A New Approach to Vision-Based Fire Detection Using Statistical Features and Bayes Classifier

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Abstract. Computer vision - based fire detection has recently attracted a great deal of attention from the research community. In this paper, the authors propose and analyse a new approach for identifying fire in videos. In this approach, we propose a combined algorithm for detecting the fire in videos based on the changes of the statistical features in the fire regions between different frames. The statistical features consist of the average of the red, green and blue channel, the coarseness and the skewness of the red channel distribution. These features are evaluated, and then classified by Bayes classifier, and the final result is defined as fire-alarm rate for each frame. Experimental results demonstrate the effectiveness and robustness of the proposed method.

Keywords: Fire detection, Pattern recognition, Bayes classification.

1 Introduction

Two main applications of vision-based fire detection are: (1) monitoring fires and burn disasters from surveillance systems [1], and (2) automated retrieval of events in newscast videos [2]. These applications play an important role in modern society. Recently, there have been a number of efficient methods proposed for vision-based fire detection in [1]-[6].

In [1], Chao-Ching Ho analysed the spectral, spatial and temporal characteristics of the flame and smoke regions in the image sequences. Then, the continuously adaptive mean shift vision tracking algorithm was employed to provide feedback of the flame and smoke real-time position at a high frame rate. P. V. K. Borges and E. Izquierdo, in [2], analysed the frame-to-frame changes of specific low-level features such as color, area size, surface coarseness, boundary roughness, and skewness within estimated fire regions to describe potential fire regions and used Bayes classifier to indicate a frame contains fire or not. In [3], Celik T. et al. developed two models, one for fire detection and the other for smoke detection. For fire detection, the concepts from fuzzy logic were used to make the classification fire and fire-like coloured objects. For smoke detection, a statistical analysis was carried out using the idea that the smoke shows grayish colour with different illumination. In [4], the authors also used a probabilistic metric

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to threshold potential fire pixels. This was achieved by multiplying the probabilities of each individual color channel being fire. Habiboglu et al. proposed a video-based fire detection method, in [6], which used color, spatial and temporal information by dividing the video into spatio-temporal blocks and used covariance-based features extracted from these blocks to detect fire. However, when the flickering behaviour of flames cannot be visible in video, the method might perform poorly.

The majority of the vision-based fire detection methods employ some type of hybrid model combining color, geometry and motion features. In general, fire detection systems first use some key features as a precondition to generate seed areas for candidate fire regions, then use the other features to determine the existence of fire in candidate fire regions. In most existing approaches, the color information and their derived descriptors like area size, surface coarseness, boundary roughness and skewness were mainly used for classification features [2]. However, using the color channels are not reliable enough to perform classification. Similarly, the classifying tasks based on the features derived from the color information can not perform properly.

In contrast to some works, we propose a new approach to solve the problem of fire detection by determining motion region, then this region is used to establish a vector of fire features. Bayes classifier uses the vector to indicate the motion region is contained fire or not. The number of detected fire regions in a frame is used to compute fire-alarm rate of the frame. The rest of this paper is organized as follows: Section 2 analyses some significations of fire in a region, these significations are motion (Section 2.1), color (Section 2.2), red channel distribution skewness (Section 2.3) and surface coarseness (Section 2.4); Section 3 presents a fire detection algorithm, it includes a brief review of Bayes classifier (Section 3.1) and a description of algorithm (Section 3.2); Section 4 presents some experimental results, followed by a relevant conclusion in Section 5.

2 Statistical Features of Fire Regions

Intuitively, fire has some unique visual signatures such as color, geometry, and motion. Some proposed methods use these characteristics as interdependent parameters, for example, area size, boundary roughness, coarseness, skewness in [2] depended on definition of color. In this proposal, the authors evaluate these visual signatures of fire as independent features. A potential fire region is determined as a motion region. The statistical features in potential fire region include color, skewness of red channel histogram, and surface coarseness.

2.1 Motion

In order to detect possible changes, which may be caused by fire, this proposal estimates the change of regions by regions. Formally, we assume F_{t1} is frame at $t1$, and F_{t2} is frame at $t2 = t1 + \Delta t$. The motion of fire leads to the changes of intensity in some pixels between F_{t1} and F_{t2}. This work determines the difference between F_{t1} and F_{t2} as follow:

1. Divide F_{t1} and F_{t2} into $N \times M$ grid, where N is number of rows and M is number of columns, Fig. 1 is an example;
2. Compute the correlation coefficient between a region on the grid of F_{t1} and corresponding region on the grid of F_{t2};
3. Decide the region on F_{t2} is a motion region if the correlation coefficient is less than or equal to a pre-defined threshold T.

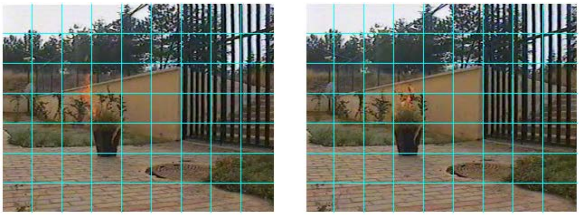

Fig. 1. F_{t1} and F_{t2} are divided into $N \times M$ grid

Let W, H be the width and height of F_{t1} and F_{t2}, divide F_{t1} and F_{t2} into $N \times M$ grid, where N is number of rows and M is number of columns. Then each region of the grid has size of $D_W = W/M$ in width and $D_H = H/N$ in height. Denote A_{kl}, B_{kl} as regions at k-th row and l-th column ($k = 1, 2, .., N, l = 1, 2, .., M$) on the grids of F_{t1} and F_{t2} respectively. The correlation coefficient between A_{kl} and B_{kl} is defined as

$$CC_{kl} = \frac{\sum_{i=1}^{D_H} \sum_{j=1}^{D_W} A_{kl}(i,j) \times B_{kl}(i,j)}{\sqrt{\sum_{i=1}^{D_H} \sum_{j=1}^{D_W} A_{kl}(i,j)^2} \times \sqrt{\sum_{i=1}^{D_H} \sum_{j=1}^{D_W} B_{kl}(i,j)^2}}. \tag{1}$$

The region B_{kl} on F_{t2} is considered as motion region if:

$$CC_{kl} \leq T \tag{2}$$

where T is a decision threshold. Each region satisfied Eq. (2) is a potential region for next step.

2.2 Color

As other works in the field of fire detection, this paper concerns only on the color of flames belongs to the red-yellow range, which are the most common type of flames seen in the nature. Other types of flames, such as blue liquefied petroleum gas flames, are not considered in this paper. For the type of flames considered, most papers presented in the fire detection literature assumed 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. However, laboratory experiments show that above assumption ignores some pixel in fire

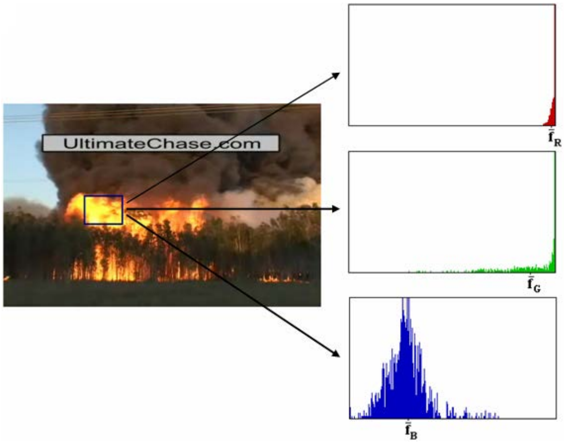

Fig. 2. Histogram and average value of red, green, and blue channels in a fire region

blobs, then any features extracted from potential fire blobs may be unreliable. To overcome that difficulty, this proposal considers the average value of each channel in a region instead of themselves. For example in Fig. 2, average value of red is greater than the average value of green and the average value of green greater than average value of blue channel.

The average value of red, green, and blue channels in a fire region are computed as

$$\bar{f}_R = \frac{1}{D_H \times D_W} \sum_{i=1}^{D_H} \sum_{j=1}^{D_W} B_{kl}^R(i,j), \tag{3}$$

$$\bar{f}_G = \frac{1}{D_H \times D_W} \sum_{i=1}^{D_H} \sum_{j=1}^{D_W} B_{kl}^G(i,j), \tag{4}$$

and

$$\bar{f}_B = \frac{1}{D_H \times D_W} \sum_{i=1}^{D_H} \sum_{j=1}^{D_W} B_{kl}^B(i,j), \tag{5}$$

where $B_{kl}^R(i,j)$, $B_{kl}^G(i,j)$, and $B_{kl}^B(i,j)$ are the red, green, and blue channels representation of $B_{kl}(i,j)$, respectively. This proposal use $\bar{f}_R$, $\bar{f}_G$, and $\bar{f}_B$ as three features of a potential region for classification in Section 3.

2.3 Skewness

Denote $p_R(v)$ as normalized histogram of red channel in a region, v is a intensity, then $p_R(v)$ gives the estimate of the probability of occurrence of intensity v. In this case, the third moment of $p_R(v)$ measures its symmetry with respect to the mean, it is also called the skewness (see [7], [8]). The skewness 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. 3. This causes the skewness of red channel distribution to have a negative value. For this reason, the skewness is used as an useful feature to identify fire regions.

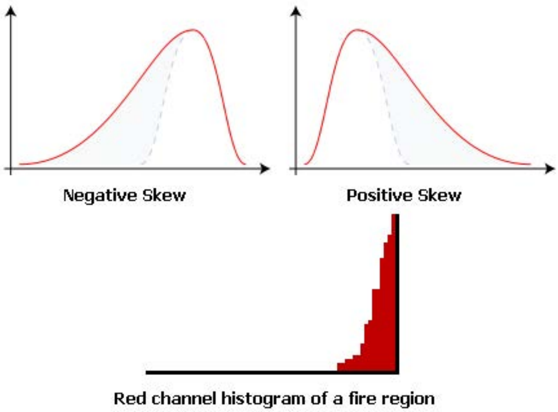

Fig. 3. Illustration of negative, positive skew and red channel histogram of a fire region

Denote s_R as the skewness of the red channel distribution of candidate region B_{kl}, it is defined as

$$s_R = \frac{\frac{1}{D_H \times D_W} \sum_{i=1}^{D_H} \sum_{j=1}^{D_W} (B_{kl}^R(i,j) - \bar{f}_R)^3}{\sigma_{f_R}^3} \tag{6}$$

where σ_{f_R} is the standard deviation of $p_R(v)$. This proposal uses s_R as one feature of a candidate region for classification in Section 3.

2.4 Coarseness

This proposal considers the spatial color variation in each potential region to distinguish between fire region and fire-like coloured region. Unlike other false-alarm regions, for example a region of red t-shirt in Fig. 4, fire regions have a significant amount of variability in the pixel values. The variance is a well-known metric (see [7], [8]) to indicate the amount of coarseness or the spatial color variation in the pixel values. Hence, this work uses the variance of the region as a feature to eliminate non-fire region from a candidate region.

Denote c as the coarseness of candidate region B_{kl}, it is defined as

$$c = \frac{\frac{1}{D_H \times D_W} \sum_{i=1}^{D_H} \sum_{j=1}^{D_W} (B_{kl}(i,j) - \bar{f}_R)^2}{\sigma_{f_R}^2} \tag{7}$$

In this proposal, c is fifth feature of a candidate region for classification.

Fig. 4. Spatial variation in fire and in a fire-like coloured object

3 Fire Detection Algorithm

3.1 Bayes Classifier

Bayesian decision theory is a fundamental statistical approach to the problem of pattern recognition. It makes the assumption that the decision problem is posed in probabilistic terms. For each candidate region, five independent features as aforementioned are evaluated and constructed a vector $\mathbf{x}$ as

$$\mathbf{x} = \begin{bmatrix} \bar{f}_R \\ \bar{f}_G \\ \bar{f}_B \\ s_R \\ c \end{bmatrix}, \tag{8}$$

and this proposal uses $\mathbf{x}$ to indicate candidate region contained fire or not by applying Bayes classifier.

Without the lost of generality, assume that we have Ω different classes. Using the Bayes inference, we can represent

$$P(\omega_i \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid \omega_i) P(\omega_i)}{p(\mathbf{x})}, \tag{9}$$

where ω_i is i-th class, $i = 1..\Omega$. One of the most useful and widely used ways to represent pattern classifier is by use of the discriminant functions

$$g_i(\mathbf{x}) = \ln p(\mathbf{x} \mid \omega_i) + \ln P(\omega_i). \tag{10}$$

The classifier is said to assign a feature vector $\mathbf{x}$ to class ω_i if $g_i(\mathbf{x}) > g_j(\mathbf{x})$ for all $j \neq i$. If the densities $p(\mathbf{x} \mid \omega_i)$ are multivariate normal - Eq. (10) will take the form

$$g_i(\mathbf{x}) = -\frac{1}{2}(\mathbf{x} - \mu_i)^T C_i^{-1} (\mathbf{x} - \mu_i) - \frac{K}{2} \ln 2\pi - \frac{1}{2} \ln |C_i| + \ln P(\omega_i) \tag{11}$$

For the case when the covariance matrices C_i are different for each category, the resulting discriminant functions will be inherently quadratic

$$g_i(\mathbf{x}) = \mathbf{x}^T W_i \mathbf{x} + w_i^T \mathbf{x} + \omega_{i0} \tag{12}$$

where

$$W_i = -\frac{1}{2} C_i^{-1}, \tag{13}$$

$$w_i = C_i^{-1} \mu_i, \tag{14}$$

and

$$\omega_{i0} = -\frac{1}{2} \mu_i^T C_i^{-1} \mu_i - \frac{1}{2} \ln |C_i| + \ln P(\omega_i), \tag{15}$$

where μ_i is the mean vector, C_i is the covariance matrix of class i.

Let ω_1 represents the fire class and ω_2 represents the non-fire class. For two-category case a single discrimination function is used

$$g(\mathbf{x}) \equiv g_1(\mathbf{x}) - g_2(\mathbf{x}), \tag{16}$$

and the following decision rule is used: Decide ω_1 if $g(\mathbf{x}) > 0$; otherwise decide ω_2.

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, this task is presented in experimental section.

3.2 Algorithm

Different from most existing fire detection algorithms in which they return two-state fire alarm containing fire or not for a input frame (or video). This paper proposes a new algorithm that give a fire-alarm rate ($FiAR$) in range $[0-1]$ for each frame. The fire-alarm rate is defined as

$$FiAR = \begin{cases} n/\Theta, & \text{if } n < \Theta \\ 1, & \text{Otherwise} \end{cases} \tag{17}$$

where n is number of region contained fire in current frame, Θ is a decision threshold, it is found out by practising. For input frame f, our proposed algorithm does following steps:

1. Determine all motion region;
2. For each motion region B_{kl}:
   (a) Evaluate vector of features $\mathbf{x}$ as presented in (8);
   (b) Indicate B_{kl} is contained fire or not by using (16).
3. Calculate the fire-alarm rate by using (17);
4. Show the $FiAR$ as output of algorithm.

A block diagram of the algorithm is given in Fig. 5.

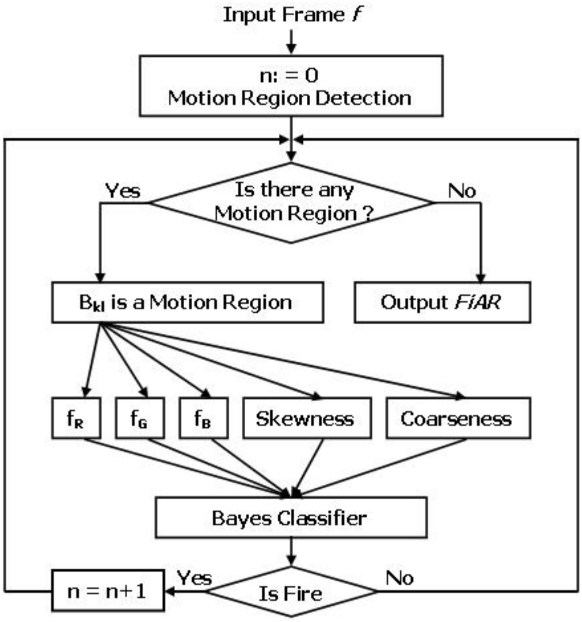

Fig. 5. Block diagram of proposed algorithm

4 Experiments

To evaluate the proposed approach, we collected 18 videos and used the data sets available from the site http://signal.ee.bilkent.edu.tr/VisiFire which consists of 10 fire videos and 8 non-fire videos. The video resolution is 320 × 240 and the frame rate varies from 15 Hz to 30 Hz.

For training data, we extracted 8645 fire regions and 11170 non-fire regions from 9 test videos, the region is divided in size of 8 × 6. Then a vector of features $\mathbf{x}$ is established for each region. These vectors of fire and non-fire class are applied for training phase to get classifier decision function (16).

4.1 Experiment 1

Assume that, when number of fire pixels is equal or greater than $n/4$, where n is number of pixels in frame f, then the accurate fire-alarm rate, denote $FiAR_A$, is 1. Approximately, the accurate fire-alarm rate can be defined as

$$FiAR_A = \begin{cases} m/\Phi, & \text{if } m < \Phi \\ 1, & \text{Otherwise} \end{cases} \tag{18}$$

where m is number of fire regions indicated manually in current frame, and $\Phi = (H \times W)/4$.

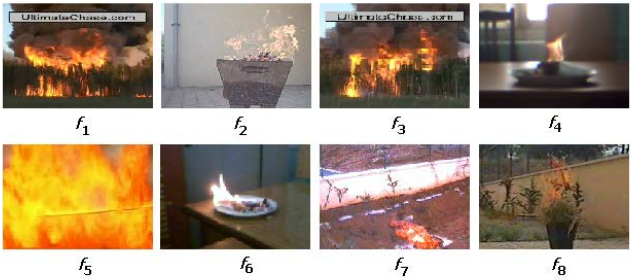

Fig. 6. Samples for fire-alarm rate comparing

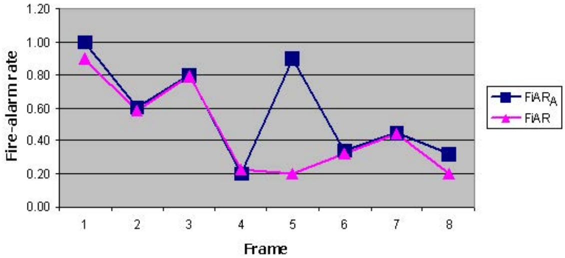

Fig. 7. Comparison of fire-alarm rate

This experiment shows the result of comparing between $FiAR$ defined by (17) and $FiAR_A$ defined by (18), and 8 frames in Fig. 6 are used.

The results of comparing is showed in Fig.7. In this, 7/8 frames have same fire-alarm rate. In the case of fame f_5, in spite of having large accurate fire-alarm rate, the proposed fire-alarm rate is small. The cause of this situation is number of detected motion region in a large fire is small.

4.2 Experiment 2

This experiment uses assumption that, frame f contains fire if $FiAR > 0$, to compare with three others: Method 1 [4], Method 2 [1] and Method 3 [2]. Data for this experiment includes 10 fire videos and 8 non-fire videos. The video resolution is 320×240 and the frame rate varies from 15 Hz to 30 Hz. There are approximately 11,676 frames. Table 1 shows the performance comparison of the proposed method and others. The proposed method outperforms other algorithms in terms of consistently increasing accuracy of fire detection and decreasing error rate.

5 Conclusions

In this paper, a new approach to vision-based fire detection is presented. By using fire characteristics in a region as a vector of statistical features, this work

Table 1. Performance comparison of the proposed method and other methods

Method	False-Positive	False-Negative
Proposed Method	0.160%	0.025%
Method 1	0.270%	0.260%
Method 2	0.680%	0.028%
Method 3	0.290%	12.360%

employed Bayes classifier for the vector to distinguish fire or non-fire region. Then a fire detection algorithm and a fire-alarm rate are presented. The experiments show that the fire-alarm rate can be used as a meaningful alarm. Moreover, the proposed method provided the output which can reach the most accurate in false-positive and false-negative. In spite of not comparing about the complexity and time consuming of our algorithm with others, it is easy to recognize this algorithm is an efficient approach for video-based fire detection.

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References

1. Ho, C.-C.: Machine vision-based real-time early flame and smoke detection. Meas. Sci. Technol. 20(4), 045502, 13 p (2009)
2. Borges, P.V.K., Izquierdo, E.: A probabilistic approach for vision-based fire detection in videos. IEEE Trans. Circuits Syst. Video Technol. 20(5), 721–731 (2010)
3. Celik, T., Ozkaramanl, H., Demirel, H.: Fire and smoke detection without sensors: image processing - based approach. In: Proc. 15th European Signal Processing Conf., pp. 1794–1798 (2007)
4. Ko, B.C., Cheong, K., Nam, J.: Fire detection based on vision sensor and support vector machines. Fire Safety J. 44(3), 322–329 (2009)
5. Duong, H.D., Tinh, D.T.: A Novel Computational Approach for Fire Detection. In: Proc. of KSE 2010 The Second International Conference on Knowledge and Systems Engineering, Hanoi, Vietname, pp. 9–13 (2010)
6. Habiboglu, Y.H., Günay, O., Çetin, A.E.: Covariance matrix-based fire and flame detection method in video. Machine Vision and Applications, doi: 10.1007/s00138-011-0369-1
7. Gonzalez, R.C., Woods, R.E.: Digital Image Processing. Addison-Wesley, Reading (1992)
8. Theodoridis, S., Koutroumbas, K.: Pattern Recognition. Academic, New York (2006)
9. Fire detection sample video clips, `http://signal.ee.bilkent.edu.tr/VisiFire`