imbalance (as typically observed in real world settings).Images are mirrored, rotated, resized and cropped to produce cases of the selected images

for a class where the number of images is lower than the other large proportion of healthy blood images in comparison with blood images. Augmentation is a common strategy for enhancing outcomes and preventing overfitting.

B. Nucleus Segmentation:

Nuclei have variable shapes in different kinds of leucocytes. Finding a significant method for shape modelling and segmenting the nucleus has always been a challenge for scientists. Among segmentation methods, active contour models have gained a lot of attention recent l. Curves are defined within an image domain and can move under the influence of internal forces within the curve itself and external forces derived from the image data. Two general types of active contour models have been introduced: parametric and geometric active contours Geometric active contour models or geodesic snakes have been proposed to address the fact that parametric active contour models cannot resolve topological changes. For our processing scheme, the segmentation is done on sub- images, so there are no topological changes since only one object of interest exists in each sub-image.

1. Smoothing the image with Gaussian filter to reduce noise and unwanted details with standard deviation, σ.
2. Gradient calculation of g(x,y) using any of the gradient operators
3. Threshold M:

Where T is chosen in a way that all edge elements be kept while most of the noise is suppressed. checks whether each non- zero MT (x,y) is greater than its two neighbours along the gradient direction θ(x,y). If it is, MT (x,y) will be kept unchanged; otherwise, it will be set to zero. This process is known as no maximal suppression. Next, these processes are implemented:

1. Ridge pixels are thresholded using two thresholds T1 and T2 with T1hT2.Ridge pixels with values between T1 and T2 are weak edge pixels, and those with values larger than T2 are strong edge pixels.
2. Edges segments in T2 are linked to form continuous edges. To do so, each segment in T2is traced to find its end, and its neighbours in T1are searched to find any edge segment in T1, which can bridge the gap until reaching another edge segment in T2.By this edge detection method, central connected object boundaries that represent the nucleus are clearly obtained. In next step, GVF of the images were calculated based one equation and used as internal andexternal forces to guide snakes to deform to nucleus boundary edges.Nucleus is the connected boundary in image and has been filled up.

C. Cytoplasm Segmentation:

By subtracting the segmented nucleus from the original sub-image, we will obtain the cytoplasm, RBC, and the background. Most of the time, RBCs appear in the image border. Looking at the grey level intensities, the cytoplasm and two other components are having almost uniform areas. Therefore, it justifies the need for segmenting these uniform components using thresholding techniques. There are many thresholding techniques available in literature Here, we set the threshold value based on Zack algorithm According to Zack's algorithm, in grey intensity histogram(h[x]) of the remaining sub- image components, a line is constructed between the highest histogram value (h[b max]) and the lowest histogram value (h[b min]), where b max and b min indicate the grey level values in which the histogram h[x] reaches its maximum and minimum, respectively.

D. Threshold Method

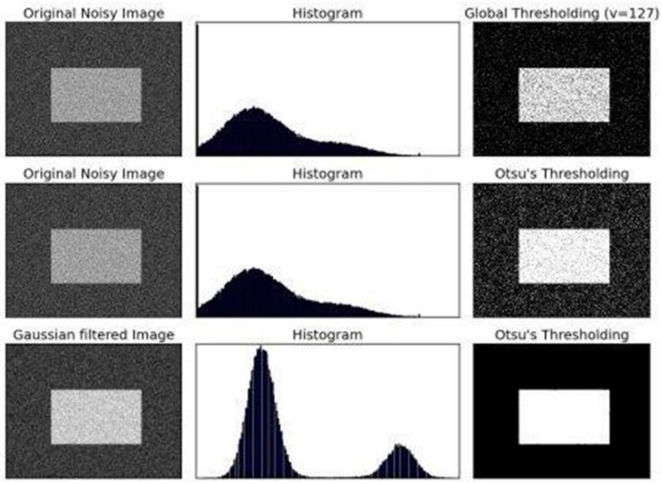
An image processing method that creates a bitonal (aka binary) image based on setting
a threshold value on the pixel intensity of the

original image. The thresholding process is sometimes described as separating an image into foreground values (black) and background values (white).

To make thresholding completely automated, it is necessary for the computer to automatically select the threshold T. Sezgin and Sankur (2004) categorize thresholding methods into the following six groups based on the information the algorithm manipulate.

- Histogram shape-based methods, where, for example, the peaks, valleys and curvatures of the smoothed histogram are analyzed
- Clustering-based methods, where the gray-level samples are clustered in two parts as background and foreground (object), or alternately are modeled as a mixture of two Gaussians
- Entropy-based methods result in algorithms that use the entropy of the foreground and background regions, the cross-entropy between the original and binarized image, etc.
- Object Attribute-based methods search a measure of similarity between the gray-level and the binarized images, such as fuzzy shape similarity, edge coincidence, etc.
- Spatial methods [that] use higher-order probability distribution and/or correlation between pixels
- Local methods adapt the threshold value on each pixel to the local image characteristics. In these methods, a different T is selected for each pixel in the image.

Color images can also be thresholded . One approach is to designate a separate threshold for each of the RGB components of the image and then combine them with an AND operation. This reflects the way the camera works and how the data is stored in the computer, but it does not correspond to the way that people recognize color. Therefore, the HSL and HSV color models are more often used; note that since is a circular quantity it requires circular thresholding. It is also possible to use the CMYK color model.

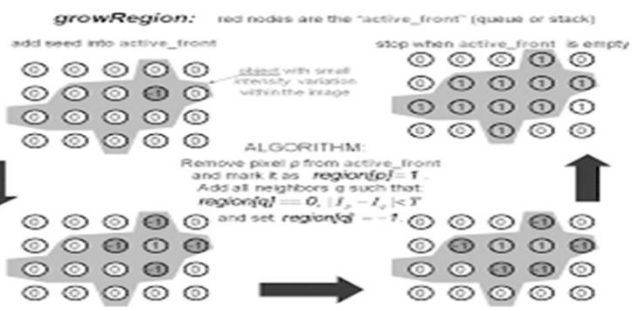


E. Edge base segmentation:

The final aim is to reach at least a partial segmentation -- that is, to group local edges into an image where only edge chains with a correspondence existing objects or image parts are present.

F. Region Based Segmentation

In the region-based approach, all pixels that correspond to an object are grouped together and are marked to indicate that they belong to one region. This process is called segmentation. Pixels are assigned to regions using some criterion that distinguishes them from the rest of the image.

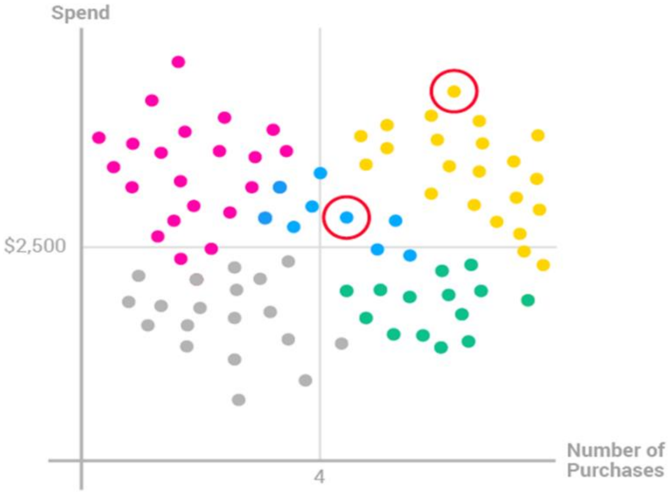


G. Clustering Based Segmentation

Clustering is a powerful technique that has been reached in image segmentation.

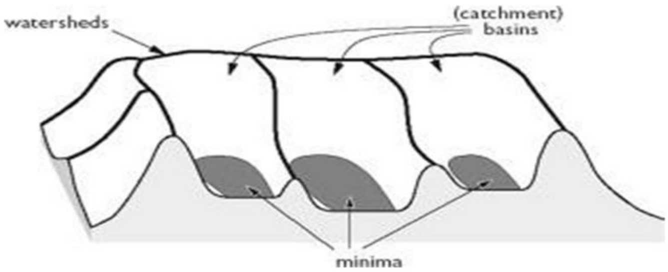
The cluster analysis is to partition an image data set into a number of disjoint groups or clusters.

The clustering methods such as k means, improved k mean, fuzzy c mean (FCM) and improved fuzzy c mean algorithm (IFCM) have been proposed.



H. Watershed Segmentation

Watershed segmentation is another region-based method that has its origins in mathematical morphology. Watersheds separate basins from each other. The watershed transform decomposes an image completely and thus assigns each pixel either to a region or a watershed.



I. Different Segmentation Methods Comparison.

Our proposed method is compared with three leukocyte segmentation methods: marker- controlled watershed, the methods of reference based on the result of the distance transformation, marker-controlled watershed divides an image into the foreground, background and uncertain region, then the watershed operation is executed according to the mark result to extract cell border, proposed an automatic sampling process for leukocyte image according to the staining knowledge of blood smears, then extreme learning machine classifier is trained online to extract WBCs. In reference an ensemble of a poly harmonic extreme learning machine is trained on-line by the pixels sampling from the fixation and non fixation area, and the procedure of "pixel sampling-learning- classification" was performed iteratively until the perception is saturated. The average F-measures of these four methods on the test set are shown. The result of CDWN is significantly higher than other methods, indicating that the proposed approach can optimize leukocyte segmentation.

IV. CONCLUSION

By using digital image processing, analysis of blood cell image is more accurate as well as this method is efficient in terms of cost and time consuming compared to existing techniques of blood cell analysis. MATLAB software use for this analysis .Day by day research work is increasing in this field and various image processing techniques are implemented in order to get more accurate result. For medical diagnosis and blood cell counting use of image processing techniques is useful and better than existing techniques provided that standardization of blood smear is done properly to obtain blood cell image.

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