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Computer Vision Based Fire Detection in Color Images

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***Abstract*—In this paper, a generic rule-based color model is proposed for fire pixel detection. The proposed algorithm exploits the *YCbCr* color space to separate the luminance from the chrominance for effectively addressing the issue of illumination variations. A set of rules defined on the *Y*, *Cb* and *Cr* color components together with the developed chrominance model on the *Cb*-*Cr* color plane are used to detect the fire pixels in color images. The performance evaluation of the developed color model and rules was conducted on a set of color images, which consists of fire, non-fire and fire-like regions. The proposed rule-based color model achieves up to 99% correct fire detection rate with 31.5% false-alarm rate. The results are compared with two other color models and show higher correct detection rate and lower false-alarm rate.**

I. Introduction

Fire detection systems are among of the most important components in surveillance systems exploited to monitor buildings and environment as part of an early-warning mechanism. Currently, almost all the fire detection systems are equipped with built-in sensors. However, such sensor-based fire detection system is impractical to cover large outdoor areas (e.g., forest) due to the requirement of regular distribution of sensors in close proximity. Computer-vision-based systems which utilize digital camera technology and image/video processing techniques play a very promising role to effectively augment or even replace conventional fire detection systems. In general, a computer-vision-based fire detection system employs three major stages: (1) moving object segmentation, (2) fire pixel detection, and (3) analysis of the candidate regions containing fire pixels detected in the first two stages.

The entire fire detection performance critically depends on the performance of its second stage, the fire pixel detector. There exist few algorithms which directly deal with the fire pixel detection worthwhile to be mentioned as follows. Krüll *et al*. [1] used low-cost CCD cameras along with other sensors to detect fires in the cargo bay of long-range passenger aircraft. The method conducts statistical measurements based on the gray-level pixel intensity of video frames, including the mean, standard deviation and higher-order moments, along with non-image features such as humidity and temperature to detect fire in the cargo compartment. The system is commercially deployed in parallel to standard smoke detectors to reduce the false alarms caused by the smoke detectors acting alone. However, the statistical image features are not considered to be used as a stand-alone fire detection system.

Most of the works on fire pixel detection in color video sequences are *rule-based*. Chen *et al*. [2] developed a set of rules over the *RGB* color space to detect the fire pixels. Instead of using the rule-based color model as in [2], Toreyin *et al*. [3] used a mixture of Gaussian distributions which are obtained from a training set of fire pixels represented in the *RGB* color space. Marbach *et al*. [4] exploits a rule-based color model in the *YUV* color space for the representation of fire in video data, and motion detection on the *Y* channel to detect the candidate fire pixels. The detected pixels are then verified based on their chrominance information *U* and *V* to determine whether the candidate pixels are the fire pixels or not. Horng *et al*. [5] developed an HSI-based color model to segment the fire-like regions for brighter and darker environments. Their fixed threshold method achieves 96.94% detection rate.

It is expected that a large amount illumination variations is quite likely incurred during the incidence of fire. Thus, how to alleviate such illumination variations is crucial to the performance of the computer vision system. For that, Celik *et al*. [6] used *normalized RGB* (*rgb*) values for building a generic color model for the detection of fire pixels. The generic model is obtained through statistical analysis, carried out in the *r*-*g*, *r*-*b*, and *g*-*b* planes. Due to the distribution of the sample fire pixels in each plane, three straight lines are used to specify a triangular region representing the region of interest for the fire pixels. That is, the triangular regions with each identified in the *r*-*g*, *r*-*b*, and *g*-*b* planes, respectively, are used to detect the fire pixels. This approach shows appreciate performance improvement compared with that of the *RGB*-based color model.

It has been further noticed that the chrominance information does not suffer from the illumination changes. By taking this fact as an advantage, it would be more reliable to establish the color model for the fire-pixel detection on the chrominance domain, rather than a mixture of illuminance and chrominance, such as *RGB* or *rgb*. For that, the *YCbCr* color space is considered in this paper for the establishment of a rule-based color model. In addition, the straight lines as above-mentioned can have a better approximation through least-squared fitted polynomials.

The paper is organized as follows. Section II describes the proposed fire pixel detection method. Section III provides experimental results of the proposed approach and comparisons with existing methods. Section IV concludes the paper.

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

Fig. 1. A demonstration of a *RGB*-recorded color image containing a fire incident and its component images represented in the *YCbCr* color space after color-space conversion: (a) original *RGB* image, (b) *Y*-channel image, (c) *Cb*-channel image, and (d) *Cr*-channel image.

II. Fire Pixel Detection

In this paper we continue to adopt *rule-based* color model approach due to its simplicity and effectiveness. For that, the color space *YCbCr* is chosen to de-correlate the luminance and chrominance for combatting illumination variations as explained in the previous section.

Given a *RGB*-represented image, it is converted into *YCbCr*-represented color image using the standard *RGB*-to-*YCbCr* conversion formula [8]. For a demonstration, see Fig. 1. The mean values of the three components *Y*, *Cb*, and *Cr*, denoted by $\hat{Y}, \hat{Cb}$, and $\hat{Cr}$, respectively, are computed as follows:

$$\begin{aligned}\hat{Y} &= \frac{1}{M\times N}\sum_{x=1}^{M}\sum_{y=1}^{N}Y(x,y),\\ \hat{Cb} &= \frac{1}{M\times N}\sum_{x=1}^{M}\sum_{y=1}^{N}Cb(x,y),\\ \hat{Cr} &= \frac{1}{M\times N}\sum_{x=1}^{M}\sum_{y=1}^{N}Cr(x,y),\end{aligned} \tag{1}$$

where (x, y) denotes the spatial location of pixels, and $M \times N$ is the total number of pixels in the given image.

Due to the color nature of fire, the fire pixel consistently saturates in its red (*R*) channel. Based on this consequence and verified by a statistical observation of a large number of test images, the following two rules can be established for detecting a fire pixel at the spatial location (x, y):

$$R_1(x,y) = \begin{cases}1, & \text{if } Y(x,y) \geq Cb(x,y);\\ 0, & \text{otherwise.}\end{cases} \tag{2}$$

and

$$R_2(x,y) = \begin{cases}1, & \text{if } Cr(x,y) \geq Cb(x,y);\\ 0, & \text{otherwise.}\end{cases} \tag{3}$$

Note that by applying each rule to each pixel location of the image, the corresponding binary mask resulted from that particular rule can be produced. Furthermore, since the fire region is generally the brightest region in the observed scene, the mean values of the three channels, $\hat{Y}$, $\hat{Cb}$ and $\hat{Cr}$ as defined in (2), contain valuable information for the formulation of the following rule:

$$R_3(x,y) = \begin{cases}1, & \text{if } (Y(x,y) \geq \hat{Y}) \cap (Cb(x,y) \leq \hat{Cb})\\ & \cap\ (Cr(x,y) \geq \hat{Cr});\\ 0, & \text{otherwise.}\end{cases} \tag{4}$$

This rule has been verified through extensive observation of a large number of test images with each containing fire event. It has been observed that the value of the *Y* component in the fire region is bigger than the mean *Y* component $(\hat{Y})$ of the overall image, while the value of *Cb* component is, in general, smaller than the mean *Cb* value $(\hat{Cb})$ of the overall image. Furthermore, the *Cr* component of the fire pixel is bigger than the mean *Cr* component $(\hat{Cr})$. To appreciate this trend, one can refer to Fig. 1 for a demonstration.

It can easily be observed from Fig. 1(c) and Fig. 1(d) that there is a significant difference between the *Cb* and *Cr* components of the fire pixels. For the fire pixel the *Cb* component is predominantly "black" (lower intensity) while the *Cr* component, on the other hand, is predominantly "white" (higher intensity). This fact can now be translated into another rule; that is,

$$R_4(x,y) = \begin{cases}1, & \text{if } |Cb(x,y) - Cr(x,y)| \geq \tau;\\ 0, & \text{otherwise.}\end{cases} \tag{5}$$

where the value of threshold τ can be reliably determined according to a *receiver operating characteristics* (ROC) curve. The ROC curve is obtained by experimenting different values of τ (ranging from 1 to 100) over 1,000 color images. First, the fire-pixel regions are manually segmented from each color image. The rules (2) through (5) (at a chosen value of τ) are then applied to the manually-segmented fire regions. For each different value of τ, the corresponding true positive (i.e., correct-detection) and false positive (i.e., false-alarm) rates are computed and recorded. The *correct detection* is defined as the same decision when an image indeed contains a fire incident, while the *false alarm* is defined as incorrect decision when an image contains no fire but mis-detected as having fire. With

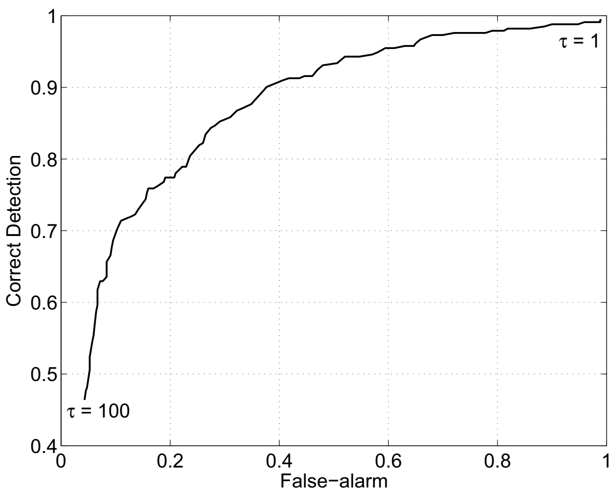


Fig. 2. The *receiver operating characteristics* (ROC) curve for determining the desired value of τ to be used in the Rule R_5.

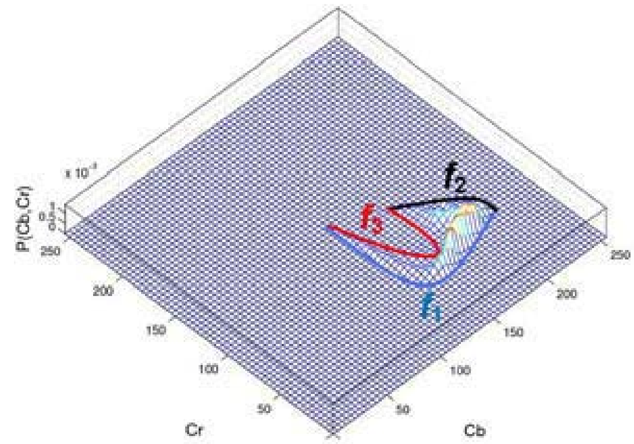


Fig. 3. A manually-labeled fire-pixel region, bounded by three polynomial curves, $f_1(Cr)$, $f_2(Cr)$ and $f_3(Cr)$, presented in the *Cb-Cr* color plane.

Color Model	Correct Detection (%)	False Alarm (%)
Chen *et al.* [2]	93.90	66.42
Celik *et al.* [6]	97.00	58.39
Proposed	99.00	31.50

TABLE I
PERFORMANCE EVALUATION AND COMPARISONS.

the established ROC curve, the value of τ is picked such that the correct-detection rate is over 90% and the false-alarm rate is less than 40% (see Fig. 2).

In addition to the above-established rules, a statistical analysis of the chrominance information in fire pixels over a larger set of images is performed. For this purpose, a set of 1,000 images, containing fire at different resolutions are collected from the Internet. The collected set of images has a wide range of illumination and camera effects. The fire regions in the 1,000 images are manually segmented, and the histogram of a total of 16,309,070 pixels is created in the *Cb-Cr* chrominance plane. Fig. 3 shows the distribution of the fire pixels in the *Cb-Cr* plane. The area containing fire pixels in the *Cb-Cr* plane can be modeled using intersections of three polynomials depicted as different colored curves in Fig. 3. The equations for the polynomials are derived using the least-squares estimation technique and formulated as follows:

$$\begin{aligned}
f_1(Cr) &= -2.62\times10^{-10}Cr^7+3.27\times10^{-7}Cr^6\\
&\quad -1.75\times10^{-4}Cr^5+5.16\times10^{-2}Cr^4\\
&\quad -9.10Cr^3-5.60\times10^{4}Cr+1.40\times10^{6}\\
f_2(Cr) &= -6.77\times10^{-8}Cr^5+5.50\times10^{-5}Cr^4\\
&\quad -1.76\times10^{-2}Cr^3+2.78Cr^2\\
&\quad -2.15\times10^{2}Cr+6.62\times10^{3}\\
f_3(Cr) &= 1.80\times10^{-4}Cr^4-1.02\times10^{-1}Cr^3\\
&\quad +21.66Cr^2-2.05\times10^{3}Cr+7.29\times10^{4}
\end{aligned} \tag{6}$$

Once the fire region defined by the three polynomials as shown in Fig. 3, another rule for classifying the fire pixel using chrominance information only can be defined as follows:

$$R_5(x,y)=\begin{cases}1, & \text{if } (Cb(x,y)\geq f_1(Cr(x,y)))\\ & \cap\,(Cb(x,y)\leq f_3(Cr(x,y)))\\ & \cap\,(Cb(x,y)\leq f2(Cr(x,y)));\\ 0, & \text{otherwise.}\end{cases} \tag{7}$$

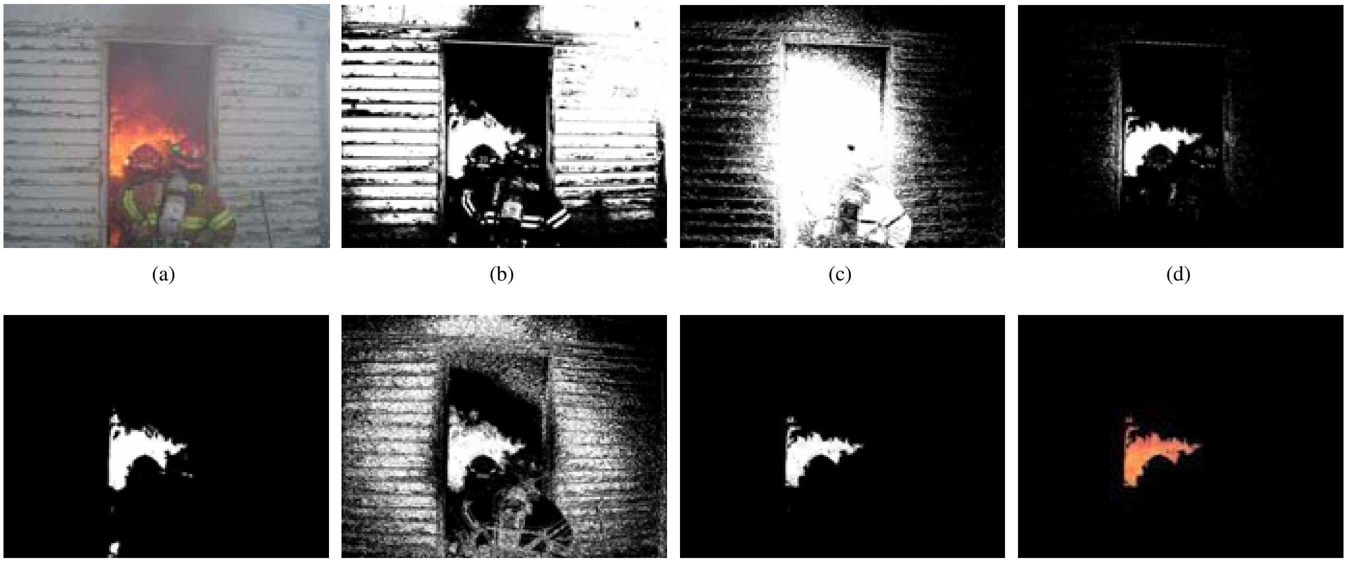
With the derived set of rules in the $YCbCr$ color space given in equations (2) through (5) and (7), one can detect whether a given pixel is a fire pixel or not. The overall segmentation process is illustrated in Fig. 4 in a step by step manner by applying all developed rules.

III. SIMULATIONS

Performance analysis is carried out by using a set of 751 color images of different sizes; they are totally different from the set used in creating color model for fire pixel detection. The set consists of 332 images which contain fire, and the rest is a collection of images which do not contain any fire. It should be noted that this set may contain fire-like objects such as the sun, red rose, etc.

The performance of the proposed fire pixel detection model is compared with the ones introduced in [2] and [6], as tabulated in Table I. The model developed by Chen *et al.* [2] uses raw *RGB* values to set up the rules. On the other hand, the model proposed by Celik *et al.* [6] exploits *rgb* (i.e., *normalized RGB*) values for the establishment of its corresponding rules. It is clear to see that the proposed model outperforms both color models in terms of higher correct fire detection rate and lower false-alarm rate.

The performance improvement is expected since the $YCbCr$ color space has the ability of discriminating luminance from chrominance information. Since the chrominance dominantly represents information without being affected by luminance, the *chrominance*-based rules and the color model defined in the chrominance plane are more reliable or robust for fire detection.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 4. Fire segmentation results of a still color image, as shown in (a), by applying different rules, one at a time, followed by a combination of all developed rules: (b) R_1 only (i.e., (2)), (c) R_2 only (i.e., (3)), (d) R_3 only (i.e., (4)), (e) R_4 only (i.e., (5)), (f) R_5 only (i.e., (7)), (g) all five rules via AND logic operation (i.e., (2)-(5) and (7)), and (h) the final segmented color image of the detected fire region — masked from the original image as shown in (a) by using the binary mask as generated in (g).

We have demonstrated fire region segmentation using four different video sequences obtained from the Wildland Fire Operations Research Group, Canada [7]. The sequences consist of different views of forest fire scenes recorded from a helicopter. The segmented fire regions using the proposed generic color model are shown in Fig. 5. Each video sequence consists of frames recorded consecutively. The color model developed in this paper is applied to each frame of video sequences. Each frame and its corresponding binary map (fire regions are shown in white) showing fire pixels is shown in Fig. 5, from which it is clear that proposed color model robustly detects fire regions in the given video sequences.

IV. Conclusion

In this paper, a generic color model for fire pixel detection is proposed. The proposed color model uses the *YCbCr* color space, which is better in discriminating the luminance from the chrominance, hence is more robust to the illumination changes than *RGB* or *rgb* color spaces. The proposed color model achieves 99.0% fire detection rate and 31.5% false alarm rate. The results are compared with two other rule-based methods and demonstrate superior performance in terms of higher correct fire detection rate and lower false alarm rate.

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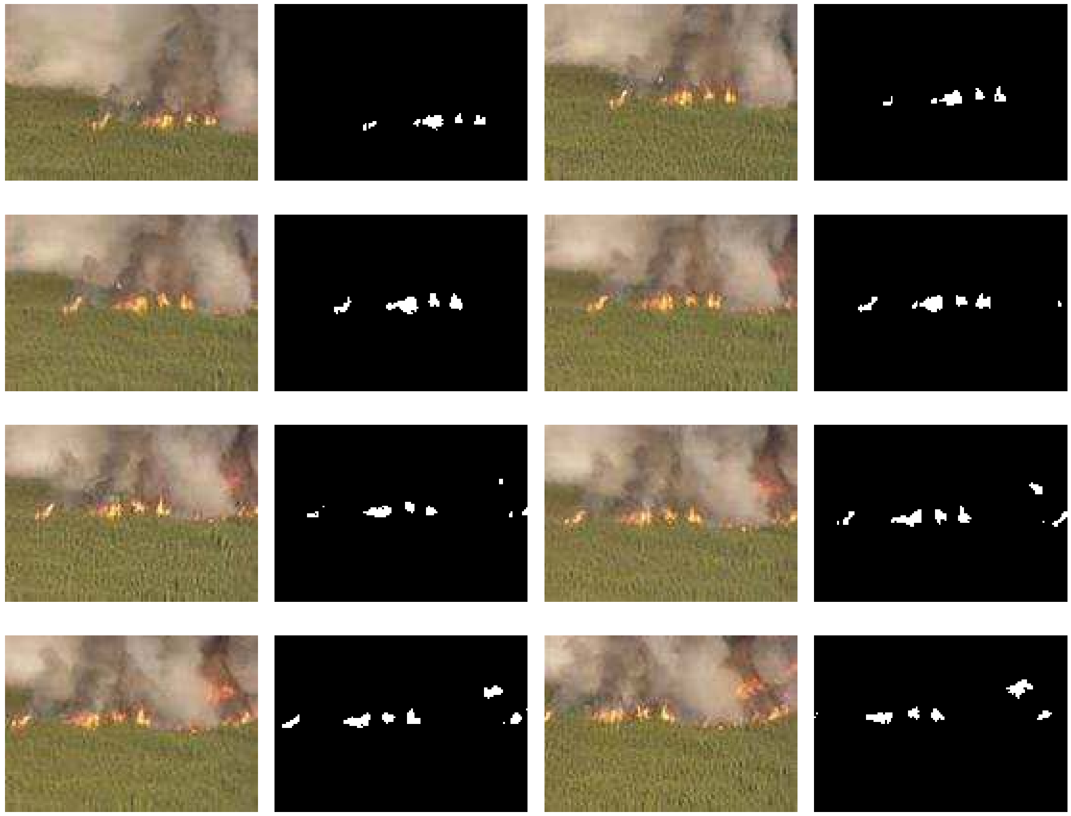
(a)

(b)



(c)

(d)

Fig. 5. Demonstrations of fire pixel detection and segmented fire regions using our proposed color model and rules in four different video sequences obtained from [7].