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Colour image segmentation using the second order statistics and a modified fuzzy C-means technique

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This paper presents a new colour image segmentation method based on Fuzzy C-means technique and the second order statistics. The importance of combining statistical features extracted from the co-occurrence matrix and the standard Fuzzy C-Means clustering algorithm in the segmentation context is studied in this paper, to obtain a more reliable and accurate segmentation results. In the first phase of segmentation, a characterization degree is employed to identify the most significant statistical features extracted from the co-occurrence matrix. In the second phase, the Fuzzy C-means (FCM) algorithm is used to cluster the statistical feature vectors into homogeneous regions. Segmentation results from the proposed method are validated and a comparative study versus existing techniques is presented. The experimental results on medical and synthetic colour images demonstrate the superiority of introducing the second order statistics in the Fuzzy C-Means algorithm for colour image segmentation.

Key words: Segmentation, medical colour images, fuzzy logic, fuzzy C-Means, second order statistics, co-occurrence matrix.

INTRODUCTION

Image segmentation is considered as a critical and an important basic operation for meaningful analysis and interpretation of images acquired (Kwon et al, 2003; Navon et al, 2005). It is considered as one of the most difficult tasks in image processing, which determines the quality of the final results analysis. The goal of image segmentation is the partition of an image into compact and homogeneous regions, according to a choice criterion, such as intensity, colour, tone or texture, etc. Generally, the gray level image segmentation techniques can be divided into four categories, thresholding, clustering, edge detection, and region extraction.

At present, these techniques can be extended to colour images expressed in different colour spaces. These spaces are obtained by using the linear and non-linear transformations of the RGB colour space. Many different techniques of colour image segmentation have been developed and detailed in the literature (Meenavathi and Rajesh, 2008; Ben et al., 2009a). The general segmentation problem consists in choosing the adopted colour model for a specific application. Non-linear colour transformations such as HIS (Cheng and Sun, 2000; Harrabi and Ben, 2010), have essential singularities which are non-removable, and there are spurious modes in the distribution of values resulting from non linear transformations.

The major problem of spaces colour which obtained by using the linear transformations is the high correlation of the three components (Harrabi and Ben, 2010; Ben et al., 2011). By high correlation, we mean that if the intensity change, all the three components will change accordingly. Using the colour space HIS can solve this problem to some extent except that hue is instable at low saturation.

In the past, many authors have addressed the colour image segmentation problems using different methods (Ben et al., 2008; Gûvenç et al., 2010; Sojodishijani et al., 2010), and several researchers have, in particular, investigated the modified fuzzy methods (Liew et al., 2000; Ahmed et al., 2002; Li et al., 2003).

Recently, most analytic fuzzy techniques have been derived from Bezdek's Fuzzy C-Means (FCM) (Bezdek, 1981). However, this algorithm remains more information from the original image than hard segmentation method

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(Duda and Hart, 1973). Unlike hard classification methods which Hard C-Means (HCM) memberships are hard (that is, 1 or 0), FCM allows pixels to belong to multiple classes with varying of memberships degrees. The major disadvantage of its use in imaging applications, however, is that the FCM algorithm does not incorporate information about spatial context. Consequently, it has a considerable drawback in noisy environment.

In this context, Zhu et al. (2002) and Ben et al. (2009b) 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.

With the same objective, Lim and Lee, (1990) have proposed a colour image segmentation method based on the thresholding and the fuzzy c-means techniques. The authors use a coarse-fine concept to reduce the computational burden required for the FCM algorithm. The thresholding technique is applied to find all major homogeneous regions in the three primitive colours, while, the FCM algorithm assigns the pixels which remain unclassified after the first step, to the closest class. Also, Raghu and Keller (1993) have formulated a new algorithm by modifying the objective function in the fuzzy c-means algorithm to generate memberships with typical interpretation.

In another study, Liew et al. (2000) have provided a new dissimilarity index that considers the influence of the neighbouring pixels on the centre pixel in the FCM algorithm. Furthermore, Ahmeh et al. (2002) have introduced a regularization term in the standard FCM algorithm to impose the neighbourhood effect. However, typical problems remain difficult to solve including the more consuming time is needed during the computation.

In this paper, a new colour image segmentation method based on statistical features and the FCM algorithm is presented. Instead of using the simple pixel value in FCM algorithm, a feature vector extracted from the co-occurrence matrix is used. The co-occurrence matrix is computed starting from a sliding window centred on the pixels of the original image. Then, the FCM algorithm is modified and used to cluster the feature vectors into homogeneous regions. This technique allows obtaining an optimal segmented image, superior to the standard FCM algorithm (Bezdek, 1981; Ben et a., 2009b), and versus existing techniques (Lim and Lee, 1990; Liew et al., 2000).

METHODS

Image segmentation consists in partition of an image into homogeneous regions. In the framework of our application, we are interested in colour image segmentation of cells in the breast images. In fact, the problem is to separate the cells from the background. The fuzzy c-means (FCM) algorithm is one of the widely used techniques for image segmentation (Yang et al, 2005; Ben et al., 2008), but it is based on only gray level and does not take into account the spatial information of pixels with respect to each other. Consequently, the statistical features extracted from the co-occurrence matrix can be used to overcome this drawback. The concept of co-occurrence matrix (Harralick, 1973; Peckinpaugh, 1991) was defined to express the image properties relating to the second order statistics.

In this paper, we employ the FCM algorithm to extract homogeneous regions in a colour image. The proposed method is divided into two stages. At the first stage, a characterization degree is applied to the data set used in the experiment to find the most significant statistical features extracted from the co-occurrence matrix (Clausi, 2001; Arvis et al., 2004), then the FCM algorithm is modified and used to obtain the final segmentation results.

Spatial information dependence method

The co-occurrence matrix (Verma et al, 2002; Morales et al, 2003), is largely related to the appearance frequency of a pixel couples from an image. It contains significant information which improves the classes' discrimination of an image, so, it plays an important role in image segmentation. Here, we define the co-occurrence matrix, also called by the spatial information dependence method, as the appearance frequency of a pixel couples separated by a distance d_1, in a particular direction θ.

Assume g_{xy} is the intensity of a pixel p_{xy} at the location (x,y) in an $(M \times N)$ image, w_{xy} is a size $(t \times t)$ window centred at (x,y) for the computation of co-occurrence matrix. Let us choose a 7×7 window for computing the co-occurrence matrix. However, w_{xy} is the local regions where the spatial information dependence method are calculated. So, the co-occurrence matrix describes the appearance frequency of a pixel couples within a local region, and relating to the relation R is calculated for each window w_{xy} as follows:

$$Cooc(i,j,R) = card \begin{cases} ((x,y),(x',y')) \in D, checking \quad R(d_1,\theta) \\ I(x,y) = i; \quad I(x',y') = j \end{cases} \tag{1}$$

where $card\{Y\}$ represent the cardinal of the ensemble Y.

Each element of $Cooc(i,j,R)$ represents the number of pixels couple (i,j), that is, how often a pixel with gray-level value i occurs horizontally adjacent to a pixel with the value j in the image. $R(d_1,\theta)$ is the space relation of the two pixels, with d_1 is the distance between the two pixels and $\theta = \{0°, 45°, 90°, 135°\}$ is the orientation of the two pixels with the horizontal.

Consequently, the co-occurrence matrix allows evaluating locally the region contents of the image, so, it makes it possible to detect the changes in the local statistics of the image. In our application, the statistical features are extracted of the $(N_c \times N_c)$ co-occurrence matrix computed from a sliding window w_{xy} centered on each pixel p_{xy} of the $(M \times N)$ Hue component (Figure 1).

The spatial scanning order of an image is performed pixel by

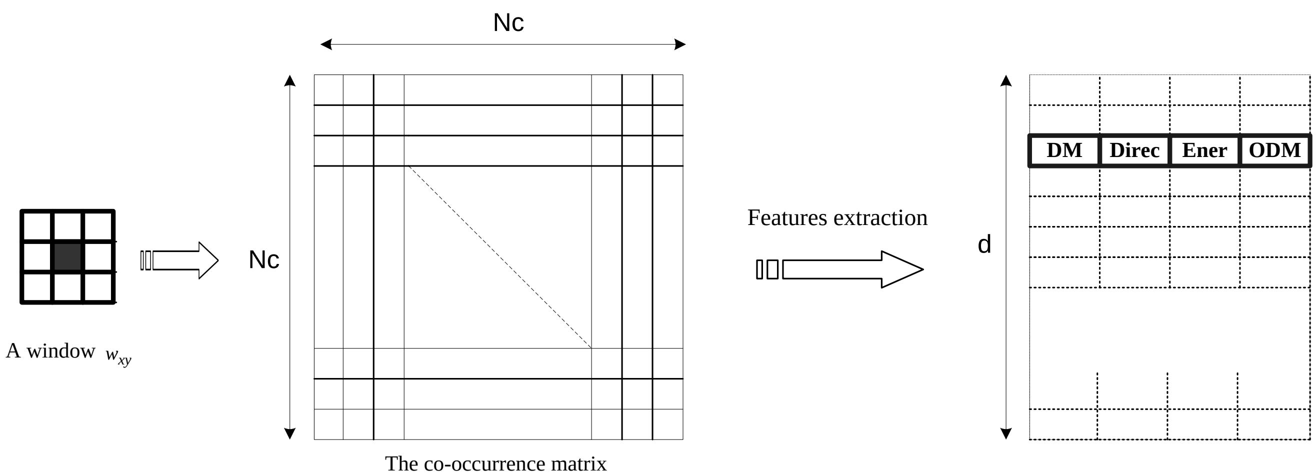


Figure 1. Features extraction from the co-occurrence matrix using a sliding window.

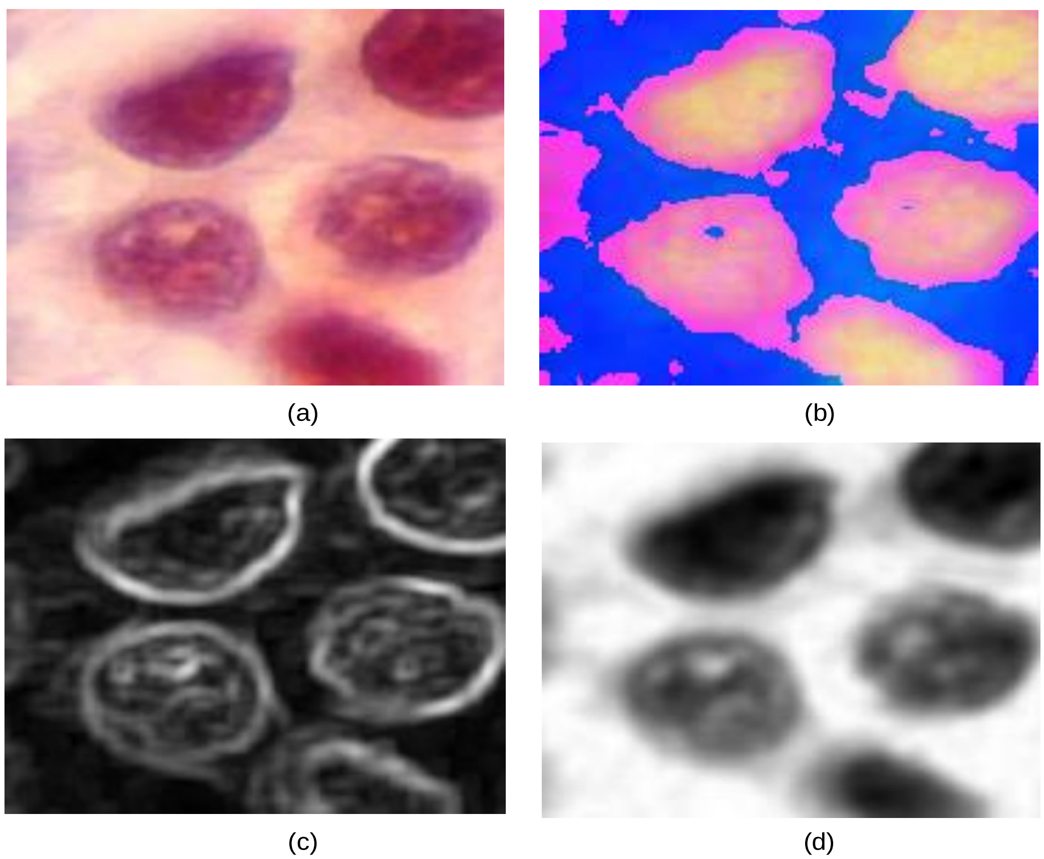


Figure 2. Attribute images. (a) Original image (256×256×3) with gray level spread on the range (0, 255); (b) original image represented in HIS colour space; (c) standard deviation image, and (d) energy image.

pixel from left to right and top to bottom (Figure 4). Hence, this technique is used to calculate the new image called the attribute image, such as energy image and standard deviation image (Figure 2). However, several attributes can be extracted from the co-occurrence matrix such as: Mean $(Mean)$, diagonal moment

However, several attributes can be extracted from the co-occurrence matrix such as: Mean $(Mean)$, diagonal moment (DM), contrast $(Cont)$, energy $(Ener)$, directivity $(Direc)$, entropy $(Entr)$, opposite differential moment (ODM), …, and

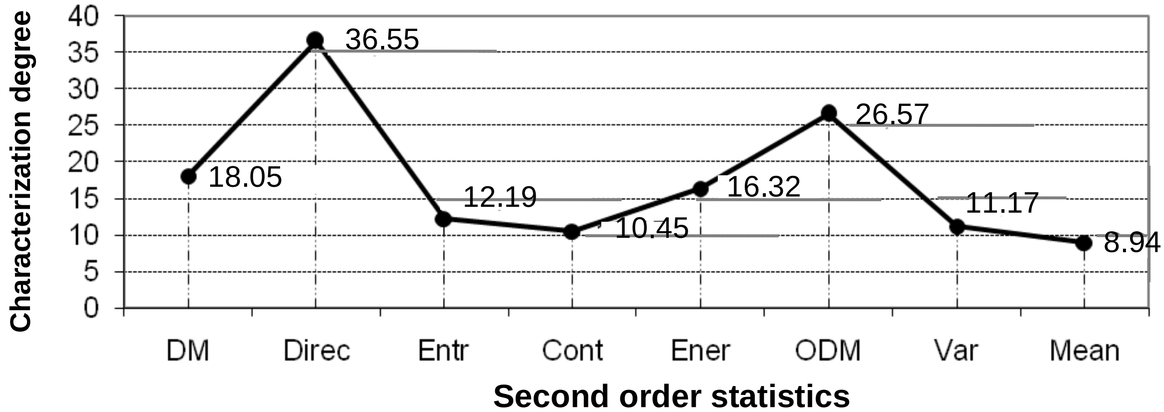


Figure 3. Characterization degree plots for different statistical features.

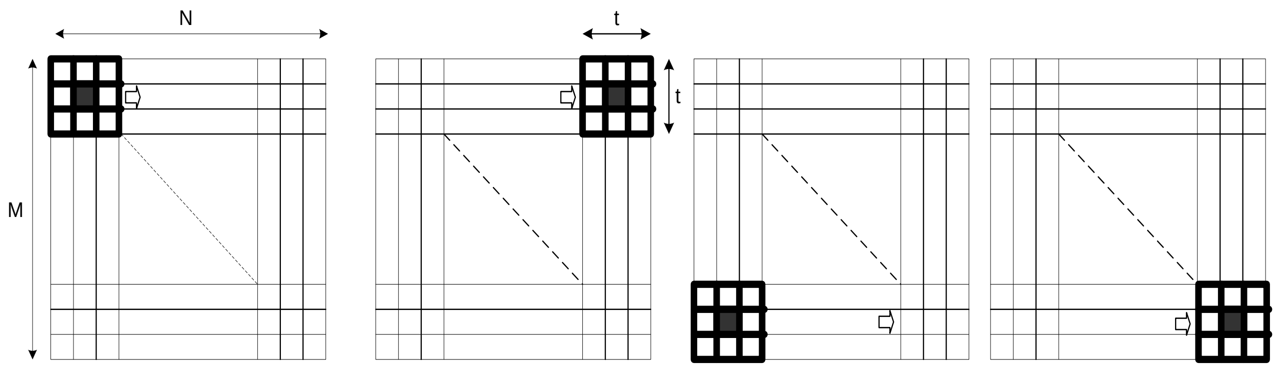


Figure 4. The adaptive sliding window from left to right and top to bottom on an ($M \times N$) image.

variance (Var). In order to obtain an ideal classification, it is necessary to select the most relevant and representative statistical features (Haralick et al., 1973).

To do this, the characterization degree ($\Im$) is applied to the data set shown in Figure 6. This criterion is based on the report/ratio of the between classes (inter-class) variance by the intra-class variance. Assume $Y_{k_1,n}$ is the n^{th} feature vector estimated for the k_1^{th} image class $(1 \le k_1 \le 12,\ 1 \le n \le 100)$, k_1 is the number of images and n is the imagettes number of each image. It should be noted that the n^{th} feature vector is calculated from the co-occurrence matrix of the n^{th} imagettes.

The mean of the feature vectors m_{k_1} is calculated for the k_1^{th} image class as follow:

$$m_{k_1} = \frac{1}{100}\sum_{k_1=1}^{100} y_{k_1,n} \quad (2)$$

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

$$m_c = \frac{1}{12}\sum_{k_1=1}^{12} m_{k_1} \quad (3)$$

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

$$S_{\text{intra}} = \frac{1}{1200}\sum_{k_1=1}^{12}\sum_{n=1}^{100}\left(y_{k_1,n} - m_{k_1}\right)\left(y_{k_1,n} - m_{k_1}\right)^t \quad (4)$$

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

$$S_{inter} = \frac{1}{12}\sum_{k_1=1}^{12}\left(m_{k_1} - m_c\right)\left(m_{k_1} - m_c\right)^t \quad (5)$$

Consequently, the characterization degree ($\Im$) is given by:

$$\Im = \text{trace}\left(S_{\text{intra}}^{-1}.S_{\text{inter}}\right) \quad (6)$$

It can be seen from Figure 3, that the best features which will be used in our application are the diagonal moment (DM), the directivity $(Direc)$, the energy $(Ener)$ and the opposite differential moment (ODM).

Assume $Cooc(i, j)$ is the appearance frequency of each pixels couple. It is obtained by calculating how often a pixel with gray-level (grayscale intensity) value i occurs horizontally adjacent to a pixel with the value j in the w_{xy} window, N_c is the maximal gray level in the sliding window w_{xy}. The 4 representative features extracted from the co-occurrence matrix are given by the following equations:

$$DM = \sum_{i=1}^{Nc}\sum_{j=1}^{Nc}\left(\frac{1}{2}(|i-j|)Cooc(i,j)\right)^{\frac{1}{2}} \quad (7)$$

$$Direc = \sum_{i=1}^{Nc}\sum_{j=1}^{Nc} Cooc(i,i) \quad (8)$$

$$Ener = \sum_{i=1}^{Nc}\sum_{j=1}^{Nc}[Cooc(i,j)]^2 \quad (9)$$

$$ODM = \sum_{i=1}^{Nc}\sum_{j=1}^{Nc}\frac{Cooc(i,j)}{1+(i-j)^2} \quad (10)$$

where $(N_c \times N_c)$ is the size of co-occurrence matrix. The size of the co-occurrence matrix is variable according to the maximum value of each window.

Use of modified FCM algorithm for image segmentation

In the framework of the segmentation of an $(M \times N)$ image, the vector $X = [x_1, x_2, \ldots, x_d]^T$ contains all the gray level of the image, scanned line by line, i.e. $d = M \times N$. The fuzzy c-means algorithm (Yang et al, 2005; Ben et al, 2008), performs the partition of the vector X into c fuzzy subsets by using the membership matrix U of element u_{ik}, where u_{ik} represents the membership of x_k in class i.

In our application, we propose to replace the dataset vector X used in the standard FCM algorithm by a matrix F containing the same number of lines, that is, d , but with 4 columns (Figure 1). The columns contain 4 second order statistical features selected by the characterization degree $(\Im)$.

Therefore, the FCM algorithm is used to cluster the obtained feature matrix F into c different homogeneous regions. The spatial scanning order of the original (input) image by a $(t \times t)$ sliding window is performed, as shown in Figure 4, pixel by pixel from left to right and top to bottom.

However, the size of the sliding window has an influence on the computation of the co-occurrence matrix, from where on feature vector calculation. The window should be big involved in the computation of the statistical feature. Experimentally, a (7×7) window for computing the co-occurrence matrix is chosen. Consequently, the proposed image segmentation technique using the FCM algorithm combined with the second order statistics can be summarized by the following steps:

i. Input an *MxN* image
ii. Compute the co-occurrence matrix

Step 1: Initialization (iteration 0)
Randomly initialize the centres 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 $(d \times 4)$ containing the statistical features extracted from the co-occurrence matrix.
From the iteration t=1 to the end of the algorithm:

Step 3: Calculate the membership matrix $u(t)$ of element u_{ik} using (11):

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|F_k - v_i\|}{\|F_k - v_j\|}\right)^{\frac{2}{m-1}}} \quad (11)$$

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:

$$v_i = \frac{\sum_{k=1}^{d} u_{ik}^m F_k}{\sum_{k=1}^{d} u_{ik}^m} \quad (12)$$

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. Finally, the proposed method can be described by a flowchart given in Figure 5.

RESULTS AND DISCUSSION

Here, several segmentation results on medical and synthetic colour images, which illustrate the ideas presented previously are given. The originally images are stored in RGB colour space. Each primitive colour (Red, Green and Blue) takes 8 bits and has the intensity range from 0 to 255.

In this work, the main application of image segmentation is a medical application. We aim at providing a help to the doctor for the follow-up the diseases of the breast cancer.

The database used in our experiment is composed of real medical cells images, obtained by a himi-histochimy colouring in the Cancer Service, Salah Azaiez Hospital, Bab Saadoun, Tunis, Tunisia. The objective is also to seek a segmentation which represents as well as possible the cells, in order to give to the doctors a schema of the points really forming part of the cells, as

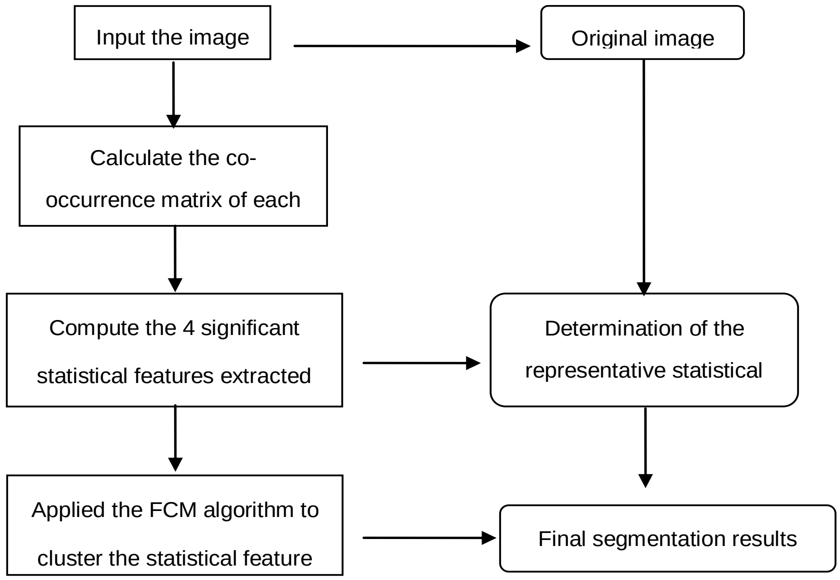


Figure 5. Flowchart of the proposed method.

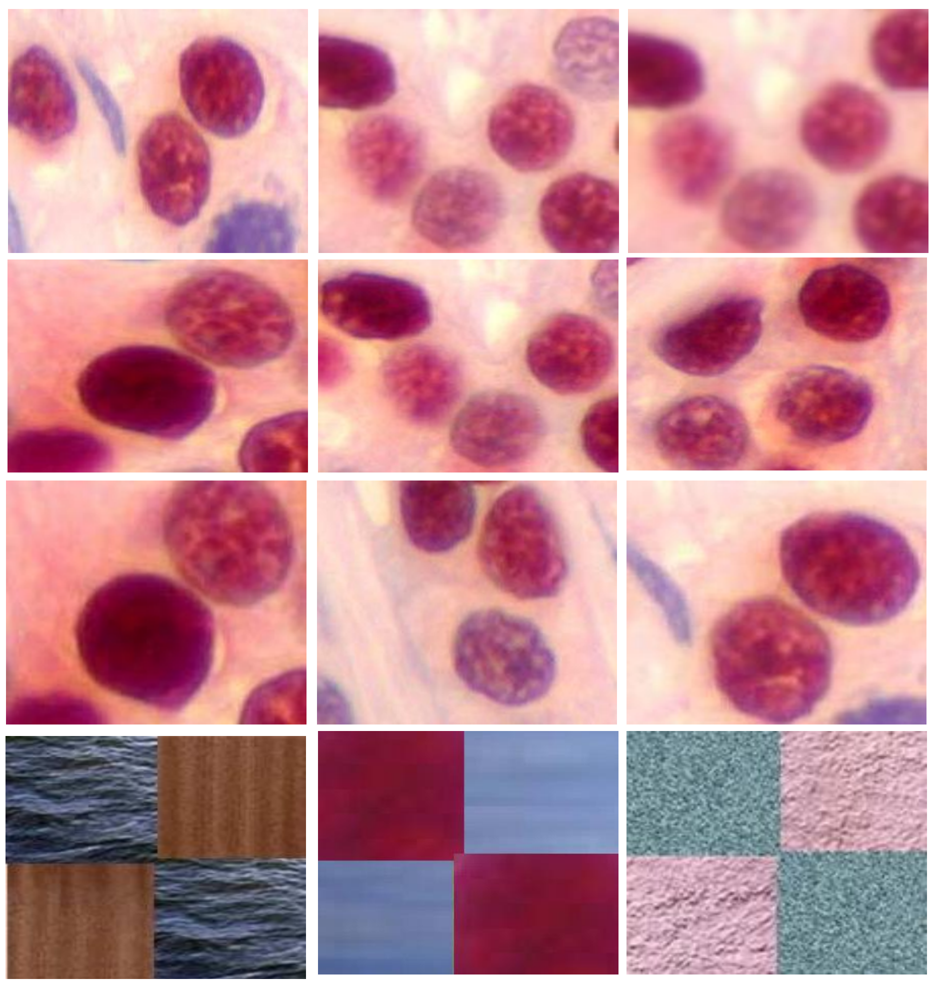


Figure 6. Data set used in the experiment. Twelve were selected for a comparison study. The patterns are numbered from 1 through 12, starting at the upper left-hand corner.

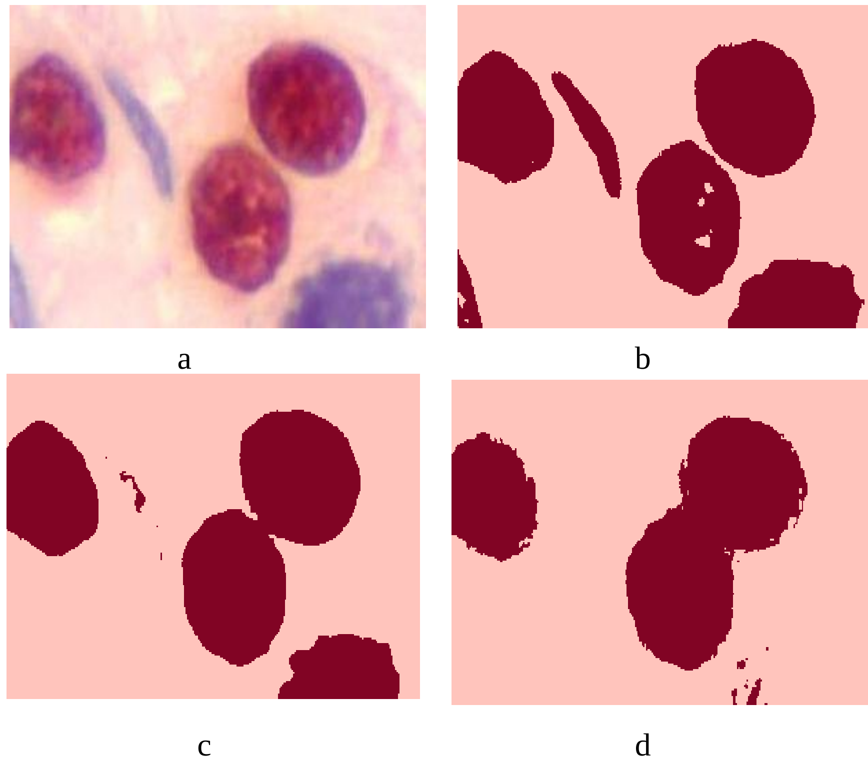


Figure 7. Segmentation results on a colour image, (a) original image (256 × 256 × 3) with gray level spread on the range (0, 255), (b) red resulting image by the (SFCM) method, (c) green resulting image by the (SFCM) method, (d) blue resulting image by the (SFCM) method (our method).

also the number of the cells.

Moreover, a synthetic image dataset is developed and used for numerical evaluation purpose. Some experimental results are shown in Figures 7 to 11.

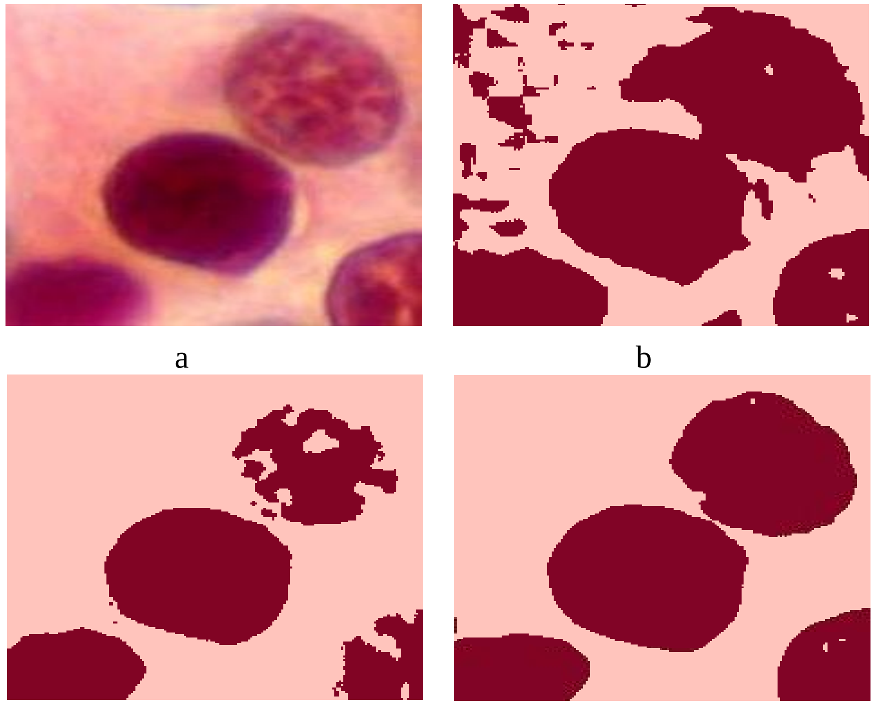
For colour images with RGB representation, the colour of a pixel is a mixture of the three primitive colours red, green, and blue. RGB is suitable for colour display, but not good for colour scene segmentation and analysis because of the high correlation among the R, G, and B components. By high correlation, we mean that if the intensity changes, all the three components will change accordingly.

Figure 7 presents the segmentation results in the RGB colour space by applying the FCM algorithm combined with the second order statistics (SFCM), to red, green and blue component images, respectively. The experiment is carried out on colour cells images of cancer disease in Figure 7a. The results are shown in Figures 7b, c and d. Comparing the results, we can find that the cells are much better segmented in red component (Figure 7b) that those in the green and blue components (Figure 7c and d, respectively).

This demonstrates the high degree of correlation among of the three components of the RGB colour space and the lack of information when using only one information source. Using the FCM algorithm combined with the second order statistics, we can solve this problem. For purpose of comparison, we apply the proposed method and some existing approaches to the same colour image segmentation expressed in the HIS colour space. The latter methods include those of Liew et al. (2000) designed by (MFCM), (Bezdek, 1981) designed by (FCM), Duda and Hart (1973) called (HCM) and Lim et al. (1990) called (TFCM) and Ben Chaabane et al. (2009b) called DSFCM. The segmentation results are shown in Figures 8 to 11.

Experiments on the segmentation based on traditional Fuzzy C-means (Bezdek, 1981) and Hard C-means (Duda and Hart, 1973) algorithms applied to hue component are conducted for comparison. In these approaches, only global information is used for the classification problem. The experimental results indicate that the proposed method which utilizes the FCM algorithm combined with the second order attributes is better than the traditional methods.

As shown in Figure 8, the different regions are identified by the proposed method (Figure 8d), but are not signified by the traditional approaches (Figure 8b and c). Figure 9 shows a comparison of the results between two existing methods TFCM (Lim and Lee, 1990), MFCM (Liew et al., 2000), DSFCM (Ben et al., 2009b) and the proposed method (SFCM). They correspond, respectively,



a b c d

Figure 8. 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): colour cells image with RGB description, (b) segmentation based on HCM method, (c) segmentation based on standard FCM method, (d) segmentation based on the proposed method.

to Figure 9b, c and d. In fact, the cells are homogeneously segmented in Figure 9d, which is not the case in Figure 9b and c. This demonstrates the superiority of introducing the statistical features in the fuzzy c-means algorithm for image segmentation. To evaluate the performance of the proposed segmentation methods, its accuracy was recorded. Tables 1 and 2 list the segmentation sensitivity of the different methods for the dataset used in the experiment. The segmentation sensitivity (Duda et al., 2000; Grau et al., 2004) is computed as follows:

$$Sens = \frac{N_{pcc}}{M \times N} \times 100 \quad (13)$$

with: $Sens$, N_{pcc}, $M \times N$ correspond respectively to the segmentation sensitivity (%), number of correctly classified pixels and dimension of the image.

The acquisition of the correct classified pixels is not a manual process; hence, software based on a reference image is run. It consists of a small program which compares the labels of the obtained pixels and the reference pixels as shown in Figure 10f.

The correctly classified pixel denotes a pixel with a label equal to its corresponding pixel in the reference image. The labelling of the original image is generated by the user based on the image used for segmentation. In the case of medical image, the image segmentation ground truth is generated manually by the doctor (specialist) using the original image. In fact, one can observe in Figure 8b and c that 12.79 and 09.43% of pixels were incorrectly segmented for the HCM and the standard FCM methods, respectively. Indeed, only 03.75% of pixels were incorrectly segmented in Figure 8d. However, errors were largely reduced in the since that the statistical features were involved in the FCM algorithm.

In Figure 10, the original image is noisy by a “salt and pepper” noise of D density (Figure 10a). This affects approximately ($D \times M \times N$). The value of D is 0.02. In fact, an obviously better result is obtained by the proposed method due to the consideration of the statistical features in the FCM algorithm, as shown in Figure 10e.

Indeed, the regions are clearly recognized, whereas there are too many misclassified pixels in Figure 10c and d. Referring to segmentation sensitivity given in Table 2, one observes that 02.27, 0.94, 0.85 and 0.12% of pixels were incorrectly segmented in Figure 10b, c, d and e

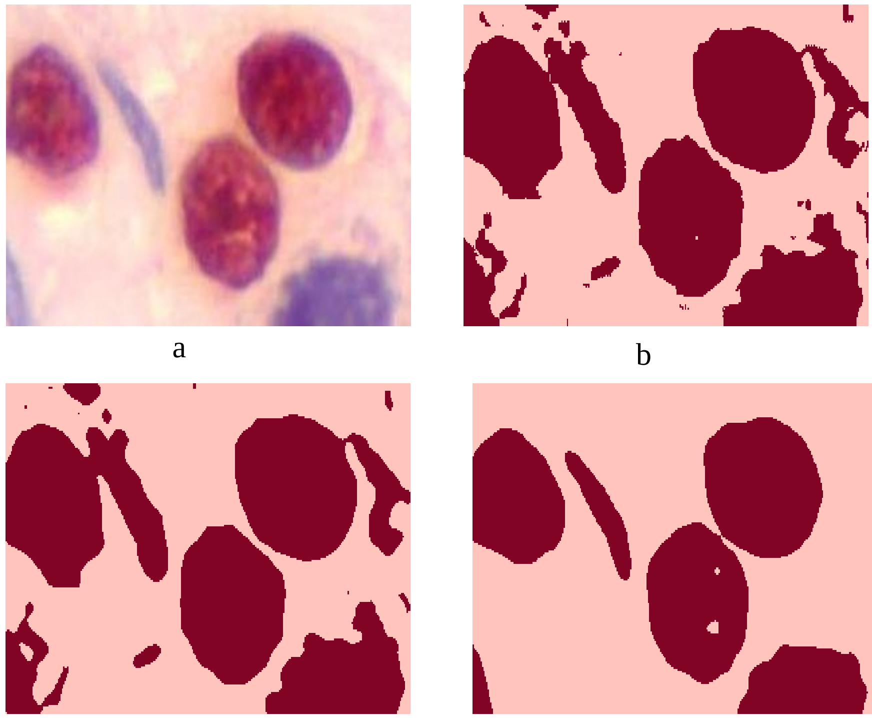


Figure 9. Comparison of the proposed segmentation method with other existing methods on a medical image (2 classes, various cells), (a) original image with RGB representation (256 × 256 × 3), (b) segmentation based on TFCM method, (c) segmentation based on MFCM method, (d) segmentation based on the proposed method.

Table 1. Segmentation sensitivity from HCM method, FCM method and the SFCM method for the data set shown in Figure 6.

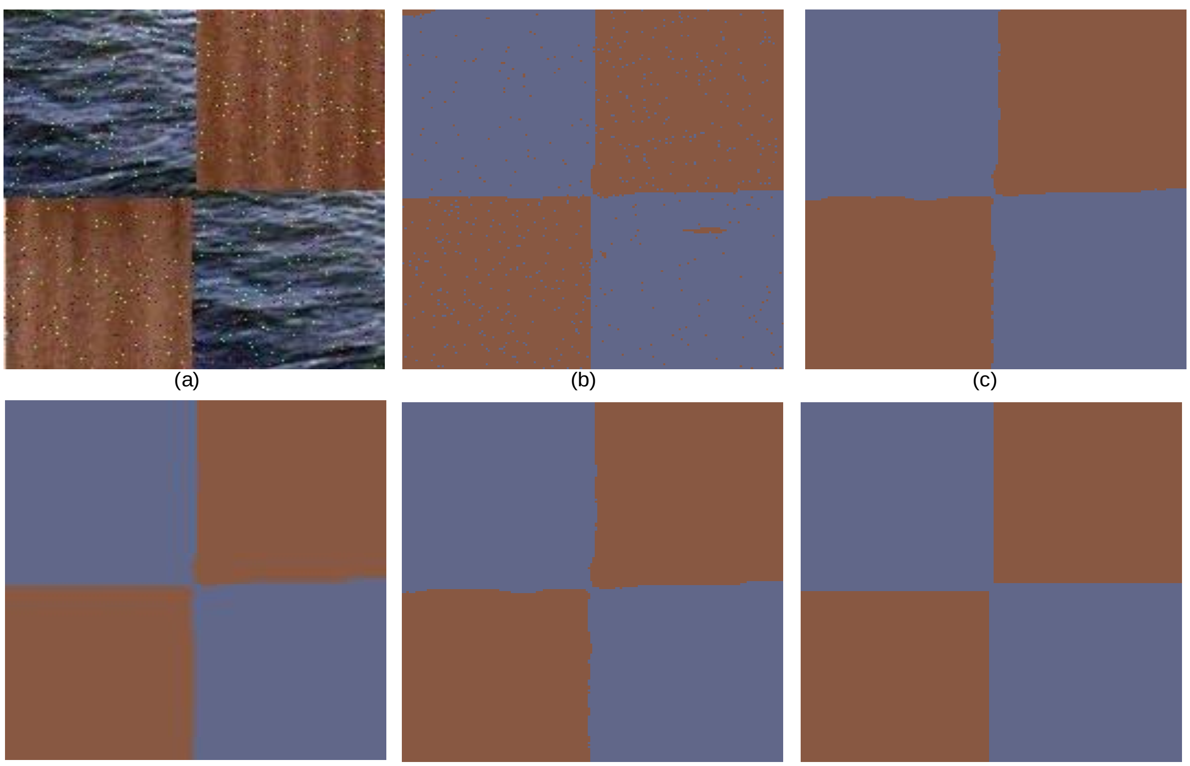
Image	HCM	FCM	SFCM (Proposed method)
	Sensitivity segmentation (%)		
1	87.96	89.61	96.57
2	86.20	92.26	95.42
3	84.58	91.77	97.77
4	87.21	90.57	96.25
5	87.46	90.54	95.24
6	85.70	90.68	97.96
7	86.41	91.06	96.29
8	87.26	91.35	97.25
9	86.96	88.93	97.09
10	86.20	96.98	99.88
11	87.69	98.34	99.79
12	89.84	96.76	98.68

respectively. In fact, the incorrectly classified pixels were largely reduced by the proposed method.

To provide in sights into the proposed method, we have compared the performance of the proposed method by using different sizes of the sliding window (3×3, 5×5… etc.). This is realized to show the influence of the sliding

Table 2. Segmentation sensitivity from MFCM method, TFCM method, DSFCM method and the SFCM method for the data set shown in Figure 6.

Image	TFCM	MFCM	DSFCM	SFCM (proposed method)
	Sensitivity segmentation (%)			
1	92.61	93.32	94.67	96.57
2	93.62	92.38	93.38	95.42
3	91.89	93.85	94.78	97.77
4	91.54	93.96	94.82	96.25
5	92.37	91.55	92.46	95.24
6	89.20	94.42	95.34	97.96
7	91.54	93.43	94.36	96.29
8	94.83	93.45	94.45	97.25
9	89.53	93.04	93.87	97.09
10	97.73	99.06	99.15	99.88
11	98.69	99.11	99.27	99.79
12	97.28	97.39	98.41	98.68



(a) (b) (c)

(d) (e) (f)

Figure 10. Segmentation results on a colour synthetic image, (a) original image disturbed with a 'salt and pepper' noise, (b) segmentation based on TFCM method (c) segmentation based on MFCM method, (d) segmentation based on DSFCM method, (e) segmentation based on the proposed method, (f) reference segmented image.

window size on the feature vector calculation.

The method was also tested on synthetic images. The comparison of the proposed approach will be presented through the next experiment. Figure 11b, c, d, e and f show the final segmentation results obtained by using a (3×3), (5×5), (7×7), (9×9) and (11×11) sliding window

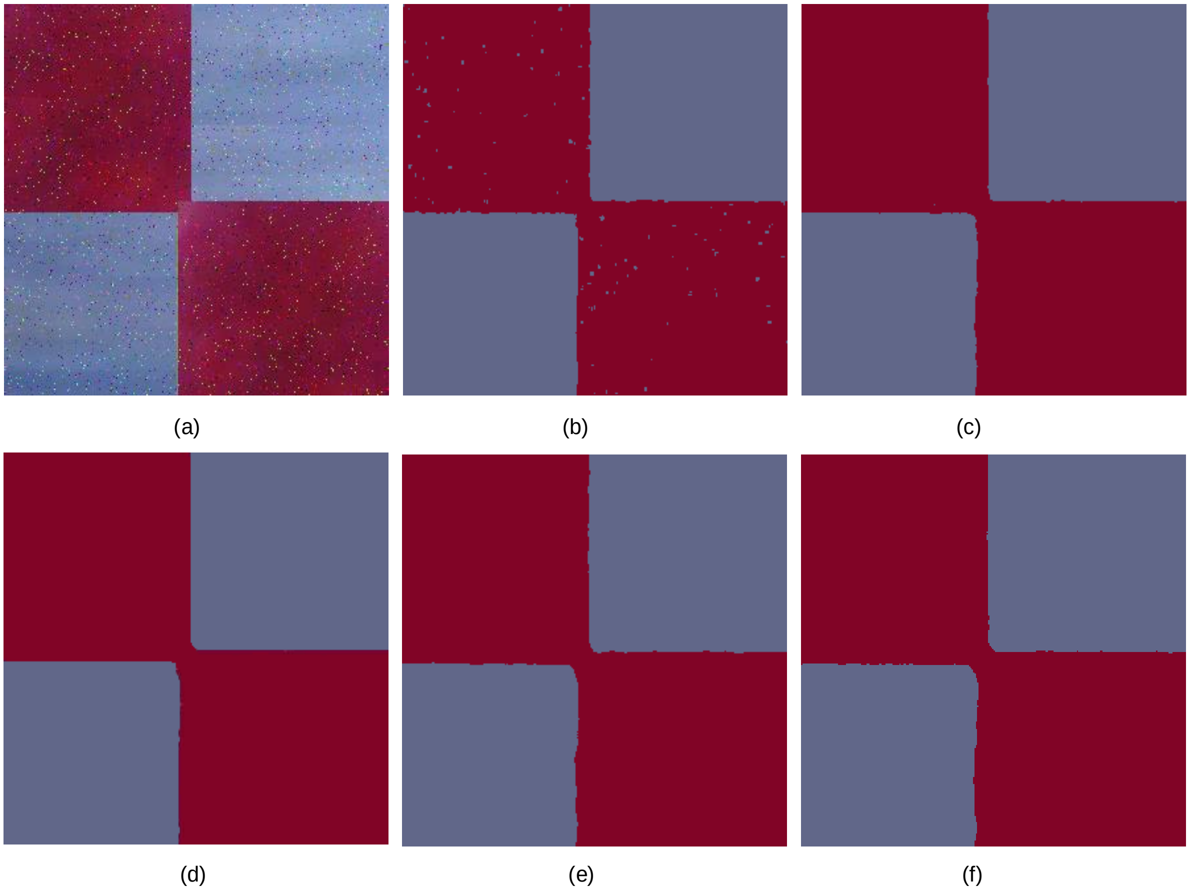


Figure 11. Segmentation results on a colour synthetic image; (a) Original image (256 × 256 × 3) with gray level spread on the range (0, 255), disturbed with a 'salt and pepper' noise, (b) Resulting image by SFCM method using a (3x3) window for computing the statistical features, (c) Resulting image by SFCM method using a (5 × 5) window for computing the statistical features, (d) resulting image by SFCM method using a (7 × 7) window for computing the statistical features, (e) Resulting image by SFCM method using a (9×9) window for computing the statistical features, (f) resulting image by SFCM method using a (11 × 11) window for computing the statistical features.

for computing the co-occurrence matrix, respectively.

In fact, the experimental result presented in Figure 11d, where we use a (7×7) window for computing the co-occurrence matrix is quite considered with the visualized colour distribution in the objects, which makes it possible to take an accurate measurement of the region volumes (Colot et al, 1998).

Conclusion

In this paper, we have proposed a new method for colour image segmentation based on the second order statistics and the fuzzy c-means technique. In the first phase, relevant and representative statistical features are identified via a co-occurrence matrix, by using a characterization degree on a colour images database. Then, the fuzzy c-means (FCM) algorithm is modified and used to obtain the final segmentation results.

The obtained results show the generic and robust character of the method in the sense that the statistical features were involved in the FCM algorithm. On the other hand, instead of using a simple pixel of value in FCM algorithm, we have used the feature vector extracted from the co-occurrence matrix by using a sliding window centered on the pixels of the input image. The results obtained demonstrated the significant improved performance in segmentation. The proposed method can be useful for colour image segmentation.

In all our work, we have considered only one image for each application, whereas, many realizations of the same image fused together may be very helpful to the segmentation process. Also, the proposed method assumes that we have a reference image, which should be labeled by the user for comparison purposes. In practice, this is not realizable; hence the research of advanced intelligent software for classification which can be used to avoid the manually labeling of the image by the user is an important aspect of our present work.

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ABBREVIATIONS: à SFCM, The method based on the second order Statistics and the Fuzzy C-Means algorithm; **à DSFCM,** the method based on the Dempster-Shafer evidence theory and the Fuzzy C-Means algorithm; **à MFCM,** the method based on the Modified Fuzzy C-Means algorithm; **à TFCM,** The method based on the Thresholding technique and the Fuzzy C-Means algorithm.

REFERENCES

Ahmed MN, Yamany SM, Mohamed N, Farag AA, Moriarty T (2002). A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data. IEEE Trans. Med. Imag., 21(3): 193-199.

Arvis V, Debain C, Berducat M, Benassi A (2004). Generalization of the cooccurrence matrix for colour images: application to colour texture classification. Image Anal. Stereol., 23: 63-72.

Ben Chaabane S, Sayadi M, Fnaiech F, Brassart E, Betin F (2011). A New Method for the Mass Functions Estimation in the Dempster-Shafer's Evidence theory: Application to colour Image Segmentation. Circuits syst. Signal Process, 30: 55-71.

Ben Chaabane S, Sayadi M, Fnaiech F, Brassart E (2009a). Dempster-Shafer Evidence Theory for Image Segmentation: Application in Cells Images. Int. J. Signal Process, 5(1): 126-132.

Ben Chaabane S, Sayadi M, Fnaiech F, Brassart E (2009b). Colour Image Segmentation using Homogeneity method and Data Fusion Techniques. Eur. J. Adv. Signal Process, 30: 55-71.

Ben Chaabane S, Sayadi M, Fnaiech F (2008). Colour Image Segmentation using Automatic Thresholding and the Fuzzy C-Means Techniques. Int. conf. IEEE MELECON, pp. 857-861.

Bezdek JC (1981). Pattern recognition with fuzzy objective function algorithms. Plenum Press, New York. 1: 256.

Cheng HD, Sun Y (2000). A hierarchical approach to colour image segmentation using homogeneity. IEEE Transac. Image Process., 9(12): 2071-2082.

Clausi DA (2001). Comparison and fusion of cooccurrence, gabor and MRF texture features for classification of SAR sea-ice imagery. Atmosphere Ocean, 39(3): 183-194.

Colot O, Devinoy R, Sombo A, Brucq D (1998). A Colour Image Processing Method for Melanoma Detection. Lecture Notes in Computer Science, pp. 562-569.

Duda R, Hart P (1973). Pattern Classification and Scene Analysis. New York, Wiley. 1: 472.

Duda RO, Hart PE, Sork DG (2000). Pattern Classification. Wiley-Interscience, New York, NY, USA. 1: 654.

Grau V, Mewes AU, Alcaniz M, Kikinis R, Warfield SK (2004). Improved watershed transform for medical image segmentation using prior information. IEEE Trans. Med. Imag., 23(4): 447-458.

Güvenç U, Demirci R, Karagül T (2010). Light refraction based medical image segmentation. J. Sci. Res. Essays, 5(10): 1127-1132.

Harrabi R, Ben Braiek E (2010). A comparative study of colour image segmentation techniques using different colour representation. JTEA, Tunisia. 1:5.

Haralick RM, Shanmugan K, Distein I (1973). Textural features for image classification. IEEE Trans. Syst., 3(6): 610-621.

Kwon MJ, Han YJ, Shin IH, Park HW (2003). Hierarchical fuzzy segmentation of brain MR images. Int. J. Imag. Syst. Technol., 13(2): 115-125.

Li X, Li L, Lu H, Chen H, Liang Z (2003). Inhomogeneity correction for magnetic resonance images with fuzzy C-mean algorithm. Proc. SPIE 5032: 995-1005.

Liew AW, Leung SH, Lau WH (2000). Fuzzy image clustering incorporating spatial continuity. IEE Proc. Visual Image Signal Process, 147(2): 185-192.

Lim YW, Lee SU (1990). On the colour image segmentation algorithm based on the thresholding and the fuzzy c-means techniques. Patt. Recogn., 23(9): 935-952.

Meenavathi MB, Rajesh K (2008). Volterra Filter for Colour Image Segmentation. World Academy of Science. Eng. Technol., 35: 209-214.

Morales DI, Moctezuma M, Parmiggiani F (2003). Urban and non urban area classification by texture characteristics and data fusion. In International Geoscience and Remote Sensing Symposium (IGARSS), 6: 3504-3506.

Navon E, Miller O, Averbuch A (2005). Colour image segmentation based on adaptive local thresholds. Image Vision Comput., 23(1): 69-85.

Peckinpaugh SH (1991). An improved method for computing grey-level co-occurrence matrix based texture measures. Graph. Models Image Process, 53: 574-580.

Raghu K, Keller JM (1993). A possibilistic approach to clustering. IEEE Trans. Fuzzy Syst., 1(2): 98-110.

Sojodishijani O, Rostami V, Ramli AR (2010). A video-rate colour image segmentation using adaptive and statistical membership function. J. Sci. Res. Essays, 5(24): 3914-3925.

Verma MS, Pratt L, Ganesh C, Medina C (2002). Hair-MAP: A prototype automated system for forensic hair comparison and analysis. Forensic Sci. Int., 129(3): 168-186.

Yang Y, Zheng C, Lin P (2005). Fuzzy C-means clustering algorithm with a novel penalty term for image segmentation. Opto-Electron. Rev., 13(4): 3.9-315.

Zhu YM, Dupuis O, Rombaut M (2002). Automatic determination of mass functions in Dempster-Shafer theory using fuzzy c-means and spatial neighborhood information for image segmentation. Opt. Eng., 41(4): 760-770.