Vision-Statistical Characteristics of Fire and Spatial-Temporal Changes based on Fire Detection using Probabilistic Model

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ABSTRACT

Automated fire detection is an active research topic in computer vision. In this paper, it proposes vision based approach for identifying fire in videos. Computer vision-based fire detection algorithms are usually applied in closed-circuit television surveillance scenarios with controlled background. This method can be applied not only to surveillance but also to automatic video classification for retrieval of fire catastrophes in databases of newscast content. In the latter case, there are large variations in fire and background characteristics depending on the video instance. This method analyzes the frame-to-frame changes of specific low-level features describing potential fire regions. These features are color, area size, surface coarseness, boundary roughness, and skewness within estimated fire regions. Because of flickering and random characteristics of fire, these features are powerful discriminants. The behavioral change of each one of these features is evaluated, and the results are then combined according to the Bayes classifier for robust fire recognition. A priori knowledge of fire events captured in videos is used to significantly improve the classification results. In this paper, the spatial temporal feature based from selecting methods to reduce the computation time.

Keywords
Fire detection, Pattern recognition, potential fire mask, temporal changes.

1. INTRODUCTION

Automated retrieval of events in newscast videos has received great attention by the research community in the last decade. This has been mainly motivated by the interest of broadcasters in building large digital archives of structured assets ready for search, retrieval, and reuse. A significant amount of time and money is spent by news networks to find in their archives events related to newly occurred event. In this context, catastrophe-related news is one of the most common topics that require automated retrieval, which require faster than real-time analysis. In this paper, it propose an efficient vision-based event detection method for identifying fire in videos. Most vision-based fire detection techniques proposed in the literature target surveillance applications with static cameras and consequently reasonably controlled or static background. Otherwise, they propose the use of filter banks [1], frequency transforms [2], and motion tracking, requiring more computational processing time, making them unsuitable for video retrieval. In the catastrophe news scope, fire events are one of the most common topics, along with bombings and floods [8]. Efficient detection of fire in video contents has proved to be an important research topic in the last few years [7].

This method is very efficient and robust when applied to detect fire catastrophes in news content. The proposed method analyses the frame-to-frame changes of specific low-level features describing potential fire regions. Five features, namely color, area size, region coarseness, boundary roughness and skewness within estimated fire regions, are used as low-level descriptors. Because of flickering and random characteristics of fire due the combustion and air flow, these are efficient classifying features.

The goal of this paper is not to identify fire pixels in a given image or video frame, but to determine if fire occurs in the frame. The goal is generic event detection for automatic classification, annotation and retrieval.

The majority of the vision-based fire detection systems employ some type of hybrid model combining color, geometry and motion information. In general, fire detection systems use color clues as a precondition to generate seed areas for possible fire regions [called a “potential fire mask” (PFM)] since color is the most discerning feature. An effective color model for potential fire pixel determination is thus essential for almost any vision-based fire detection system.

2. RELATED WORK

Inside the vision-based scope, the first works used purely a color-based model [3], which is the initial step for many other algorithms.

Another method [4] uses pixel colors and their temporal variations. They use an approach that is based upon creating a Gaussian-smoothed color histogram to determine the fire colored pixels, and then using the temporal variation of pixels to determine which of these pixels are actually fire. However, this algorithm is also essentially color based, and does not exploit other statistical characteristics of potential fire regions. In addition, temporal variation in image pixel color does not capture the temporal property of fire which is more complex and benefits from a region level representation. As observed in [2], for example, pixels in the core of the fire exhibit less temporal variation than the other pixels.

Another algorithm [6] 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.

3. STATISTICAL CHARACTERISTICS OF FIRE

It is well known that fire has unique visual signatures. Color, geometry, and motion of fire region are all essential features for efficient classification. In general, in addition to color, a region that corresponds to fire can be captured in terms of the spatial structure defined by the boundary variation within the region. The shape of a fire region often keeps changing and exhibits a stochastic motion, which depends on surrounding environmental factors such as the type of burning elements and wind.

Based on these factors, in the following it propose several useful features for detecting fire:

- color
- randomness of fire area size
- fire boundary roughness
- surface coarseness
- skewness

A. Color

According to most fire detection that fire has very distinct color characteristics, and although empirical, it is the most powerful single feature for finding fire in video sequences. Based on tests with several images in different resolutions and scenarios, it is reasonable to assume that generally the color of flames belongs to the red-yellow range Other types of flames, such as blue liquefied petroleum gas flames, are not considered since they do not represent the typical flame seen in a surveillance or catastrophe scene. For the type of flames considered (hydrocarbon flames), it is noticed that for a given fire pixel, the value of red channel is greater than the green channel, and the value of the green channel is greater than the value of blue channel.

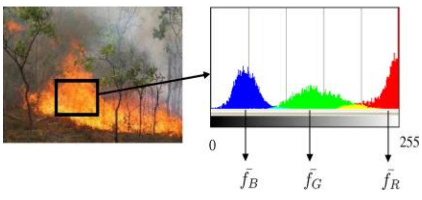

Fig. 1. Histogram of a fire region inside the black square, for the red, green, and blue channels.

Color detection metric is used to generate the PFM, which will then be further analyzed with the other non-color fire features.

Proposed Color Based Detection Metric*:*

Let a fire pixel at position (*m*,*n*) in an image be represented by **f**(*m*,*n*), where

$$f(m,n) = \begin{pmatrix} f_R(m,n) \\ f_G(m,n) \\ f_B(m,n) \end{pmatrix} \quad (1)$$

\and f_R, f_G, and f_B are the red, green, and blue channels representation of f, respectively.

Let $\overline{f}_R$, $\overline{f}_G$ and $\overline{f}_B$ represent the sample average of the pixels in a fire image region, for the red, green, and blue channels.

Interpreting $\overline{f}_R$, $\overline{f}_G$ and $\overline{f}_B$ as random variables, it employ a Gaussian model for these variables, such

$$\overline{f}_R \sim N(\mu_{\overline{f}_R}, \sigma^2_{\overline{f}_R}) \quad (2)$$

$$\overline{f}_G \sim N(\mu_{\overline{f}_G}, \sigma^2_{\overline{f}_G}) \quad (3)$$

$$\overline{f}_B \sim N(\mu_{\overline{f}_B}, \sigma^2_{\overline{f}_B}) \quad (4)$$

Notice that a distinction should be made between the distribution of the pixels in $\overline{f}_R$ and the distribution of $\overline{f}_R$, i.e., the distribution of the sample average of the pixels in f_R. The same is valid for $\overline{f}_G$, and $\overline{f}_B$. With these assumptions, let us define

$$D_{C_R} = p_{\overline{f}_R}(\overline{f}_{R_{obs}}) / p_{\overline{f}_R}(\mu_{\overline{f}_R}) \quad (5)$$

$$D_{C_G} = p_{\overline{f}_G}(\overline{f}_{G_{obs}}) / p_{\overline{f}_G}(\mu_{\overline{f}_G}) \quad (6)$$

$$D_{C_B} = p_{\overline{f}_B}(\overline{f}_{B_{obs}}) / p_{\overline{f}_B}(\mu_{\overline{f}_B}) \quad (7)$$

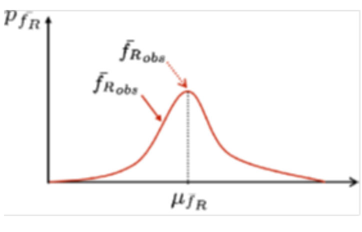

Fig. 2. Graphical representation of the parameters, Maximum confidence is obtained when $\overline{f}_{R_{obs}} = \mu \overline{f}_R$

Where $p_x = (x_0)$ represents the evaluation of the probability density function (PDF) of a random variable x at value x_0 . In this case, $\overline{f}_{R_{obs}}$ represents the average value in the red channel of an observed set of pixels. Fig.2 illustrates that the maximum value for D_{C_R} is obtained when $\overline{f}_{R_{obs}} = \mu \overline{f}_R$.

D_{C_R} can be normalized metric that indicates the probability that a given region represents fire according to the red channel distribution. $\overline{f}_{R_{obs}}$ is very close to $\mu \overline{f}_R$, D_{C_R} is very close to 1 and it assume with probability D_{C_R} that the observed region represents a fire region (considering the red channel only). To extend this to the three color channels, in the following it employ D_{C_R}, D_{C_G}, and D_{C_B}.

The detection metric D_C to indicate whether the observed region represents fire is given as

$$D_C = D_{C_R} + D_{C_G} + D_{C_B} - (D_{C_R} D_{C_G} + D_{C_R} D_{C_B} + D_{C_G} D_{C_B}) + D_{C_R} D_{C_B} D_{C_G} \tag{8}$$

If $\overline{f}_{R_{obs}}, \overline{f}_{G_{obs}}$, and $\overline{f}_{B_{obs}}$ can be assumed independent, DC can be interpreted as the degree of confidence—represented by a probability—that a set of pixels represents a fire region (based only on color analysis). If it assume that $\overline{f}_{R_{obs}}, \overline{f}_{G_{obs}}$, and $\overline{f}_{B_{obs}}$ are correlated, D_C is an approximation that depends on the correlation level. In practice, however, D_C yields meaningful results.

Based on the metric D_C a binary image PFM is generated for each frame, such that

$$PFM(m,n) = \begin{cases} 0, if.D_C(m,n) < \lambda c \\ 1, otherwise \end{cases} \tag{9}$$

where λ_C is a confidence threshold level and the values 1 or 0 indicate the presence of absence of fire at the corresponding location in the image f. The threshold λ_C is the same for all pixel locations.

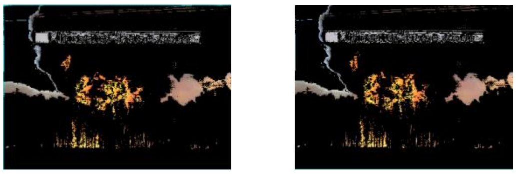

Fig. 3. Illustration of the change in fire pixel area from frame to frame.

The threshold λC should be very permissive and many non-fire regions may be included in the PFM. For this reason, additional analysis is necessary to further refine the results. To define a real burning fire, using chromatics, statistical and dynamic features are usually adopted to distinguish other fire [9].

B. Randomness of Area Size

For the estimated fire pixel area, because of the fire flickering, a change in the area size of the PFM occurs from frame to frame, as illustrated in Fig. 3. Non-fire areas have a less random change in the area size. The normalized area change Δ *Ai* for the *i*th frame is given by

$$\Delta A_i = \frac{|A_i - A_{i-1}|}{A_i} > \lambda_A \tag{10}$$

where *Ai* corresponds to the area of the fire blobs representing the potential fire regions in the PFM.

C. Boundary Roughness

It propose the use the boundary roughness of the potential fire region as a feature, given by the ratio between perimeter and convex hull perimeter. The convex hull of a set of pixels *S* is the smallest convex set containing *S*, as illustrated by the red curve in Fig. 4. The boundary roughness is given by

$$B_R = P_S/P_{CHs} \tag{11}$$

Where *PS* is the perimeter of *S* and *PCHS* is the perimeter of the convex hull of *S*.

Fig. 4. Illustration of the convex hull (red line) used to evaluate the boundary roughness of the blob.

D. Surface Coarseness

Unlike other false-alarm regions, like a yellow traffic sign, for example (Fig. 5), fire regions have a significant amount of variability in the pixel values. In the case of fire, however, it is very hard to describe its texture with any given model. The randomness observed in fire can vary significantly in frequency response (periodicity is often not present) and gradient angles, for example. Hence, it use the variance of the blobs as a feature to help eliminating non-fire blobs in the PFM. Therefore, fire is assumed if the blob has a variance $\sigma > \lambda\sigma$, where $\lambda\sigma$ is determined from a set of experimental analyses.

Fig. 5 illustrates how the use of the variance can reduce the false alarm rate of the PFM, for an illustrative threshold $\lambda = 50$.

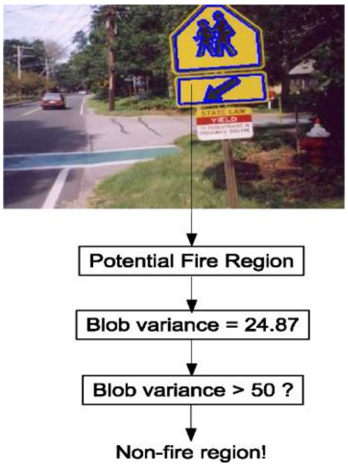

Fig. 5. Example of eliminating potential fire regions through variance analysis only.

E. Skewness

The skewness measures the degree of asymmetry of a distribution around its mean. It is zero when the distribution is symmetric, positive if the distribution shape is more spread to the right and negative if it is more spread to the left, as illustrated in Fig. 6. Fire regions have high pixel values for the green and especially for the red channel.. This causes the skewness of this distribution to have a high negative value. For this reason, it employ the skewness as an useful feature to identify fire regions. Let the sample skewness *γR* of the red channel be defined as

$$\gamma_R = \frac{\frac{1}{J^2}\sum_{m=1}^{J}\sum_{n=1}^{J}[f_R(m,n) - \overline{f}_R]^3}{\sigma_{f_R}^3} \quad (12)$$

where *J* is the number of pixels in the blob.

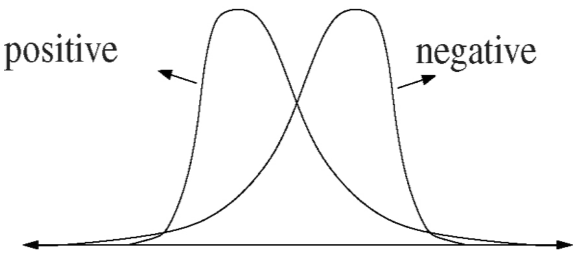

Fig. 6. Illustration of the effect of positive and negative skew ness on a distribution.

Classification

Stochastic interpretation of the features is considered. The Bayes classifier is employed to combine the features, although it is clear that different statistical classifiers could also be tested.

For each frame i, naive set of PFM s is initially created based on the set of rules for color. For each PFM, a vector d of features is obtained as

$$D = \begin{pmatrix} A \\ B_R \\ \sigma \\ \gamma_R \end{pmatrix} \quad (13)$$

The features used are the ones discussed in the previous section: area size change, boundary roughness, variance, and red channel skewness. The features are combined according to the Bayes classifier. In order to classify the class fire from the class non-fire, the Bayes classifier needs to estimate the mean and the variance of each class. Therefore, it requires a statistical “training,” based on observed values, to determine a decision function that separates the classes. Let b indicate a flag that represents one of the two possible classes: b = 1 represents the fire class and b = 0 represents the non-fire class.

4. FIRE DETECTION WITH TEMPORAL CHANGING PROPERTY

The fire detection is done with the help of potential fire mask. Based on the metric DC a binary image PFM is generated for each frame.

In order to deal with such changes, it compare [5] the current transition map with the transition map obtained 3 frames earlier and the dissimilarity measure between these maps is defined as

follows:

$$d(T_n, T_{n-3}) = \sum_{(x,y)\in T}(T_n(x,y) \otimes T_{n-3}(x,y)) \quad (14)$$

$$if\,(d(T_n, T_{n-3}) < th) TR_n = TR_{n-3}$$

Otherwise, find new TR_n Where T_n and T_{n-3} denote the potential fire mask obtained from the nth frame and the (n-3)th frame, respectively. TR_n and TR_{n-3} denote the detected overlay text regions in the nth frame and the (n-3)th frame respectively. $\otimes$ denotes the XOR operator. In other words, if the values on the nth frame and the (n-3)th frame potential fire mask are same, the result of $\otimes$ between two values is set to be 0. Otherwise, the result of $\otimes$ between two values is set to be 1.

Usually this process is done for each frame. Using this potential fire mask, it can find the correlation between the sequences of frames. With the help of this potential fire mask, the spatial temporal changes of the frames can be properly estimated.

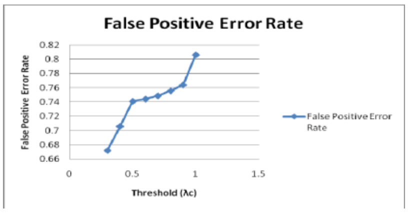

Fig.7. Plot of the theoretical false-positive error rate based only the color metric *DC*.

5. EXPERIMENTAL RESULTS

This experiment illustrates the applicability of the metric *DC*. Moreover, it shows an excellent correspondence between the error rate analysis and error rates from synthetic simulations. In Fig. 7, the theoretical false-positive error rate is plotted. In this figure, the points represent the experimental error rates from synthetic simulations, where no real video is analyzed. Notice that the error rate increases as the threshold approaches 1.

To find the temporal changes, it compare the current transition map with the transition map obtained 3 frames earlier. Usually this process is done for each frame. Using this potential fire mask, it can find the correlation between the sequences of frames. With the help of this potential fire mask, the spatial temporal changes of the frames can be properly estimated. Table.1 shows the computation time between the temporal changes of vision based approach.

Table.1 performance of fire detection in the mode of computation time.

Approaches	Computation time(sec)
Vision based approach	5.27
Vision based approach with temporal sequence	4.32

In the experimental results, the table shows that the vision based approach has the computation time 5.27 and the temporal changes have the computation time 4.32. Fig. 8 shows the analysis of fire detection.

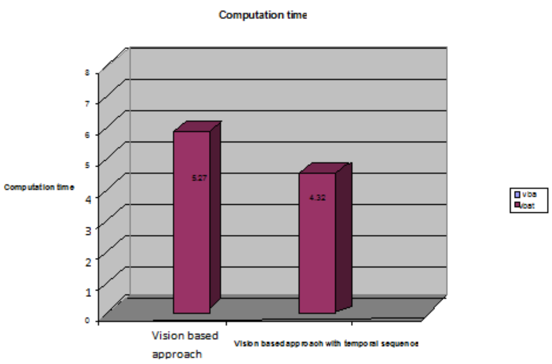

Fig.8. Analysis of fire detection.

From the above result it can find out that the approach with the temporal sequence analysis improves the computation time with the vision based all frame analysis process. The experiments illustrate the applicability of the method, with an average false-positive rate of 0.68%. The result shows that it detect the fire in the threshold value of 0.98.

Fig.9 Fire detection in various frames

6. CONCLUSION

It has proposed a new detection metric based on color for fire detection in videos. In addition, it has exploited important visual features of fire, like boundary roughness and skewness of the fire pixel distribution. The skewness, in particular, is a very useful descriptor because of the frequent occurrence of saturation in the red channel of fire regions. Also, it has proposed modifications to motion based features. For newscast videos, it models the probability of occurrence of fire as a function of the position, yielding an efficient performance. In contrast to other methods which extract complicated features, the features allow very fast processing, making the system applicable not only for real time fire detection, but also for video retrieval in news contents, which require faster than real-time analysis. Using this potential fire mask, it can find the correlation between the sequences of frames. With the help of this potential fire mask, the spatial temporal changes of the frames can be properly estimated.

7. FUTURE ENHANCEMENT

Future work will be detected and extract the smoke detection to extend the algorithm for more advanced and intelligent applications. Further work includes using a Markovian approach to formalize the feature dependence between adjacent frames and how the features evolve in time.

8. ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their comments that helped to improve the presentation of the paper.

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