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Color Image Segmentation Using Fuzzy Clustering and Fusion: Application to Biomedical Images

Salim Ben Chaabane¹

¹Computer and Information Technology, Tabuk University. Kingdom of Saudi Arabia - PO Box: 4279 - Tabuk: 71491

SIME Research Laboratory, ENSIT University of Tunis, 5 Av. Taha Hussein, 1008, Tunis, Tunisia

Abstract: In this paper, a new color image segmentation method based on Fuzzy clustering and data fusion techniques is presented. The proposed segmentation consists in combining the three component images (R, G and B) of the same image, to gather, in order to increase the information quality and to get an optimal segmented image. In the first step, the segmented images are obtained by applying fuzzy c-means clustering to the information's coming from the three independent component images. In the second step, on the obtained segmented images with specific primitive colors, a combination rule is used to integrate the segmentation results over the three-color components.

Experimental investigations and comparative studies with the other previous methods are carried out showing thus the robustness and superiority of the proposed method in terms of medical and textured image segmentation.

Index Terms: Segmentation, biomedical image, fuzzy c-means, fuzzy fusion, conflict, and data fusion.

I. INTRODUCTION

The image segmentation is the process of partitioning an image into homogeneous regions. The goal of segmentation is to locate objects and boundaries in images [1] [2]. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics, such as intensity, color, tone or texture, etc. However, processing images in levels is easy and fast compared to color images. Nevertheless, the color image processing [3] is a very important task when the objects cannot be extracted using gray scale information but can be extracted using color information. The color images processing is one of the important areas. It is used in different domains and many techniques have been proposed.

Color images can be represented using several color models such as RGB, HSI, YCbCr etc. [3]. It is also possible to convert between color models using the linear and non-linear transformations of the RGB color space. Each color representation has its advantages and disadvantages [4] [5]. There is still no color representation that can dominate the others for all kinds of color images yet.

The major problem of color image segmentation is the high correlation and spatial redundancy of multi-band image histograms and the difficulty of clustering using multi-dimensional histograms. Hence, the general segmentation problem consists in choosing the adopted color model in a specific domain [5] [6].

In the past, many authors have addressed the color image segmentation problems using different methods [7] [8] [9] [10], and several researchers have, in particular, investigated the data fusion techniques and fuzzy logic [11] [12] [13]. Preliminary works using fuzzy techniques such as Fuzzy C-Means (FCM) [14] and Hard C-Means (HCM) algorithms [15][16] have also been reported in literature.

In this context, ben Chaabane et al. have been tested the hard c-means and fuzzy c-means algorithms and the histogram of homogeneity for color image segmentation [4]. Recently, Zhu et al. [13] have proposed a segmentation method based on fuzzy sets and Dempster-Shafer (DS) evidence theory. The idea is to assign, at each image pixel level, a mass function that corresponds to a membership function in fuzzy logic. The membership degree of each pixel is determined by applying the FCM algorithm to the gray levels of the image. Then, the DS combination rule and decision are applied to obtain the final segmentation. However, the major problem in the use of Dempster Shafer evidence is the determination of mass function.

In this context, ben Chaabane et al. [4] have proposed a model of information representation based on the Assumption of Gaussian Distribution and histogram thresholding (HHDS) and applied on synthetic and biomedical images that contain only two classes. This technique is used to take into account heterogeneous data coming from different sources, in order to obtain an optimal set of objects for investigation

In this paper, we present a new color image segmentation method based on fuzzy clustering technique and fusion. The objective is to rebuild each cell from the three component images (R, G and B). In the first step, the segmented images are obtained by applying

fuzzy c-means clustering to the information's coming from the three independent component images. In the second step, on the obtained segmented images with specific primitive colors, a combination rule is used to integrate the segmentation results over the three-color components. Consequently, the proposed algorithm uses a centralized fusion model that requires the availability of all the images simultaneously, and no intermediate decision is taken before fusion.

Section 2 introduces the proposed method for color image segmentation. The experimental results are discussed in Section 3, and the conclusion is given in Section 4.

A. The Proposed Method

Image segmentation consists in partition of an image into homogeneous regions [17] [18] [19], or to detect the boundaries between the regions [20] [21]. In the framework of our application, we are interested to segment the breast cancer cells images into homogeneous regions, where we aim at providing a help to the doctor for the follow-up of the diseases of the cancer cells. In fact, the problem is to separate the cells from the background. To do this, the fuzzy c-means (FCM) algorithm can be used to determine the membership degree of each pixel and segment the three component images.

From an initial segmentation obtained by using fuzzy c means technique, a combination rule is applied to obtain the final segmented image. This is performed to represent as better as possible the cells, and to show to the doctors an appropriate schema of the set of points really forming part of the cells, as well as a suitable representation of the cells to be easily counted and checked. Hence, the main idea of the proposed method is to fuse, one by one, the pixels of the three segmented images.

B. Fuzzy c-means clustering

Fuzzy c-means (FCM) [13] is an unsupervised clustering algorithm, which is frequently used in pattern recognition. It is based on minimization of the following objective function:

$$J_m(u, v) = \sum_{k=1}^d \sum_{i=1}^c u_{ik}^m d^2(x_k, v_i) \quad (1)$$

Where m is the fuzzy factor greater than 1. $X = \{x_1, x_2, \dots, x_d\} \subset R^s$, s is the dimension of space, d is the number of samples, c is the number of clusters ($1 \leq c \leq d$). $d_{ij} = \|x_j - v_i\|$ is the distance between the sample x_j and clustering center $v_i, v_i \in R^s$ with ($1 \leq i \leq c$). u_{ij} is the membership of the jth sample to the ith clustering center, $U = \{u_{ij}\}$ is a matrix of size (c×d). $V = [v_1, v_2, \dots, v_c]$ is a matrix of size (c×s).

with:

$$\sum_{i=1}^c u_{ij} = 1, \quad 1 \leq j \leq d \quad (1a)$$

$$u_{ij} \geq 0, \quad 1 \leq i \leq c, 1 \leq j \leq d \quad (1b)$$

$$\sum_{j=1}^d u_{ij} > 0, \quad 1 \leq i \leq c \quad (1c)$$

The FCM algorithm minimizes the objective function $J_m(u, v)$ with respect to the membership functions u_{jk} and the centroids v_k .

. The FCM clustering technique can be summarized by the following steps:

-
- Input an (N × M) image with gray levels zero to 255.
 - Step 1: Initialization (iteration 0)
 - Scan the image line by line to construct the vector X containing all the gray level of the image.
 - Randomly initialize the centers of the classes vectors V(0)
 - From the iteration t=1 to the end of the algorithm:
-

Step 2: Calculate the membership matrix $U(t)$ of element u_{ik} using (2a):

$$u_{ik} = \frac{1}{\sum_{j=1}^c \left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}}$$

(2a)

u_{ik} is a matrix of size $(c \times n)$

Step 3: Calculate the vector $V(t) = [v_1, v_2, \dots, v_c]$ using:

$$v_i = \frac{\sum_{k=1}^n u_{ik}^m x_k}{\sum_{k=1}^n u_{ik}^m}$$

(2b)

Step 4: Convergence test:

If $\|V^{(t)} - V^{(t-1)}\| > \varepsilon$, then increment the iteration t , and return to the step 2, otherwise,

stop the algorithm. ε is a chosen positive threshold.

In our application, the fuzzy C-means algorithm is used to determine the membership degree of each pixel and used to segment the three component colors. After calculating the membership degree for each pixel coming from the three information sources, a combination rule is used to integrate the segmentation results over the three-color components.

C. Use Of Combination Rule For Image Segmentation

The purpose of segmentation is to partition the image into homogeneous regions [17]. The idea of using fuzzy theory to find the membership degree et to segment the three image components. Then, a combination rule is used to fuse one by one the pixels coming from the three images (R, G and B).

Given the membership degree: $(u_R, u_G, \text{ and } u_B)$ respectively for the three primitive colors, the $(S_R, S_G \text{ and } S_B)$ functions classify the pixel on the Red, Green and Blue components, into two opposite classes: Cells-pixels versus non cells pixels, as:

$$S_R(x, y) = \begin{cases} 1, & \text{cellspixel if } u_{1R}(x, y) \geq u_{2R}(x, y) \\ 0, & \text{non - cellspixel if } u_{1R}(x, y) < u_{2R}(x, y) \end{cases} \quad (3)$$

$$S_G(x, y) = \begin{cases} 1, & \text{cellspixel if } u_{1G}(x, y) \geq u_{2G}(x, y) \\ 0, & \text{non - cellspixel if } u_{1G}(x, y) < u_{2G}(x, y) \end{cases} \quad (4)$$

(5)

The membership degree $(u_R, u_G, \text{ and } u_B)$ are automatically determined by the fuzzy c-means technique, as described in Section A. The pixel (x, y) of each primitive color is classified as an cell pixel if its membership degree $u_1(x, y)$ is higher than the membership degree of the background $u_2(x, y)$, in which case is set to 1. Otherwise, it is classified as a non-cell pixel and is set to 0.

as an cell-pixel if it is so classified by at least one of its three color components, in which case $S(x, y)$ is set to 1. Otherwise, it is classified as a non-cell pixel and $S(x, y)$ is set to 0. The joint segmentation is calculated according to the following formula:

$$S(x, y) = \begin{cases} 1, & \text{cellspixel if } S_R(x, y) = 1 \cup S_G(x, y) = 1 \\ & \cup S_B(x, y) = 1 \\ 0, & \text{non - cellspixel, otherwise} \end{cases} \quad (6)$$

The proposed method can be described by a flowchart given in Figure 1.

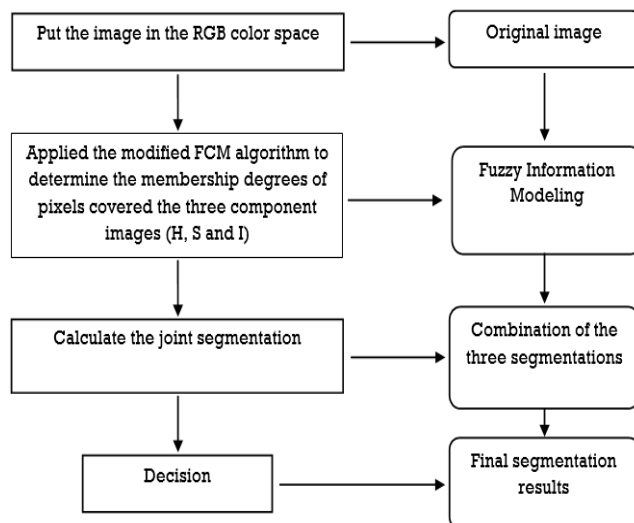


Figure 1: Flowchart of the proposed method.

II. EXPERIMENTAL RESULTS

In this section, a large variety of biomedical images is employed in our experiments. The images represented in Figure 2, show real medical cells images. These images are stored in the RGB color space with gray level spread on the range [0, 255]. Some experimental results are shown in Figures 5, 6, 7 and 8.

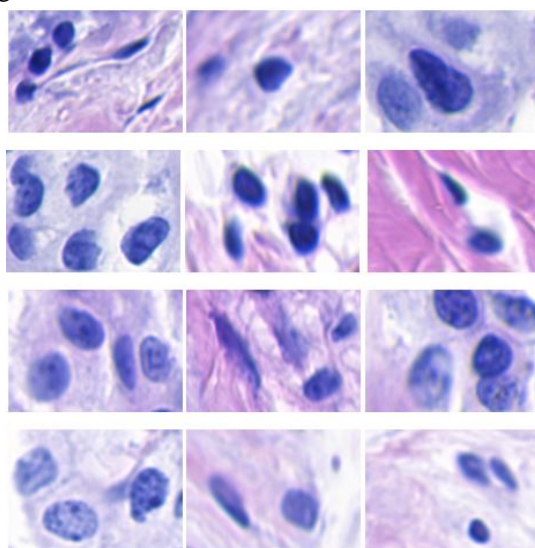


Figure 2: Data set used in the experiment. Twelve were selected for a comparison study. The patterns are numbered from 1 through 12, starting at the upper left-hand corner.

that some unclassified pixels are presented. The resulting images (Fig. 3(b), Fig.3(c) and Fig.3 (d)) contain some misclassified pixels. This shows that the RGB space has a strong correlation of its three components, and hence, the use of a single information source leads to bad results. This demonstrates the necessity of using the fusion process.

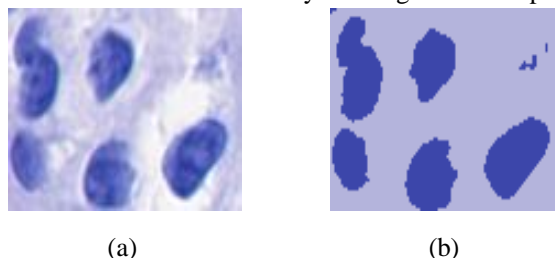




Figure 3: Segmentation results on a color image, (a) Original image (256x256x3) with gray level spread on the range [0,255]. (b) Red resulting image by FCM method. (c) Green resulting image by FCM method. (d) Blue resulting image by FCM method.

Table 1. Segmentation sensitivity From HCMHH, FCMHH and FCMF for the Data set Shown in Figure 2.

	<i>HCMHH</i>	<i>FCMHH</i>	<i>FCMF</i> <i>(proposed method)</i>
<i>Sensitivity segmentation (%)</i>			
<i>Image 1</i>	0.9506	0.9722	0.9850
<i>Image 2</i>	0.9242	0.9434	0.9836
<i>Image 3</i>	0.9472	0.9446	0.9869
<i>Image 4</i>	0.9576	0.9585	0.9719
<i>Image 5</i>	0.9274	0.9678	0.9818
<i>Image 6</i>	0.9546	0.9548	0.9692
<i>Image 7</i>	0.9523	0.9531	0.9624
<i>Image 8</i>	0.9666	0.9668	0.9873
<i>Image 9</i>	0.9473	0.9728	0.9704
<i>Image 10</i>	0.9087	0.9331	0.9782
<i>Image 11</i>	0.9907	0.9905	0.9973
<i>Image 12</i>	0.9746	0.9841	0.9884

Table 2. Segmentation sensitivity From DDS, FCMDs, HHDS and FCMF for the Data set Shown in Figure 2.

	<i>DDS</i>	<i>FCMDs</i>	<i>HHDS</i>	<i>(proposed method)</i>
<i>Sensitivity segmentation (%)</i>				
<i>Image 1</i>	0.9515	0.9731	0.9720	0.9850
<i>Image 2</i>	0.9251	0.9444	0.9772	0.9836
<i>Image 3</i>	0.9482	0.9456	0.9467	0.9869
<i>Image 4</i>	0.9585	0.9594	0.9648	0.9719
<i>Image 5</i>	0.9284	0.9687	0.9696	0.9818
<i>Image 6</i>	0.9555	0.9557	0.9627	0.9692
<i>Image 7</i>	0.9532	0.9540	0.9596	0.9624
<i>Image 8</i>	0.9675	0.9677	0.9788	0.9873
<i>Image 9</i>	0.9483	0.9737	0.9689	0.9704
<i>Image 10</i>	0.9096	0.9341	0.9378	0.9782
<i>Image 11</i>	0.9917	0.9915	0.9962	0.9973
<i>Image 12</i>	0.9755	0.9851	0.9759	0.9884

To provide insights into the proposed method, we have compared the performance of the proposed method with those of the corresponding Hard (HCMHH) and Fuzzy C-Means (FCMHH) and Homogeneity method. The segmentation results are shown in Figure 4. They correspond, respectively, to Figures 4(b), 4(c), and 4(g) in Figure 4. The cells are exactly and homogeneously segmented in Figure 4(g), which is not the case of Figures 4(b) and 4(c).

To evaluate the performance of the proposed segmentation algorithm, its accuracy was recorded. Regarding the accuracy, Tables 1, 2 list the segmentation sensitivity of the different methods for the dataset used in the experiment.

The segmentation sensitivity [4] [6] is computed using:

$$Sen(\%) = \left(\frac{N_{pcc}}{N \times M} \right) \times 100 \tag{9}$$

Where Sen(%), Npcc, N × M are, respectively, the segmentation sensitivity(%), number of correctly classified pixels, and dimension of the image.

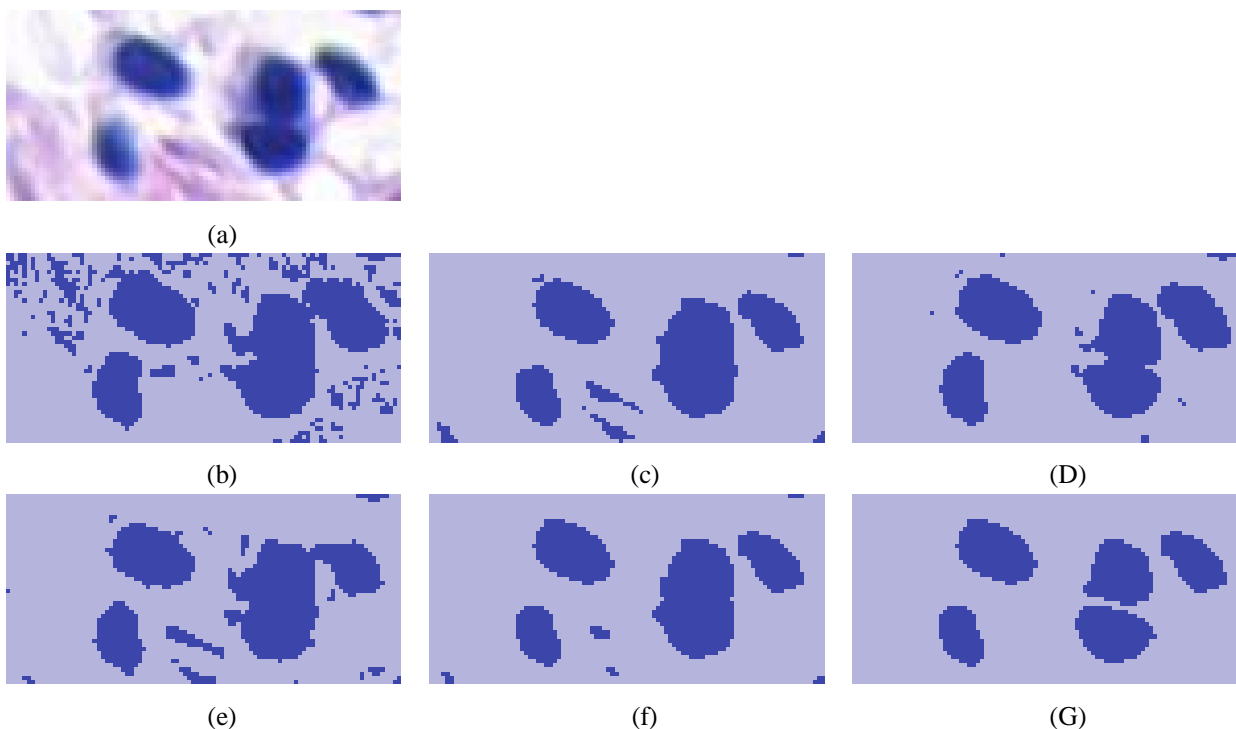


Figure 4: Comparison of the proposed segmentation method with other existing methods on a complex medical image (2 classes, various cells). (a) Original image (256 × 256 × 3): color medical image with RGB description, (b) segmentation based on HCMHH method (c) segmentation based on FCMHH method, (d) segmentation based on DDS method, (e) segmentation based on Fuzzy C-means and DS (FCMDS), (F) segmentation based on HHDS method, (G) segmentation based on Fuzzy C-means (FCM) and Fusion (F), (our method).

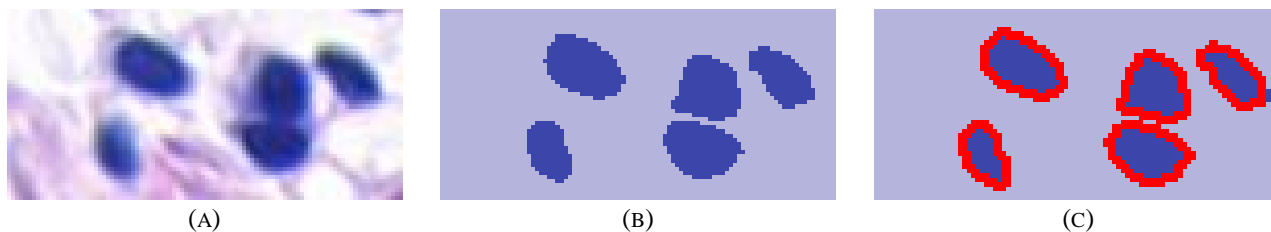


Figure 5. Color edges detection, (a) Original image (256 × 256 × 3): color medical image with RGB description, (b) segmentation based on Fuzzy C-means (FCM) and Fusion (F), (our method), (G) Color edges detection.

Figures 4(d), (e), (f), and (g) show the final segmentation results obtained from the DDS, the FCMDS and the HHDS methods and our FCMF algorithm, respectively. In fact, the partition resulting by the DDS, the FCMDS and the HHDS algorithms are less accurate, and the partition resulting by these methods is not satisfactory either. The performance of the proposed method is quite acceptable.

From Table 1, one can observe in Figures 4(b) and 4(c) that 7.26% and 3.22% and 1.72% of pixels were incorrectly segmented for the HCMHH, FCMH and FCMF methods, respectively. However, this demonstrates that the cells can be identified by the proposed method.

In fact, the experimental results indicate that the proposed method, which uses the FCM algorithm and fusion techniques, is more accurate than the traditional methods in terms of segmentation quality as denoted by segmentation sensitivity, see Table 2.

From Table 2, one can observe in Figures 4(d), 4(e), 4(f) and 4(g) that 7.16%, 3.12%, 3.04% and 1.72% of pixels were incorrectly segmented for the DDS, FCMDS, HHDS and FCMF methods, respectively. However, the two regions are correctly segmented in Figure 4(g).

Comparing Figure 4(b), (c), (d), (e), and (f) with (g), it is clear that the resulting image by the proposed method is much better than the one by the other methods. In fact, the different regions are correctly classified in Figure 5(g) which is not the case in Figures (b), (c), (d), (e), and (f), also, the cells can be correctly located.

Figure 5 illustrates the result for a biomedical image, where the edges in red color are superimposed on the original image.

III. CONCLUSION

In this paper, a new method of color images segmentation based on fuzzy clustering technique and fusion have been proposed. This method use the Fuzzy c-means algorithm for the modeling of the information of the three component images and a combination rule to combine the three segmentation results for the (R, G and B) component colors, respectively.

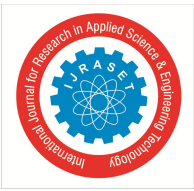
In addition, this new algorithm can be used successfully for modeling the input information and for segmenting the color images. Classification accuracies show that the proposed method is consistent. This methodology can also be extended for combining data from information sources by defining suitable representation model.

IV. ACKNOWLEDGMENT

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AUTHORS' BIOGRAPHY



Slim BEN CHAABANE born in 1979 in Chebba (Tunisia), she received the BSc degree in Electrical Engineering and the DEA degree in Automatic and Signal Processing at the High school of sciences and techniques of Tunis, respectively in 2004 and 2006.

It received the PhD in Digital image processing at the High school of sciences and techniques of Tunis in collaborating with University of Picardie Jules Verne, French in 2009.

Its research interests are focused on signal Processing, image processing, classification, segmentation and data fusion.



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