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Bio-Medical Image Segmentation using Wavelet Based Fusion Technique

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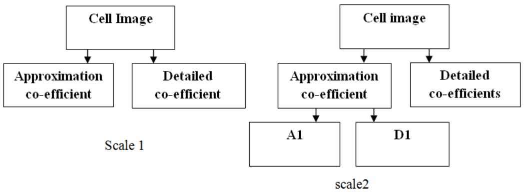
In recent years, bio-medical image segmentation is established itself as base for image analysis. This article proposes a new method in developing a robust wavelet based medical image fusion technique for image segmentation. A GLCM (Gray Level Co-occurrence Matrix) based statistical method is used to extracts the texture features of the image decomposed at single level and the image is segmented based on region growing method. The combination of these two along with fusion technique gives a new segmented image. The results indicate the efficiency of the proposed method in segmenting the both normal cell images as well as darker cell images.

Keywords: Cell image; GLCM; Image analysis; Region growing; Segmentation; Wavelet transform.

The advances in digital technology as well as in the light microscopy field in recent years, resulted in growing importance of digital cellular imaging and computerized image analysis in cell biology. The use of medical image processing techniques, increase the speed of analysis and can supersede some limitations inherent to the human visual system. They also provide better and early solutions for medical emergencies, including, detection of abnormalities in critical medical conditions. The cell image analysis is an important step in biological applications to understand cell behavior and its response to different cell culturing conditions etc. The use of image segmentation algorithms increases the accuracy of data analysis which forms the basis for further analysis of the image. There are several image segmentation techniques used for these kind of analysis. Image segmentation uses features extracted from image using mathematical morphological operations[1,2], based on erosion and dilation of the image. The watershed segmentation is obtained by partitioning an image into primitive regions using gradient magnitude and markers[3,4]. The segmentation by indexing pixel clustering technique is very useful in gray level as well as in color image segmentation[5]. The K-means algorithm is an unsupervised technique, which separates the clusters based on user requirement and helps in finding specified number of clusters (K), which are denoted by their center point[6]. FCM (fuzzy C-means clustering) algorithm is a form of image segmentation technique, in which each point is assigned based on probability criteria corresponding to that cluster, with varying degree of membership [7-14]. The GLCM (Gray Level Co-occurrence Matrix) is mainly used to drawing out texture features of image, and is more useful in segmentation of remote sensing images, medical images and texture based images[15-23]. Region growing method is one of the efficient region based segmentation method, which gives the segmented image by performing region based operations[24-27]. This method is mainly used in detecting tumor in brain image, cancer cell detection in liver images[28,29].

Discrete wavelet transform (DWT)

In DWT, the digital image is divided into four sub-images and named as A1 (approximation coefficient or A1 band) and D1 (detailed coefficients or H1, V1, D1 bands). However D1 contains edge/texture details of the image, whereas A1 represents most of the visual details of the image[1-3,6]. A1 sub-image is subjected to the further preprocessing steps as it contains most of the image information. The A1 sub-image is subjected to second level of decomposition and so on[16, 18,19, 30-33].



Gray level co-occurrence matrix

There are various algorithms available for extracting texture features of the images. Texture feature is nothing but pattern of data, involving structure of image and its statistical information[15,16]. The GLCM approach is a popular method based on texture feature of gray level consociation probability[17,18]. It measures the second-order statistical properties of the digital images and brings out the spatial relationship of specific pair of pixel values and it occurs in neighboring pixels in an image[19,20]. The GLCM properties allows faster recognition of various types of cell images with high accuracy, consumes less time for execution and provides good sensitivity dependent features after preprocessing stages[21-23].

A GLCM is a statistical method, where, the each rows and columns is equal to the number of gray levels, G, in the image. The array element $P(i, j| \Delta x, \Delta y)$ shows frequency ratio between the two pixels, which are isolated by a pixel spacing $(\Delta x, \Delta y)$, and occur within a given vicinity, one having intensity $'i'$ and another with intensity $'j'$. Moreover the array element $P(i, j \mid d, \theta)$ contains the second order statistical probability values for variations between gray levels and at a certain shift in spacing 's' and at a certain angle[19,22,23]. Given a neighborhood of an input image containing G gray levels from 0 to, let is the intensity at selected m, line n of the neighborhood. The relative frequency matrix is given by,

$$P(i, j|\Delta x, \Delta y) = WQ(i, j \mid \Delta x, \Delta y) \quad ...(1)$$

where,

$$W = \frac{1}{(M-\Delta x)(N-\Delta y)} \text{and } Q(i, j \mid \Delta x, \Delta y) = \sum_{n=1}^{n-\Delta y}\sum_{m=1}^{m-\Delta x} A$$

$$A = \begin{cases} 1 \text{ if } f(m, n) = i \text{ and } f(m+\Delta x, n+\Delta y) = j \\ 0 \text{ elsewhere} \end{cases} \quad ...(2)$$

Region growing

Region growing is a form of image segmentation method, which selects the particular region to segment the interested area of the image. It groups the pixels according the pre-defined criteria[24,25]. The algorithm grows the seed regions until all image pixels have been incorporated and finally, method identifies the individual regions to be segmented[26]. This method provides clear edge properties and separates regions in a simple way, by choosing multiple criteria at the same time[27]. It performs well with respect to noise and it has less algorithm complexity compare to FCM based methods.

The region growing method works on the following rules. Here represents the ith region and predicts the region of interest in a logical way and is the null set.

All the interested pixels must include in a region to finish the segmentation process.

$$\cup_{i=1}^{n} Ri = I \quad ...(3)$$

The regions must be disjoint.

$$Ri \cap Rj = \emptyset \quad \forall i = 1,2,3, \dots n \quad ...(4)$$

Region of interest must be connected with often predefined criteria.

$$P(Ri) = TRUE, \quad \forall i \quad ...(5)$$

$$P(Ri \cup Rj) = false \quad ...(6)$$

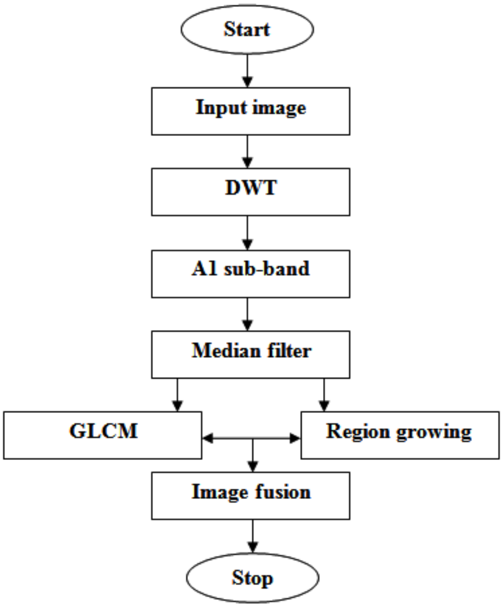


Fig. 1. Schematic flowchart of the proposed method

In the proposed method, the combination of both Region growing and GLCM segmented images are fused to obtain more meaningful segmented results. Sample images are taken from cellaVision and CellAtlas, and the experimental studies are focused mainly, on blood cells like proerythroblast, basophilic erythroblast which comes under erythropoiesis family. The attributes of these cells are large, round and centrally placed nucleus with fine chromatin structure and narrow dark blue cytoplasma edges. This paper aims to identify and extract this proerythroblast, basophilic erythroblast nucleus.

This paper is divided into four sections, the Section 1, carries introduction, Section 2, covers the proposed method, section 3, portraits the flowchart and algorithm of the proposed work. The results of the proposed method are presented in section 4, and conclusions are furnished in section 5.

Proposed method

The proposed segmentation method is carried out on cell images. In this method, first, the cell image is subjected to median filter to denoise

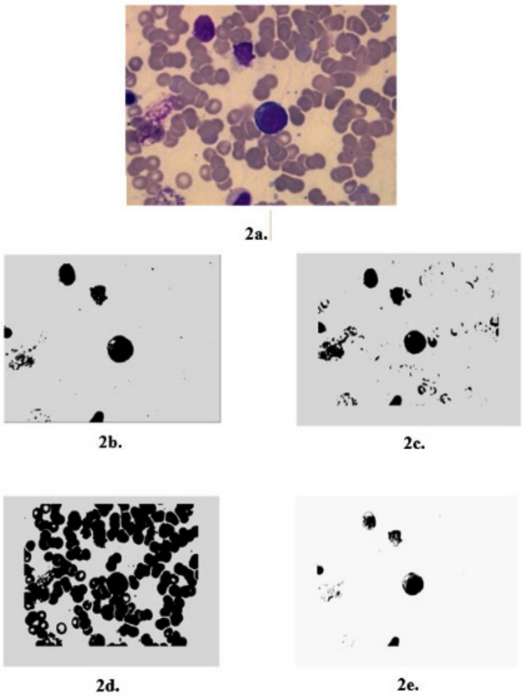


Fig. 2. a. Input cell image1, b. Groundtruth image, c. FCM thresholding segmented image, d. FCM clustering segmented image, f. Proposed method segmented image.

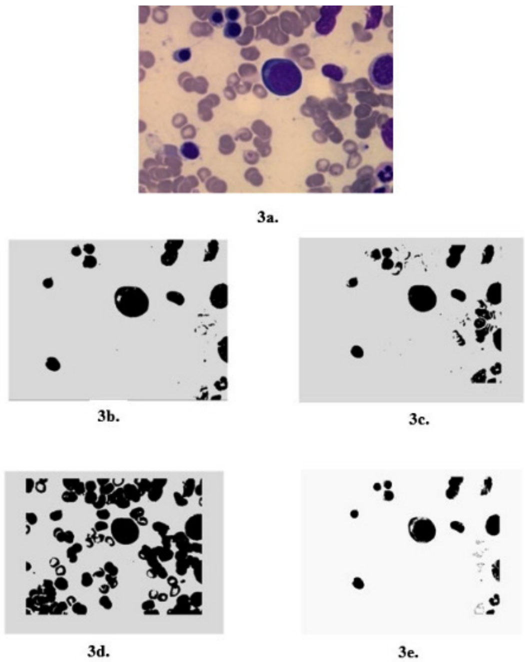


Fig. 3. a. Input image, b. Groundtruth image, c. FCM thresholding segmented image, d. FCM clustering segmented imge, f. Proposed method segmented image.

the image without losing edge details. A statistical GLCM method is used to extract the textural information from the filtered image. Then, this median filtered image is segmented using region growing method to separate the regions based on some pre-defined criteria. In this work, single seed region growing techniques is employed, where the difference between the mean of region and pixel intensity value are used as the measure of similarity.

Image fusion method adds the two or more processed images of the same object type into a solo image[12]. The endower of image fusion, especially in bio-medical imaging, is to create new images that are more meaningful for human visual perception[27]. The segmentation of cell images is mainly based on abrupt changes in image features, like color information, intensity, boundary/texture features and statistical information's. In this work, the average fusion technique of the GLCM segmented image and region growing segmented images are taken in order to reach desired and meaningful result, which leads a new segmented image. The proposed work is very useful to extract the required

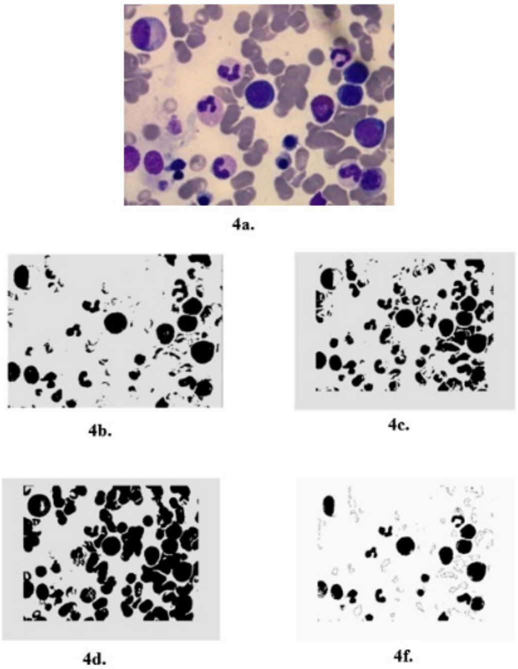


Fig. 4. a. Input image, b. Groundtruth image, c. FCM thresholding segmented image, d.FCM clustering segmented imge, e.Proposed method segmented image.

Table 1. Comparison of segmentation results

Image	Accuracy			Sensitivity			Dice co-efficient			Jaccard co-efficient		
	FCMC	FCMT	Our method	FCMC	FCMT	Ourmethod	FCMC	FCMT	Our method	FCMC	FCMT	Our method
Cell image 1	92.8%	97.3%	97.5%	96.5%	97.9%	1	96.2%	98.6%	98.7%	95.6%	97.2%	97.4%
Cell image 2	89.3%	96.7%	96.8%	97.3%	97.3%	99.9%	94.3%	98.2%	98.3%	89.3%	96.4%	96.6%
Cell image 3	81.0%	89.3%	90.7%	96.9%	89.6%	99.9%	89.4%	93.3%	94.7%	80.9%	87.4%	90.0%

Table 2. Execution time comparison of segmentation methods

Image	Time in sec		
	FCMC	FCMT	Proposedmethod
Cell image 1	9.731	54.628	11.340
Cell image 2	13.680	39.714	11.894
Cell image 3	13.190	29.834	14.031

area of the cell image.

Start

Flow chart

Algorithm steps:

Input: Cell image to be segmented

Output: Segmented image

- A DWT (discrete wavelet transform) decomposes the cell image into scale 1.
- Sub-image (A1) is denoised by using median filter.
- GLCM texture feature classifier is used to extract the essential information from A1 and A1 is segmented simultaneously using region growing method.
- Final image obtained by fusing of two segmented outcomes.

RESULTS AND DISCUSSIONS

Performance matrices

• Accuracy

It specifies the pixels of the image which are perfectly classified. Perfection of the segmentation technique[34] is given by

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \quad ...(7)$$

Pixels which are perfectly incorporated to the given class are represented by TP and TN represents the pixels which are not belonging to the given class. FN is wrongly predicted pixels, which are not belonging to the given class.

• Sensitivity

Sensitivity is calculated through positive predictive and negative predicted values, which is the ratio of true outcome of all segmented results[34].

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \quad ...(8)$$

• Dice co-efficient

Dice-coefficient examines the identical things in between segmented image and the ground truth image, which is retrieved from manual segmentation. Dice coefficient of segmented image[35] is given by

$$\text{DC} = \frac{2|\text{M} \cap \text{N}|}{|\text{M}| + |\text{N}|} \quad ...(9)$$

where, $|M|$ and $|N|$ cardinalities of two sets.

• Jaccard co-efficient

Jaccard co-efficientis as same as the dice coefficient, which calculates the commonness in-between ground truth data with different segmentation methods employed in this paper and[35] is given by

$$\text{JC} = \frac{|\text{M} \cap \text{N}|}{|\text{M} \cup \text{N}|} \quad ...(10)$$

Experimental results

CONCLUSION

This paper presents a new algorithm called wavelet based fusion technique, combines GLCM based statistical method and region growing methods efficiently via image fusion technique to produce a better segmented image. However, the utilization of median filter followed by level 1 wavelet decomposition is one of the key feature to achieve the effective segmentation.

The results of this method are compared with that of wavelet based FCM thresholding and FCM clustering methods and found that segmentation using wavelet based fusion technique increases the efficiency of the segmentation, significantly, in terms of correctness, sensitivity, dice co-efficient and jaccard co-efficient. The algorithm is computationally fast and efficient. The results show that the proposed method performs better even for the darker cell images. It is found that sensitivity parameter in performance metrics increases approximately 5% and this improve in sensitivity and accuracy are the major contribution of this work and is evident from the results obtained from the developed algorithm.

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