Color Image Segmentation Based on a Modified Fuzzy C-means Technique and Statistical Features

R. Harrabi and E. Ben Braiek
CEREP, ESSTT, 5 Av. Taha Hussein, 1008, Tunis, Tunisia

Abstract:
In this paper, a novel method of color image segmentation based on the Fuzzy C-means algorithm and statistical features is presented. The role of including first order statistical feature vector in the Fuzzy C-means technique is studied in this paper to obtain the optimally segmented image. Instead of using the simple pixel value, feature vectors are extracted from sliding window centered on the pixels. The Fuzzy C-means (FCM) algorithm is used to cluster the obtained feature vectors into several classes corresponding to the different regions of the image. Classification accuracies of the proposed technique are compared with those of the recent techniques in literature for the same image data. The experimental results on medical and textures color images demonstrate the superiority of combining statistical features and the standard Fuzzy C-Means algorithm for image segmentation.

Keywords— Texture segmentation, Medical color image, Fuzzy Logic, Fuzzy C-means, Statistical features.

I. INTRODUCTION

The image segmentation is an essential component which determines the quality of the final results and analysis [1]. It consists in partition of an image into homogeneous regions, according to a choice criterion. In the case of color images segmentation, the used characteristic is the colorimetric components of the pixel.
Several approaches of different complexity already exist to color images segmentation [1] [2]. Until now there is no general technique that can solve all the different image segmentation types. Generally, the image segmentation approaches can be divided into four categories, thresholding, clustering, edge detection, and region extraction.
Monochrome image segmentation techniques can be extended to color image, such as histogram thresholding, clustering, region growing, edge detection, fuzzy logic and neural networks, by using RGB or their transformations (linear/non-linear) as shown in Fig. 1. Monochrome segmentation methods can be directly applied to each component of a color space, then the results can be combined in some way to obtain the final segmentation results.

Color Segmentation Approaches	=	**Monochrome Segmentation Approaches**	+	**Color Spaces**
		Histogram Thresholding, Region Based Approaches, Edge Detection Approaches, Fuzzy Approaches, Neural Networks,		RGB, YIQ, YUV, HSI, YC_bC_r CIEL*u*v*

Fig. 1. Commonly used color image segmentation approaches**.**

The acquisition of color image consists in getting three primitive colors representing the components red (R), green (G) and blue (B). The superposition of the three components gives the color original image. Different spaces colors have been developed by several authors [3] [4] [5]. These spaces are obtained by using the linear and non-linear transformations of the RGB color space. Each color representation has its advantages and disadvantages. There is still no color representation that can dominate the others for all kinds of color images yet. Nonlinear color transformations such as HSI have essential singularities which are non-removable, and there are spurious modes in the distribution of values resulting from non linear transformations. RGB is suitable for color display, but not good for color scene segmentation and analysis because of the high correlation among the R, G, and B components [6] [7]. By high correlation, we mean that if the intensity changes, all the three components will change accordingly. Hence, linear spaces are very difficult to discriminate highlights, shadows and shading in color images.
Using HSI can solve this problem to some extent except that hue is unstable at low saturation [8]. Hence, the main problem of the color image segmentation is the choice of the adapted color model for a specific application.

Several methods [9] [10], are proposed for color images segmentation including fuzzy homogeneity and fuzzy logic [3] [11] [12] [13].
In this context, S. B. Chaabane et al. [3] have proposed a method of color image segmentation based on fuzzy homogeneity and data fusion techniques. The fuzzy homogeneity vector is used to determine the fuzzy region in each primitive color, whereas, the evidence theory is employed to merge different data sources in order to increase the quality of the information and to obtain an optimal segmented image.
In the same objective, Cheng et al. [11] have provided a segmentation approach using homogeneity. In the first segmentation, uniform regions are identified via multilevel thresholding on homogeneity histogram (MTHH). An efficient peak-finding algorithm is employed to identify the most peaks histogram. In the second phase, a histogram analysis is performed for each uniform region obtained in the first phase.
Also, Cheng et al. [12], have presented a color images segmentation approach based on homogram thresholding and region merging. Fuzzy entropy is utilized as a tool to perform homogram analysis for finding all major homogeneous regions at the first stage. Then region merging process is carried out based on color similarity among these regions to avoid oversegmentation.
The key point of this approach is that homogram analysis is used to extract all major homogeneous regions at the first stage and the region merging process is performed iteratively based on color similarity among these regions to solve the problem of oversegmentation.
In another study, S. B. Chaabane et al. [13] have proposed a method of color images segmentation based on fuzzy c-means and data fusion techniques (FCMDS). The fuzzy algorithm is used to determine the membership degrees of each pixel covering the three components images (R, G and B), whereas, the evidence theory is employed to merge different data sources in order to increase the quality of the information and to obtain an optimal segmented image.
Furthermore, a combination of different segmentation approaches is often utilized for color image segmentation. In this context, Y. Lim et al. [14] have proposed a color image segmentation method based on the thresholding and the fuzzy c-means (FCM) techniques. The methodology uses a coarse-fine concept to reduce the computational technique burden required for the FCM.
The coarse segmentation attempts to segment coarsely using the thresholding technique wile the fine segmentation assigns the pixels, which remain unclassified after the coarse segmentation, to the closest class using the FCM. In this context, S. B. Chaabane et al. [15] have presented a color image segmentation approach based on automatic thresholding and the Fuzzy C-Means Techniques (ATFCM). The FCM algorithm is used to extract homogeneous region in each primitive color, and the fuzzy combination rule is applied to obtain the final segmentation results.
The most widely used clustering method is the Fuzzy C-Means (FCM) algorithm, which is a "fuzzy relative" to the simple C-means technique [16]. There has been considerable interest, recentlys, in the use of fuzzy segmentation methods, which retains more information from the original image than hard segmentation methods. The Fuzzy C-means algorithm (FCM), in particular, can be used to obtain a segmentation via fuzzy pixel classification. Unlike hard classification methods which force pixels to belong exclusively to one class, FCM allows pixels to belong to multiple classes with varying degrees of membership. A major disadvantage of its use in imaging applications, however, is that FCM does not incorporate information about spatial context, causing it to be sensitive to noise and other imaging artifacts.
Recently, some approaches [17] [18] have been proposed for increasing the robustness of FCM to noise by directly modifying the objective function. In this context, Raghu et al. [19] reformulate the fuzzy clustering problem so that the clustering method can be used to generate memberships with typical interpretation. They argue that the existing fuzzy clustering methods do not provide appropriate membership values for applications in which memberships are to be interpreted as degrees of compatibility or possibility. For that, the authors formulate a new algorithm by modifying the objective function in the fuzzy C-means algorithm to obtain a good possibilistic partition of the data.
Also, Liew et al. [17] have provided a new dissimilarity index that considers the influence of the neighboring pixels on the center pixel, this in the goal to replace the conventional normed distance in the FCM algorithm. However, this method can handle only a small amount of noise [20]. With the same objective, Ahmed et al. [21] have introduced a regularization term into the standard FCM to impose neighborhood effect. Later, Li et al. [18] incorporated this regularization term into the adaptive FCM (AFCM) algorithm [22] to overcome the noise sensitivity of AFCM algorithm. Although this method is promising, it is computationally expensive that means more consuming time is needed during the computation.
In this paper an investigation of how the user can choose the best statistical features for segmenting the color images using the fuzzy C-means algorithm is described. This work may be seen to be straightforwardly complementary to that in the paper proposed by M. Sayadi et al. [23]. In their paper, the authors have proposed a clustering method for grey level texture segmentation based on a modified fuzzy C-means algorithm. Hence, this paper is devoted to this task, applied to colour image segmentation that contains more than two classes. The idea is based on the fuzzy C-means algorithm and the statistical features.
Instead of using the simple pixel value in the FCM method, we propose in this paper to extract a feature vector from a sliding window centred on the pixels. The Fuzzy C-means algorithm is modified and used to cluster the obtained feature vectors into

several classes corresponding to the different regions of the image. This technique allows obtaining excellent color image segmentation results, superior to the classical version of the FCM algorithm [24].
The rest of the paper is organized as follow: Section 2 briefly describes the Fuzzy C-means algorithm. Section 3 gives a detailed description of the proposed MFCM method. The experimental results and discussions are in section 4. Finally, conclusions are in section 5.

Ii. Ecall of the fuzzy c-means clustering

The Fuzzy C-means (FCM) [25], an unsupervised clustering algorithm, has been applied successfully to a number of clustering problems. The algorithm minimizes the objective function for the partition of data set, $X = \{x_1, x_2, ..., x_n\} \subset R^s$, given by:

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

with

$$\sum_{i=1}^{c} u_{ij} = 1, \quad 1 \le j \le n \qquad (1a)$$

$$u_{ij} \ge 0, \quad 1 \le i \le c, 1 \le j \le n \qquad (1b)$$

$$\sum_{j=1}^{n} u_{ij} > 0, \quad 1 \le i \le c \qquad (1c)$$

where $X = \{x_1, x_2, ..., x_n\} \subset R^s$, s is the dimension of space, n is the number of samples, c is the number of clusters $(1 \le c \le n)$, m is the fuzzy factor $(m > 1)$, $d_{ij} = \|x_j - v_i\|$ is the distance between the sample x_j and clustering center v_i, $v_i \subset R^s$ with $(1 \le i \le c)$. u_{ij} is the membership of the j[th] sample to the i[th] clustering center, $U = \{u_{ij}\}$ is a matrix of size (c×n). $V = \lfloor v_1, v_2, ... v_c \rfloor$ is a matrix of size (c×s).
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 $N \times M$ 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):

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

u_{ik} is a matrix of size (c×n)

Step 3: Calculate the vector V(t) =[v_1, v_2,…,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 $\left\| V^{(t)} - V^{(t-1)} \right\| > \varepsilon$, then increment the iteration t, and return to the step 2, otherwise, stop the algorithm. ε is a chosen positive threshold.

The algorithm above can also start from membership matrix $U^{(0)}$.

III. The proposed method

Recently, most analytic fuzzy approaches have been derived from Bezdek's Fuzzy C-means (FCM) [26]. The FCM algorithm is an iterative clustering method that produces a C partition by minimizing the weighted within group sum of squared error objective J_m. Like the Hard C-means algorithm, the Fuzzy C-means aims to minimize an objective function.
On the other hand, this algorithm has a considerable drawback in noisy environments, and the memberships degree resulting from FCM do not correspond to the intuitive concept of belonging or compatibility. Also, the Hard C-means (HCM) [27] is one of the oldest clustering methods. This method is used to learn the prototype of clusters or classes, and the cluster centers are used as prototypes. But, HCM memberships are hard (i. e, 1 or 0).
However, the Fuzzy C-means algorithm is better than the Hard C-means (HCM) algorithm, since in HCM algorithm feature vectors of the data's set can be partitioned into hard clusters, and the feature vector can exactly be a member of one cluster only.
Instead, the FCM relaxes the condition, and allows the feature vector to have multiple membership grades to multiple clusters, Suppose the data set with known clusters and a data point which is close to both clusters but also equidistant to them. Fuzzy clustering gracefully copes with such dilemmas by assigning this data point equal but partial memberships to both clusters, that is the point may belong to both clusters with some degree of membership grades varies from 0 to 1.
However, in an image processing system an image or its derivatives can be represented in various feature spaces. An image can be represented in terms of pixels, which are associated with a location and a gray level value. It can also be represented by its derivatives, e.g., regions with features like average greyscale value, standard deviation, variance, entropy, third order moment, gradient, etc. Features for clustering can be extracted from regions masked by a window $(n \times n)$. By applying FCM, a partition of the feature vectors into new regions can
be found. Combination of statistical features characterization and fuzzy clustering has some advantages for both techniques.

A. Modified FCM method (MFCM method)

The purpose of segmentation is to partition the image into homogeneous regions. In this paper, we employ the MFCM algorithm to cluster the feature vectors into several classes with every class corresponding to one region in the segmented image. The MFCM algorithm is applied to the Hue component of the original image represented in HSI color space. The idea is to replace the vector X used in the image segmentation method based on the pixel value and the FCM algorithm by a matrix F containing the same number of lines, i.e. n, but with 4 columns. These columns contain 4 statistical features extracted from the sliding window centered around every pixel. Hence, this algorithm scans the image using a (n×n) sliding window, as shown in Fig. 2, from left to right and top to bottom. A feature vector is extracted from each block.
However, the selection of the best attributes is based on the characterization degree (¥) [28]. This criterion is based on the report/ratio of the between classes (inter-class) variance by the intraclass variance.
Assume $y_{k,n}$ is the n^{th} feature vector estimated for the k^{th} image class $(1 \le k \le 12,\ 1 \le n \le 100)$, k is the number of images and n is the imagettes number of each image.

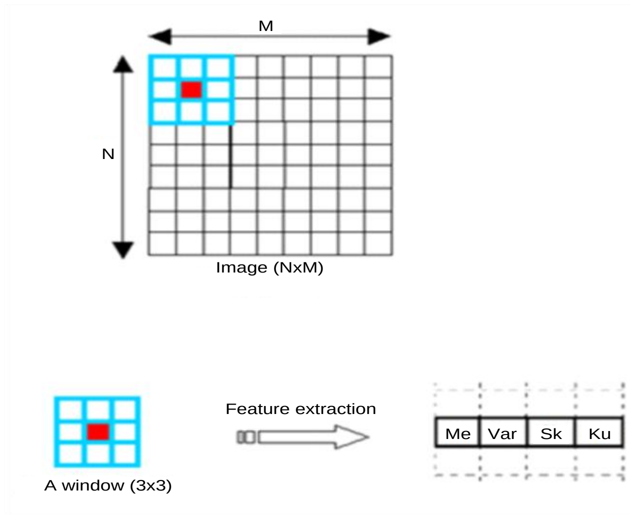


Fig. 2. Features extraction using a sliding window

The mean of the feature m_k vectors is calculated for the k^{th} image class as follow:

$$m_k = \frac{1}{100}\sum_{k=1}^{100} y_{k,n} \quad (3)$$

and the total mean of the features vectors m_c is determined as follow:

$$m_c = \frac{1}{12}\sum_{k=1}^{12} m_k \quad (4)$$

The mean of the intraclass dispersion matrices which represents the maximum likelihood estimation of the covariance matrix of the class, is given by the matrix:

$$S_{intra} = \frac{1}{1200}\sum_{k=1}^{12}\sum_{n=1}^{100}(y_{k,n} - m_k)(y_{k,n} - m_k)^t \quad (5)$$

whereas, the mean of the between (inter-class) dispersion matrices which describes the scattering of the class sample means is computed using:

$$S_{inter} = \frac{1}{12}\sum_{k=1}^{12}(m_k - m_c)(m_k - m_c)^t \quad (6)$$

Consequently, the characterization degree (¥) is given by:

$$¥ = \mathrm{trace}\,(S_{intra}^{-1} . S_{inter}) \quad (7)$$

In the present study, the best features are the mean *Me*, the variance *Var*, the third order moment *Sk* and the forth order moment *Ku* of the window.

Assume $g(i,j)$ is the intensity of a pixel $p(i,j)$ at the location (i,j) in an $(N \times M)$ image, w_{ij} is a size $(t \times t)$ window centred at pixel $p(i,j)$.

A feature vector for a pixel is then extracted from the windowed block. The 4 features extracted from the window centered at pixel (i,j) are given by the following equations:

$$Me = \frac{1}{t \times t}\sum_{k=-\frac{t-1}{2}}^{\frac{t-1}{2}}\sum_{l=-\frac{t-1}{2}}^{\frac{t-1}{2}} g(k+i, l+j) \quad (8)$$

$$Var = \frac{1}{t \times t} \sum_{k=-\frac{t-1}{2}}^{\frac{t-1}{2}} \sum_{l=-\frac{t-1}{2}}^{\frac{t-1}{2}} (g(k+i, l+j) - Me)^2 \qquad (9)$$

$$Sk = \frac{1}{t \times t} \sum_{k=-\frac{t-1}{2}}^{\frac{t-1}{2}} \sum_{l=-\frac{t-1}{2}}^{\frac{t-1}{2}} (g(k+i, l+j) - Me)^3 \qquad (10)$$

$$Ku = \frac{1}{t \times t} \sum_{k=-\frac{t-1}{2}}^{\frac{t-1}{2}} \sum_{l=-\frac{t-1}{2}}^{\frac{t-1}{2}} (g(k+i, l+j) - Me)^4 \qquad (11)$$

where $(t \times t)$ and $g(i,j)$ are respectively the size of sliding window and the gray scale value of pixel $p(i,j)$, $\frac{t+1}{2} \le i \le N - \frac{t-1}{2}$ and $\frac{t+1}{2} \le j \le M - \frac{t-1}{2}$.
Notes that t must have an odd value to obtain a centered window around each pixel. So, the fuzzy C-means algorithm is used to cluster the obtained feature matrix *F* into *c* different classes. Every class corresponds to one region in the segmented image. The spatial scanning order of an image is performed, as shown in Fig. 3, pixel by pixel from left to right and top to bottom.

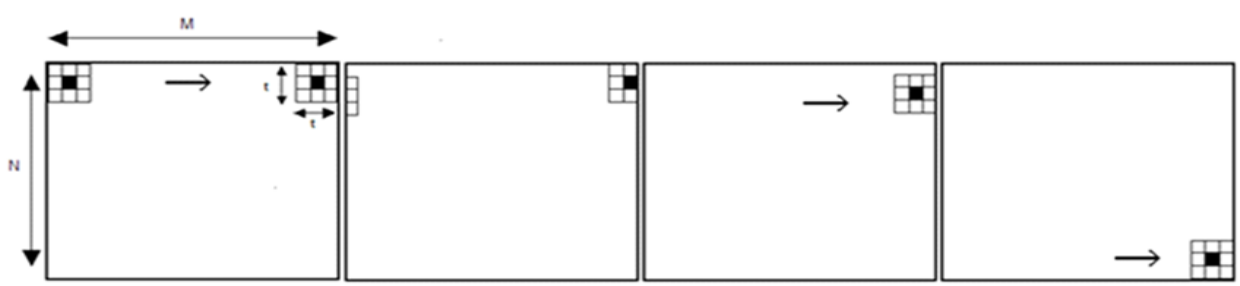


Fig. 3. The adaptive sliding window from left to right and top to bottom

However, the size of the window has an influence on the calculation of the feature vectors. The window should be big enough to allow enough information to be involved in the computation of the feature vectors. As shown in Fig.9, the regions are identified by MFCM method using a (3x3) window for computing the feature vector (see Fig. 9(b)), but are not signified using a (5x5) and (7x7) window (see Fig 9(c) and Fig. 9(d), respectively). Experimentally, a (3×3) window for computing the feature vector is chosen.
The proposed image segmentation technique using the FCM algorithm combined with the statistical features can be summarized by the following steps:

- Input an $N \times M$ image
Step 1: Initialization (iteration 0)
Randomly initialize the centers of the classes vectors V(0) of size $(c \times 4)$ containing the centers of the classes.
Step 2: Compute the matrix F of size $(n \times 4)$ containing the statistical features extracted from the image.
From the iteration t=1 to the end of the algorithm:
Step 3: Calculate the membership matrix U(t) of element u_{ik} using (12):

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|F_k - v_i\|}{\|F_k - v_j\|} \right)^{\frac{2}{m-1}}}$$

(12)

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

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

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

(13)

Step 5: Convergence test:

If $\left\| V^{(t)} - V^{(t-1)} \right\| > \varepsilon$, then increment the iteration t, and return to the step 3, otherwise, stop the algorithm. ε is a chosen positive threshold.

B. Fuzzy segmentation using color feature hue

Color is perceived by human as a combination of tristimuli R (red), G (green) and B (blue) which are usually called three primary colors.

From RGB, we can calculate different kinds of color representations by using linear or nonlinear transformations. Several color representations (spaces) such as RGB, HSI, CIEL*u*v*, etc., are employed for color segmentation, but none of them can dominate the others of all kinds of colors images.

Each color representation has its advantages and disadvantages. Nonlinear color transformations such as HSI and normalized color space have essential singularities which are non-removable, and there are spurious modes in the distribution of values resulting from nonlinear transformations. The major problem of linear color spaces is the high correlation of the three components, which makes them dependent upon each other and associates strongly with intensity. Using HSI can solve this problem to some extent except that hue is unstable at low saturation [29].

The HSI system separates color information of an image from its intensity information. Color information is represented by hue and saturation values, while intensity, which describes the brightness of an image, is determined by the amount of the light. Hue is the most useful attribute in color segmentation since it is less influenced by the nonuniform illumination such as hade, shadow, or reflect lights [30].

Hue can be obtained by a nonlinear transformation from R, G and Blue color features [31]:

$$Hue = \arctan\left(\frac{\sqrt{3}(G-B)}{(R-G)+(R-B)}\right) \qquad (14)$$

Hue represents basic colors, and is determined by the dominant wavelength in the spectral distribution of light wavelengths. It reflects the predominant color of an object and has a great capability in subjective color perception [32].

In our application, instead of using the segmentation method based on the pixel gray-level value and the standard FCM algorithm, we propose in this paper to extract a feature vector from a sliding window centered on the pixel of the color feature hue. The fuzzy c-means clustering technique is then used to cluster the obtained feature vectors into several classes with every class corresponding to one region in the segmented image. Therefore, the pixels are divided into several groups with each group having similar colors. The proposed method can be described by a flowchart given in Fig. 4.

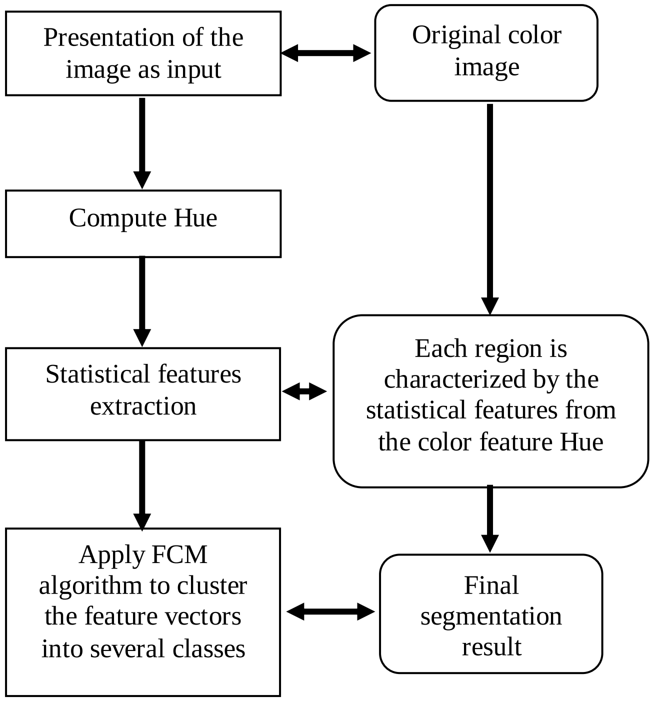


Fig. 4. Flowchart of the proposed method

IV. Experimental results

In order to illustrate the method presented in the previous section, a large variety of medical and synthetic colour images (Fig. 5) are employed in our experiments. Also, several simulation results of color image segmentation illustrating the ideas presented in the previous section are performed.

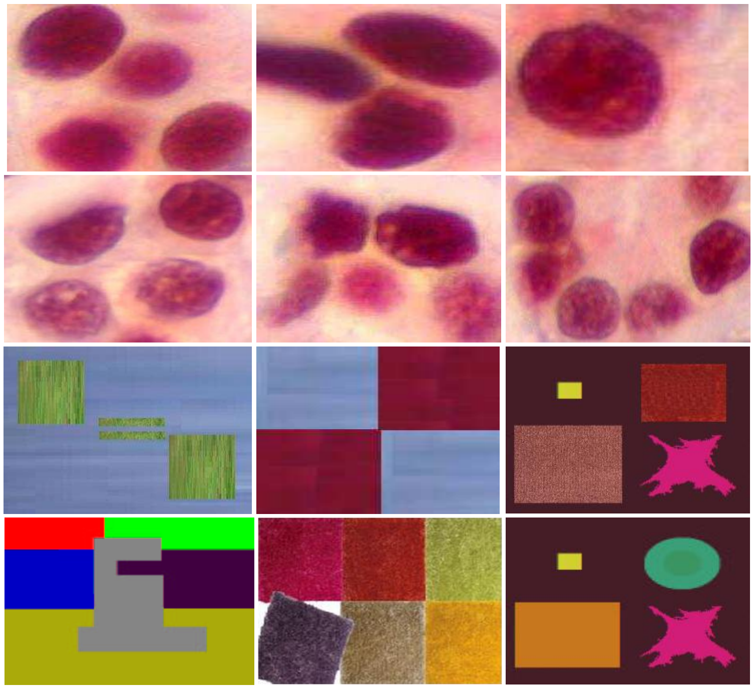


Fig. 5. Data set used in the experiment. Twelve images were selected for a comparison study. The patterns are numbered from 1 to 12, starting at the upper left-hand corner.

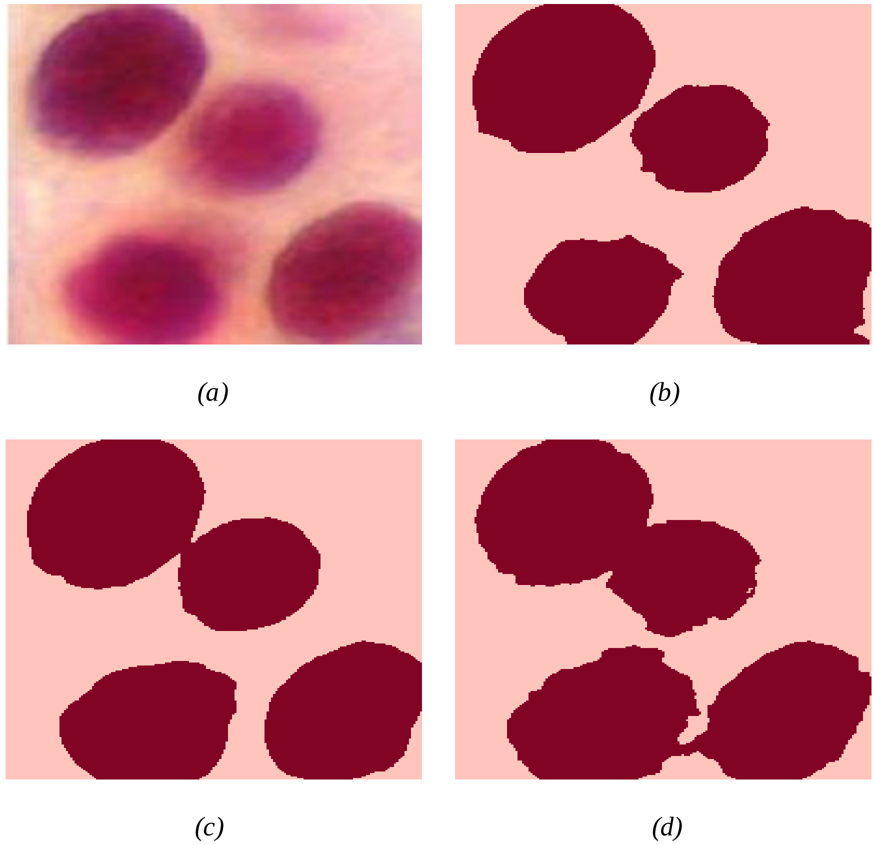


Fig. 6. Segmentation results on a colour image, (a) Original image (256x256x3) with gray level spread on the range [0,255]. (b) Red resulting image by MFCM method. (c) Green resulting image by MFCM method. (d) Blue resulting image by MFCM method.

Some experimental results are shown in Figs. 6-12. The images are originally stored in RGB format. Each of the primitive colors (red, green and blue) is represented by 8 bits and has an intensity ranging from 0 to 255.

In order to evaluate the performance of the proposed method based segmentation algorithm on color cells images segmentation, the segmentation results of the datasets are described in this section. Consequently, a synthetic image dataset is developed and used for numerical evaluation purpose.

Figs. 6-12 demonstrate the results of the proposed approach. Fig. 6 presents the segmentation results in the RGB color space by applying the MFCM algorithm to the red, green and blue color features, respectively.

In this case, a region is recognized in red component but is not identified by green and blue components. 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.

Comparing the results, we can find that the cells are much better segmented in (b) than those in (c) and (d). Also, the first resulting images contain some missing features in one of the cells, which do not exist in the other resulting images.

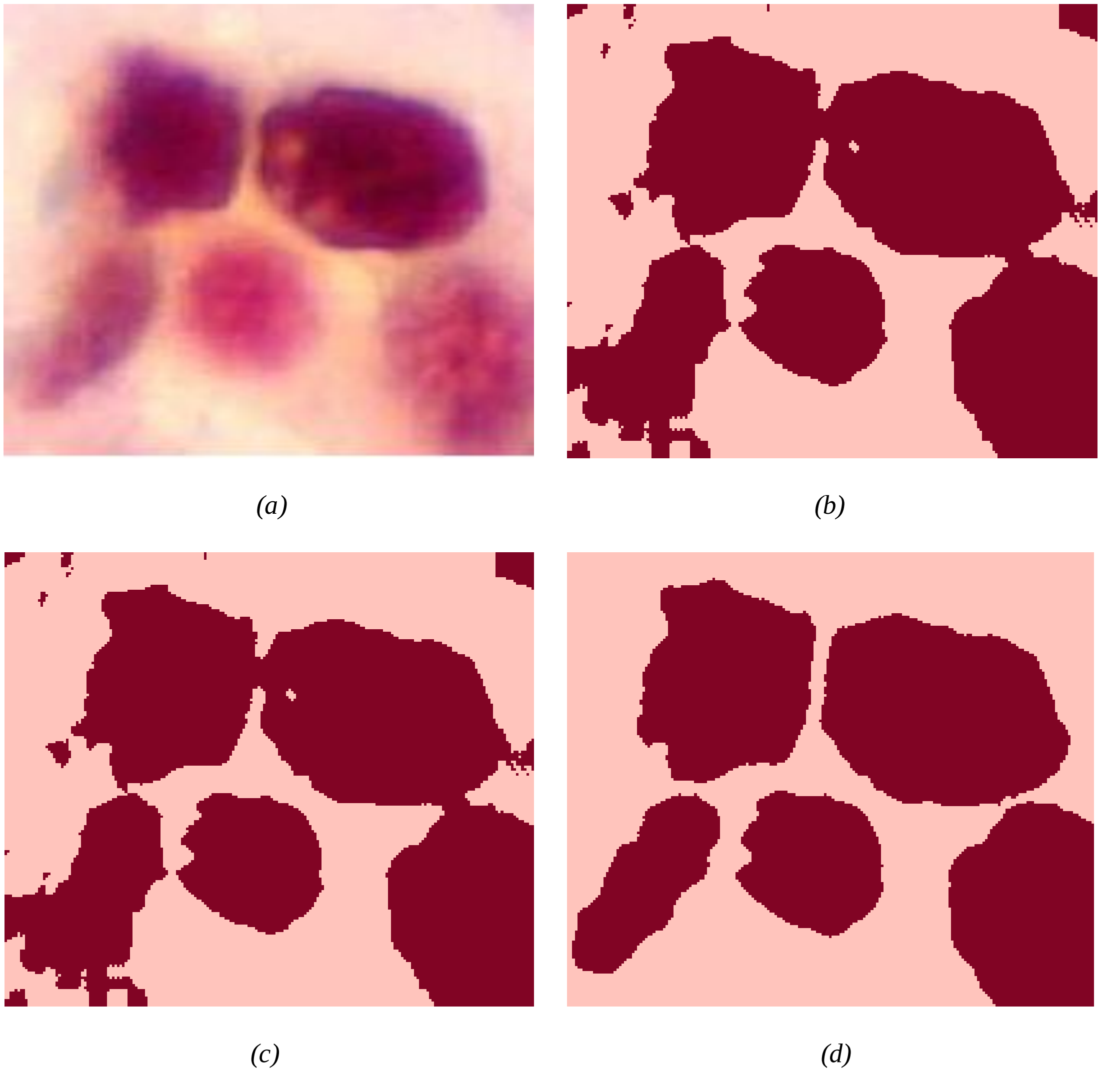


Fig. 7. Comparison of the proposed segmentation method with other existing methods on a medical image (2 classes, 1 cell), (a) Original image with RGB representation (256x256x3), (b) Hue resulting image by HCM method (c) Hue resulting image by FCM method, (d) Hue resulting image by MFCM method (our method).

The experimental results indicate that the proposed approach, which combines statistical features and the standard Fuzzy C-Means clustering algorithm, is better than the traditional methods (HCM and FCM). As shown in Fig. 7, the cells are better recognized by the proposed approach. The difference of the segmentation result lies in the combination of statistical features and the fuzzy classification.

The pixels of the cells are grouped into the same region in the color segmentation based on FCM algorithm due to the similarity of the statistical features from each block on the color feature hue.

In fig. 7, the red color of the cells is identified by the proposed approach (see fig. 7(d)), but is not signified by the traditional approaches (see fig. 7(b) and fig. 7(c)).

In fact, the experimental results indicate that the proposed method, which combines the statistical features and the fuzzy classification, is more accurate than the traditional methods (HCM and FCM) in terms of segmentation quality as denoted by the segmentation sensitivity, see Table 1.

TABLE I

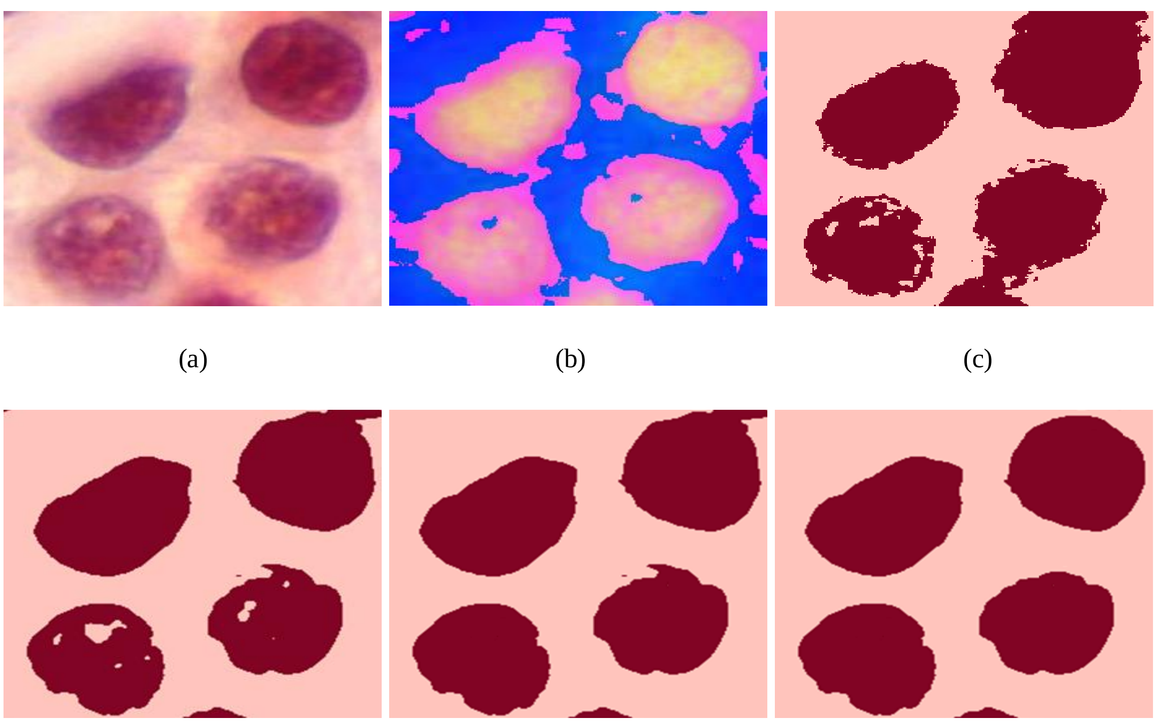
Segmentation sensitivity from HCM algorithm, FCM algorithm and MFCM method for the Data set Shown in Fig. 5

	HCM	FCM	MFCM
		Segmentation sensitivity (%)	
Image 1	80.41	90.21	94.54
Image 2	64.74	85.12	88.88
Image 3	72.10	80.25	91.10
Image 4	82.14	86.52	97.64
Image 5	74.89	89.25	95.12
Image 6	75.45	85.74	90.80
Image 7	69.95	77.84	96.92
Image 8	72.12	84.74	90.50
Image 9	87.32	92.21	98.04
Image 10	78.74	84.01	95.80
Image 11	86.41	91.78	97.55
Image 12	83.73	93.47	98.21

For purpose of comparison, we apply the proposed approach and some existing approaches to the same color image segmentation. The latter methods include those of Cheng and Sun (*THH*) [11], Ben Chaabane et al. (*DSFCM*) [13], Lim and Lee (*TFCM*) [14], J. C. Bezdek (*FCM*) [26] and R. Duda et al. (*HCM*) [27]. The segmentation results are shown in Figs. 8, 9, 10, 11 and 12.

Figure 8 shows a comparison of the results between the traditional methods HCM [27], FCM [26], and the proposed method. They correspond, respectively, to Fig. 8(c), Fig. 8(d) and Fig. 8(e).

In fact, obviously a better result is obtained by the proposed method due to the combination of statistical features and the fuzzy classification, as shown in Fig. 8(e).



(a) (b) (c)

(d) (e) (f)

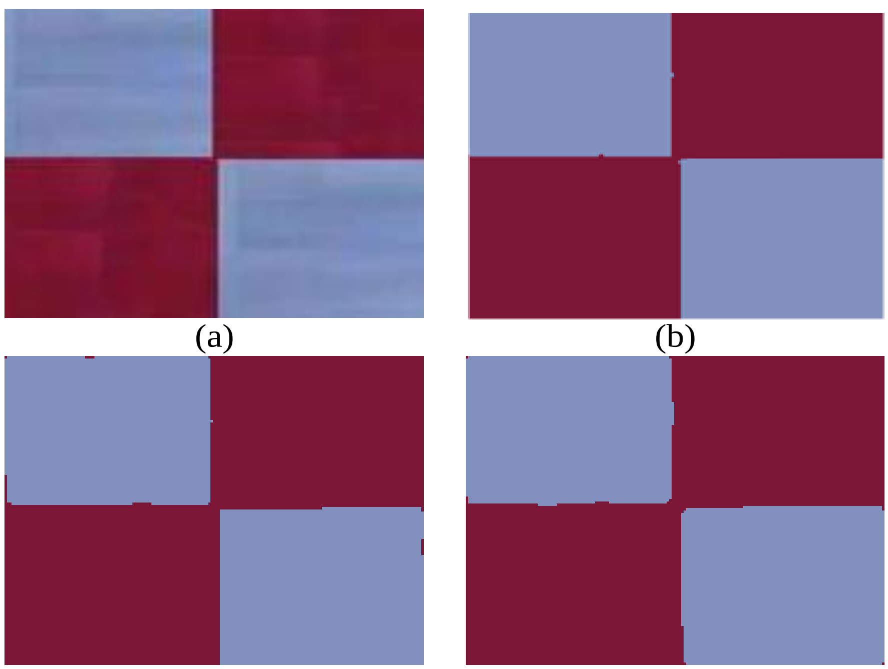
Fig. 8. Comparison of the proposed segmentation method with other existing methods on a medical image (2 classes), (a) Original image with RGB representation (256x256x3), (b) Original image with HSI representation (256x256x3), (c) Hue

resulting image by HCM method (d) Hue resulting image by FCM method, (e) Hue resulting image by MFCM method, (f) reference segmented image. (The various medical images used in this paper are provided with permission fromCancer Service, Salah Azaiez Hospital, Bab Saadoun, Tunis, Tunisia).

Comparing Figs 8(c), 8(d), and 8(e), we observe that the two regions are correctly segmented in Fig 8(e), showing that the quality of the segmentation result is much improved by combining statistical features and the Fuzzy C-means algorithm.
It can be seen from Table 1 that 17.86% and 13.48% of the pixels were incorrectly segmented by HCM and FCM based methods, respectively, but only 02.36% are incorrectly segmented pixels by our proposed method.
Comparing Fig. 8(c) and 8(d) with 8(e), we can see that the image resulting from the proposed method is clearer than the one resulting from the HCM and FCM based methods.
To evaluate the performance of the proposed segmentation algorithm, its accuracy was recorded.
Regarding the accuracy, Tables 1 and 2 list the segmentation sensitivity of the different methods for the data set used in the experiment.
The segmentation sensitivity [33] [34] (Sens %) is computed using:

$$Sens = \frac{Np_{cc}}{N \times M} \times 100 \qquad (15)$$

where: Sens, Npcc and N×M correspond to the segmentation sensitivity (%), number of correctly classified pixels and the image sizes, respectively.



(a) (b) (c) (d)

Fig. 9. Segmentation results on a colour image, (a) Original image (256x256x3) with gray level spread on the range [0,255]. (b) Resulting image by MFCM method using a (3x3) window for computing the feature vector. (c) Resulting image by MFCM method using a (5x5) window for computing the feature vector.. (d) Resulting image by MFCM method using a (7x7) window for computing the feature vector.

The correctly classified pixel denotes a pixel with a label equals to its corresponding pixel in the reference image as shown in Fig. 8 (f). The labeling of the original image is generated by the user based on the image used for segmentation. Consequently, the image segmentation ground truths is generated manually by the doctor (specialist) using the original image. Fig. 8(f) shows the ideal segmented image.
To provide insights into the proposed method, we have compared the performance of the proposed method with those of the corresponding Hard and Fuzzy C-Means algorithms. The method was also tested on synthetic images and compared with other existing methods based on fuzzy homogeneity (*THH*) [11], data fusion techniques (*DSFCM*) [13] and a modified FCM algorithm (*TFCM*) [14].

The comparison of the proposed approach will be presented through the next experiment. Fig. 10(c), (d), (e) and (f) show the final segmentation results obtained from the *THH* method, the *DSFCM* method, the *TFCM* method and the *MFCM* method, respectively, when a ''salt and pepper" noise of *D* density is added to the original image *I*, shown in Fig. 10(a). This affects approximately ($D \times (N \times M)$) pixels. The value of *D* is 0.02.
As shown in fig. 10(c), the fuzzy homogeneity approach (*THH*) is applied to Hue component to partition the color space into several clusters.
However, the cells and the background are not correctly segmented in Fig. 10(c). This indicates that the segmentation results depend on the optimal threshold selection.

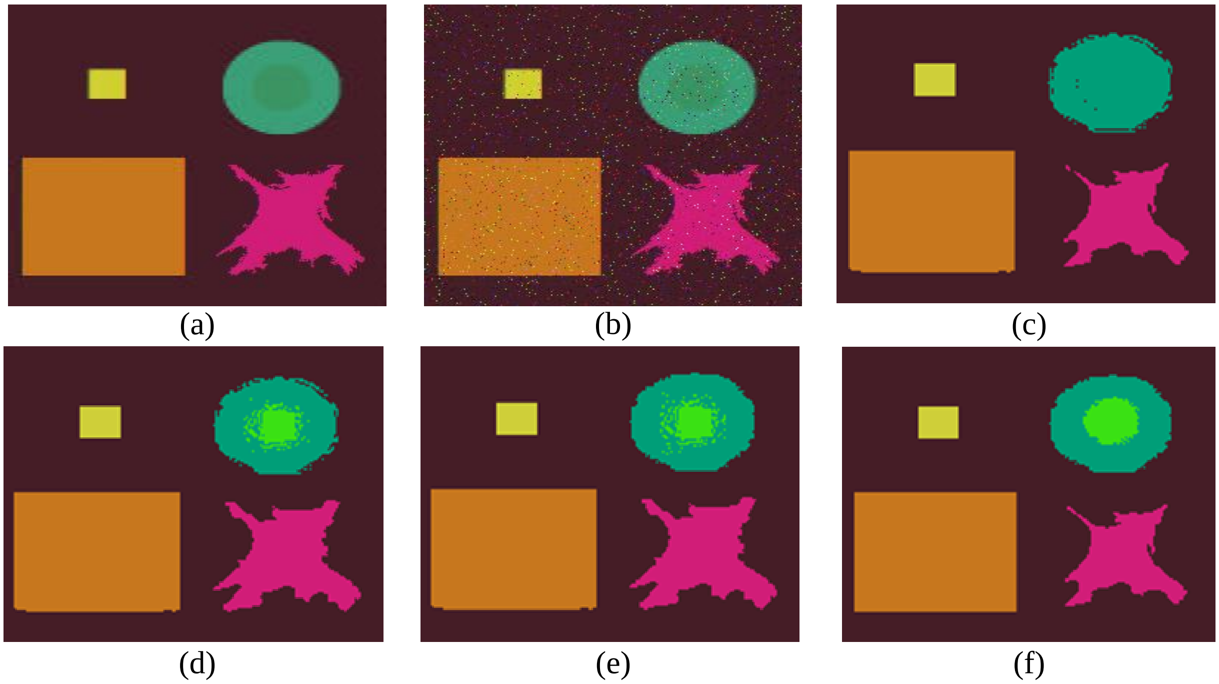


Fig. 10. Comparison of the proposed segmentation method with other existing methods on a synthetic image (6 classes), (a) Original image with RGB representation (256x256x3), (b) Original image (256x256x3) disturbed with a "salt and pepper" noise and with grey level zero to 255 of each primitive colors, (c) Hue resulting image by THH method (d) Hue resulting image by DSFCM method, (e) Hue resulting image by TFCM method, (f) Hue resulting image by MFCM method (our method).

TABLE II

SEGMENTATION SENSITIVITY FROM THH METHOD, DSFCM METHOD, TFCM METHOD AND MFCM METHOD FOR THE DATA SET SHOWN IN FIG. 5

	THH	DSFCM	TFCM	MFCM
	Segmentation sensitivity (%)			
Image 1	92.45	93.88	90.80	94.54
Image 2	87.09	87.89	86.42	88.88
Image 3	84.55	88.54	82.11	91.10
Image 4	91.29	95.16	89.20	97.64
Image 5	92.37	93.97	90.89	95.12
Image 6	88.09	90.20	87.45	90.80
Image 7	93.41	95.01	79.65	96.92
Image 8	82.77	86.44	87.08	90.50
Image 9	95.97	97.15	94.78	98.04
Image 10	95.09	96.52	94.92	95.80
Image 11	94.64	95.03	93.10	97.55
Image 12	96.18	97.01	94.09	98.21

Also, the segmentation method based on the thresholding and the fuzzy c-means techniques (*TFCM*), do not consider the spatial dependencies among the pixels, there are some isolated pixels that are remaining (see fig. 10(d)).
Furthermore, the methods based on data fusion techniques (*DSFCM*) require a lot of computation time, due to the large number of iterations and the number of operations (multiplications, addition and exponent) that are necessary for the computation of the mass functions for the simple and composite classes, and the performance of such a segmentation scheme is largely conditioned by the appropriate estimation of mass functions in the DS evidence theory (see fig. 10(e)).
Comparing Figs 10(c), 10(d), 10(e) and 10(f), we observe that the two regions are correctly segmented in Fig 10(f), showing that the new method is very efficient for color images segmentation.
It can be seen from Table 2 that 03.82%, 02.99% and 0.5.91% of the pixels were incorrectly segmented by *THH*, *DSFCM* and *TFCM* based methods, respectively, but only 01.79% are incorrectly segmented pixels by our proposed method. Comparing Fig. 10(c), 10(d) and 10(e) with 10(f), we can see that the image resulting from the proposed method is much more clearer than the one resulting from the *THH*, *DSFCM* and *TFCM* based methods.
The segmentation sensitivity values reported in Table I and 2 are plotted in Figures 11 and 12, respectively.
Figure 11 shows three segmentation sensitivity plots using traditional methods such as HCM and FCM compared with the proposed method plot.
Figure 12 shows three other segmentation sensitivity plots using traditional methods such as THH, DSCM and TFCM compared with the proposed method plot.
As seen on both Figures 11 and 12, the proposed method plot is clearly located on the top of the other methods plots.

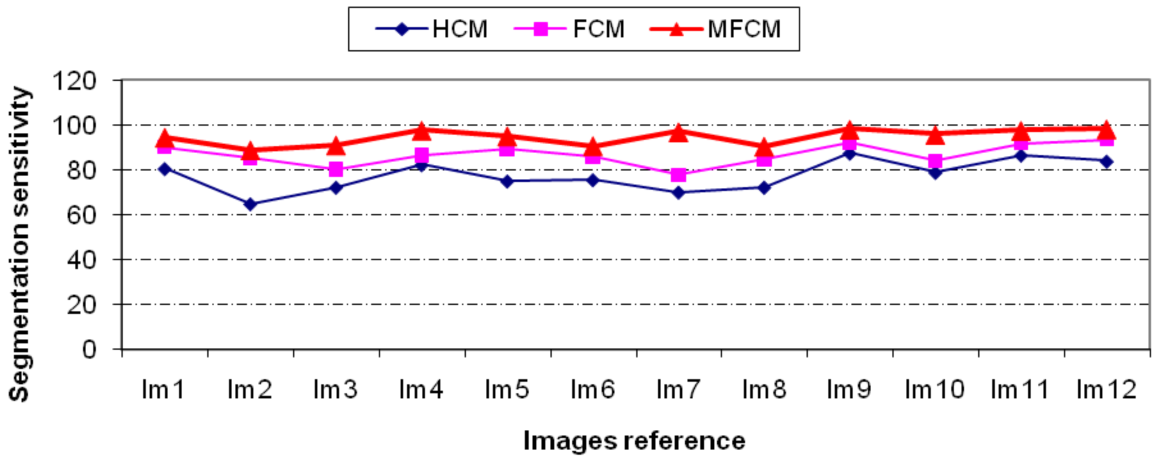


Fig. 11. Segmentation sensitivity plots using HCM algorithm, FCM algorithm and MFCM method for the Data set Shown in Fig. 5.

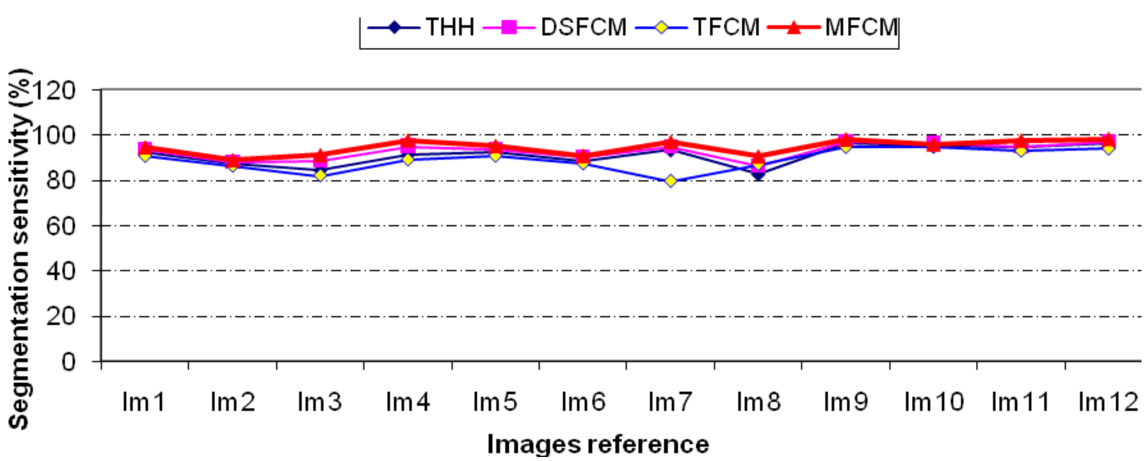


Fig. 12. Segmentation sensitivity plots using THH method, DSFCM method, TFCM method and MFCM method (our method) for the Data set Shown in Fig. 5.

Referring to segmentation sensitivity plots given in Fig. 11, one observes that 25.11% and 10.75% of pixels were incorrectly segmented in Figs. 7(b) and 7(c), respectively, but only 04.88% are incorrectly segmented pixels by our proposed method. Comparing Fig. 7(b) and 7(c) with 7(d), the resulting image by the proposed method is much more clearer than the one given by the HCM and *FCM* based methods.
Hence, the experimental result presented in Fig. 7(d) is quite consistent with the visualized color distribution in the objects, which makes it possible to take an accurate measurement of the cells volumes [35].

V. Conclusion

In this paper, we propose a new fuzzy classification method to color image segmentation. In the first phase, the feature vector containing the statistical features is identified in each block on the color feature hue. While the feature vector is calculated in each block, the Fuzzy C-means algorithm is used to cluster the feature vectors into several classes with every class corresponding to one region in the segmented image. The color feature hue is proved to be more efficient than RGB color features by this research. The experimental results show that the MFCM method tends to be more effective to find homogeneous regions. The proposed method can be useful for color image segmentation.

REFERENCES

1. D. Keren and A. Gotlib, "Denoising Color Images Using Regularization and Correlation Terms", Journal of Visual Communication and Image Representation, 2002, Vol. 9, no. 4.
2. M. B. Meenavathi and K. Rajesh, "Volterra Filter for Color Image Segmentation", International Journal of Computer Science and Engineering, 2008, Vol. 2, no.1.
3. S. Ben Chaabane, M. Sayadi, F. Fnaiech and E. Brassart, "Colour Image Segmentation using Homogeneity method and Data Fusion Techniques," Eurasip journal on advances in signal processing, 2009.
4. N. Ohta, "Correspondance between ceilab and cieluv color differences", 1977, Vol. 2, no. 4, pp. 178-182.
5. G. Wyszecki and W. S. Stiles, "Color Science: Concepts and Methods, Quantitative Data and formulae", John Wiley and Sons, second edition, 1982.
6. X. Gao, K. Hong, P. Passmore, L. Podladchikova, and D. Shaposhnikov, "Colour Vision Model-Based Method for Segmentation of Traffic Signs", EURASIP Journal on Image and Video Processing, October 2008.
7. E. Littmann and H. Ritter, "Adaptive colour segmentation – a comparison of neural and statistical methods", IEEE Trans. Neural Network, 1997, Vol. 8, no. 1, pp. 175–185.
8. P. W. M. Tsang and W. H. Tsang, "Edge detection on object color", IEEE Intern. Conf. On Image Processing-C, 1996, pp. 1049-1052.
9. E. Navon, O. Miller and A. Averbuch, "Colour image segmentation based on adaptive local thresholds", Image and Vision Computing, 2005, Vol. 23, no. 1, pp. 69-85.
10. R. E. Cummings, P. Pouliquen, and M. A. Lewis, "A Vision Chip for Colour Segmentation and Pattern Matching", EURASIP Journal on Applied Signal Processing, 2003, no. 7, pp. 703-712.
11. H. D. Cheng and Y. Sun, "A hierarchical approach to color image segmentation using homogeneity", IEEE Transaction on Image Processing, 2000, Vol. 9, no. 12, pp. 2071-2082.
12. H. D. Cheng, X. H. Jiang and J. Wang, " Color image segmentation based on homogram thresholding and region merging", Pattern Recognition, 2002, pp. 373-393.
13. S. Ben Chaabane, M. Sayadi, F. Fnaiech and E. Brassart, "Dempster-Shafer Evidence Theory for Image Segmentation: Application in Cells Images", International Journal of Signal processing, IJSP, 2009, Vol. 5, no. 2, pp. 126-132.
14. Y. W. Lim and S. U. Lee, "On the color image segmentation algorithm based on the thresholding and the fuzzy c-means techniques", Pattern Recognition, 1990, Vol. 23, no. 9, pp. 935-952.
15. S. Ben. Chaabane, M. Sayadi and F. Fnaiech, "Color Image Segmentation using Automatic Thresholding and the Fuzzy C-Means Techniques", IEEE MELECON, 2008, pp. 857-861.
16. Y. Yang, Ch. Zheng and P. Lin, "Fuzzy C-means clustering algorithm with a novel penalty term for image segmentation", Opto-Electronics Rev, 2005, Vol. 13, no. 4.
17. A. W. C. Liew, S. H. Leung and W. H. Lau, "Fuzzy image clustering incorporating spatial continuity", IEE Proc. Visual Image Signal Process, 2000, no. 147, pp. 185-192.
18. X. Li, L. Li, H. Lu, D. Chen and Z. Liang, "Inhomogeneity correction for magnetic resonance images with fuzzy C-mean algorithm", Proc. SPIE 5032, , 2003, pp. 995-1005.
19. K. Raghu and J. M. Keller, "A possibilistic approach to clustering ", IEEE Transactions on Fuzzy Systems, 1993, Vol. 1, no. 2.
20. M. J. Kwon, Y. J. Han, I. H. Shin and H. W. Park, "Hierarchical fuzzy segmentation of brain MR images", Int. J. Imaging Systems and Technology, 2003, no. 13, pp. 115-125.
21. M. N. Ahmed, S. M. Yamany, N. Mohamed, A. A. Farag and T. Moriarty, "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data", IEEE Trans. On Medical imaging, 2002, no. 21, pp. 193-199.

22. D. L. Pham and J. L. Prince, “Adaptive fuzzy segmentation of magnetic resonance images”, IEEE Trans. Medical Imaging, 1999, no. 18, pp. 737-752.
23. M. Sayadi, L. Tlig and F. Fnaiech, “Texture Segmentation Based on a Modified Fuzzy C-Mean Algorithm and Statistical Features”, Applied Mathematical Sciences, 2007, Vol. 1, no. 60, pp. 2999–3007.
24. Y. A. Tolias and S. M. Panas, “On applying spatial constraints in fuzzy image clustering using a fuzzy rule-based system”, IEEE Signal Processing Letters, 1998, Vol. 5, no. 10, pp. 245-247.
25. M. N. Ahmed, S. M. Yamany, N. Mohamed, A. A. Farag, and T. Moriary, “A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data”, IEEE Trans. On Medical Imaging, 2002, vol. 21, pp. 193-199.
26. J. C. Bezdek, “Pattern recognition with fuzzy objective function algorithms”, Plenum Press, New York, 1981.
27. R. Duda and P. Hart, “Pattern Classification and Scene Analysis”, New York, Wiley, 1973.
28. G. Van de Wouwer, P. Scheunders, and D. VanDyck, “Statistical texture characterisation from discrete wavelet representation”, IEEE Transactions on Image Processing, 1999, vol. 8, no. 4, pp. 592-598.
29. P. W. M. Tsang and W. H. Tsang, “edge detection on object color”, IEEE International Conference on Image Processing-C, 1996, pp. 1049-1052.
30. D. C. Tseng and C. H. Chang, “Color segmentation using perceptual attributes,” in IEEE Int. Conf. Image Processing, 1992, pp. 228–231.
31. D. Hoy, “On the use of color imaging in experimental applications”, Exper. Tech., July/Aug. 1997.
32. W. Kim and R. Park, “Color image palette construction based on the HSI color system for minimizing the reconstruction error”, in IEEE Int. Conf. Image Processing, 1996, pp. 1041–1044.
33. V. Grau, A. U. J. Mewes, M. Alcaniz, R. Kikinis, and S. K. Warfield, “Improved watershed transform for medical image segmentation using prior information”, IEEE Transactions on Medical Imaging, 2004, Vol. 23, no. 4, pp. 447–458.
34. R. O. Duda, P. E. Hart, and D. G. Sork, “Pattern Classification”, Wiley-Interscience, New York, NY, USA, 2000.
35. O. Colot et al., “A Colour Image Processing Method for Melanoma Detection”, Lecture Notes in Computer Science, Springer, Berlin, 1998.

BIOGRAPHIES

Rafika Harrabi born in 1981 in Kairouan (Tunisia), she received the BSc degree in Electrical Engineering and the DEA degree in Automatic and Signal Processing from the High school of sciences and techniques of Tunis, respectively in 2007 and 2009. Currently, she is in the last preparation year of its PhD. Its research interests are focused on signal Processing, image processing, classification, segmentation and data fusion.

Ezzedine Ben Braiek obtained his HDR on 2008 in Electrical engineering from ENSET Tunisia. He is, presently, professor in the department of electrical engineering at the technical university ESSTT and manager of the research group on vision and image processing at the CEREP. His fields of interest include automatics, electronics, control, computer vision, image processing and its application in handwritten data recognition.