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A real-time video fire flame and smoke detection algorithm

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Abstract

Real-time video fire flame and smoke detection method based on foreground image accumulation and optical flow technique is presented. Accumulation images are calculated of the foreground images which are extracted using frame differential method. Two parameters are used for the foreground image accumulation to differentiate flame candidate areas from that of smoke. The flame regions are recognized by a statistical model build by foreground accumulation image, while the optical flow is calculated and a motion feature discriminating model to recognize smoke regions is used. The algorithm could realize the real-time fire detection of the following three detection cases: fire with flame and none smoke, fire with smoke and none flame, and fire with both flame and smoke.

Keywords: Video fire detection; Foreground accumulation image; Motion features; Optical flow

Nomenclature	
$I(x,y,k)$	pixel values of (x,y) in the k-th frame
L	the threshold of frame differential method
$FD(x,y,k)$	the foreground image
$H_\tau(x,y,k)$	the foreground accumulation image
b_1 and b_2	the threshold of foreground accumulation image
d_{opt}	the vector form of Pyramidal Lucas-Kanade feature optical flow
$f(x)$	the result of Neural Network

1. Introduction

With the development of economy, the number of large high buildings is increasing. Generally, for the complex application, high load of fire and intensive staff, major property damage and heavy casualties will be easily caused if fire happens in these places, and has a bad social impact. So difficult technical problems of fire detection and alarm are urgently be solved to obtain more valuable time for extinguish and evacuation.

In large rooms and high buildings, conventional fire detectors can hardly detect characteristic parameters of fire like smoke, temperature, vapor and flame in the very early time of fire, and cannot meet the demand of early fire detection in these places. Compared to conventional fire detectors, video fire detectors which have many advantages, such as fast response, long distance of detection, large protection area et al, are particularly applicable to large rooms and high buildings.

But most of current methods for video fire detection have high rates of false alarms. Researchers all over the world have done a lot of work on this new technique. Up to now, most of methods make use of the visual features of fire flame or

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smoke including color, textures, geometry, flickering and motion. Yamagishi and Yamaguchi [1, 2], Celik et al. [3], Chen et al. [4] used color information to segment flame regions. Liu and Ahuja [5] and Yuan et al. [6] do Fourier coefficients analysis to flame contours. Ugur et al. [7], and Dedeoglu et al. [8] propose temporal and spatial wavelet method to analyze flame.

Compared to flame, the visual characteristics of smoke like color and grads are less trenchancy, and smoke is harder to be differentiated from its disturbances. So the extraction of smoke features becomes more complicated. In the study of Xiong et al. [9], they thought smoke and flames were both turbulent phenomena, the shape complexity of turbulent phenomena might be characterized by a dimensionless edge/area or surface/volume measure. Yuan [10] gave an accumulated model of block motion orientation for smoke detection. Toreyin et al. [11] extracted the edge blurring feature of smoke in wavelet domain.

There are few studies on video fire detection that can detect both flame and smoke. In Ho [12] actually recognize flame and smoke individual with different models. Chen et al. [4] and Çelik et al. [13] establish a color model to recognize fire flame and smoke. Generally speaking, most of studies of video smoke detection focus on grayish smoke from the smoldering phase, while few on black smoke produced with flame. With the high growth of current market demand, video fire detection techniques that could detect both flame and smoke will be applied to more scenes, will certainly be the development trend in the future.

The aim of this paper is to propose a real-time video fire detection method that could detect both flame and smoke. This paper is organized as follows. Section 2 analyzes the image features of flame and smoke. Section 3 briefly describes fire flame and smoke detection algorithm. In Section 4, results of this method are described. And this paper is concluded in the last section.

2. Feature analysis of fire flame and smoke

In point of general fires, the flames usually display reddish colors. A color model could be built to recognize flames. Unfortunately, some fire-like regions in an image may have the same colors as fire, and these fire-similar areas are usually extracted as the real fire from an image. These fire aliases are generated by two cases: non-fire objects with the same colors as fire and background with illumination of fire-like light sources. In the first case, the object with reddish colors may cause a false extraction of fire-flames. The second reason of wrong fire-extraction is that the background with illumination of burning fires, solar reflections, and artificial lights has an important influence on extraction, making the process complex and unreliable.

The key to distinguishing between flame and flame-colored objects and smoke and smoke-colored objects is the nature of their physical movement. So to validate a real burning fire, in addition to using color feature, motion features are usually adopted. These fire dynamic features include sudden movements of flames, changeable shapes, growing rate, and oscillation. Smoke and flames are both turbulent phenomena. In point of turbulent flow, the chaotic nature of fire is an important feature. If the contours of an object exhibit rapid time-varying behavior, then this is an important sign of the presence of flame or smoke in the scene. The fire flame dances around the fire source, and any particular pixel in the intermittent regions will only see as fire pixels for a fraction of time. This kind of temporal periodicity is commonly known as flickering. But in this paper, a foreground image accumulation method is adopted which could also describe the temporal periodicity feature of flame.

3. Fire feature extraction algorithm

In this section, we will introduce our algorithm of flame and smoke detection. The proposed fire detection method can be divided into four major phases: First, moving pixels and regions are extracted from the image using frame differential method developed by Collins et al. [14]. Second, two color models are used to find flame and smoke candidate regions. Third, foreground accumulation images are built of both flame and smoke. In the last phase, motion features of flame and smoke are each calculated based on block image processing and optical flow technique.

3.1. Frame differential method

The moving pixels and regions of the images are determined by using a frame differential method which is carried out as follows:

$$FD(x,y,k)=\begin{cases}1 & \text{if } \left|I(x,y,k)-I(x,y,k-1)\right|>L \\ 0 & \text{otherwise}\end{cases} \tag{1}$$

where (x, y) represent the coordinates of the pixels that are formulated with long direction as x axis and the other direction as y axis. $I(x,y,k)$ represents the pixel values of (x, y) in the current frame. $I(x,y,k-1)$ represents the pixel values of (x, y) in the previous frame. L is the threshold. The points with values 1 in the differential result image $FD(x,y,k)$ forms the foreground image

Foreground image may contain both fire and disturbances which are to be differentiated in the following phases.

3.2. Color models of flame and smoke

- Flame color model

Flame usually displays reddish colors. As we know, RGB color model has less computation complexity than other color models. But in flame image recognition, HIS color model is often adapted, because it is suitable for providing a more people-oriented way of describing the colors. Our experimental results show that each HIS pixel of fire flames should satisfy the following conditions:

$$\begin{aligned}&\text{(i) } 0 \le H \le 60^{\circ}\\ &\text{(ii) } 0 \le S \le 0.2\\ &\text{(iii) } 127 \le I \le 255\end{aligned} \tag{2}$$

The pixels that pass the above color decision rule are set as flame candidate regions.

- Smoke color model

Smoke usually displays grayish colors [4], and the condition $R \pm a = G \pm a = B \pm a$ and with I (intensity) component of HIS color model $K_1 \leqslant I \leqslant K_2$. The rule implies that three components R, G, and B of smoke pixels are equal or so.

Here we made a small modification. The decision function for smoke recognition is that for a pixel point (i, j):

$$\begin{aligned}m &= \max\{R(i,j), G(i,j), B(i,j)\}\\ n &= \min\{R(i,j), G(i,j), B(i,j)\}\\ I &= \frac{1}{3}(R(i,j), G(i,j), B(i,j))\end{aligned} \tag{3}$$

If the pixel FD (x, y, k) satisfies both the conditions $m-n<a$ and $K_1 \leqslant I \leqslant K_2$ at the same time, then FD (x, y, k) is considered as a smoke pixel, otherwise FD (x, y, k) is not a smoke pixel.

Our experimental results show that typical value a ranges from 5 to 20 and light-gray and dark-gray smoke pixel threshold ranges from 80 to 150 and 190 to 255. The pixels that pass the color decision rule are set as smoke candidate regions.

3.3. Foreground accumulation image

Consider that foreground images appear in the same regions during a consecutive time window. In order to describe this feature, we build Eq. (4).

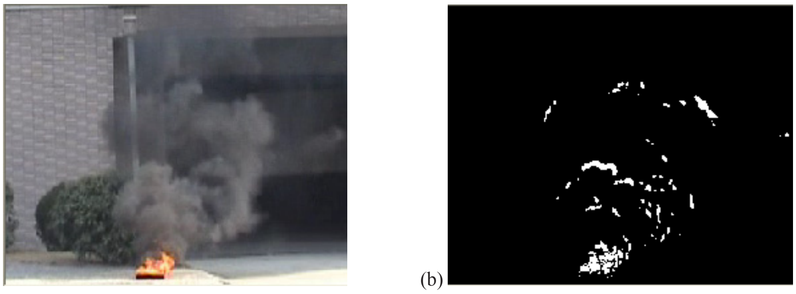
$$H_\tau(x,y,k)=\begin{cases}H_\tau(x,y,k-1)+b_1 & \text{if } FD(x,y,k)=1\\ \max(0, H_\tau(x,y,k-1)-b_2) & \text{otherwise}\end{cases} \tag{4}$$

The results of Eq. (4) are named foreground accumulation images, in which the values of pixels represent the times of foreground images appear in the same pixel region during a consecutive time window. Value b_1 is the accumulation augmenter, while value b_2 is the accumulation attenuation. Value b_2 is set to 1 generally.

The correlation in space of foreground images of consecutive image frames is used in foreground accumulation image. Foreground accumulation images are the results from the weighted stack of foreground images of consecutive image frames. So more times the same region of foreground images appears in consecutive frames, the bigger of the pixels' values of the corresponding pixels in foreground accumulation image. The pixel values will decrease to zero, if the corresponding region no longer appears in foreground images.

From observing video images, we found that as the grads variation of color and brightness of flame is vivid, and every pixel value of flame is relatively acuity changing with time, so the whole flame region in the images could be extracted using frame differential method. If b_1 and b_2 are set 1, the value of H_τ will increase clearly with time.

However, smoke presents clouds diffusing movement, and the pixel brightness is locally unchanged in a short time. As shown in Fig. 1, the results using frame differential method are mostly the edge pixels of smoke movement, of which the coordinates are always changing. So in order to get the foreground accumulation image of smoke, the parameters b_1 and b_2 can be set as $b_1 > b_2$. By this means, the flame and smoke regions can also be separated.

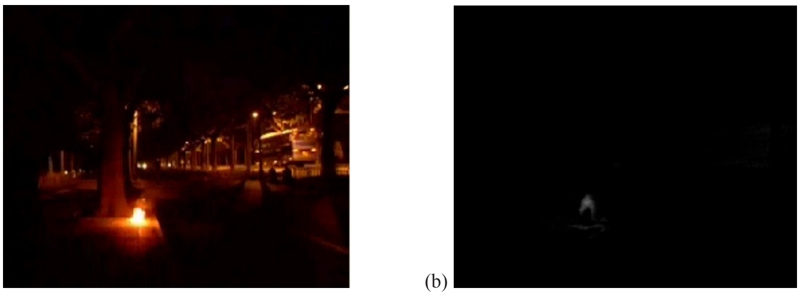


(a) (b)

Fig. 1. Frame differential result of smoke.

3.4. Flame region recognition

Block image processing technique is used to recognize a flame motion features. As we know, flame combustion is a turbulent movement with source. If there is no effect of wind or airflow, the regions of continuous flame and intermittent flame will be recurring at regular intervals in a certain area. So the pixels' value of flame regions in the foreground accumulation image will become bigger. As the frequency of fire flickering is between 2 Hz and 12 Hz, ordinary CCD cameras with sampling rate of 25 frames per second can capture at least one cycle movement of fire flickering. The foreground image using frame differential method contains the regions of continuous flame and intermittent flame generally. In a certain time intervals T, flames accumulate in the same regions.



(a) (b)

Fig. 2. Foreground accumulation image result of flame.

To extract the above flame motion features, block image processing is used here. Firstly, each image of video sequences is divided into blocks with the resolution 8×8. Then the values of pixels within a block are summed up satisfying the condition:

$$H_\tau(x, y, t) > T \tag{5}$$

T is a predetermined threshold meaning a given time window. If the videos have 25 frames per second, experiments show that T can be set as 50. And if more than half of all pixels in a block satisfy Eq. (5), then this block could be considered as a flame block.

3.5. Smoke region determination method

Compared to flame, the visual characteristics of smoke such as color and grads are less trenchancy, so that smoke is harder to be differentiated from its disturbances. So the extraction of smoke visual features becomes more complicated.

Block image processing and optical flow technique [15, 16] are combined here to extract the motion features of smoke. The pixels in the center of each smoke block are considered as feature points here and do the optical flow calculations which will greatly decrease the computation complexity.

Firstly, each foreground accumulation image of smoke video sequences is also divided into blocks with the resolution 8 × 8. Then we sum up the values of pixels within a block satisfying the Eq. (5), T is set as 50, and parameters b_1 and b_2 in Eq. (4) are set as 3 and 1. And if more than half of all pixels in a block satisfy Eq. (5), then this block could be considered as a smoke block.

Then find the coordinates of the center points of all smoke blocks, and its optical flow vectors will be calculated as follows.

The Pyramidal Lucas-Kanade feature optical flow vector is

$$d_{opt} = G^{-1}\overline{b} \tag{6}$$

Denote

$$G = \sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x} \sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \tag{7}$$

$$\overline{b} = \sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x} \sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y} \begin{bmatrix} \delta I \cdot I_x \\ \delta I \cdot I_y \end{bmatrix} \tag{8}$$

For the pyramid representation process, build pyramid representation of I recursively according to Eq. (9):

$$\begin{aligned} I^L(x,y) = {} & \frac{1}{4} I^{L-1}(2x,2y) + \\ & \frac{1}{8}(I^{L-1}(2x-1,2y) + I^{L-1}(2x+1,2y) + I^{L-1}(2x,2y-1) + I^{L-1}(2x,2y+1)) + \\ & \frac{1}{16}(I^{L-1}(2x-1,2y-1) + I^{L-1}(2x+1,2y+1) + I^{L-1}(2x-1,2y+1) + I^{L-1}(2x+1,2y+1)) \end{aligned} \tag{9}$$

And the result of the Eq. (9) is propagated to the next level L-1 by passing the new initial guess, this procedure goes on until the finest image resolution is reached. So the solution may be expressed in the following form:

$$d = \sum_{L=0}^{L_m} 2^L d^L \tag{10}$$

Finally, we use a Back-Propagation Neural Network for the smoke feature classification. .

In Richard and Lippmann [17], they presented step of the back-propagation training algorithm and explanation. The output layer uses a log-sigmoid transfer function, so the outputs of network are constrained between 0 and 1.

The sigmoid function is defined by the expression

$$f(x) = \frac{1}{1+e^{-cx}} \tag{11}$$

The constant c in the paper is 1 arbitrarily. If the result is fire, the y is set to be 1, or else is 0.

4. **Experiment results**

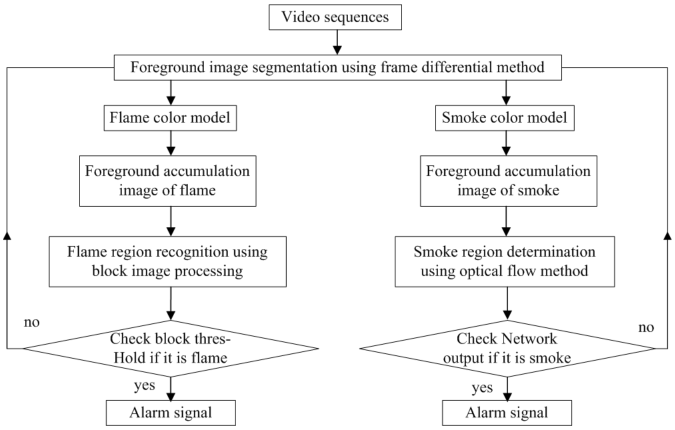


Fig. 3. Flow chart of the method.

The algorithm presented in this paper is implemented using Visual C++ and OpenCV library. And the flow chart of the method is showed in Fig. 3.

Fig. 4. Recognition results of the method.

We have tested it on some videos, some which are provided by the fire detection group of SKLFS of USTC, while others from http://signal.ee.bilkent.edu.tr/VisiFire/Demo/SampleClips.html. The computation can do 25 frames per second, and all videos are normalized to 320x240 pixels. The flame blocks are shown in red rectangles while the smoke blocks are shown in green. The calculation results of optical flow vectors are real numbers. For intuitive, they are indicated by the arrows, the starting points and direction of which are the coordinates of the center points of smoke blocks and the optical flow direction. Some of the extraction results are shown in Fig. 4.

Video 7 to 9 show results of video sequences with disturbances. It can be clearly seen that some non-smoke regions are wrongly extracted. These regions here will be further checked by the optical flow feature determination.

The optical flow computation is done to the candidate flame and smoke blocks determined by fire color models and foreground accumulation images. The fire alarm results performed of this method are shown in Table1. Fire alarms are given from Video 1 to Video 6. And the disturbances wrongly extracted by color models and foreground accumulation images cannot pass optical flow feature determination and there are no fire alarms are given from Video 7 to 9.

Table 1. Alarm performance of the method

video sequences	Fire alarm(Y/N)	description	video sequences	Fire alarm(Y/N)	description
Video 1	Y	Only smoke	Video 6	Y	Smoke and flame
Video 2	Y	Only smoke	Video 7	N	Car lights
Video 3	Y	Only flame	Video 8	N	Car lights
Video 4	Y	Only flame	Video 9	N	Tunnel accident
Video 5	Y	Smoke and flame			

5. Conclusions

In this paper, a real-time video fire flame and smoke detection method based on foreground image accumulation and optical flow technique is presented. Foreground image accumulation is used to extract the motion feature of flame and smoke, and can distinguish the flame color or smoke color disturbances. Besides, some noises can be attenuated to zero in consecutive frames using the method of foreground accumulation image which therefore this method has the ability to suppressing noise.

Most disturbances like lights and other fire-like color objects can be differentiate from flame efficiently using foreground accumulation image, except that the lights are turned on and off in a same frequency like flame which is found in our experiments. The proposed method will be further improved in our future work.

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