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Investigation of a novel image segmentation method dedicated to forest fire applications*

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Abstract
To face fire it is crucial to understand its behaviour in order to maximize fighting means. To achieve this task, the development of a metrological tool is necessary for estimating both geometrical and physical parameters involved in forest fire modelling. A key parameter is to estimate fire positions accurately. In this paper an image processing tool especially dedicated to an accurate extraction of fire from an image is presented. In this work, the clustering on several colour spaces is investigated and it appears that the blue chrominance Cb from the YCbCr colour space is the most appropriate. As a consequence, a new segmentation algorithm dedicated to forest fire applications has been built using first an optimized *k*-means clustering in the Cb-channel and then some properties of fire pixels in the RGB colour space. Next, the performance of the proposed method is evaluated using three supervised evaluation criteria and then compared to other existing segmentation algorithms in the literature. Finally a conclusion is drawn, assessing the good behaviour of the developed algorithm.

Keywords: image processing, colour space, fire segmentation, supervised evaluation, forest fire metrology

(Some figures may appear in colour only in the online journal)

1. Introduction

Forest fires have been increasing since the beginning of the new millennium due to climate changes, especially global warming. Consequences of this phenomenon include loss of lives, goods, infrastructure, deterioration of the natural environment and degradation of ecosystems. This growing threat can be illustrated by some figures such as the following ones from recent events: four years ago (in 2009) Australia was dramatically affected with 200 deaths and 300 000 hectares burnt; three years ago, during the summer, Russian authorities were frightened by the wildland fires close to the nuclear power plant of Snejinsk which also killed more than 50 persons and burnt nearly 800 000 hectares; a few months later (December 2010) around 40 people died in northern Israel due to the massive burning on Mount Carmel. Despite the dramatic rise of forest fires all around the world (currently, 11 hectares per second burn in the whole world), it is noticeable that forest managers have always tried to increase their efforts towards fighting forest fires, but in many cases the main problem comes from determining the current state of the fire front. This valuable information is described by its geometrical (positions, tilt angle, length . . .) and physical parameters (fire intensity, flame temperature . . .) that can be determined by several experimental tools.

* This paper is dedicated to the memory of Dr Olivier Séro-Guillaume (1950–2013), CNRS Research Director.
[4] Deceased.

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A wide range of experimental apparatus is used in forest fire metrology and such devices can be divided into two groups (Rudz *et al* 2009b): discrete (thermocouples, conducting wires and cotton or nylon threads) or continuous (heat flux sensor, image processing). Discrete tools were first used in fire experiments for studying the rate of spread of fire propagation over a fuel bed (Rothermel 1972, Iverson *et al* 2004, Zhou *et al* 2005, Chetehouna *et al* 2005, Pastor *et al* 2006) but the main drawback of such methodology is that the fire front is implicitly considered as rectilinear. Regarding continuous methods, one can note that an attempt based on heat flux measurements has been developed by Chetehouna *et al* (2008a), providing more information with better accuracy than discrete methods. Another continuous method is the use of image processing, because some recent works (Martinez-de Dios *et al* 2008, Chetehouna *et al* 2008b, Pastor *et al* 2006) have pointed out that such an approach is a possible alternative for determining the fire location, the rate of spread and some geometric properties of a fire front such as flame length, flame inclination angle and fire base contour. Moreover, the coupling of these two kinds of continuous approach proposed in Rudz *et al* (2011) leads to the design of an adequate metrological device able to determine both geometrical and physical characteristics of flame in a shorter computational time than that based on just the heat flux methodology (Chetehouna *et al* 2008a). Nevertheless this previous study (Rudz *et al* 2011) pointed out that an accurate determination of the geometrical characteristics of a fire front, which clearly depends on the efficiency of the chosen existing segmentation method, is necessary. In both fire safety and image processing literature, several segmentation algorithms have been designed for fire images cropped from wildland or urban fire scenes (Celik and Demirel 2009, Chen *et al* 2004, Rossi *et al* 2011). These methods are based on different colour spaces and most of them use some discriminative properties on the colour space used to extract the fire regions in the image. Nevertheless, even if those algorithms have shown good performance, there is little information about the efficiency of one method compared to others. In a previous work (Rudz *et al* 2009a), a comparative study of several existing fire segmentation methods was performed. Unfortunately, it has been pointed out in Rudz *et al* (2009a, 2009b) that the mentioned methods can be improved according to supervised evaluation criteria working either in a contour (Pratt *et al* 1978) or a region-based approach (Hafiane *et al* 2007, Unnikrishnan *et al* 2007, Chabrier 2005, Vinet 1991, Huang and Dom 1995, Yasnoff *et al* 1977, Martin *et al* 2001) and the development of a new segmentation algorithm becomes a key to achieving the coupling of applications described above.

The aim of this paper is to propose a novel segmentation algorithm for fire images that is able to extract accurately the fire region for different forest fire experiments, to evaluate its performance and to compare it with other existing algorithms. The images database (original images and their ground truths annotated by an expert) used in this development is obtained from various fire databases on the web, ForestryImages.org and WildlandFire.com, and from experiments performed in Vigan (southern France) in 2007 on heterogeneous vegetation. The second section is dedicated to the description of three supervised evaluation criteria. These criteria are used to design the new segmentation method: the choice of the most interesting colour space for clustering and optimization of parameters. Also based on these criteria, a comparative study with other existing algorithms is conducted in the fourth section.

2. Supervised evaluation criteria

Based on the comparison between a segmentation result I_s and a given ground truth I_{gt} assessed by an expert's annotations, several supervised evaluation metrics have been proposed in the literature to quantify the performance of segmentation algorithms (Hafiane *et al* 2007, Unnikrishnan *et al* 2007, Chabrier 2005, Vinet 1991, Huang and Dom 1995, Yasnoff *et al* 1977, Martin *et al* 2001). Each of these metrics relies on overlap measures combined in different ways. In order to check if the choice of evaluation metric greatly influences the final conclusions, we implemented three metrics (Hafiane *et al* 2007, Martin *et al* 2001) commonly used for the evaluation of segmentation methods and evaluated as the most efficient ones (Hemery *et al* 2010).

2.1. Martin's criteria (MAR_{gce} and MAR_{lce})

Martin *et al* (2001) defined a local refinement error between segmented image I_s and its ground truth I_{gt} which is not symmetric:

$$E(I_{\mathrm{gt}}, I_s, k) = \frac{\mathrm{card}\left(I_{\mathrm{gt}\backslash s}^{r(k)}\right)}{\mathrm{card}\left(I_{\mathrm{gt}}^{r(k)}\right)} \qquad (1)$$

where $r(k)$ corresponds to the region containing pixel k. From this error, which only measures a refinement from image I_{gt} to image I_s, they create two symmetric error measures for the entire image, the global consistency error (gce) and local consistency error (lce):

$$\mathrm{MAR}_{\mathrm{gce}}(I_{\mathrm{gt}}, I_s) = \frac{1}{\mathrm{card}(I)} \min\left[\sum_{k\in I} E(I_{\mathrm{gt}}, I_s, k), \sum_{k\in I} E(I_s, I_{\mathrm{gt}}, k)\right] \qquad (2)$$

$$\mathrm{MAR}_{\mathrm{lce}}(I_{\mathrm{gt}}, I_s) = \frac{1}{\mathrm{card}(I)} \sum_{k\in I} \min[E(I_{\mathrm{gt}}, I_s, k), E(I_s, I_{\mathrm{gt}}, k)] \qquad (3)$$

where I is the common support image of I_{gt} and I_s.

Forcing all local refinements to be in the same direction (either from I_{gt} to I_s or from I_s to I_{gt}), $\mathrm{MAR}_{\mathrm{gce}}$ is tougher than $\mathrm{MAR}_{\mathrm{lce}}$, which allows refinement in both directions.

2.2. Hafiane's criterion (HAF)

Hafiane's criterion (Hafiane *et al* 2007) is defined as follows:

$$\mathrm{HAF} = \frac{M_I + m \times \eta}{1 + m} \qquad (4)$$

Table 1. Evaluation of the best clustering on each colour space.

	Martin's criteria						Hafiane's criterion		
Channel	n	k	$\mathrm{MAR}_{\mathrm{gce}}$ (%)	n	k	$\mathrm{MAR}_{\mathrm{lce}}$ (%)	n	k	HAF(%)
a	1	9	86.2	1	9	94.1	1	9	52.7
b	1	3	88.3	1	5	95.5	1	9	55.3
Cr	1	4	89.3	2	7	95.1	1	7	58.5
Cb	1	4	94.0	1	4	98.5	1	6	62.3
							1	4	60.8
U	1	8	84.2	1	8	92.4	1	9	52.8
V	1	5	89.9	1	9	96.4	1	9	58.4

The matching index M_I is defined as a weighted overlap ratio over all classes:

$$M_I = \sum_{j=1}^{NC_s} \frac{\mathrm{Card}\left(C_{\mathrm{gt}}^{i*} \cap C_s^j\right)}{\mathrm{Card}\left(C_{\mathrm{gt}}^{i*} \cup C_s^j\right)} \times \frac{\mathrm{Card}\left(C_s^j\right)}{\mathrm{Card}(I_s)} \tag{5}$$

where $i^* = \underset{i=1}{\overset{\mathrm{NC_{gt}}}{\mathrm{argmax}}}(\mathrm{Card}(C_{\mathrm{gt}}^i \cap C_s^j))$ is the index of the class in the ground truth with the largest overlap (pixel-by-pixel basis) compared to one class in the segmentation result, C_s^j. $\mathrm{NC_{gt}}$ and NC_s are the numbers of classes in the ground truth and segmented image respectively (in our application, $\mathrm{NC_{gt}} = \mathrm{NC}_s = 2$, fire or not-fire class).

The over- and under-segmentation penalty factor η takes into account the numbers of connected regions in the ground truth $\mathrm{NR_{gt}}$ and in the segmented image NR_s obtained after labelling:

$$\eta = \begin{cases} \dfrac{\mathrm{NR_{gt}}}{\mathrm{NR}_s} & \text{if } \mathrm{NR}_s \geqslant \mathrm{NR_{gt}} \\ \log\left(1 + \dfrac{\mathrm{NR}_s}{\mathrm{NR_{gt}}}\right) & \text{otherwise.} \end{cases} \tag{6}$$

The weighting factor m, controlling the importance of over- or under-segmentation errors in the judgment, has been set to 0.5.

3. Presentation of the method

In such an application, image segmentation can be considered as a clustering problem focusing on the grouping of pixels presenting the same colour characteristics. For fire images, the goal is to group all pixels belonging to fire regions into one group. In order to achieve this objective, the first step of the proposed method consists in a k-means clustering, a widely used method in image segmentation (McQueen 1967). This classifier minimizes the following objective function:

$$\sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - m_i\|^2 \tag{7}$$

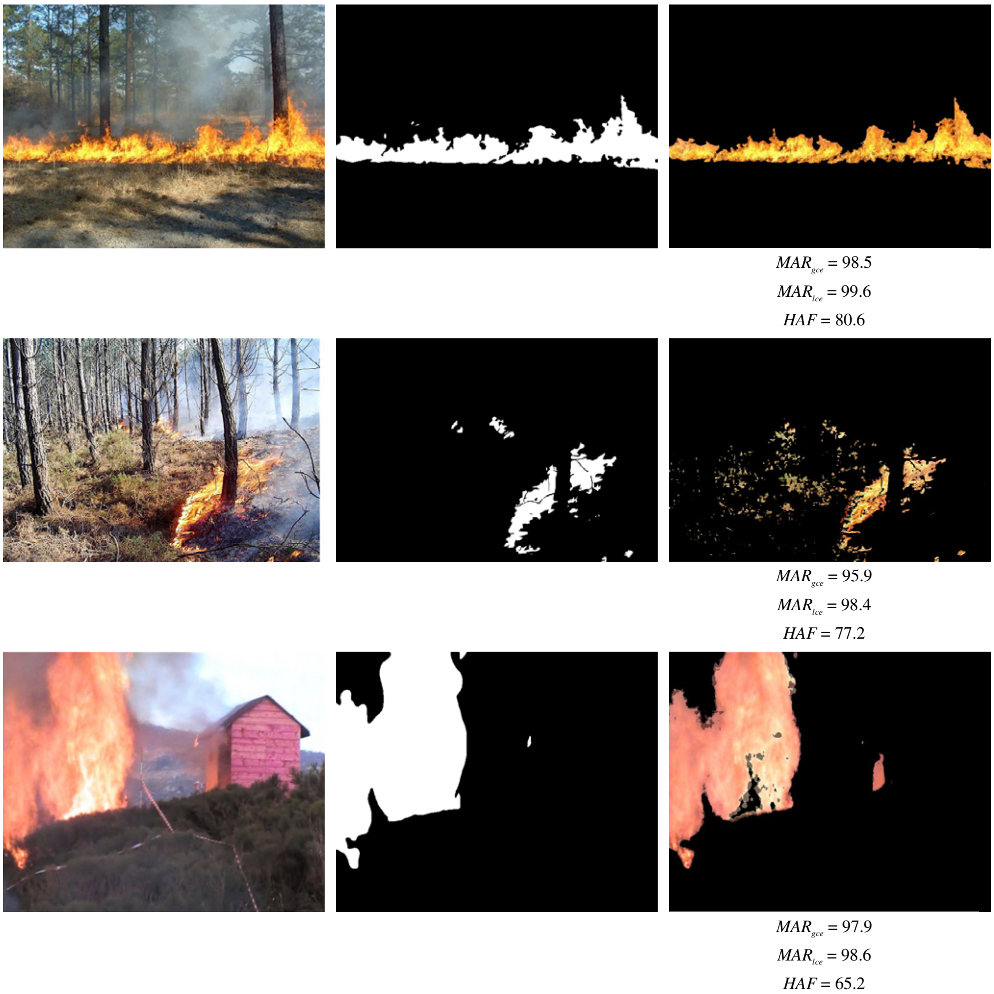
where k is the number of clusters, C_i represents the cluster i, m_i is the centroid of all points $x_j \in C_i$ and $\| \cdot \|$ denotes the usual Euclidian norm.

k-means only requires one input parameter: the number of classes k. However, this parameter is very sensitive because it determines into how many clusters pixels should be divided in the feature space. As a consequence this parameter has to be set carefully. Moreover, in fire safety literature some fire segmentation methodologies are driven by the use of different colour spaces: YCbCr (Celik and Demirel 2009), HSI and RGB (Chen *et al* 2004) and YUV (Rossi *et al* 2011). The problem underlined here is that the choice of a specific colour space remains unclear to better separate fire from the rest of a scene. Recently, Rudz *et al* (2010) has pointed out that chrominance channels such as 'a' and 'b' components of Lab colour space or 'U' and 'V' of YUV or 'Cr' and 'Cb' of YCbCr have more discriminative properties for extracting fire in an image.

In order to solve both the choice of colour space and the determination of the parameter k, we conducted a study on several chrominance components: U, V, Cr, Cb, a and b. On each channel, we performed the k-means algorithm over the whole database with k ranging from 2 to 9 and kept successively the n classes closest to the fire reference histograms (composed of more than 2×10^6 fire pixels obtained through expert assessment), i.e. n ranging from 1 to $k - 1$. Evaluation of the best clustering, presented in table 1, is given with the three supervised evaluation criteria presented in the previous section: $\mathrm{MAR_{gce}}$, $\mathrm{MAR_{lce}}$ and HAF.

According to all criteria, the blue chrominance channel 'Cb' is the most adapted colour space to perform the k-means algorithm. Nevertheless not all criteria agree on an optimal pair (n, k). Indeed both $\mathrm{MAR_{gce}}$ and $\mathrm{MAR_{lce}}$ criteria allow (1, 4) as the best values of (n, k) whereas HAF allows (1, 6) as the best pair. However, the value of HAF on the Cb component with parameters (1, 4) is equal to 60.8%, which is still very close to that obtained with the pair (1, 6). As a consequence, we conclude that the chrominance 'Cb' of the YCbCr colour space with parameters (1, 4) gives the most adapted values to separate fire in an image. As we can see in figure 1, this first step can yield results very close to the ground truth in a few cases, but in many cases some improvements are needed.

These improvements are performed just after this k-means step. All regions are first labelled and, depending on their size, the algorithm is different. We can take into account two kinds of segmented regions: large ones and small ones. If a region has more than 256 pixels, it is considered as large, otherwise it is



(*a*) Original images (*b*) Ground truths (*c*) *k*-means results

Figure 1. Some examples of *k*-means results, using Cb chrominance with pair (1, 4).

considered as small. The second step eliminates the remaining false pixels as follows:

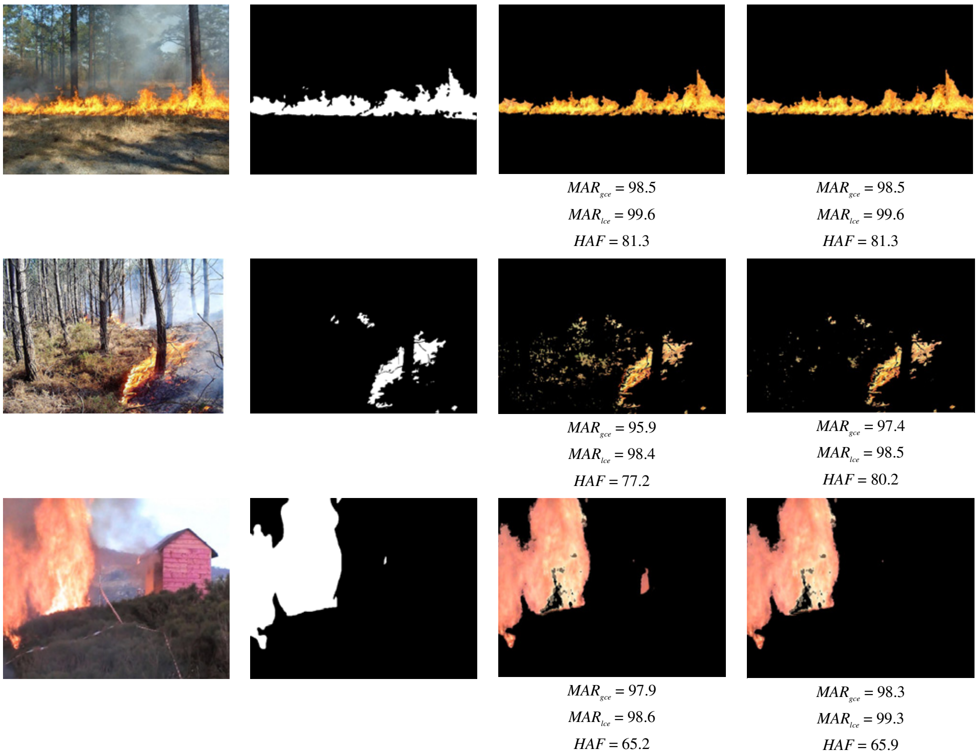
$$\begin{array}{l}\text{For a large region}\\ \begin{cases}\text{rule1: } \left\|\text{hist}_{\text{R}}^{\text{ref}} - \text{hist}_{\text{R}}\right\| < \tau_{\text{R}}\\ \text{rule2: } \left\|\text{hist}_{\text{G}}^{\text{ref}} - \text{hist}_{\text{G}}\right\| < \tau_{\text{G}}\\ \text{rule3: } \left\|\text{hist}_{\text{B}}^{\text{ref}} - \text{hist}_{\text{B}}\right\| < \tau_{\text{B}}\end{cases}\\ \text{if (rule1) and (rule2) and (rule3)} = \text{true}\\ \text{then: pixel is fire}\\ \text{else: pixel is not fire}\end{array} \tag{8}$$

$$\begin{array}{l}\text{For a small region}\\ \begin{cases}\text{rule1: } \left\|\mu_{\text{R}}^{\text{ref}} - \mu_{\text{R}}\right\| < c_{\text{R}} \times \sigma_{R}^{\text{ref}}\\ \text{rule2: } \left\|\mu_{\text{G}}^{\text{ref}} - \mu_{\text{G}}\right\| < c_{\text{G}} \times \sigma_{G}^{\text{ref}}\\ \text{rule3: } \left\|\mu_{\text{B}}^{\text{ref}} - \mu_{\text{B}}\right\| < c_{\text{B}} \times \sigma_{B}^{\text{ref}}\end{cases}\\ \text{if (rule1) and (rule2) and (rule3)} = \text{true}\\ \text{then: pixel is fire}\\ \text{else: pixel is not fire}\end{array} \tag{9}$$

In equations (8) and (9), R, G and B denote respectively the channels R, G and B of the RGB colour space. In those relations the parameters hist^{ref}, μ^{ref} and σ^{ref} are respectively the reference histogram, the mean and the standard deviation of fire pixels in the considered channel. Those reference parameters have been calibrated on one third of the database, taking the images randomly. It has to be pointed out that the database is heterogeneous and has been built taking images of a fire scene from various materials in various parts of the world in order to design a general segmentation method. The other parameters involved, τ and c on each channel, have been optimized on the same part of the database. To achieve this task a direct pattern search method (Lewis and Torczon 1999) has been used where the objective function to maximize was the F-score. Derived from performance ratios, the F-score was introduced by the information retrieval community and corresponds to the harmonic mean of precision and recall (Wolf and Jolion 2006). The choice of this metric for the optimization allows it to be independent of the others presented previously.

In this experiment $\tau_{\text{R}}, \tau_{\text{B}}, \tau_{\text{G}}, c_{\text{R}}, c_{\text{G}}$ and c_{B} have been respectively optimized to 40.1, 74, 74, 1.4, 9 and 9. As shown in figure 2, this second step allows the majority of non-fire pixels to be eliminated without removing the real fire pixels segmented with the *k*-means step using $(n, k) = (1, 4)$.

The use of the second step allows the non-fire pixels remaining after the first step to be eliminated without removing fire pixels. As a consequence, the results provided are closer than before to the ground truth. The purpose of the next section



(*a*) Original image (*b*) Ground truth (*c*) First step: *k*-means (*d*) Second step: filtering

Figure 2. Some results of the proposed method.

is to evaluate and compare the results of the new method with other existing algorithms (Celik and Demirel 2009, Chen *et al* 2004, Rossi *et al* 2011, Chitade and Katiyar 2010).

4. Performance study

In this performance study Martin's criteria and Hafiane's criterion are used again. Moreover, a comparative study between the proposed algorithm and some segmentation algorithms (dedicated to fire or not) from the literature is also provided in this section. Three segmentation methods dedicated to fire applications have been selected from the state of the art (Celik and Demirel 2009, Chen *et al* 2004, Rossi *et al* 2011) because of their promising possibilities for fire pixel detection (Rudz *et al* 2009a). Another algorithm not dedicated especially to fire application (Chitade and Katiyar 2010) has been selected because it is based on colour features, like the proposed method. Before presenting the results, a brief description of these algorithms is given.

4.1. Segmentation methods from the state of the art

The four fire segmentation algorithms present various ways to succeed, using different colour spaces or a combination of colour spaces and various models for fire thresholding segmentation. Throughout this section, common notations are used: (x, y) is the location of a pixel, $I_i(x, y)$ is the colour value of a pixel for the ith colour channel, μ_i and σ_i are respectively the mean value and the standard deviation for channel i.

(i) *Method 1*

This method (Celik and Demirel 2009) works on the YCbCr colour space and allocates a pixel to the fire region if its characteristics satisfy all of the following rules:

$$\begin{cases} I_{\mathrm{Y}}(x,y) > I_{\mathrm{Cb}}(x,y) \\ I_{\mathrm{Cr}}(x,y) > I_{\mathrm{Cb}}(x,y) \\ |I_{\mathrm{Cr}}(x,y) - I_{\mathrm{Cb}}(x,y)| \geqslant \tau \\ I_{\mathrm{Y}}(x,y) > \mu_{\mathrm{Y}} \text{ and } I_{\mathrm{Cb}}(x,y) < \mu_{\mathrm{Cb}} \text{ and } I_{\mathrm{Cr}}(x,y) > \mu_{\mathrm{Cr}} \\ I_{\mathrm{Cb}} \geqslant fu(I_{\mathrm{Cr}}) \cap I_{\mathrm{Cb}} \leqslant fd(I_{\mathrm{Cr}}) \cap I_{\mathrm{Cb}} \leqslant fl(I_{\mathrm{Cr}}) \end{cases} \tag{10}$$

where $fu(I_{\mathrm{Cr}})$, $fd(I_{\mathrm{Cr}})$ and $fl(I_{\mathrm{Cr}})$ are three polynomial functions whose intersections contain fire area in the Cr–Cb plane. They were obtained with the use of an annotated database specially created by the authors for the experiments; the threshold τ has been set to 40, according to the authors' recommendations.

(ii) *Method 2*

This method (Chen *et al* 2004) combines RGB space with the saturation channel of HSI colour space. A pixel is designated as a fire pixel if it fulfils the three *following decision rules:*

$$\begin{cases} \text{condition 1: } I_{\mathrm{R}}(x,y) > \mathrm{R}_T \\ \text{condition 2: } I_{\mathrm{R}}(x,y) \geqslant I_{\mathrm{G}}(x,y) > I_{\mathrm{B}}(x,y) \\ \text{condition 3: } I_{\mathrm{S}}(x,y) \geqslant (255 - I_{\mathrm{R}}(x,y))\frac{\mathrm{S}_T}{\mathrm{R}_T} \end{cases} \tag{11}$$

where S_T and R_T are respectively two thresholds for S and R channels. According to their various experimental results, the authors propose values ranging from 55 to 65 and 116 to 135 respectively for S_T and R_T. For our experiments, S_T and R_T are respectively optimized to 55 and 125.

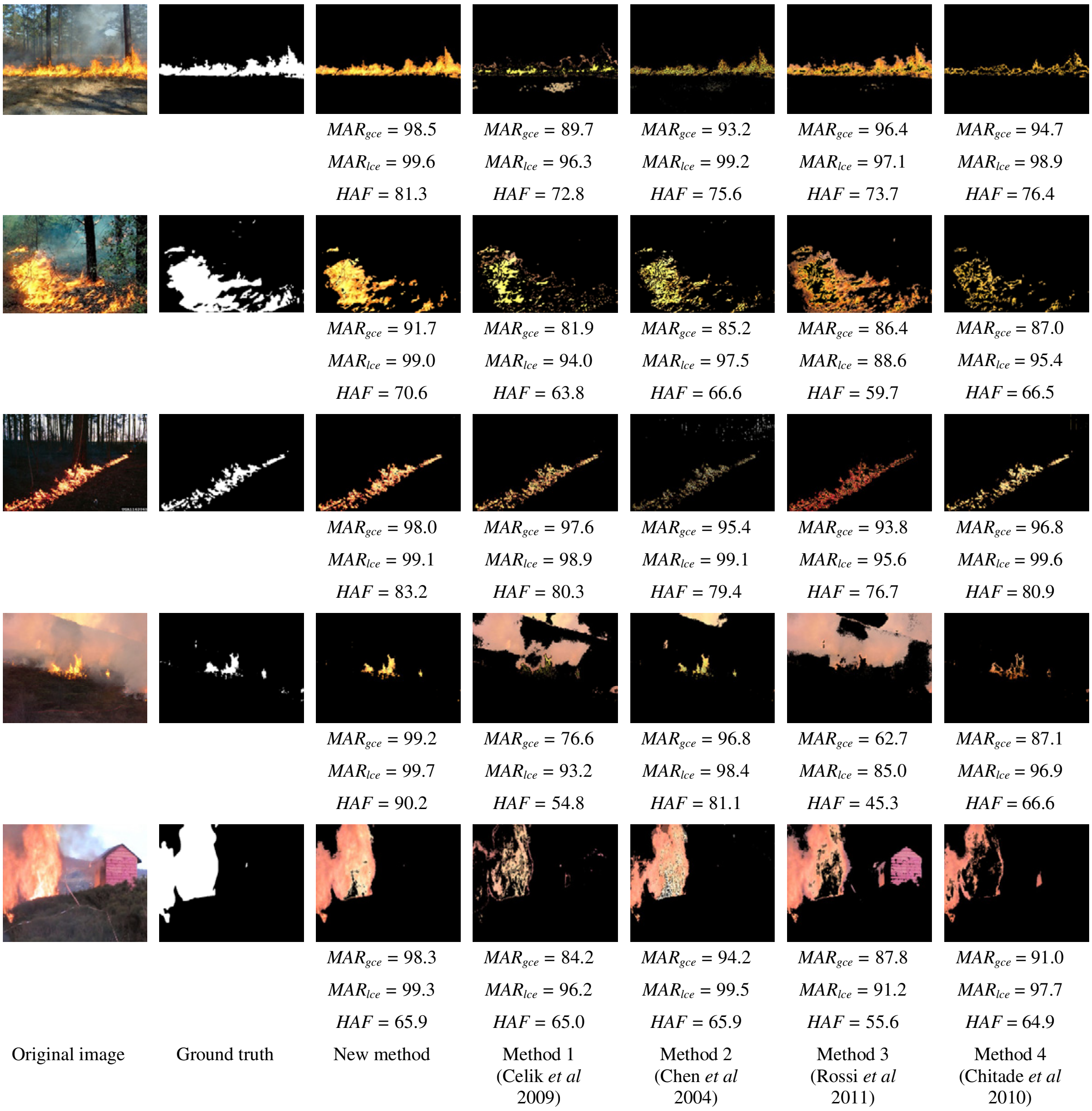


Figure 3. Some segmentation results of the images database.

(iii) *Method 3*

This method (Rossi *et al* 2011) is divided into two steps. A k-means clustering is first computed on the V channel of YUV to find fire and non-fire areas in the image, i.e. $k = 2$, assuming that this red chrominance channel is the most efficient. The biggest region in the clustered V channel is then considered as corresponding to fire area. The authors thereafter use a 3D Gaussian model, defined by the following mean and standard deviation, in RGB colour space to compute a reference model for colour classification of fire pixels:

$$\begin{cases} \mu = (\mu_{\mathrm{R}}, \mu_{\mathrm{G}}, \mu_{\mathrm{B}}) \\ \sigma = \max(\sigma_{\mathrm{R}}, \sigma_{\mathrm{G}}, \sigma_{\mathrm{B}}) \end{cases} \tag{12}$$

Each pixel is represented by its colour component $I = (I_{\mathrm{R}}, I_{\mathrm{G}}, I_{\mathrm{B}})$ and is assigned according to:

$$\begin{cases} \|I(x,y) - \mu\| \leqslant c \times \sigma : I(x,y) \text{ is fire pixel} \\ \text{otherwise} \qquad\qquad : I(x,y) \text{ is not fire pixel} \end{cases} \tag{13}$$

where $\|\cdot\|$ is the Euclidean norm and c a constant.

(iv) *Method 4*

This method (Chitade and Katiyar 2010), not especially dedicated to fire applications, uses colour features in channels 'a' and 'b' of Lab colour space with k-means clustering. This work is divided into two main stages: first decorrelation stretching in order to make discrimination easier by exaggerating colours and second k-means clustering to classify pixels by colours.

4.2. Results and discussion

The above described algorithms are applied to our images database and their fire segmentation results are evaluated with Martin's criteria and Hafiane's criterion. Note that all parameters involved in the different methods had been optimized. The mean scores on the whole database for these supervised evaluators are presented in table 2.

All criteria yield the first rank for the proposed method. Figure 3 provides some fire segmentation results of the

Table 2. Mean score on the images database.

Different methods	Martin's criteria MAR_{gce} (%)	Martin's criteria MAR_{lce} (%)	Hafiane's criterion HAF(%)
Proposed method	94.2	98.6	65.9
Method 1 (Celik and Demirel 2009)	87.6	96.3	57.2
Method 2 (Chen *et al* 2004)	91.5	98.1	59.7
Method 3 (Rossi *et al* 2011)	88.6	94.8	52.8
Method 4 (Chitade and Katiyar 2010)	93.4	98.5	62.0

five presented methods. For each segmentation result, the corresponding MAR_{gce}, MAR_{lce} and HAF values are given as percentages. This figure clearly illustrates the global behaviour of the tested segmentation methods over the images database. We can notice that method 1 is penalized by under-segmentation: segmented pixels are, most of the time, fire pixels but a lot of real fire pixels are ignored. Concerning method 2, their rules are too restrictive, so fire zones are mostly under-segmented. Method 3 is penalized when fire pixels are in the yellow range, due to the clustering on the red chrominance channel V. Finally, method 4, using only colour features is penalized when some elements, like ground or sky, have the same colour as fire because the clustering is based only on kernels given by the *k*-means clustering.

5. Conclusion

Over recent decades, several attempts to segment fire in an image have been conducted, leading to different methodologies in various colour spaces. In this paper a new methodology is proposed, evaluated and compared to those recent works. This algorithm can be divided into two steps: clustering then filtering. For the first step, a study has been done to assess the most relevant channel and the best number of clusters to keep from the total clusters. This first result established that the blue chrominance Cb of the YCbCr colour space and the use of the *k*-means algorithm, keeping one cluster from four, outclasses all other combinations. The second step is based on the comparison of local histograms coming from the first step with outdoor fire reference histograms of our database. It enables us to eliminate false fire pixels without removing true ones. The supervised evaluation protocol shows that our method outperforms those in the literature.

In a future work, we plan to apply this new image segmentation algorithm coupled to the thermal methodology in order to determine accurately both physical and geometrical parameters of flames in prescribed burning experiments for any shape of fire front. Moreover, to increase the efficiency of the presented methodology, the combination of different colour channels in the first step of the proposed segmentation algorithm could be investigated in further development.

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