A Hybrid Technique for Color Image Segmentation: Application to the Fire Forest Images

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Abstract: ***This works deals with hybrid method for color image segmentation. The role of introducing the statistical features in clustering technique and that of data level and feature level fusion applied to color image segmentation are studied in this paper to obtain an optimal segmented image and to detect the fire in Forest images. The proposed segmentation approach is conceptually different and based on a new strategy. In fact, instead of considering an existing segmentation procedure, our technique rather explores the benefit of combining several approaches. However, the segmentation procedureis performed in two steps. In the first step, the segmentation of an image is obtained by integrating the statistical features and fuzzy clustering technique. For this propose, a modified Fuzzy c-means clustering is used to represent the information as fuzzy sets and to segment each image component into homogeneous regions. In the second step, on the obtained segmentation maps with specific primitive color, a combination rule and decision are employed to merge the segmentation results over different channels, in order to increase the quality of the information and to obtain an optimal segmented image. The classification accuracy of the proposed method is evaluated and a comparative study versus existing techniques is presented. The experimental results on synthetic and forest fire images demonstrate the value of integrating the statistical features in fuzzy clustering technique for image segmentation.***

Keywords: Segmentation, Fire forest images, Fuzzy logic, Fuzzy C-Means, Fusion, first order statistical features

1. Introduction

Image segmentation is considered as an important basic operation for meaningful analysis and interpretation of acquired image [1] [2] [3]. It consists in partition of an image into homogeneous regions, according to a choice criterion, such as intensity, color, tone or texture, etc.

Several segmentation techniques of different complexity, either in gray level or color images, were presented in the literature and many methodologies have been proposed [4] [5][6]. At present, color image segmentation methods 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 [7].

In this context, Ben Chaabane et al. [1] have proposed a segmentation method using homogeneity histogram and data fusion techniques (HHDF). In the first step, an initial segmentation is obtained by using the histogram thresholding. In the second step, the evidence theory is employed to merge the information's coming from the three images (R, G, and B). The authors have shown through empirical studies that a good model of the mass functions estimation in the DS evidence theory is based on the assumption of Gaussian distribution (GD) and the homogeneity histogram analysis technique.

Also, R. Harrabi et al. [8] have proposed a segmentation method (TSOMDS), that consists in combining many realizations of the same image, together, in order to increase the information quality and to get an optimal segmented image. Firstly, the most significant peaks of the histogram are identified. For this purpose, an optimal multi-level thresholding based on the two-stage Otsu optimization approach is used. Secondly, the evidence theory is employed to merge several images represented in different color spaces, in order to get a final reliable and accurate segmentation result.

Recently, fuzzy clustering methods [9] [10] [11] have shown good ability to generate the membership update equations for an iterative algorithm. Most analytic fuzzy approaches are derived from Bezdek's Fuzzy C-Means (FCM) algorithm [12], applied to the grey levels to automatically determine the membership degree of each pixel. However, this algorithm has a considerable difficulty in noisy environments, and the memberships resulting from FCM do not always correspond to the intuitive concept of degree of belonging or compatibility. The membership degrees are computed using only the grey levels and do not take into account the spatial information of pixels with respect to one another. Also, the Hard C-Means (HCM) [13] [14], is one of the oldest clustering methods in which HCM memberships are hard (i.e., 1 or 0). This method is used to learn the prototypes of clusters or classes, and the cluster's centres are used as prototypes. At the same time, one should point out the lack of methods for automatically generating the membership functions from the training data; this is a serious problem in many applications. A comprehensive survey of fuzzy clustering methods is provided in [15].

In this paper, the problem of color images segmentation is addressed using fuzzy clustering techniques and fusion precedure. We reformulate the fuzzy clustering problem [12], so that the clustering method can be used to generate membership with typical interpretation. Hence, this paper is devoted to fuse the segmentation maps obtained by the modified fuzzy c-means. More precisely, the idea is to assign a measure to each information trough using the concept of fuzzy logic. To do this, a modified fuzzy c-means (MFCM) algorithm is used to represent the input information as fuzzy sets. Each information is then characterized by its membership values in classes. Once, the segmentation maps are obtained for each image to be fused, the 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. Proposed Method

In the framework of our application, we are interested to color image segmentation of forest images [16] [17]. We aim to detect the fire in the forest images [18] [19]. The objective is to rebuild each pixel of the fire area from a series of N redundant component images provided by the input image expressed in Ns color spaces.

The segmentation method proposed in this paper is a hybrid segmentation technique, which integrates both the results of the statistical method, and the fuzzy clustering technique, in which the statistical features are used as the initial seed for the clustering procedures. Segmentation results for the three redundant component images provided by {RGB, YCbCr and HSV} color spaces are then fused through a combination rule to obtain the final segmentation, hence, to localize the interest objects.

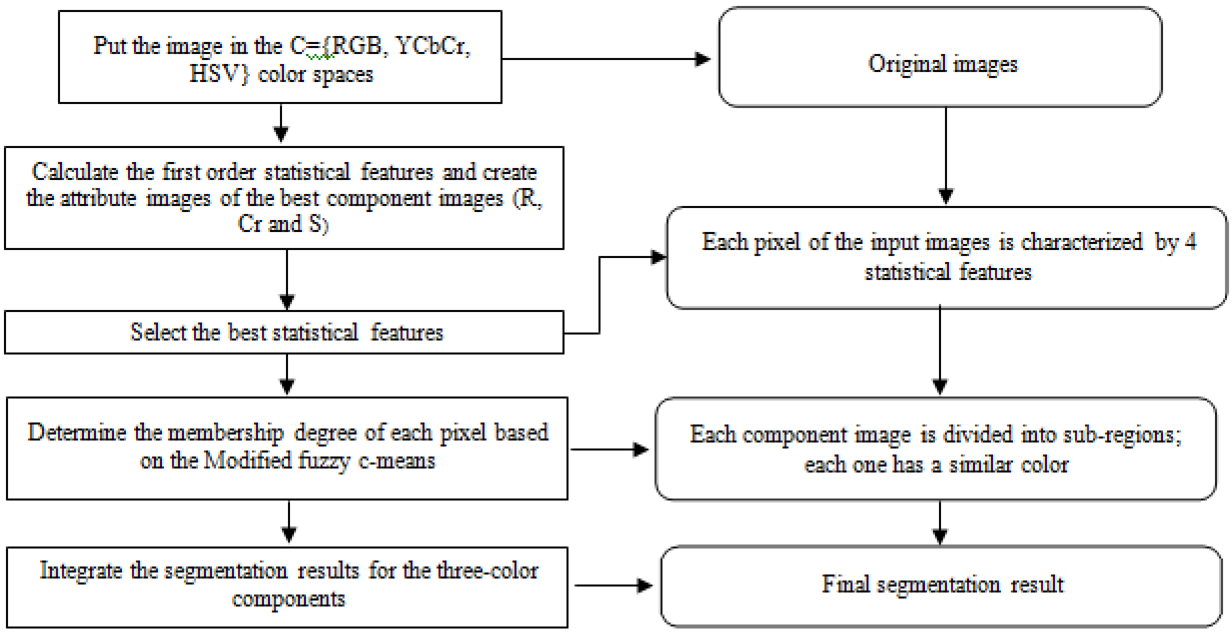


Figure 1: Flowchart of the proposed method.

In this paper, instead of using the information pixel, statistical features forming the feature vectors are extracted from the sliding window centred around every pixel. Each element of the feature vector represents the best first order statistical feature, where the selection of the best and representative statistical features of each pixel is based on the segmentation sensitivity criterion [20] [21]. Meaningfully, the proposed method is divided into two stages. At the first stage, the best statistical features are extracted from the sliding window centred around every pixel of each component image, and the standard fuzzy c-means algorithm is modified and used to obtain the segmentation maps of the different images to be fused. In the second stage, the combination rule and decision are used to obtain the final segmentation result. The main steps of the proposed segmentation technique are depicted in the flowchart shown in Fig.1.

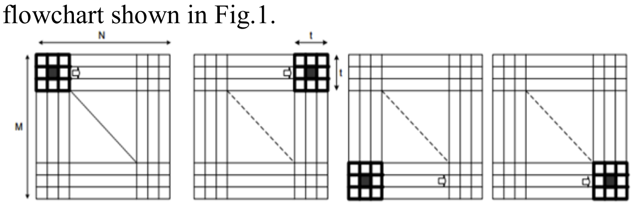


Figure 2: The adaptive sliding window from left to right and top to bottom on an $(M \quad N)$ image.

2.1. Segmentation Procedure

In our application, we propose to classify the pixels in Hybrid Color Space, which is composed by a set of three color features. Taking into account the K available color spaces, it used a specific informational criterion to select a set of three (Ns=3) most discriminating color spaces. Experimental results show that R, Cr and S color features are selected.

Consequently, the perceptual color spaces RGB, YCbCr and HSV may be more suitable for segmenting the fire forest images.

In this application, instead of implementing an existing segmentation procedure, our technique rather explores the benefit of combining several approaches. To achieve that, an improved segmentation technique based on the fuzzy clustering technique and fusion procedure is developed.

In our study, the task of image segmentation is to classify the pixels into two opposite classes namely fire and background (forest) classes. Each component image may be taken as a two-dimensional (2D) light intensity function I(x,y), which contains (M×N) pixels, each with a value of brightness, i.e., grey level, from 0 to Ng. Grey level 0 is the darkest and grey level Ng is the brightest.

However, the statistical features are extracted from a sliding windoww_{xy} centred on each pixel p_{xy} of the original image. The spatial scanning order of an image is performed pixel by pixel from left to right and from top to bottom, (see Figure 2). Hence, this technique is used to calculate the new image called the attribute image.

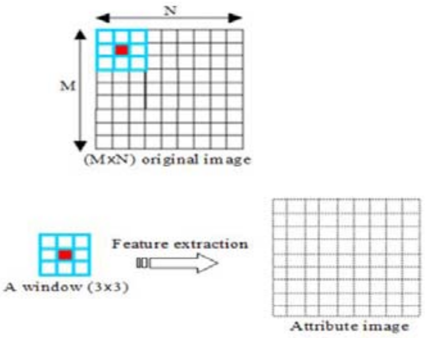


Figure 3: Determination of the attribute images using a sliding window.

As shown in Figure 3, the value of the attribute image $I_a(x, y)$ at the location (x, y) contains the values of the attribute computed from a sliding window w_{xy} centred on each pixel p_{xy} of the original image.

Assume w_{xy} is a size $(t \quad t)$ window centered at (x, y), which represent the local region where the statistical features for pixel are calculated. However, the size of the window has an effect on the computation of the statistical features. The window should be big enough to allow enough information provided to the computation the statistical feature of each pixel.

Furthermore, a larger window causes significant processing time. As a trade choice, experimentally a (3×3) window is chosen for computing the statistical feature of each pixel p_{xy}.

Moreover, several attributes may be extracted from the original image such as: Mean (Me), contrast (Cont), energy (Ene), entropy (Ent), variance (Var), Skewness (Ske), Kurtosis (Kur) etc.

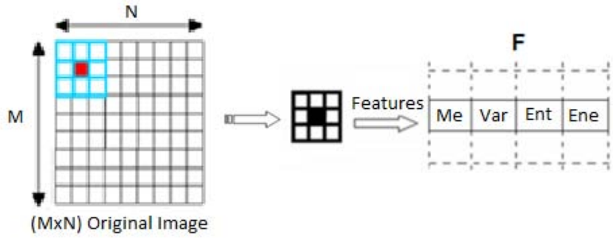


Figure 4: Features Extraction from the sliding window.

The standard deviation, which represents one of the representative statistical features, describes the contrast within a local region [20] [21], and is calculated for a pixel p_{xy} as follows:

$$v_{xy} = \sqrt{\frac{1}{t^2}\sum_{p=x-(\frac{t-1}{2})}^{x+(\frac{t-1}{2})}\sum_{q=y-(\frac{t-1}{2})}^{y+(\frac{t-1}{2})}(g_{pq}-\mu_{xy})^2} \qquad (1)$$

where $x \geq 2$, $p \leq M-1$, $y \geq 2$ and $q \leq N-1$.
μ_{xy} is the mean of the gray levels within window μ_{xy} and is defined by:

$$\mu_{xy} = \frac{1}{t^2}\sum_{p=x-(\frac{t-1}{2})}^{x+(\frac{t-1}{2})}\sum_{q=y-(\frac{t-1}{2})}^{y+(\frac{t-1}{2})} g_{pq} \qquad (2)$$

Given the membership degree for each pixel, the fuzzy c-means algorithm classify the pixels coming from the nine component images $\{R, G, B, Y, Cb, Cr, H, S \text{ and } V\}$provided by the three redundant $\{RGB, YCbCr \text{ and } HSV\}$ color spaces into two opposite classes: fire pixels versus non-fire pixels, as:

$$(\ , \ ) = \begin{cases} 1, & \_ \ (\ , \ ) > \_ \ (\ , \ ) \\ 0, & - \ \_ \ (\ , \ ) < \_ \ (\ , \ ) \end{cases} \qquad (3)$$

$$(\ , \ ) = \begin{cases} 1, & \_ \ (\ , \ ) > \_ \ (\ , \ ) \\ 0, & - \ \_ \ (\ , \ ) < \_ \ (\ , \ ) \end{cases} \qquad (4)$$

$$(\ , \ ) = \begin{cases} 1, & \_ \ (\ , \ ) > \_ \ (\ , \ ) \\ 0, & - \ \_ \ (\ , \ ) < \_ \ (\ , \ ) \end{cases} \qquad (5)$$

The membership degree of pixels covered each component images, are automatically determined by the fuzzy c-means technique, as described in Section 2.2. The pixel (x,y) of each primitive color is classified as a fire pixel if its membership degree is higher than the membership degree of the non-fire pixel (forest pixel), in which case is set 1. Otherwise, it is classified as non-fire pixel and is set to 0.

Segmentation results for the three color components are then integrated through the fusion rule, shown in Eq. 6. Pixel (x,y) is classified as an fire pixel if it is so classified by at least one of its three color components, in which case S(x, y) is set to 1. Otherwise, it is classified as a non-fire pixel and S(x, y) is set to 0. The joint segmentation is calculated as:

$$(\ , \ ) = \begin{cases} 1, & (\ , \ ) = 1 \cup \ (\ , \ ) = 1 \cup \ (\ , \ ) = 1 \\ 0, & - \quad , \end{cases} \qquad (6)$$

2.2. Fuzzy Clustering

The standard Fuzzy C-means (FCM) algorithm is one of the widely used techniques for monochrome image segmentation, but 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. A comprehensive survey of fuzzy clustering methods is provided in [15]. Sayadi et al. [22], have proposed a statistical method to overcome this limitation. In this paper, we employ the concept of the statistical features combined with standard Fuzzy C-means to determine a membership degree with typical interpretation.

Assume g_{xy} is the intensity of a pixel p_{xy} at the location (x,y) in an $(M \quad N)$ image, $X=[x_1,x_2,\ldots,x_d]$ is the vector containing all the gray level of the image, where $\{x_1=g_{11}, x_2=g_{12}, \ldots x_d=g_{MN}\}$, n_c designate the number of clusters in which X will be classified and $L=[l_1,l_2,\ldots l_{n_c}]$ 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:

$$\begin{cases} \sum_{i=1}^{n_c} u_{ik}=1; \quad 1\le i\le n_c, 1\le k\le d \\ u_{ik}\in[0,\ 1]; 1\le i\le n_c \\ \sum_{k=1}^{d} u_{ik}>0; \quad 1\le i\le n_c \end{cases} \tag{7}$$

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

$$J_m(u,v)=\sum_{k=1}^{d}\sum_{i=1}^{n_c}(u_{ik})^m\|x_k-v_i\|^2 \tag{8}$$

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

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

$$=\frac{1}{\sum_{=1}\left(\frac{}{}\right)^{\frac{2}{-1}}} \tag{9}$$

$$=\frac{\sum_{=1}}{\sum_{=1}} \tag{10}$$

In the context of our application, a new version of the FCM can be used. The algorithm is based on a statistical feature vector to describe each pixel. In this case, each element of the feature vector represents the first order statistical features values calculated using a sliding window centered around every pixel.

The idea is to replace the vector by a matrix F containing the same number of lines, i.e. $(d=N \quad M)$, but with 4 columns, as shown in Figure 4. These columns contain 4 representative statistical features extracted from the sliding window centered around every pixel. Hence, this algorithm scans the image using a $(t\times t)$ sliding window, as shown in Fig.2, from left to right and top to bottom. A feature vector is extracted from each block.

So, the modified fuzzy C-means algorithm is used to determine the membership degree of each pixel characterized by 4 statistical features. The proposed method using the FCM algorithm combined with the statistical features is outline in the following steps:

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

Step 1: *Initialization (iteration 0)*

Randomly initialize the centers of the classes vectors L(0) of size (c 4) containing the centers of the classes.

Step 2: *Compute the matrix F of size (d 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 using (Eq.11):*

$$=\frac{1}{\sum_{=1}\left(\frac{\|\ -\ \|}{\|\ -\ \|}\right)^{\frac{2}{-1}}} \tag{11}$$

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

Step 4: *Calculate the vector L(t) composed of 4 columns l_i using:*

$$=\frac{\sum_{=1}}{\sum_{=1}} \tag{12}$$

Step 5: *Convergence test:*

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

3. Experimental Results

In order to illustrate the methods presented in the previous section, a large variety of fire forest and synthetic color images are employed in our experiments. The used images database is shown in Fig. 5.

In fact, to evaluate the efficiency and accuracy of the proposed segmentation method, we applied the proposed method on color forest 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.

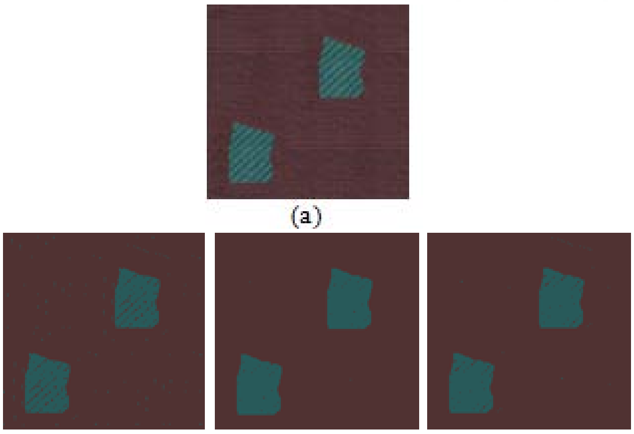
To illustrate the segmentation results obtained by the method based on fuzzy clustering technique and fusion procedure, called (MFCMF), we applied the modified fuzzy c-means algorithm to the synthetic image of the figure (FIG. 6(a)) where the number of classes is limited to two and the fuzzy coefficient m is set to 2.

Figure 5: 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.

By applying the Modified Fuzzy C-Means algorithm independently to the nine component images of the input image expressed in the three space colors RGB, HSV and YCbCr, does not give better results and does not take sufficient account of the initial correlation.

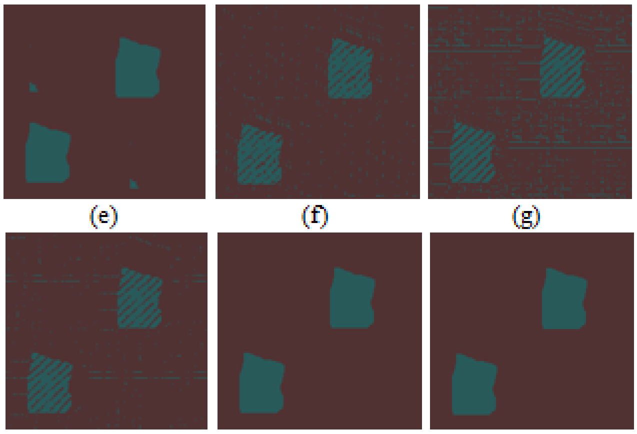
(a) (b) (c)

Figure 6: Examples of test images used in the experiment. (a) Synthetic image, (b) and (c) real fire forest images



(a)

(b) (c) (d)



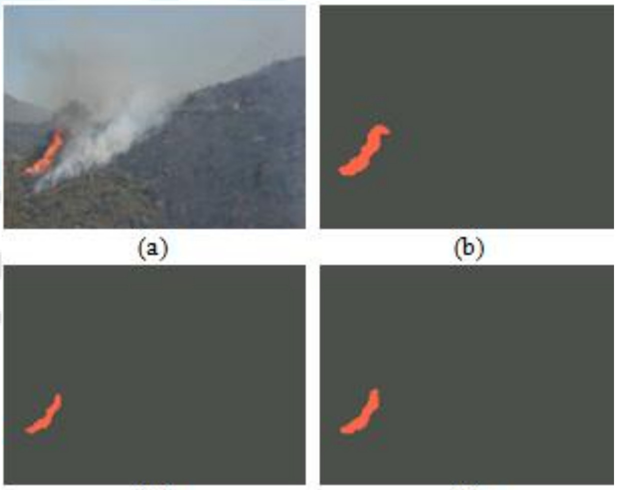
(e) (f) (g)

(h) (i) (j)

Figure 7: Segmentation results on a color image. (a) Original synthetic image (256×256×3) with gray level spread on the range [0, 255]. (b) Red resulting image by MFCM algorithm. (c) Green resulting image by MFCM algorithm. (d) Blue resulting image by MFCM algorithm. (e) Hue resulting image by MFCM algorithm. (f) Saturation resulting image by MFCM algorithm. (g) Value resulting image by MFCM algorithm. (h) Y resulting image by MFCM algorithm. (i) Cr resulting image by MFCM algorithm. (j) Cb resulting image by MFCM algorithm.

This shows that the use of a single information source leads to bad results.

The segmentation results obtained by applying the MFCM algorithm to each color features are shown in Figs. 7(b), (c), (d), (e), (f), (g), (h), (i) and (j), respectively.



(a) (b)

(c) (d)

Figure 8: Comparison of the proposed segmentation method with other existing methods on a fire forest image. (a) Original image with RGB representation (256 × 256 × 3), (b) segmentation based on HHDF method, (c) segmentation based on TSOMDS method, (d) segmentation based on MFCM and Fusion method (our method).

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 modified Fuzzy C-means (MFCM) algorithm applied independently to the best component images (N=3)of the original image represented in the three-color spaces (RGB, YCbCr and HSV).

Figure 8 shows a comparison between our method and other methods, HHDS [1] and TSOMF [8].However, the image shown in Figure 8(a) represents the original fire forest image.

The figures 8(b) and 8(c) show the segmentation results obtained by the methods (HHDS) and (TSOMF), respectively. Fig 8(f) shows the segmentation result obtained by the proposed method (MFCMF).

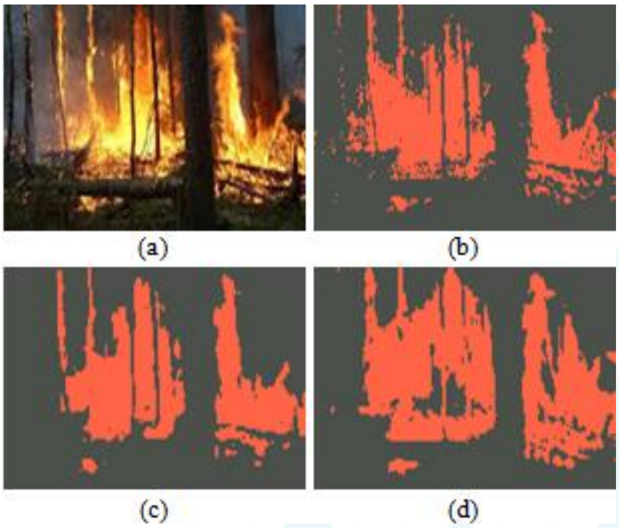


Figure 9: Comparison of the proposed segmentation method with other existing methods on a fire forest image (6 classes). (a) Original image (256×256×3): color fire forest image with RGB description, (b) segmentation based on HCM and Fusion, (c) segmentation based on FCM and Fusion, and (d) segmentation based on MFCM and Fusion

In fact, one can find that the different objects presented in the original image are much better segmented in figure (FIG. 8(d)) than those in the figures (FIG. 8(b) and (c)), from where the detection of fire area in the forest images.

Consequently, the experimental results are improved by the proposed approach.

So, the fusion of segmentation maps obtained by applying the modified FCM algorithm to the three component images can be used to segment the forest images where the resulting partition data can be interpreted as compatibility points with the different types of classes covering image.

The experimentation is carried out on fire forest image in Fig. 9(a) and this image is used as original image. The segmentation results are obtained using the HCM, FCM and NFCM clustering algorithms as the initial seed for the segmentation techniques, followed by the fusion procedure. They correspond, respectively, to Figs. 9(b), (c) and (d).

Table 1: Segmentation sensitivity From HHDS, TSMODS, and the proposed method (MFCMF) for the data set shown in Fig. 5.

	HHDS	TSOMF	Proposed Method
	Segmentation Sensitivity (%)		
Image 1	80.6189	80.3817	84.7137
Image 2	87.4035	96.3124	98.9023
Image 3	79.1688	64.6115	83.7135
Image 4	94.6366	99.0476	99.3024
Image 5	68.2913	61.3566	75.8710
Image 6	94.7285	94.9290	95.1713
Image 7	73.0687	83.0241	86.4466
Image 8	80.0147	71.7630	82.6382
Image 9	92.7074	88.4924	92.8409
Image 10	98.2145	98.1248	99.7849
Image 11	96.3537	99.4015	99.6592
Image 12	97.2548	98.5091	99.7892

Table 2: Segmentation sensitivity from HCM and DS, FCM and DS and the proposed method (MFCMF) for the data set shown in Figure 5.

	HCM and DS	FCM and DS	Proposed Method
	Segmentation Sensitivity (%)		
Image 1	80.8855	81.1657	84.7137
Image 2	77.9741	83.0075	98.9023
Image 3	68.2581	75.3300	83.7135
Image 4	81.5957	86.7544	99.3024
Image 5	76.6345	82.7613	85.8710
Image 6	82.6558	84.2356	95.1713
Image 7	72.8368	74.7904	86.4466
Image 8	78.1597	79.9956	82.6382
Image 9	81.0616	87.1945	92.8409
Image 10	98.9786	98.9884	99.7849
Image 11	95.9527	98.7777	99.6592
Image 12	99.1637	99.4728	99.7892

Figure 10: Color edge detector

However, in the standard fuzzy approaches HCM and FCM, only the gray level information is used to determine the membership degree of each pixel, which leads to the presence of many incorrectly classified pixels. Hence, the fires are exactly and homogeneously segmented in Fig. 9(d), which is not the case in Fig. 9(b) and (c).

Fig. 9(d) shows the segmentation results obtained by the proposed method. In fact, the obtained results are quite consistent with the visualized color distributions in the objects, which make it possible to localize the fire area in the forest images (see Fig. 10(c)).

In short, the proposed algorithms 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.

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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 [21] [23] is computed using:

$$= \frac{}{\times} \times 100 \qquad (13)$$

where Sens, 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 2, one can observe in Figures 9(b) and 9(c),that 19.1145% and 18.8343% of pixels were incorrectly segmented for the HCM and FCM methods, respectively.

However, this demonstrates that the HCM and FCM algorithms are instable in noisy environments and the membership degree resulting from the two algorithms; do not always correspond to the intuitive concept of degree of belonging or compatibility. However, errors were largely reduced when exploiting simultaneously the three component images through the use of the fusion rule including the modified fuzzy clustering.

Indeed, only 15.2863% of pixels were incorrectly segmented in Figure 9(d). This good performance between these methods can also be easily assessed by visually comparing the segmentation results.

In fact, this experiment shows the validity of our fusion procedure and also the significant improved performance in segmentation.

Consequently, the proposed method can be useful for color image segmentation.

Fig. 10 illustrates the final results for the used images data base (Fig. 6), where the edges in white color are superimposed on the original images.

4. Conclusion

In this paper, we have proposed a new method for color image segmentation based on fuzzy clustering and fusion procedure. In the first phase, the segmentation maps are obtained from the component images of the original image expressed in three-color spaces via the modified fuzzy c-means algorithm. Then, segmentation results for the nine color components are integrated through the fusion rule.

Instead, for considering an existing segmentation procedure, our technique rather explores the benefit of combining several approaches in order to get good consistency segmentations.

Moreover, the results of fuzzy clustering and statistical features are integrated to provide more accurate segmentation of images. Application of the proposed image segmentation algorithm to automatic fire detection in the forest images is also discussed. The obtained results demonstrated the significant improved performance in segmentation.

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