Automatic fire pixel detection using image processing: A comparative analysis of Rule-based and Machine Learning-based methods

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Abstract This paper[1] presents a comparative analysis of state of the art image processing based fire color detection rules and methods in the context of geometrical characteristics measurement of wildland fires. Two new rules and two new detection methods using an intelligent combination of the rules are presented and their performances are compared with their counterparts. The benchmark is performed on approximately two hundred million fire pixels and seven hundred million non-fire pixels extracted from five hundred wildland images under diverse imaging conditions. The fire pixels are categorized according to fire color and existence of smoke, meanwhile, non-fire pixels are categorized according to the average intensity of the corresponding image. This characterization allows to analyze the performance of each rule by category. It is shown that the performances of the existing rules and methods from the literature are category dependent and none of them is able to perform equally well on all categories. Meanwhile, a new proposed method based on machine learning techniques and using all the rules as features outperforms existing state of the art techniques in the literature by performing almost equally well on different categories. Thus, this method, promises very interesting developments for the future of metrologic tools for fire detection in unstructured environments.

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1 Introduction

Wildland fires are responsible for serious damages. They cause deforestation and desertification, air pollution, economic losses and loss of lives among the public and firefighters. The fight against this major risk is all the more effective when it is possible to anticipate its behavior over time. Geometrical characteristics like position, rate of spread, length, surface, volume are needed to understand and model the phenomena occurring during fire propagation [10,20]. In the last 10 years, frameworks using cameras have been developed in order to be used as complementary metrological instrument in fire experiments [17]. The first and most important step for computer vision processing is the fire pixel detection because it determines the accuracy of the following treatments. In the visible spectrum, the main difficulties encountered by the detection methods are due to the fire color and the smoke. Indeed, the color can be inhomogeneous and different (depending on the background and the luminosity) ; the smoke can superimpose the fire areas.

Several fire detection algorithms are proposed in the literature [4]. In the visible spectrum, the algorithms often use color rules in different color spaces RGB [19,24,3,14], YC_bC_r [2], YUV [16], $L^*a^*b^*$ [1], HSI [13], HSV [15] or combination of different color spaces [6,5,22]. Most of these works are used in an early fire detection context, were the real time performance is very important but in this paper, we are in-

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terested in the analysis of the performance of fire pixel detection algorithms.

In the context of wildland fires, two studies [8, 23] were carried out comparing the efficiency of Chen [6], Celik [2], Chitade [7], Ko [14] and Rossi [22] methods. Each study was done using a different set of images and the maximum number of pictures in the set was seventy six. This small number of images and the lack of information concerning the fire images does not allow to select the best color space and rules to detect wildland fire pixels.

Most of fire color detection methods use combination of rules on a color space because it is a fast and simple way to detect fire pixels on images. In order to determine which fire detection methods are more appropriate for wildland fire detection and how their performances depend on fire characteristics (fire color, brightness, presence of smoke), an analysis of the performances of the fire detection methods from the literature tested in a large number of outdoor vegetation fire images is necessary. Also, how the rules should be associated in order to obtain a better fire detection method deserves to be studied.

This article emphasizes on color spaces and rules used in fire pixel detection methods. It presents twenty nine well-known color rules from the fire color detection literature. As these rules are not efficient on all type of images, this paper proposes two new rules to perform a better rule-based fire pixel detection. Two new detection algorithms that use the studied rules are also presented in this paper. One method combines rules with the same weight and the other uses machine learning with all the rules as input. For the first time, a fire pixel detection method that combines weighted rules using machine learning is presented. A benchmark of the all rules and detection algorithms is performed on a set of nine hundred millions labeled pixels and the results are presented for each image category.

The paper is organized as follows: Section 2 describes the state of the art fire pixel detection rules and the new proposed ones. Section 3 describes two new fire detection methods. Section 4 presents the image dataset and section 5 presents the performances of the new detection rules and all the detection methods. Section 6 concludes this paper.

2 Fire pixel detection rules

In general, each fire pixel detection method can be considered as logical combination of basic units; rules. Rules are composed of basic mathematical operations. In this section, twenty nine rules found in the literature of fire color detection methods and two new rules are described.

The following notation is used, unless otherwise stated: $I_c(\mathbf{x})$ is the intensity value of a pixel located at spatial location $(\mathbf{x})$ in color channel c of the corresponding color space.

All rules are defined with the following format:

$$r_k(\mathbf{x}) = f_k(\mathbf{x}) - c_k(\mathbf{x}), \tag{1}$$

where $r_k(\mathbf{x})$ is the rule k, $f_k(\mathbf{x})$ is the functional form of the rule and $c_k(\mathbf{x})$ is a constant. A pixel $\mathbf{x}$ of an image is labeled as fire if it verifies the following equation

$$r_k(\mathbf{x}) \geq 0. \tag{2}$$

The definition of rule given in Eqn. (1) allows to fairly compare different schemes on the same dataset by learning the corresponding constants on a common training set through maximizing a performance metric. In this article, a training set of one million pixels extracted from a dataset of five hundred images is used. The F-score [9] is used as a performance metric to evaluate detection methods and rules. Given a detection method and a ground truth, there are four possible outcomes. If the ground truth of the pixel $\mathbf{x}$ is fire and it is detected as fire, it is counted as a true positive (TP); if it is detected as non-fire, it is counted as a false negative (FN). If the ground truth of the pixel $\mathbf{x}$ is non-fire and it is detected as non-fire, it is counted as a true negative (TN); if it is detected as fire, it is counted as a false positive (FP). The detector performance is quantitatively measured using F-score according to:

$$F = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{3}$$

where

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{4}$$

The higher is the value of F-score the better is the performance.

2.1 Fire pixel detection rules from the litterature

Phillips *et al.* [19] proposed a supervised learning-based method which builds a 3D histogram from labeled fire images in *RGB* color space. The $256 \times 256 \times 256$ Gaussian smoothing histogram is computed for the *RGB* color space as follows: for each fire pixel of the image, a 3D Gaussian distribution with a standard deviation $\sigma = 2$ is added to the color histogram centered in the pixel (R, G, B) value and for each background pixel a 3D Gaussian distribution with $\sigma = 1$ is subtracted from the color histogram. Then the values of the Gaussian histogram have positive values for colors that are probably fire and negative values for background colors. Let $H(\mathbf{x})$ be the value of the Gaussian smoothed histogram for the *RGB* value of pixel $\mathbf{x}$. Then, the Phillips' detection can be expressed as the following rule

$$r_1(\mathbf{x}) = H(\mathbf{x}). \tag{5}$$

Chen *et al.* [6] have developed a fire detection procedure based on *R*, *G*, *B* color channels and saturation (*S*) values. It is a fast and efficient method and the rules have been reused in other fire detection methods [11]. The first two rules are for a rapid detection of pixels of color in the range of red to yellow. Red channel of fire pixels should be higher than their green channel and their green channel should be higher than their blue channel, i.e.,

$$r_2(\mathbf{x}) = I_R(\mathbf{x}) - I_G(\mathbf{x}), \qquad (6)$$

$$r_3(\mathbf{x}) = I_G(\mathbf{x}) - I_B(\mathbf{x}). \qquad (7)$$

As the fire is a light source, fire pixels are expected to have high red values, i.e.,

$$r_4(\mathbf{x}) = I_R(\mathbf{x}) - \tau_R, \qquad (8)$$

where τ_R is a threshold. The fourth rule of Chen *et al.* uses the saturation value of pixels in order to eliminate some fire like regions due to background illumination, i.e.,

$$r_5(\mathbf{x}) = I_S(\mathbf{x}) - (255 - I_R(\mathbf{x}))\frac{\tau_S}{\tau_R}, \qquad (9)$$

where τ_S is a threshold. In [6], the two thresholds τ_R and τ_S are not specified. In our study, they have been estimated from our dataset using a pattern search optimization procedure [12]. This procedure computes the values τ_R and τ_S that maximize the mean *F*-score of combination of the rules r_2 to r_5 on the learning dataset. The thresholds $\tau_R = 135$ and $\tau_S = 53$ give the best results.

Horng *et al.* [13] proposed a rule-based detection method in *HSI* color space. Rules on *H*, *S* and *I* channel values are defined to classify a pixel as belonging to the fire. The following three rules are introduced,

$$r_6(\mathbf{x}) = -|I_H(\mathbf{x}) - \tau_{H1}| + \tau_{H2}, \qquad (10)$$

$$r_7(\mathbf{x}) = -|I_S(\mathbf{x}) - \tau_{S1}| + \tau_{S2}, \qquad (11)$$

$$r_8(\mathbf{x}) = -|I_I(\mathbf{x}) - \tau_{I1}| + \tau_{I2}, \qquad (12)$$

where τ_{H1}, τ_{H2}, τ_{S1}, τ_{S2}, τ_{I1} and τ_{I2} are threshold values. In order to find these values, Horng *et al.* use *H*, *S* and *I* histograms of 70 flame images. In our study the training set were used to compute the histograms and it was found that the fire pixels have *H* values (respectively *S* and *I*) in [-45, 65] (respectively in [17, 200] and [35, 215]). The thresholds corresponding to these ranges are $\tau_{H1} = 10$, $\tau_{H2} = 55$, $\tau_{S1} = 108.5$, $\tau_{S2} = 91.5$, $\tau_{I1} = 125$ and $\tau_{I1} = 90$.

Celik *et al.* [3] developed six rules in *RGB* color space. They first used the first two rules of Chen *et al.* and instead of rule r_4, they proposed to use the following rule:

$$r_9(\mathbf{x}) = I_R(\mathbf{x}) - R_{Mean}, \qquad (13)$$

where R_{Mean} is the mean of pixel values in *R* channel. As the illumination of the scene is related to the luminance and chrominance changes in an image, the authors proposed three additional rules using *RGB* ratios that represent at the same time the chrominance and the luminance:

$$r_{10}(\mathbf{x}) = -\left|\frac{I_G(\mathbf{x})}{I_R(\mathbf{x})+1} - \tau_{C1_1}\right| + \tau_{C1_2}, \qquad (14)$$

$$r_{11}(\mathbf{x}) = -\left|\frac{I_B(\mathbf{x})}{I_R(\mathbf{x})+1} - \tau_{C2_1}\right| + \tau_{C2_2}, \qquad (15)$$

$$r_{12}(\mathbf{x}) = -\left|\frac{I_B(\mathbf{x})}{I_G(\mathbf{x})+1} - \tau_{C3_1}\right| + \tau_{C3_2}, \qquad (16)$$

where the thresholds are chosen by Celik *et al.* thanks to observation on the values of channels ratios on hundred fifty fire images from Internet. Using the same method than before, the thresholds corresponding to our dataset are obtained as $\tau_{C1_1} = 0.565$, $\tau_{C1_2} = 0.315$, $\tau_{C2_1} = 0.415$, $\tau_{C2_2} = 0.415$, $\tau_{C3_1} = 0.08$, $\tau_{C3_2} = -0.08$.

Ko *et al.* [14] proposed a probabilistic approach to detect fire in *RGB* color space. *R*, *G*, *B* color channels of fire pixels are assumed to be independent and each channel is modeled with a unimodal Gaussian distribution, i.e.,

$$p_c(I_c(\mathbf{x})) = \frac{1}{\sqrt{2\pi\sigma_c^2}}\exp\left(-\frac{(I_c(\mathbf{x}) - \mu_c)^2}{2\sigma_c^2}\right), \qquad (17)$$

where $c \in \{R, G, B\}$, μ_c and σ_c^2, respectively, are the mean and variance of the data from colour channel *c*.

$$p_f(\mathbf{x}) = \prod_{c \in \{R,G,B\}} p_c(I_c(\mathbf{x})). \qquad (18)$$

Using the above equation, the following rule is introduced

$$r_{13}(\mathbf{x}) = p_f(\mathbf{x}) - \tau_K, \qquad (19)$$

where τ_K is a threshold value not specified in [14]. It is optimized in this study with pattern search on our dataset at $\tau = 3.43 \times 10^{-5}$.

In [2], Celik *et al.* developed eight rules on YC_bC_r color space in order to alleviate the problems caused from illumination changes and to use the consistency in chromicity representation. The first two rules are the translation of the rules r_2, r_3 and r_9 into YC_bC_r color space, i.e.,

$$r_{14}(\mathbf{x}) = I_Y(\mathbf{x}) - I_{C_b}(\mathbf{x}), \qquad (20)$$

$$r_{15}(\mathbf{x}) = I_{C_r}(\mathbf{x}) - I_{C_b}(\mathbf{x}). \qquad (21)$$

For the next three rules, the mean of pixels intensity is used to segment the brighter region of the image, i.e.,

$$r_{16}(\mathbf{x}) = I_Y(\mathbf{x}) - Y_{Mean}, \qquad (22)$$

$$r_{17}(\mathbf{x}) = C_{b_{Mean}} - I_{C_b}(\mathbf{x}), \qquad (23)$$

$$r_{18}(\mathbf{x}) = I_{C_r}(\mathbf{x}) - C_{r_{Mean}}, \qquad (24)$$

where Y_{Mean}, $C_{b_{Mean}}$ and $C_{r_{Mean}}$ are the mean of pixel values in *Y*, C_b and C_r channels respectively. The next rule comes from the fact that in their observations, the authors noticed

a significant difference between the C_b and C_r intensities of the fire pixels, i.e.,

$$r_{19}(\mathbf{x}) = \left| I_{C_b}(\mathbf{x}) - I_{C_r}(\mathbf{x}) \right| - \tau_C, \tag{25}$$

where they optimized the threshold thanks to ROC curves analysis [9] on one thousand images. In our study, it has been optimized to $\tau_C = 40$ with pattern search procedure. The last two rules are tied to the observation that the distribution of fire pixels on the $C_B - C_r$ plane is enclosed by curves, i.e.,

$$r_{20}(\mathbf{x}) = f_1(I_{C_r}(\mathbf{x})) - I_{C_b}(\mathbf{x}), \tag{26}$$

$$r_{21}(\mathbf{x}) = I_{C_b}(\mathbf{x}) - f_2(I_{C_r}(\mathbf{x})). \tag{27}$$

In our study the curves f_1 and f_2 are computed on the training set and defined as follow:

$$f_1(x) = 7.79 \times 10^{-3} x^2 + 2.10x - 2.25, \tag{28}$$

$$f_2(x) = \begin{cases} 4.47 \times 10^{-2} x^2 - 16.94x + 1513.52 & \text{if } x \le 142 \\ 3.39 \times 10^{-5} x^2 + 0.77x - 98.31 & \text{otherwise} \end{cases}. \tag{29}$$

Celik [1] proposed four detection rules based on the CIE $L^*a^*b^*$ colorspace. He assumed that the fire region is the brightest area in the image and has a color near the red color, the following rules are defined

$$r_{22}(\mathbf{x}) = I_{L^*}(\mathbf{x}) - L_{Mean}^*, \tag{30}$$

$$r_{23}(\mathbf{x}) = I_{a^*}(\mathbf{x}) - a_{Mean}^*, \tag{31}$$

$$r_{24}(\mathbf{x}) = I_{b^*}(\mathbf{x}) - b_{Mean}^*, \tag{32}$$

$$r_{25}(\mathbf{x}) = I_{b^*}(\mathbf{x}) - I_{a^*}(\mathbf{x}), \tag{33}$$

where L_{Mean}^*, a_{Mean}^* and b_{Mean}^* are the mean values of the intensity in the L^*, a^* and b^* color channels, respectively.

Chen *et al.* [5] studied fire pixel saturation. Thanks to this study, the authors introduced a color saturation constraint. Indeed, they observed that the fire pixels are in a bounded region enclosed by two curves, i.e.,

$$r_{26}(\mathbf{x}) = 100 \times I_S(\mathbf{x}) - f_3(I_B(\mathbf{x})), \tag{34}$$

$$r_{27}(\mathbf{x}) = f_4(I_B(\mathbf{x})) - 100 \times I_S(\mathbf{x}). \tag{35}$$

In our training set, the equations of the curves f_3 and f_4 are defined as follows

$$f_3(x) = 80 \exp\left(\frac{x}{25}\right), \tag{36}$$

$$f_4(x) = 6.5 \times 10^{-3} x^2 - 0.55x + 100. \tag{37}$$

They also used the rules r_2, r_3 and r_4 in combination with r_{26} and r_{27} to detect fire on images.

Rossi and Akhloufi [21] proposed a method that combines information from *RGB* and *YUV* color spaces. The *k*-means clustering technique with $k = 2$ is applied to V channel of *YUV* color space in order to separate pixels into low-intensity and high-intensity classes. This operation is similar to a threshold on the V channel. In order to study it in this paper, the rule is expressed as follow:

$$r_{28}(\mathbf{x}) = I_V(\mathbf{x}) - \tau_V, \tag{38}$$

where τ_V is computed with the Otsu method [18]. Pixels selected with this rule are further analyzed according to a fire color model defined in *RGB* color space. Fire color model is represented with 3D Gaussian model and corresponding model parameters are obtained from a labeled dataset. The second rule is then defined as follows

$$r_{29}(\mathbf{x}) = -\sqrt{\sum_{C \in \{R,G,B\}} (I_C(\mathbf{x}) - m_C)^2} + \tau_\sigma * \sigma, \tag{39}$$

where m_C is the mean of the channel C for pixels that verify the rule r_{28} and $\sigma = \max_{\{R,G,B\}}(\sigma_C)$ where σ_C is the standard deviation of the channel C for pixel that verify the rule r_{28}. The threshold τ_σ is not specified in [21]. In this study, the threshold is optimized to $\tau_\sigma = 2.5$ with a pattern search procedure on the learning set of pixels.

2.2 New fire pixel detection rules

The rules presented in the previous section are not always efficient for all types of fire pixels. In the following we present two new rules that obtain better performances.

The first rule uses a^* and b^* channels from the $L^*a^*b^*$ color space. Red and orange fire regions are clearly separable in the $a^* + b^*$ images even in presence of smoke. This demarcation comes from the fact that positive values of a^* channel represent shades of red and positive values of b^* channel represent shades of yellow which is represented as new rule as follows:

$$r_{30}(\mathbf{x}) = I_{a^*}(\mathbf{x}) + I_{b^*}(\mathbf{x}) - t_1, \tag{40}$$

where $t_1 = 32.4$ is a threshold obtained using a pattern search procedure on the learning set.

The second rule uses the *RGB* colorspace and the fact that for reddish and orange colors, the channel R is much higher than G or B channels. The rule identifies fire pixels when the difference between their red value and green or blue value is higher than a threshold t_2, i.e.,

$$r_{31} = I_R(\mathbf{x}) - \min(I_R(\mathbf{x}), I_G(\mathbf{x}), I_B(\mathbf{x})) - t_2, \tag{41}$$

where $t_2 = 72$ is a threshold obtained using the same method that was used to compute t_1.

3 Expert systems

A combination of rules using different color spaces may give a better score than that achieved by individual rules but the difficulty is to choose the rules to be combined and their weights in association. In this section, two new fire pixel detection methods based on combination of rules are presented. The first method uses a majority voting of all rules. The second method uses machine learning, specifically logistic regression, to combine rules.

3.1 Majority voting

The majority voting considers outputs of all rules to produce a final output. Thus, if a pixel verifies a certain number of rules, it is considered as a fire pixel. So a pixel is labeled fire if the following condition is verified

$$\left(\sum_{k=1}^{31} \varphi_k(\mathbf{x}) \right) \geq \tau_{MV}, \tag{42}$$

were φ_k is defined as follows

$$\varphi_k(\mathbf{x}) = \begin{cases} 1 & \text{if } r_k \geq 0 \\ 0 & \text{otherwise} \end{cases}, \tag{43}$$

and τ_{MV} is a threshold value. In order to find τ_{MV}, all values of τ_{MV} in $[1, 31]$ are tested using the F-score. In our training set, the best F-score is obtained with $\tau_{MV} = 23$.

3.2 Learning from rules using logistic regression

Logistic regression is a probabilistic classification method. The classifier learns a hypothesis $h_{\mathbf{w}}$ that is parameterized by $\mathbf{w} \in \mathbb{R}^{(d+1) \times 1}$ for feature vector $\mathbf{x} \in \mathbb{R}^{(d+1) \times 1}$, i.e.,

$$h_{\mathbf{w}}(\mathbf{x}) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}}, \tag{44}$$

where $(\cdot)^T$ is vector transpose, $\mathbf{w} = [w_0, \cdots, w_d]^T$, $\mathbf{x} = [x_0, \cdots, x_d]^T$, $x_0 = 1$, $x_k = r_k, k = 1, \ldots, d$, are specific features and $h_{\mathbf{w}}(\mathbf{x}) \in [0, 1]$.

The parameters of $h_{\mathbf{w}}$ are learned using a training set $\left\{ \left(\mathbf{x}^{(i)}, y^{(i)} \right) \right\}_{i=1}^{N}$ of size N, where each training sample $\left(\mathbf{x}^{(i)}, y^{(i)} \right)$ represents the corresponding feature vector $\mathbf{x}^{(i)}$ with a label $y^{(i)}$ of fire ($y^{(i)} = 1$) or non-fire ($y^{(i)} = 0$). The parameters are iteratively learned by minimizing a mean square error ($J(\mathbf{w})$) between the real labels $y^{(i)}$s and the predicted labels $h_{\mathbf{w}}\left(\mathbf{x}^{(i)} \right)$s resulting from the regression, i.e.,

$$J(\mathbf{w}) = \frac{1}{N} \sum_{i=1}^{N} \left(y^{(i)} - h_{\mathbf{w}}\left(\mathbf{x}^{(i)} \right) \right)^2. \tag{45}$$

As a minimizer of the mean square error function, gradient descent algorithm is employed to obtain the following iterative equations:

$$w_k \leftarrow w_k - \alpha \frac{1}{N} \sum_{i \in N} \delta^{(i)}, \tag{46}$$

where

$$\delta^{(i)} = h_{\mathbf{w}}\left(\mathbf{x}^{(i)} \right) - y^{(i)}, \tag{47}$$

and $\alpha \in (0, 1]$ stands for the learning rate.

Since, by definition, logistic regression trains a hypothesis function which is the sigmoid function, the result of the logistic regression is a continuous value bounded to the interval $[0, 1]$. Thus, it produces a likelihood $h_{\mathbf{w}}(\mathbf{x})$ that a feature vector $\mathbf{x}$ is a fire feature vector. In other words, one can threshold the hypothesis $h_{\mathbf{w}}(\mathbf{x})$ according to $h_{\mathbf{w}}(\mathbf{x}) > T_h$ to obtain a crisp value that the corresponding feature vector is a fire feature vector or not. The threshold $T_h = 0.5$ is used in experiments, but a different value can be used.

In order to learn from rules, the rules defined in previous sections are used as feature values, i.e.,

$$x_k = r_k, \tag{48}$$

and the corresponding parameter set of the hypothesis is obtained from the training set of pixels.

4 Image dataset

A set of five hundred *RGB* images of outdoor vegetation fires at different sizes (from 183×242 pixels to 4000×3000 pixels) and different image formats (jpg, ppm, bmp) has been created. The dataset is composed of free images collected from Internet and images from firefighters and researchers taken during real fires and experiments. The images were selected in order to represent the largest number of different fire contexts with heterogeneous environment (forest, maquis shrubland, rocks, snow,...) and different luminosity characteristics (sunny, cloudy, gray sky, blue sky, night, day,...). Figure 1 shows example images from the dataset.

For each image, the fire area was manually segmented by an expert. This region is called ground truth. Using *HSI* color space, the fire pixels are labeled in color type which can be red ($-57° < I_H(\mathbf{x}) < 14°$ and $50 < I_I(\mathbf{x}) < 200$), orange ($14° < I_H(\mathbf{x}) < 42°$ and $50 < I_I(\mathbf{x}) < 200$), white-yellow ($42° < I_H(\mathbf{x}) < 64°$ and $50 < I_I(\mathbf{x})$, or $200 < I_I(\mathbf{x})$) or other color for the other cases. A learning procedure using Support Vector Machine is used to classify pixels as "smoke" and "smokeless". The brightness of background pixels is obtained by analyzing the I channel of the *HSI* color space. Three levels of intensity can be assigned to a pixel: "high intensity" ($115 < I_I(\mathbf{x})$), "medium intensity"($50 <$

Fig. 1 Example of images from the dataset.

			Number of pixels	Percentage
Fire Pixels	Red	Smoke	19 334 066	8.1%
		No Smoke	43 373 644	18.2%
	Orange	Smoke	32 812 298	13.8%
		No Smoke	115 227 509	48.4%
	White-Yellow	Smoke	18 519 389	7.8%
		No Smoke	2 426 830	1.0%
	Other	Smoke	578 832	0.2%
		No Smoke	5 332 683	2.2%
	All		237 950 619	100%
Non-fire Pixels	Low Intensity		170 088 686	21.9%
	Medium Intensity		259 874 877	33.5%
	High Intensity		345 107 529	44.5%
	All		775 071 092	100%

Table 1 Distribution of the dataset pixels by category

$I_I(\mathbf{x}) < 115$) and "low intensity"($I_I(\mathbf{x}) < 50$). Table 1 gives the pixel distribution by category in the dataset. This distribution shows that the fire pixels are in majority orange and that the fire pixel labeled "other" can be ignored due to the low percentage of these pixels.

In order to build a learning set of pixels, fifty images are chosen randomly among the five hundred images. The fire pixels of these fifty images are sorted in six categories depending to the color of the pixels (red, orange, white-yellow) and the presence of smoke. The non fire pixels are classified using three levels of intensity (low medium and high). 500 000 non fire pixels and 500 000 fire pixels are chosen in the following way. For each category, each pixel is represented with a feature vector constructed from color features from different color spaces. An average feature vector is computed for each category and the pixels are sorted according to the distance of their feature vectors to the average feature vector. The pixels are then sampled uniformly to obtain the desired number for each category. According to the observations of the Table 1, the pixel distribution is done as follows: 50% of orange pixel, 33% of red pixel and 17% of white-yellow pixel for fire pixels and 20% of low intensity pixel, 40% of medium intensity pixels and 40% of high intensity pixel for non-fire pixels. This set has been used to compute the functions and constants for the rules and also to train the logical regression based approach. The fifty images used

to build the learning set are not included in the testing set which therefore contains four hundred fifty images.

5 Performances evaluation

5.1 Performances of rules

In this section a comparative analysis of thirty one rules on the pixels of the testing image set is presented. The performances of rules are analyzed by pixel category. In our testing set there are approximately two hundred twelve millions fire pixels and six hundred ninety one millions non-fire pixels. Every fire pixel is categorized according to the categorization given in the Table 1 except for the "other" color category which is ignored. So the fire pixels can be regrouped in six groups and the non-fire pixels in three groups. Every rule is then evaluated on the types of pixels, computing the true positive and false negative pixels for fire pixels and false positive and true negative pixels for non-fire pixels. The table 2 presents the true positives (TP) and true negatives (TN) percentages for all the rules in each pixel category. For a better readability, scores are presented in shades of gray where white correspond to the best score. The first six rows of the table represent the true positives according to the cathegory of the fire pixels and the 3 next row are the true negatives according to the cathegory of non-fire pixels

The rule r_1 seems to be very efficient as it has high TP rates and high TN rates. It is less efficient for detecting white-yellow pixels, because of their similarity to sky pixels.

The rules r_2, r_3, r_4, and r_5 detect well the fire pixels except for red pixel for the rules r_3, r_5 and even for the rule r_4 that work on reddish color. But these rules give a low ratio of TN pixels, except for the rule r_4 which high ratio of TN pixels for low and medium intensity.

The rules r_6, r_7, and r_8 have high TP rates but also low TN rates. This is due to the fact that the thresholds were selected in order to have a maximum of fire pixel in the intervals, and that the intervals are wide due to the diversity of images.

The rules r_9, r_{10}, r_{11}, and r_{12} have high TP rates except for yellow color fires for rules r_{10} and r_{12} but they have low TN rates except for high intensity pixels for rules r_{10} and r_{11}. The rule r_9 has high TP rates and a high TN rates for medium and low intensity. This shows its efficiency detecting fires in low or medium intensity environments. It should be noted that the threshold of rule r_9 is dependent to the image characteristics. Rule r_{12} has very lower TN rates compared to its good TP rates in general. This last rule is not suitable for fire segmentation.

Rule r_{13} does not seem to be appropriate to fire detection. Indeed, it has a very low TP rates even if its TN rates are good.

The rules r_{14}, r_{15}, r_{16}, r_{17}, r_{18}, r_{19}, r_{20}, and r_{21} have high TP

Table 2 True negatives and true positives Scores of fire segmentation methods. The whiteness of the boxes indicates the efficiency

		Phillips	Chen 2004			Horng			Celik *RGB*				Ko			Celik *YC_bC_r*						Celik *L*a*b**				Chen 2010		Rossi		New rules	
		r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}	r_{13}	r_{14}	r_{15}	r_{16}	r_{17}	r_{18}	r_{19}	r_{20}	r_{21}	r_{22}	r_{23}	r_{24}	r_{25}	r_{26}	r_{27}	r_{28}	r_{29}	r_{30}	r_{31}
Red	Smoke																															
	No Smoke																															
Orange	Smoke																															
	No Smoke																															
Yellow	Smoke																															
	No Smoke																															
	Low intensity																															
	Medium intensity																															
	High intensity																															
All	TP																															
	TN																															

rates for orange and yellow colors but rules r_{14}, r_{16}, and r_{19} have lower rated for reddish colors. The rules r_{17}, r_{18}, and r_{19} have good TN rate. The rules r_{20}, and r_{21} (using pixel distributions enclosed by curves in two color channels plane) have low TN values. This is due to the fact that they select non-only fire pixels but also a lot of environment pixels.

For the rules r_{22}, r_{23}, r_{24}, and r_{25}, there is a high TP rates for orange pixels and also for yellow pixels for rules r_{22}, r_{24} and r_{25}.

The rules r_{26} and r_{27} give too low TN rates. The rule r_{26} selects approximatively all pixels (fire and non-fire). This rule is not a suitable option for file detection. The rule r_{27} removes only 11% of background pixel of medium intensities and 5% for high intensity, making it less interesting for an efficient detection of fire pixels.

The rules r_{28} and r_{29} give better result for fire pixels without smoke, especially for orange colors. The rates of TN are very high for the rule r_{28}.

The new rules are also more efficient on fire without smoke, especially for orange pixel and have very high TN rates.

5.2 Performances of the proposed methods

The new proposed two methods are evaluated and compared with the other methods presented in this paper. The results are shown in the Table 3. The scores obtained are dependent of the pixel categories. Among the methods from the literature, Phillips *et al.* gives the best result and is robust to smoke. The Chen 2004 and Chen 2010 methods give good scores for orange and yellow pixels. Celik YC_bC_r and Celik $L^*a^*b^*$ methods obtain high scores for orange pixels. Rossi

method is efficient for fire pixels without smoke and particularly for orange pixels.

The proposed methods perform equally well on different categories and gives comparable results. The logistic regression method using rules as features is the overall best performing method. It gives the best results for nine categories of pixels and get high scores for the others. It is indeed robust to smoke and color changes.

6 Conclusion

In this paper, twenty nine rules of the literature were presented and two new rules were introduced for wildland fire color pixel detection. A dataset of five hundred fire images is used to compare these rules. More than two hundred thirty seven millions of fire pixels are classified according to their color and to the presence of smoke and more than seven hundred seventy five millions of background pixels are classified according to their luminosity. This categorization is used to show the specific effect of rules on the different types of pixels. The analysis of the performances showed the efficiency of the rules of Phillips *et al.* , Rossi *et al.* and the new proposed rules. Two different ways to combine the rules for fire pixels detection were also proposed. One of the new methods introduced here uses a machine learning technique involving logistic regression. This method obtains the overall best performance compared to all the state of the art benchmarked techniques. It is also robust to color changes and the presence of smoke. The obtained results are promising and show the possibility of developing more robust fire detection techniques in unstructured environments.

Table 3 Scores of fire segmentation methods with the same weight for fire and non fire pixels

			Phillips 2002 [19]	Chen 2004 [6]	Horng 2005 [13]	Celik RGB 2007 [3]	Ko 2009 [14]	Celik YC_bC_r 2009 [2]	Celik $L^*a^*b^*$ 2010 [1]	Chen 2010 [5]	Rossi 2010 [21]	Majority Voting	Logistic Regression
Red	Smoke	Low	0.95	0.80	0.87	0.81	0.39	0.56	0.00	0.88	0.79	0.93	0.97
		Medium	0.92	0.78	0.78	0.79	0.37	0.56	0.00	0.85	0.78	0.88	0.92
		High	0.89	0.73	0.86	0.77	0.37	0.55	0.00	0.74	0.78	0.85	0.88
	No smoke	Low	0.93	0.85	0.89	0.83	0.82	0.50	0.10	0.85	0.87	0.93	0.97
		Medium	0.90	0.83	0.80	0.80	0.77	0.50	0.10	0.83	0.85	0.88	0.92
		High	0.87	0.78	0.87	0.78	0.78	0.49	0.10	0.72	0.86	0.86	0.88
Orange	Smoke	Low	0.98	0.98	0.90	0.97	0.66	0.89	0.86	1.00	0.90	0.98	0.98
		Medium	0.95	0.96	0.81	0.95	0.62	0.89	0.86	0.98	0.89	0.93	0.93
		High	0.92	0.91	0.89	0.93	0.62	0.87	0.84	0.86	0.89	0.90	0.89
	No smoke	Low	0.97	0.97	0.78	0.81	0.82	0.85	0.88	0.97	0.96	0.98	0.98
		Medium	0.94	0.95	0.69	0.79	0.78	0.85	0.88	0.95	0.94	0.92	0.93
		High	0.91	0.90	0.76	0.77	0.78	0.84	0.86	0.84	0.95	0.90	0.89
Yellow	Smoke	Low	0.87	0.94	0.78	0.59	0.09	0.78	0.20	0.94	0.52	0.96	0.98
		Medium	0.85	0.92	0.69	0.57	0.09	0.77	0.20	0.92	0.51	0.91	0.93
		High	0.81	0.86	0.76	0.56	0.09	0.76	0.20	0.80	0.51	0.88	0.89
	No smoke	Low	0.97	0.98	0.58	0.25	0.14	0.92	0.47	0.98	0.88	0.97	0.97
		Medium	0.95	0.96	0.50	0.24	0.13	0.92	0.47	0.96	0.86	0.92	0.92
		High	0.91	0.91	0.56	0.24	0.13	0.90	0.46	0.84	0.87	0.89	0.88
All			0.91	0.88	0.78	0.79	0.68	0.76	0.67	0.86	0.88	0.90	0.91

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