A New Method Based On Evidence Theory and Fuzzy Clustering For the Breast Cancer Cells Images Segmentation

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Abstract: In this paper, a new method is proposed to segment the cells images especially when only one breast cancer cells image is available for each patient. The method is approached by fusing the information of pixels coming from the original image and different information pixels associated to the same original image represented in another space colors with Dempster–Shafer (DS) theory. The estimation of the mass functions of each single hypothesis is obtained from the membership function of applying fuzzy c-means (FCM) clustering to the gray levels coming from the images to be combined. Then, multiple hypotheses are generated according to the single hypothesis. The classification accuracy of the proposed method is evaluated and a comparative study versus existing techniques is presented. The experimental results on medical and synthetic color images demonstrate the value of introducing fuzzy clustering in the data fusion theory for image segmentation.

Key words: Breast cancer cells images, color, segmentation, fuzzy c-means, Dempster–Shafer's evidence theory, fuzzy clustering, conflict.

1. Introduction

Image segmentation [1] [2], is one of the key tasks in most image processing and computer vision applications. The purpose of image segmentation is to divide images into different regions for future processing based on given criteria [3] [4] [5] [6]. . At present, color image segmentation methods [7] [8], are mainly extended from gray level segmentation approaches by being implemented in different color space. Gray level segmentation methods are directly applied to each component images of color space, then the combination rule and decision related to a particular fusion theory are used to achieve the final segmentation result [9] [10] [11] [12].

In this context, Max Mignotte [8] has proposed the fusion model which combines the several input segmentations in the within-cluster variance sense since in order to get the final accurate segmentation result by employing a K-means algorithm based fusion scheme. Also, Navon et al. [13] have proposed an algorithm based on color image segmentation using a local threshold values. The aim of this technique is to partition an image into homogeneous regions by using a local threshold values. The threshold values are determined with the usage of merging process.

In the same way, S. ben chaabane et al [12] have proposed a segmentation approach based on homogeneity histogram and data fusion techniques. This technique is employed to merge different data sources in order to increase the quality of the information and to obtain an optimal segmented image. Also, Navon et al. [13] have proposed an algorithm based on color image segmentation using a local threshold values. The aim of this technique is to partition an image into homogeneous regions by using a local threshold values. The threshold values are determined with the usage of merging process.

Histogram thresholding is one of the widely used techniques for gray level image segmentation [14] [15]. As for color images, the situation is different due to the multi-features. Since the color information is represented by the three component images R, G and B or some linear/nonlinear transformation of RGB, representing the histogram of a color image in the three dimensional (3-D) array and selecting threshold in the histogram is not a trivial job [16]. To solve this problem, several methods have been developed for storing and processing the information of the image in the 3-D color space. In this context, Gautier et al. [17] vise to furnish a help to the doctor for the follow-up of the maladies of the spinal column. The goal of this technique is to reconstruct each vertebral lumbar rachis from a set of cross-sections. The procedure is based on the operation of the belief theory to fusion information

With the same objective, Zimmermann and Zysno [18] have shown through empirical studies that the efficient Model for Membership Functions is defined as function of the Distance of a point from a prototypical member (MMFD). However, one of the dominant factors that impact the determination of convenient groups of points is the “distance measure” chosen for the problem at hand. Otsu’s method [19] choose an optimum threshold by maximizing the between class variance in a gray image. However, the results proven are unsatisfactory. Huang and Wang

[20] presented a version of Otsu's method in order to improve performance by reducing the computation cost for multilevel threshold.

In addition, Ohlander et al. [21] have demonstrated that the nine features (R, G, B, Y, I, Q, H, S and V) provided by the {RGB, YIQ and HSV} color spaces are redundant and complementary. In this context, image segmentation using data fusion techniques appears to be an interesting method. This paper is devoted to fuse nine redundant features provided by three different color spaces, applied to color image segmentation, where we aim at providing a help to the doctor for the follow-up of the diseases of the breast cancer. So, this work may be seen to be straightforwardly complementary to that in the paper proposed by Ohlander et al. [21]. In their paper, the authors suggested that the user has to search the significant peak in the histograms of the nine redundant features and then a threshold is determined to segment the input image. Although, selecting threshold in the histogram is not a trivial job. Hence, this paper is devoted to fuse one by one the pixels coming from different features provided by three color spaces. The idea is based on fuzzy clustering algorithm and data fusion techniques. The different informations are fused together by the DS evidence theory using as input features, the mass functions, previously estimated and associated to each pixel. The idea here is to assign a mass function to each information trough using the concept of fuzzy logic. To do this, a Fuzzy c-means (FCM) algorithm is used to represent the input information as fuzzy sets. Each information is then characterized by its membership values in classes. The mass function assigned to a pixel for the classes are derived from the membership functions. Once the mass functions are determined for each image to be fused, the DS combination rule and decision are applied to obtain the final segmentation result. 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.

2. The proposed method

In this section, a new method is introduced to segment the color cells images to decrease the adverse effects the uncertainty in segmentation. The FCM algorithm is applied to the images to be combined corresponding to the gray level to obtain the mass functions. The estimation of the mass functions of a single hypothesis is obtained with the membership of each gray level in each cluster. Multiple hypotheses are developed when the gray level can be assigned to several single hypotheses credibly. Then DS theory is used to fuse the pixels coming from the different images to be combined.

The objective is to rebuild each cell from a series of N redundant component images provided by the input image expressed in Ns color spaces. Hence, the idea of using the Dempster-Shafer (DS) evidence theory is to fuse one by one the feature vectors of each pixel coming from the nine redundant component images provided by the {RGB, YIQ and HSV} color spaces.

2.1. Fuzzy clustering

The standard Fuzzy C-means (FCM) algorithm is one of the widely used techniques for monochrome image segmentation. A comprehensive survey of fuzzy clustering methods is provided in [13] [14].In this paper, we employ the concept of Fuzzy C-means algorithm to determine the mass function in the Dempster Shafer evidence theory as membership degrees.

Assume $\boldsymbol{g_{xy}}$ is the intensity of a pixel $\boldsymbol{p_{xy}}$ at the location $(\boldsymbol{x}, \boldsymbol{y})$ in an $(\boldsymbol{M} \times \boldsymbol{N})$ image, $\boldsymbol{X} = [\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_d}]$ is the same data or information given in a Table must not be repeated in a Figure and vice versa. It is not acceptable to repeat extensively the numbers from Tables in the text or to give lengthy explanations of Tables or Figures.

vector containing all the gray level of the image, where $\{x_1 = g_{11}, x_2 = g_{12}, .. x_d = g_{MN}\}$, n_c designate the number of clusters in which X will be classified and $V = [v_1, v_2, \dots v_{n_c}]$ is the vector of the cluster centers. A fuzzy n_c-partition of X is represented by a matrix $U = [u_{ik}]$, where $u_{ik} = u_i(x_k)$ expresses the membership degree of the element x_k in cluster i, and verifies the following constraints:

$$\begin{cases} \sum_{i=1}^{n_c} u_{ik} = 1; \quad 1 \leq i \leq n_c, 1 \leq k \leq d \\ u_{ik} \in [0,1]; 1 \leq i \leq n_c \\ \sum_{k=1}^{d} u_{ik} > 0; \ 1 \leq i \leq n_c \end{cases}$$

In FCM algorithm, a good partition U of X is obtained by minimizing the objective fun

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

Where m is the fuzzy factor $(m > 1)$, $d_{ik} = \|x_k - v_i\|$ is the distance between the sample x_k and clustering centerv_i.

In fact, (U, V) may minimize $\mathrm{J_m}$ only if:

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

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

The proposed estimation mass function method using the standard FCM algorithm is outline in the following steps:

Input an $(N \times M)$ image with gray levels zero to 255.

Step 1: Initialization (iteration 0)

Randomly initialize the centers of the classes vectors V(0) of size $(c \times 1)$ containing the centers of the classes.

From the iteration t=1 to the end of the algorithm:

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

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

In the modified method, the F_k and v_i are vectors of size (1×4).

Step 4: Calculate the vector V(t) composed of 4 columns v_i using:

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

Step 5: Convergence test:

If $\left\| V^{(t)} - V^{(t-1)} \right\| > \varepsilon$, then increment the iteration t, and return to the step 2, otherwise, stop the algorithm. ε is a chosen positive threshold.

2.2. Use of DS Evidence Theory for Image Segmentation

The proposed method consists to partition the color image into homogeneous regions. The idea of using the DS evidence theory [22] [23] is to fuse one by one the characteristic vectors of each pixel coming from the nine component images $\{\boldsymbol{R}, \boldsymbol{G}, \boldsymbol{B}, \boldsymbol{Y}, \boldsymbol{I}, \boldsymbol{Q}, \boldsymbol{H}, \boldsymbol{S}\ \boldsymbol{and}\ \boldsymbol{V}\}$ provided by the three redundant $\{\boldsymbol{RGB}, \boldsymbol{YIQ}\ \boldsymbol{and}\ \boldsymbol{HSV}\}$ color spaces.

To achieve that, the membership degrees of each pixel are estimated by using the FCM algorithm. Then, a method is used to determine the simple and composite classes in DS evidence theory from the obtained membership degree. Once the mass functions are determined for each image to be fused, the DS combination rule and decision are employed to merge the input images, in order to increase the quality of the information and to obtain an optimal segmented image.

In the case of using the evidence theory for image segmentation, the determination of mass function is a crucial step of fusion process, and the performance of the segmentation scheme is, however, largely conditioned by the appropriate determination of the mass functions. In the present study, the method of generating the mass functions of the simple and double classes is performed in fuzzy logic domain.

2.3.1 Mass Function of Simple Hypotheses

In our application, the number $\mathbf{n_c}$ of classes $\mathbf{C_i}$ will be taken as the number of the simple hypotheses. These classes form the frame of discernment which is symbolized by:

$$\{\mathbf{H_1}, \mathbf{H_2}, \mathbf{H_3}, \dots, \mathbf{H_{n_c}}\} = \{\mathbf{C_i}\};\ \mathbf{1} \leq \mathbf{i} \leq \mathbf{n_c}$$

Masses of simple hypotheses$\boldsymbol{H_i}$ are directly obtained from the membership degree $\boldsymbol{u_{xy}(C_i)}$ of the gray level $\boldsymbol{g_{xy}}$at the location $(\boldsymbol{x}, \boldsymbol{y})$ in the $\boldsymbol{q}^{\text{è}\boldsymbol{me}}$ image to be combined:

$$\boldsymbol{m_{xy}^q(C_i) = u_{xy}^q(C_i)};\ \mathbf{1} \leq \mathbf{i} \leq \mathbf{n_c}$$

This equation indicates that for a given gray level $\mathbf{g_{xy}}$ of a pixel $\mathbf{p_{xy}}$ at the location $(\mathbf{x}, \mathbf{y})$ in the $\mathbf{q}^{\text{ème}}$ image to be combined, its share of belief placed strictly on $\boldsymbol{C_i}$ is directly given by its membership degree to the same cluster.

2.3.3 Mass Function of double Hypotheses

The mass function assigned to double hypotheses depends on the mass functions of each hypothesis. Once the double hypotheses (composed of two simple hypotheses) are formed, their joint mass is calculated according to the following formula:

$$\boldsymbol{m_{xy}^{q}\left(C_i \cup C_j\right) = \left(1 - u_{xy}^{q}(C_i)\right) . \left(1 - u_{xy}^{q}\left(C_j\right)\right);}$$

In the case where the double hypotheses C_j are composed of more than two simple hypotheses, their joint mass is determined as follows:

$$m_{xy}^{q}\left(C_j = C_1 \cup C_2 \cup \ldots \cup C_M\right) = \prod_{i=1}^{M}\left(1 - u_{xy}^{q}(C_i)\right);\ 1 \leq \mathrm{i} \leq \mathrm{M}$$

2.3.3 The output fusion

Once the mass functions of the nine components images are estimated, their combination is performed using the orthogonal sum that can be represented as follows:

with $\oplus$ is the sum of DS orthogonal rule.

Specifically, the combination (called the joint m^{12}) is calculated from the aggregation of two mass functions m^{1} and m^{2} associated to the 1^{th} and the 2^{th} features, i.e., the Red and the Green features and given as follows:

$$\forall\, C_i \subseteq \Omega, \qquad m^{12}(C_i) = \frac{1}{1-k} \sum_{A_1 \cap A_2 = C_i} m^1(A_1).\, m^2(A_2)$$

where A_1 and A_2 are subsets of 2^{Ω}, and

K evaluates the conflict between the sources $S_1$and S_2.

After calculating the orthogonal sum of the mass functions for the nine features, a decision module is used for labeling each pixel respecting the combined mass functions. The decisional procedure for classification purpose consists in choosing one of the most likely hypotheses C_i. The proposed method can be described by a flowchart given in Figure 1.

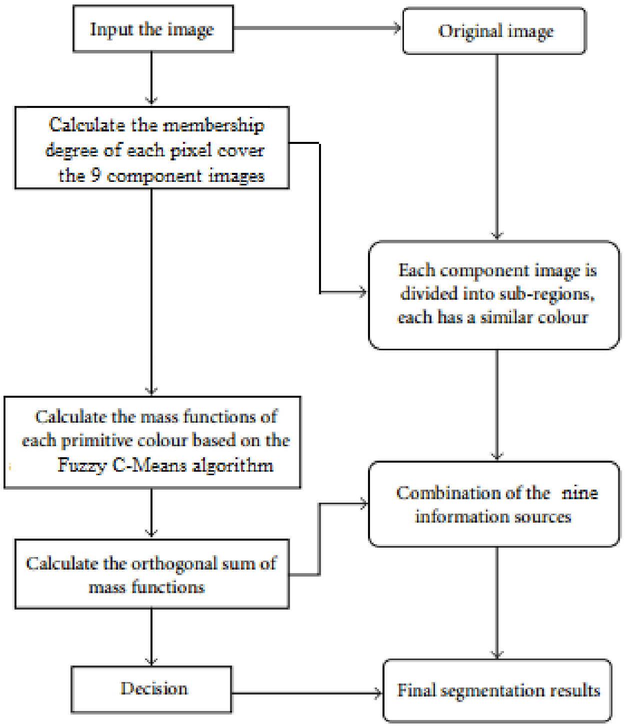


Figure 1. Flowchart of the proposed method.

3. Results

In order to illustrate the methods presented in the previous section, a large variety of medical and synthetic color images are employed in our experiments. The used images data base is shown in Figure 2.

In fact, to evaluate the efficiency and accuracy of the proposed segmentation method, we applied the proposed method on color cells images. Also, a synthetic image dataset is developed and used for numerical evaluation purpose. The segmentation results are compared versus existing methods, as described earlier.

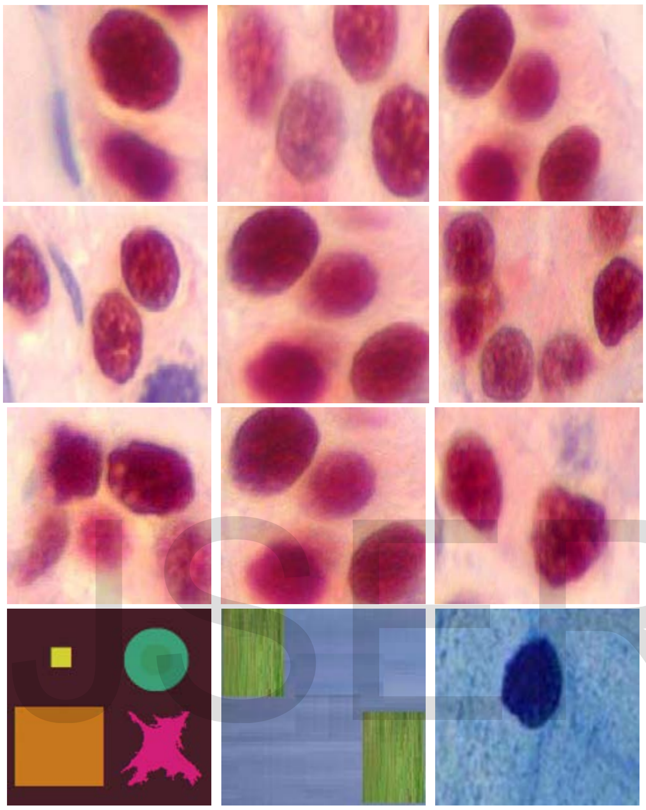


Figure 2: Data set used in the experiment. Twelve were selected for a comparison study.

The patterns are numbered from 1 through 12, starting at the upper left-hand corner. To illustrate the segmentation results obtained by the method based on data fusion techniques and fuzzy classification algorithm, called (DSFCM), we applied the modified fuzzy c-means algorithm to the input image of the figure (FIG. 3(a)) where the number of classes is limited to two and the fuzzy coefficient m is set to 2.

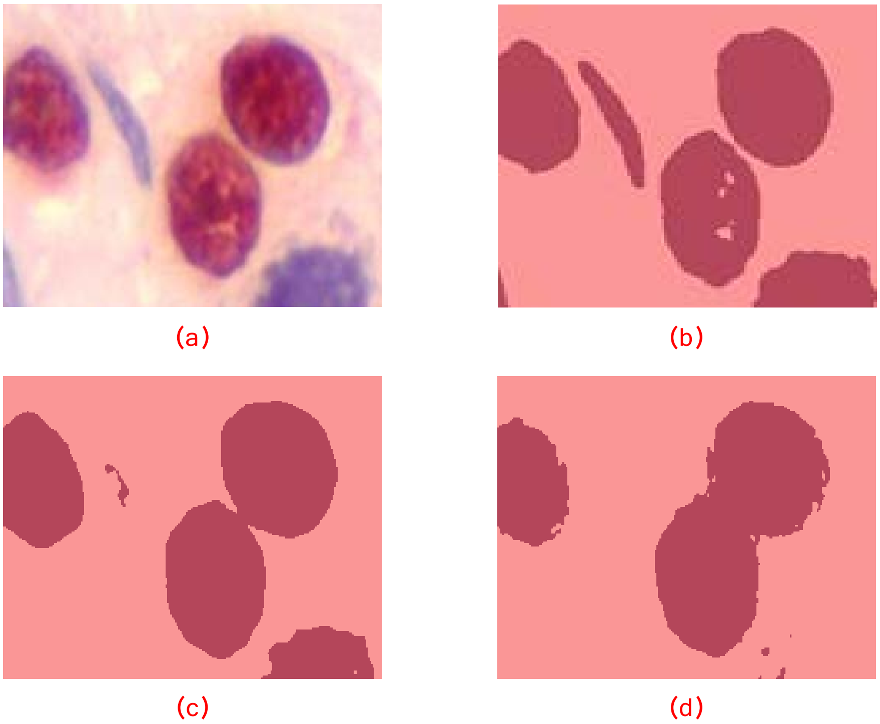
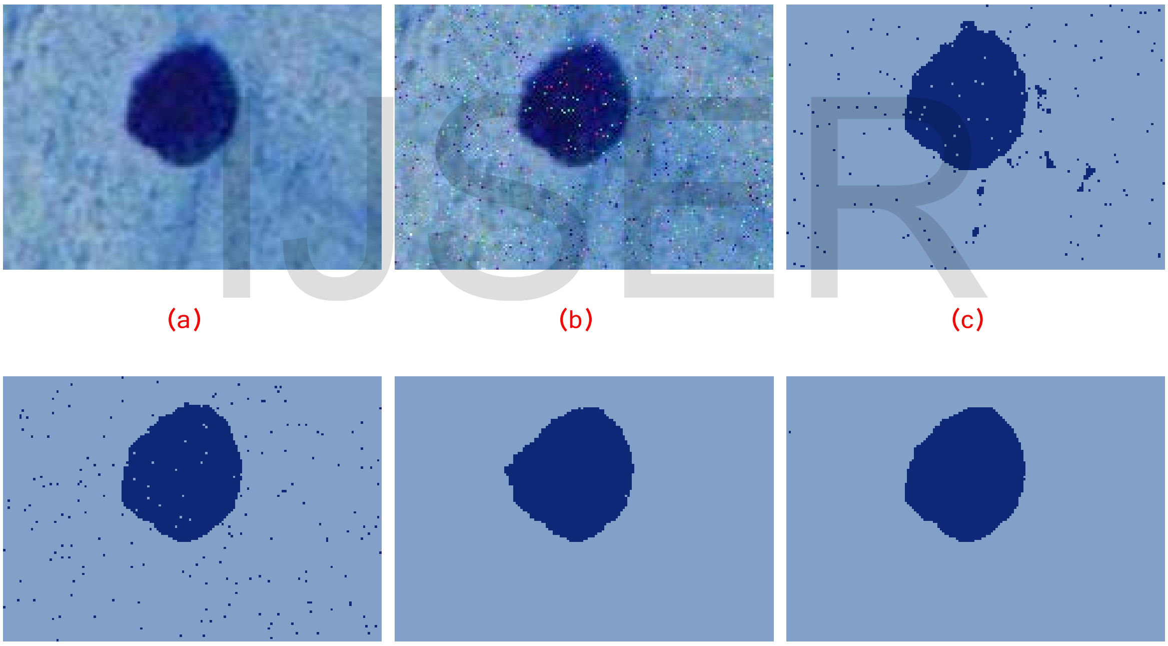


Figure 3: Segmentation results on a color image. (a) Original image ($256\times256\times3$) with gray level spread on the range [0, 255]. (b) Red resulting image by Fuzzy c-means algorithm. (c) Green resulting image by Fuzzy c-means algorithm. (d) Blue resulting image by byFuzzy c-means algorithm.

By applying the Fuzzy c-means algorithm independently to the component images of the input image expressed in the space color $\{RGB \ or \ YIQ \ or \ HSV\}$, does not give a better results and does not take sufficient account of the initial correlation. This shows that the use of a single information source leads to bad results.

The segmentation results obtained by applying the FCM algorithm to the red, green and blue color features are shown in Figs. 3(b), (c), and (d), respectively. In these figures, a label to each pixel corresponding to the class to which it belongs is affected. However, for easy viewing, the label of each class is selected as the average color of the pixels that compose this class. It is noted that the two classes are not well built. In this context, image segmentation using data fusion techniques appears to be an interesting method. To do this, we propose to combine the results obtained by the Fuzzy C-means (FCM) algorithm applied independently to the nine component images of the original image represented in the three color spaces (RGB, HSV and YIQ).

Figure 3 shows a comparison between our method and other methods such as HHDS [13] and the method proposed by R. Harrabi et al. [23].



(a) (b) (c)

(d) (e) (f)

Figure 4: Comparison of the proposed segmentation method with other existing methods on a medical image (2 classes, 1 cell). (a) Original image with RGB representation (256 × 256 × 3), (b) color cell image disturbed with a "salt and pepper" noise, (c) segmentation based on HHDS method (d) segmentation based on MTDS method, (e) segmentation based on FCM algorithm and DS, and (f) reference segmented image.

However, the image shown in Figure 4(b) represents the original image I where a "salt and pepper" noise of D density was added. This affects approximately $D \times (N \times M)$ pixels. The value of D is 0.02. The figures 4(c), 4(d) and 4(e) show the segmentation results obtained by the methods (HHDS), (MTDS) and the proposed method (FCMDS), respectively. Fig 4(f) shows the ideal segmentation result (reference image).

In fact, one can find that the different objects presented in the original image are much better segmented in figure (FIG. 4(f)) than those in the figures (FIG. 4(c), and (d)). Consequently, the experimental results are improved by the proposed approach. So, the FCM algorithm can be used to produce mass functions that have typical interpretations, also, the resulting partition data can be interpreted as compatibility points with the different types of classes covering image.

The experimentation is carried out on medical images of cancer disease type in Fig. 5(a) and these images are used as original images. The segmentation results are obtained using the Gaussian distribution (GD), HCM and FCM clustering algorithms for the determination of the mass functions in the DS theory. They correspond, respectively, to Figs. 5(b), (c) and (d).

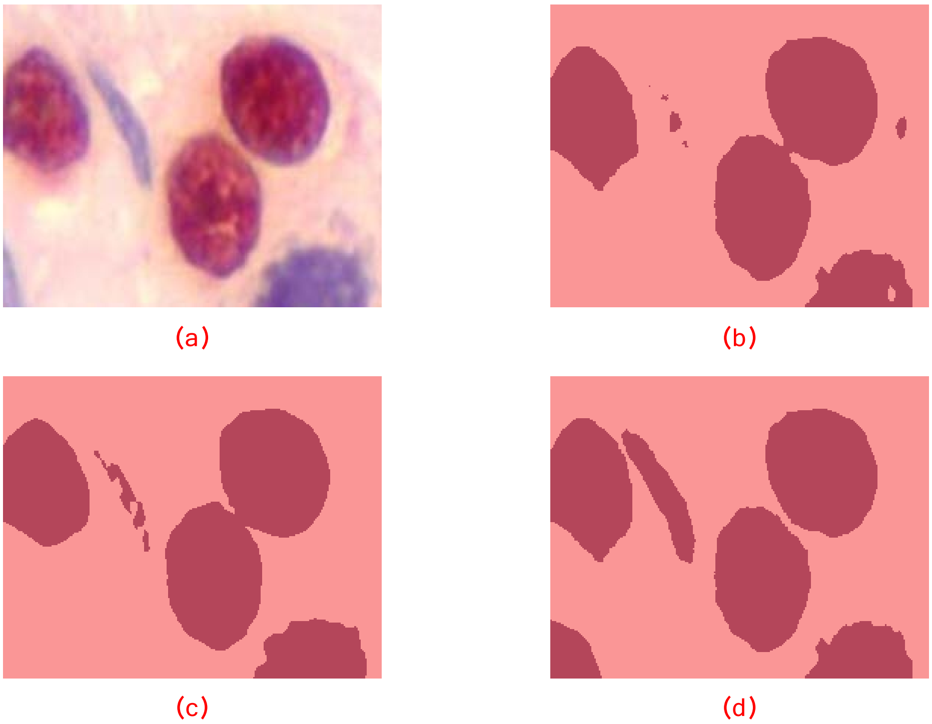


Figure 5: Comparison of the proposed segmentation method with other existing methods on a complex medical image (2 classes, various cells). (a) Original image (256 × 256 × 3): color medical image with RGB description, (b) segmentation based on HCM and DS, (c) segmentation based on GD and DS, and (d) segmentation based on FCM and DS.

Table 1. Segmentation sensitivity From HCMDS, HHDS, GDDS and FCMDS for the data set shown in Fig. 2.

	HCMDS	HHDS	GDDS	FCMDS (Proposed Method)
	Segmentation sensitivity (%)			
Image 1	0.8245	0.8945	0.8647	0.9441
Image 2	0.7845	0.8754	0.8712	0.9834
Image 3	0.7513	0.8594	0.8996	0.9216
Image 4	0.8112	0.8854	0.8455	0.8995

Image 5	0.7451	0.7964	0.8972	0.9462
Image 6	0.7845	0.8792	0.8324	0.8774
Image 7	0.6798	0.7811	0.7798	0.9726
Image 8	0.7215	0.7397	0.7894	0.9511
Image 9	0.7849	0.7987	0.8772	0.9349
Image 10	0.8561	0.8991	0.9247	0.9848
Image 11	0.8765	0.9248	0.9456	0.9821
Image 12	0.8936	0.9174	0.9228	0.9893

However, in the Gaussian model and standard fuzzy approach HCM, the membership probability and the membership degree of each pixel, which leads to the presence of many incorrectly classified pixels. Hence, the cells are exactly and homogeneously segmented in Fig. 5(d), which is not the case in Fig. 5(b) and (c).

Hence, the experimental results presented in Figure 5(d) are quite consistent with the visualized color distributions in the objects, which make it possible to do an accurate measurement of cell volumes.

In short, the proposed algorithm outperforms all these well-known segmentation algorithms in terms of segmentation sensitivity (Sen(%)).

To evaluate the performance of the proposed segmentation algorithm, its accuracy was recorded. Regarding the accuracy, Tables 1 lists the segmentation sensitivity of the different methods for the data set used in the experiment. The segmentation sensitivity [24] [25] is computed using:

$$\text{Sens} = \frac{N_{\text{pcc}}}{N \times M} \times 100,$$

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

The performance of the proposed method is quite acceptable. In fact, from table 1, one can observe in Figures 5(b), 5(c), and 5(d) that 18.88%, 15.45% and 10.05% of pixels were incorrectly segmented for the HCMDS, GDDS and FCMDS methods, respectively.

This experiment shows the validity of our fusion procedure and also the significant improved performance in segmentation.

The three images, shown in Fig.5 (b), (c) and (d), were used in order to visually assess the quality of segmentation results.

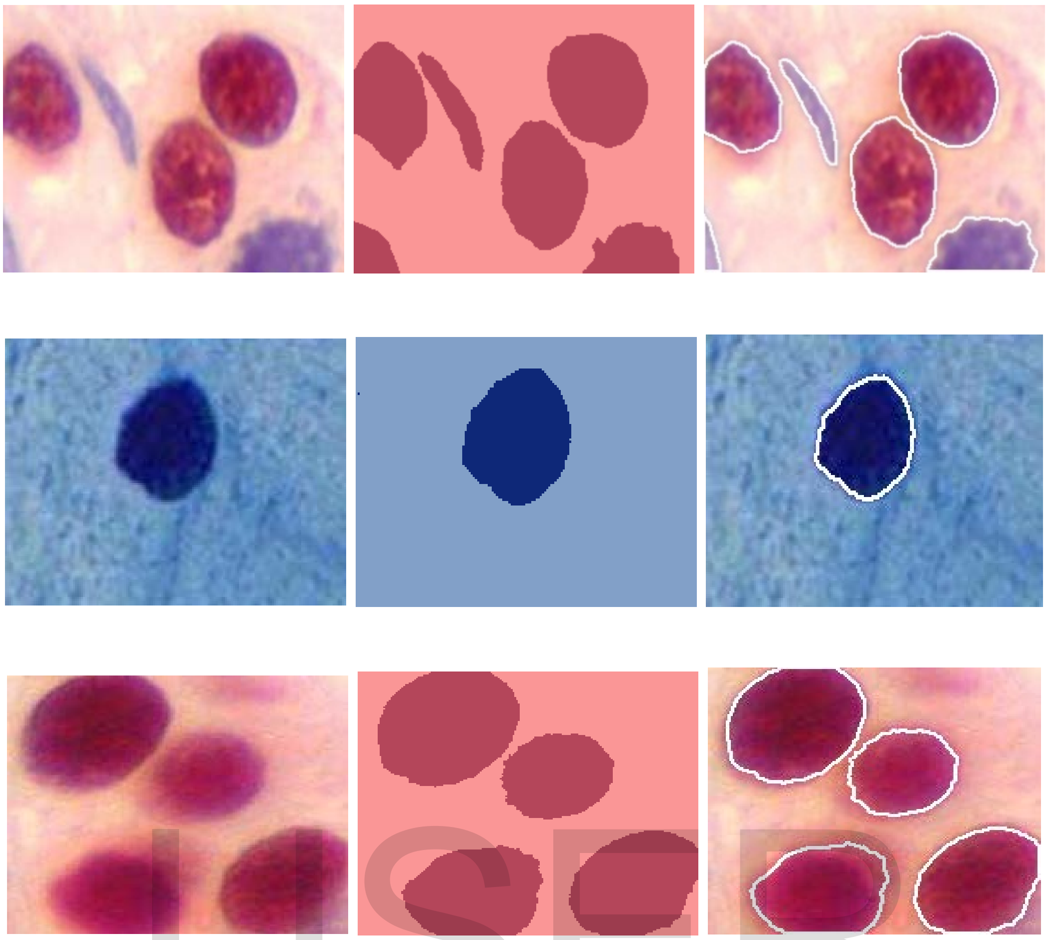


Figure 6. Color edges detection.

In fact, from an initial segmentation obtained by using the fuzzy c-means, one seeks a segmentation which means to detect the cells in medical images of cancer disease (see Fig. 5(d)), as also the number of the cells. Consequently, the proposed method can be useful for color image segmentation.

Figure 6 illustrates the final results for the three images selected from the used images data base (Fig.5), where the edges in white color are superimposed on the original images.

4. Conclusion

In this paper, we have proposed a new color image segmentation method for based on Fuzzy C-means algorithm and Dempster-Shafer evidence theory. This method consists of two steps. In the first step, the automatic estimation of mass functions in the DS evidence theory is determined from the Fuzzy C-means algorithm. In the second step, the DS combination rule and decision are applied to fuse the nine components images of the input image expressed in three-color spaces.

The proposed segmentation approach is conceptually different and explores a new strategy. In fact, instead of considering only one image for each application, many component images of the same image fused together may be very helpful to the segmentation process. The idea is to fuse one by one the pixels coming from different information sources, in order to get a final reliable and accurate segmentation result.

The obtained results demonstrated the significant improved performance in segmentation. The proposed method can be useful for color image segmentation.

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