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An Efficient VLSI Design for Extracting Local Binary Pattern

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Abstract— The nonspecific nature of the signs and symptoms of Acute Myelogenous leukaemia typically results in wrong designation. Diagnostic confusion is additionally display because of imitation of comparable signs by alternative disorders. Careful microscopic examination of stained blood smear or bone marrow aspirate is that the solely thanks to effective designation of leukaemia. Now a days, a statistic approach to texture analysis has been developed, during which the distributions of straightforward texture measures supported native ternary patterns (LTP) are used for texture details. This paper shows that a selected set of patterns encoded in LTP forms together with wavelets transform primarily based frequency domain parameters extraction is an economical and sturdy texture description which may bring higher classification rates compared with the prevailing ways.

Key Words— Acute myelogenous leukemia (AML), classification, color conversion, feature extraction, segmentation

1. INTRODUCTION

Acute myelogenous leukemia (AML) has many additional names, comprising acute myelocytic leukemia, acute myeloid leukemia, acute granulocytic leukemia. Leukemias are cancers that start in cells that would normally develop into different types of blood cells. "Acute" expands that this leukemia can progress quickly if not treated, and would be probably mortal in a few months. "Myeloid" means to the type of cell this leukemia starts from. Most cases of AML develop from cells that would turn into white blood cells (other than lymphocytes), but some cases of AML progress in other types of blood-forming cells. AML starts in the bone marrow (the soft inner part of certain bones, where new blood cells are created), but in most cases it quickly moves into the blood [3], [6], [8]. It can sometimes expansion to other parts of the body incorporating the lymph nodes, liver, spleen, central nervous system and testicles. Other types of cancer can start in these organs and then spread to the bone marrow. But these cancers that start somewhere else and then spread to the bone marrow are not leukemias. Bone marrow is the soft inner part of some bones such as the skull, shoulder blades, ribs, pelvic (hip) bones and backbones. The bone marrow is formed up of a little number of blood stem cells, more fully developed blood-forming cells, fat cells, and upholding tissues that aid cells grow. Blood stem cells go through a series of changes to make new blood cells. Throughout this process, the cells grow into either lymphocytes (a sort of white blood cell) or other blood forming cells, which are classes of myeloid cells. These kind of blood-forming cells can grow up into one of the three main kind of blood cell components: Red blood cells, Platelets, White blood cells (more than lymphocytes).

Diagnosis of leukemia is really hard due to the similar signs of other disorders. Careful microscopic tests of stained blood smear and bone marrow is the only way for powerful diagnosis of leukemia. Here color, Shape and texture features are used to extract the cancer cells. Usually the images taken from the microscopes are RGB in color and to do the segmentation easily, RGB to L*a*b color conversion [1] is carried out. Here the RGB images are converted into L*a*b color space images. Segmentation is carried out using K-means clustering.

2. RELATED WORKS

Segmentation of solitary leukocytes is straightforward and fairly good results can be achieved using successive threshold operations as shown in several papers. In all of these, clusters [2] are excluded. Though, the clustering tendency varies amid different leukocyte subclasses (especially in pathological conditions). Simply ignoring clusters may therefore affect the result of the differential count. Poon et all [4] proposed a cluster splitting method in which touching cells are separated by first locating two concavity in the cytoplasm mask boundary and then cutting the cells apart along the straight line between them. This algorithm crudely separates pairs of cells hut cannot handle complex clusters.

Kovalev et all [5], [7], [10] developed an algorithm that uses threshold to detect nuclear blobs, which are then assembled using a rule-based scheme. Once the nucleus has been assembled the cytoplasm is approximated using a circle, which is then further processed. Although it was not designed for cluster separation, it can split minor clusters at the nucleus level hut inter-cytoplasmic boundaries are not located and touching nuclei are not divided up.

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dense, complex clusters from peripheral blood and bone-marrow. In this paper the segmentation process is further improved and I also give an evaluation of its accuracy.

Recently I introduced a segmentation algorithm targeted for the cluster-separation problem. I have shown that it is capable of separating dense, complex clusters from peripheral blood and bone-marrow. In this paper the segmentation process is further improved and I also give an evaluation of its accuracy.

3. PROBLEM DEFINITION

By only using Local Binary Pattern (LBP), I cannot select the best features in feature selection and it leads to poor accuracy. Here I am using both LBP and LTP and it will give high accuracy.

4. PROCESS OVERVIEW

The system proposed ensures step-by-step processing. Fig. 1 depicts the process overview. The system overview gives a complete illustration of the alignment of steps that are to be followed for efficient categorization of acute leukemia. The first step entails preprocessing the entire images to get over any background non-uniformity due to uneven illumination. Preprocessing also comprises color correlation where RGB images are modified to L∗a∗b color space images. This step confirms perceptual equality. This step is followed by K-means clustering to get out the nucleus of each cell. Segmentation [9] is carried out and feature extraction is finally performed.

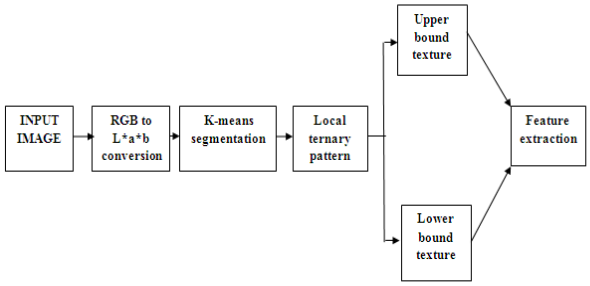

Fig. 1. Process Overview

5. PREPROCESSING

5.1 Image Acquisition

For AML, I accessed the American Society of Hematology (ASH) for their online image bank of leukemia cells. The ASH image bank is a internet-based image library that offers comprehensive and growing collections of images relating to a wide range of hematology categories. They provide fine-quality images captured using different microscopes in mismatched resolutions. Our database for AML comprised 80 images— 40 from AML patients and 40 from non-AML patients. The resolution used for our classification was 184×138 pixels.

5.2 CIELAB Color Features and Color Correlation

The images captured by digital microscopes are generally in RGB color space, which is very hard to segment. In operation, the blood cells and image background differs significantly with esteem to color and intensity. This can be based by many reasons such as camera settings, changing illumination, and aging stain. In order to construct the cell segmentation robust with respect to these alterations, an adaptive approach is used: the RGB input image is changed into the CIELAB or, more accurately, the CIE L∗a∗b∗ color space [12], [13]. The key causes for these are, first, to decrease memory requirement and to enhance the computational time. Second, the perceptual variation between colors is equivalent to the Cartesian distance in the CIELAB color space. Therefore, the color imbalance between two samples can be computed by using a Euclidean distance. Third, it has two color components (a and b), and it is mapped to approximate human vision the L component closely matches human perception of lightness or it can be used to correct the lightness contrast using the L component. Eventually, a and b components can be used to make exact color balance corrections. In extra 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 location between yellow and blue. Due to its perceptual uniformity, L∗a∗b makes equivalent change visually for a change of the same amount in color value. This confirms that every minute difference in the color value is published visually.

6. NUCLEI SEGMENTATION

The aim of image segmentation is to extract valuable information from an input image. It plays a key part since the capability of succeeding feature extraction and classification depends very much on the correct determination of the myeloblasts. A large number of algorithms for segmentation have been expanded for gray-level images [14], [15]. Segmentation is executed here for extracting the nuclei of the leukocytes using color-based clustering. Here cluster analysis is the conventional study of techniques and algorithms for grouping, or clustering, objects according to be measured or perceived intrinsic characteristics or similarity between them. Here cluster analysis does not use category labels that tag objects with prior identifiers (class labels). K-means, which is one of the very best unsupervised learning algorithm and is also a simple clustering algorithm. Still K-means algorithm is broadly used. This speaks to the problems in designing a general-purpose clustering algorithm and the ill-posed problem of clustering [16], [17]. In this paper, I chose clusters corresponding to nucleus (high saturation), background (high luminance and low saturation), and other cells. Here, all the pixels are assigned to one of these classes using the properties of the cluster center.

6.1 K-Means Clustering Algorithm

The K-means algorithm needs three user-specified parameters: the number of clusters k, cluster initialization (basic), and distance metric (total distance). A K-means clustering approach is used to allocate every pixel to one of the clusters. Every pixel is allocated to one of these classes using the properties of the center of the cluster. Every pixel of an object is sorted into k clusters, based on the corresponding ∗a and ∗b values in the L∗a∗b color space value. As a result, every pixel in the L∗a∗b color space is sorted into any of the k clusters by finding the Euclidean distance between the pixel and each indicated color. These clusters match to nucleus (highest saturation), background (highest luminance and lowest saturation), and other cells (e. g., erythrocytes and leukocyte cytoplasm). Every pixel of the whole image will label to a particular color depends on the least distance from each indicator. I have considered only the cluster that contains the blue nucleus, which is needed for the feature extraction. When performing K-means segmentation of whole images, it was noted that, in some of the segmented images, only the edges of the nuclei were obtained as against to the whole images of the nuclei. This limitation was get over by retaining morphological filtering [18]. An image is divided into many regions rely on the features to be extracted. Employing morphological filtering ensures that perceptibility and visibility of these regions will be improved.

7. FEATURE EXTRACTION

Feature extraction in image processing is a technique of redefining a large set of redundant data into a set of features of decreased dimension. Transforming the input data into the set of features is defined as feature extraction. Feature selection extremely affects the classifier performance; As a result, a correct choice of features is a very critical step. In order to establish the powerful feature set, many published articles were studied, and their feature selection procedure was noted. It was observed that certain features were broadly used as they gave a good classification. I implemented these features on whole images in our system.

7.1 LBP

The concept of local binary pattern (LBP) was introduced for texture classification [19], [20]. This technique has many benefits. For example, the LBP texture features have the sequent characteristics: 1) They are powerful against illumination changes; 2) they are very quick to compute; 3) they does not need many parameters to be set; 4) they are ordinary features; 5) they are not variant with respect to monotonic grayscale transformations and scaling; and 6) it runs very well in many computer vision image retrieval applications. The LBP method has proved to perform many living methods, including the linear discriminate analysis (LDA) and the principal component analysis (PCA). In order to deal with textures at variety of scales, then LBP operator was extended to use neighborhoods of varying sizes. Describing the local neighborhood as a set of sampling points uniformly spaced on a circle centered at the pixel will be labeled allows any radius and number of sampling points. While a sampling point does not fall in the center of a pixel, linear interpolation will be employed, in the LBP method where each pixel is replaced by a binary pattern that is derived from the pixel's neighborhood.

7.2 LTP

Local ternary pattern (LTP) is an extension of LBP. Here it uses a threshold constant to threshold the pixels which gives very high accuracy for feature selection.

8. RESULTS AND DISCUSSION

The proposed technique has been applied on 108 peripheral blood smear images obtained from the American Society of Hematology. A microscopic blood image of size 512*512 (Figure 2) is considered for evaluation. The input image is processed sequentially as per the steps mentioned in Section 5. The segmented output of cell nucleus image obtained after applying K-means clustering algorithm is shown in Fig. 6. The cluster image containing only blue nucleus is used to obtain the sub images containing a single nucleus is shown in Figure 7 and 8.

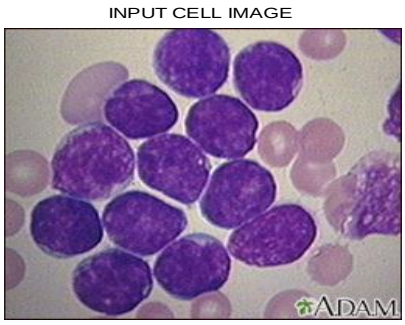

Fig. 2. Input cell image

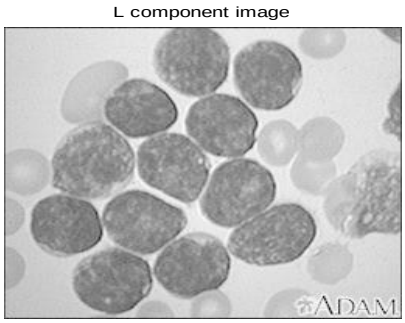

Fig. 3. L component image

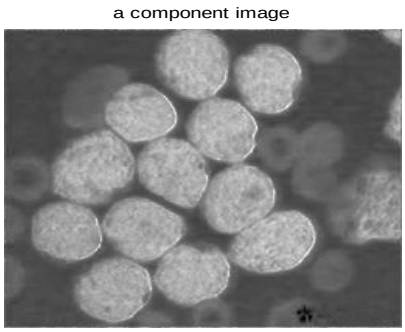

Fig. 4. a component image

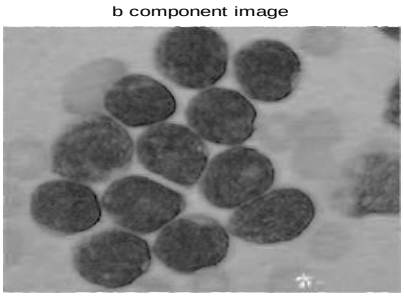

Fig. 5. b component image

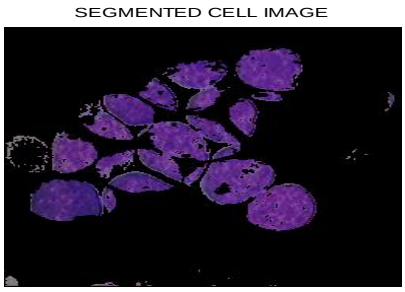

Fig. 6. Segmented cell image

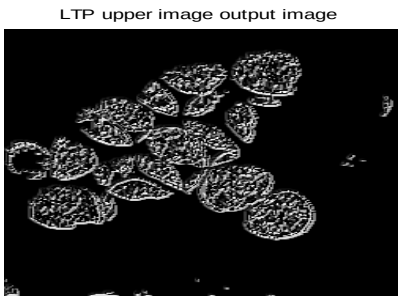

Fig. 7. LTP upper image

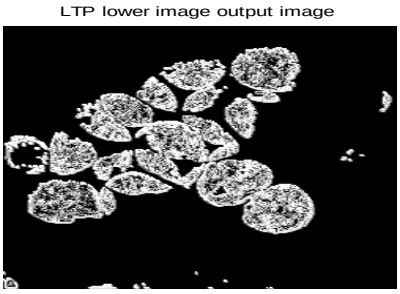

Fig. 8. LTP lower image

9. CONCLUSION AND FUTURE WORK

In this paper I improved the accuracy of segmentation using K-means clustering and feature extraction by using LBP. Future work can be enhanced by using Local Ternary Pattern (LTP) in future extraction and Genetic Algorithms can be used to select the best features.

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