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A Novel Computational Approach for Fire Detection

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Abstract: *This paper proposes a model for detecting fire captured in video data by combining the methods of correlation coefficient, Gaussian Mixture Model - GMM and turbulent analysis. The method of correlation efficient is used to determine movement objects. We use GMM to cluster fire-colored pixel in the RGB space. The objective of turbulent analysis is to detect the flame of fire. A model built on three above methods will be presented and the experimental results are discussed in Section III.*

I. INTRODUCTION

Fire alarm and detection is an important issue in protecting our society. It has attracted a great deal of attention from the research community, especially from the field of computing. Conventional fire detection systems usually use thermal sensors or smoking sensors. They work well and efficiently in some particular conditions and situations. However, conventional fire detection systems have some serious disadvantages such as detecting fire lately; depending on environmental conditions and arranging the sensors.

Visual fire detection was initialized in early 1990s. This technique was showed to be useful in situations where conventional fire detectors cannot be used. Visual fire detection has significant advantages such as improved detection, additional descriptive information about fire location, size, and growth rate ([1], [2]).

There are a number of visual fire detection algorithms in the literature ([2], [3], [5], [7], [8], [10]). These methods make use of various visual signatures including color, motion and geometry of fire regions, particular positions of surveillance and different features of cameras. In addition, these methods rely on an assumption that the burning material is normal and the camera's position is static. However, most of existing visual fire detection techniques have the disadvantage such as false alarm in some certain situations, and a high level of computational complexity.

This paper proposes an approach for the problem of fire detection with less computational complexity. It combines the methods of correlation coefficient, Gaussian Mixture Model and turbulent analysis.

The paper is organized as follows. A model for determination of motion object is presented in Section 2.1. The method to detect fire-colored is explained in Section 2.2. In order to distinguish fire or other fire-color object, turbulent of fire regions is analyzed in Section 2.3. The complete algorithm for fire detection is showed in Section 2.4. The experimental results are presented in Section III and Section IV is our conclusion.

II. FIRE DETECTION ALGORITHM

This algorithm for fire detection is a combination of three components: the first one is the determination of motion regions, the second one is the detection of Fire-Colored pixels and the last one is the turbulent analysis.

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2.1 Determination of motion regions

In order to detect possible changes, which may be caused from fire, we need to use an effective background-modeling algorithm. The algorithm should be simple and robust to achieve a real-time detection of the fire. Existing background models ([3], [5], [8], [9]) commonly use the difference between pixels by pixels to describe the changes; this approach may either (1) be very computationally expensive in order to improve accuracy of the algorithm or (2) obtain quite a light computation workload with unreliable results.

The method is applied here manages to get a simple algorithm with reliable results by estimating the change of regions by regions. Formally, we assume F_{t1} is image frame at $t1$; and F_{t2} is image frame at $t2$ ($t2=t1+\Delta t$). The motion of fire leads to the change of intensity in some pixels between F_{t1} and F_{t2}. Determining the difference between F_{t1} and F_{t2} is as follow:

1. Partitioning F_{t1} and F_{t2} into same fixed size grid rectangles. Figure 1 is an example;
2. Computing the correlation coefficient between each grid cell on F_{t1} and each same position grid cell on F_{t2};
3. Estimating the motion region by collect the grid cells have correlation coefficient greater than a threshold T.

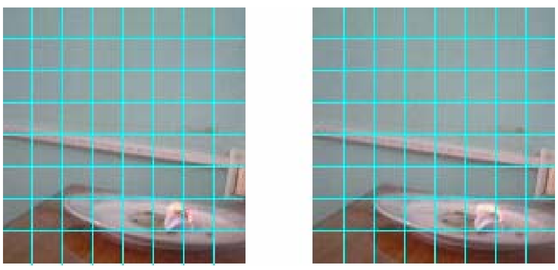

Figure 1 - Partition of F_{t1} and F_{t2} into fixed size grid rectangle

Let W, H be the width and height of F_{t1} and F_{t2}; divide F_{t1} (and F_{t2}) into M columns and N rows, then each cell or region has size of $D_W = W/M$ width and $D_H = H/N$ height. Let A_{kl}, B_{kl} are a cell at k-th column and l-th row ($k=\{1,2,..,M\}$, $l=\{1,2,..,N\}$) of F_{t1} and F_{t2} respectively. The correlation coefficient between A_{kl} and B_{kl} is calculated as follows:

$$CC(k,l) = \frac{\sum_{i=1}^{D_W}\sum_{j}^{D_H} A_{kl}(i,j) * B_{kl}(i,j)}{\sqrt[2]{\sum_{i}^{D_W}\sum_{j}^{D_H} A_{kl}(i,j)^2} * \sqrt[2]{\sum_{i}^{D_W}\sum_{j}^{D_H} B_{kl}(i,j)^2}} \quad (1)$$

The cell at k-th column and l-th row on F_{t2}, B_{kl} is considered as motion if:

$$CC(k,l) \geq T \quad (2)$$

Then, the motion region S is defined as:

$$S_M = \{B_{kl}: CC(k,l) \geq T\} \quad (3)$$

2.2 Fire-Colored pixels detection

Color values of pixels in moving region S are compared with predetermined color distribution, which represents possible fire-colors in videos in the RGB color space. The fire-color distribution is obtained from sample images containing fire regions.

We used 250 different images from collected videos. We then segmented each image into fire and non-fire regions and got values of Red, Green and Blue channel of 2.453.007 fire pixels as statistic data. A part of set of fire pixels has chart as in Figure 2.

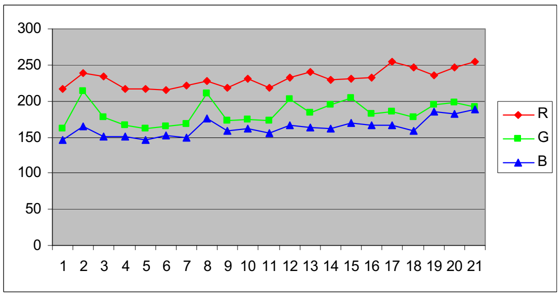

Figure 2 - Piece of chart of R,G,B fire pixels

It is noticed that, for each pixel in a fire blob, the value of Red channel is greater than the Green channel, and the value of Green channel is greater than the value of Blue channel. A similar result is found in [5]. So for a pixel located at spatial location of (x,y), the first condition must be as follows:

$$R(x,y) > G(x,y) \quad (3)$$

$$G(x,y)>B(x,y) \tag{4}$$

$$R(x,y) \geq R_0 \tag{5}$$

where $R(x,y)$, $G(x,y)$, and $B(x,y)$ are Red, Green and Blue values for a pixel located spatially at (x,y), R_0 is a threshold to make sure pixel located at (x,y) is light enough.

The fire-colored pixel is a pixel in S_M that satisfied three conditions (3), (4) and (5); the fire-colored region S_F is:

$$S_F = \{(x,y): (x,y) \text{ satisfied (3), (4), (5) and } (x,y) \in S_M\} \tag{6}$$

2.3 Turbulent analysis

Two features of fire including motion and fire-colored are not enough to distinguish fire regions and fire-like regions. In this proposed algorithm, the turbulent of fire is additional to model of fire to improve the accuracy of the algorithm.

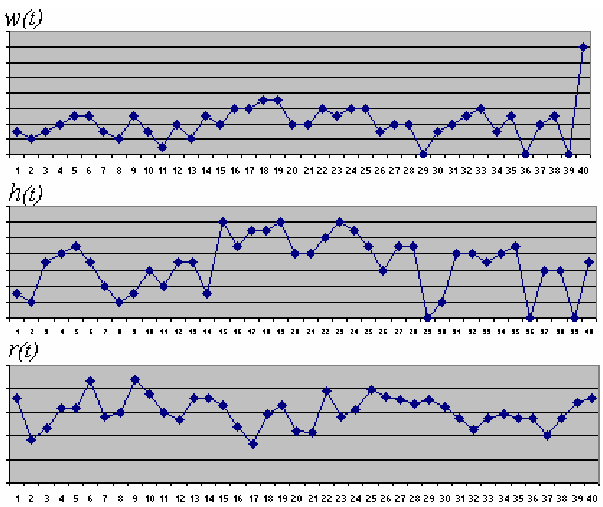

Figure 3 - Functions $w(t)$, $h(t)$ and $r(t)$

In order to describe the turbulent of fire, this method uses some geometric of fire regions. Assume that S is a set of pixels on F_{t2} that satisfies the condition of motion and fire-colored regions; w and h are the width and the height of rectangle that contains S respectively; ratio $c = \max(w, h)/\min(w, h)$ is the eccentricity of S and r is distance from centre of S to origin of coordinate. Also, assume that $w = w(t)$, $h = h(t)$ and $r = r(t)$ are functions of time. With the experimental videos, the results of these functions on the perpendicular coordinates are showed as Figure 3.

From figure 3, intuitively, when the shape of fire region change turbulently then $w(t)$, $h(t)$ and $r(t)$ waver around the its average values; equivalent transformation by move vertical axis to its average, the wave of $w(t)$, $h(t)$ and $r(t)$ can be described as the number of zero-crossing.

In this proposed algorithm, following formula is used to determinate the turbulent of fire regions S_F:

$$T(S_F) = \left[\begin{array}{l} ZC(w) \geq C_w \\ ZC(h) \geq C_h \\ ZC(r) \geq C_r \end{array}\right. \tag{7}$$

where ZC(y) is a function that returns the number of y is zero-crossing; C_w, C_h, C_r is a threshold for $w(t)$, $h(t)$ and $r(t)$ respectively. Eccentricity c is used to check the symmetry of S.

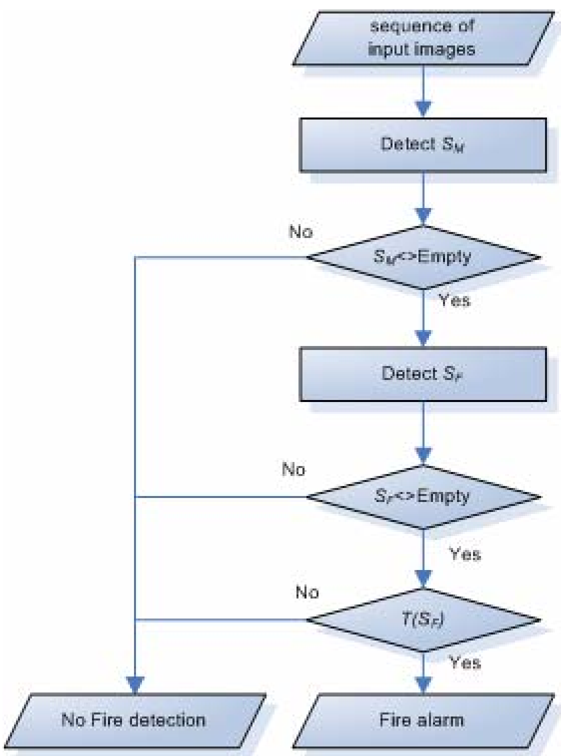

Figure 4 - Complete Algorithm

2.4 A complete algorithm

The proposed algorithm here is a combination of three above mentioned components. The diagram algorithm is descriptive as in Figure 4.

III. EXPERIMENTAL RESULTS

The proposed method, Method 1, is implemented. It is tested for a large variety of conditions in comparison with the method utilizing only the color and temporal variation information, which we call Method 2, described in [10]. The scheme described in [15] is also implemented for comparison and it is called as Method 3. The results for some of the test sequences are presented in Table 1.

Table 1
The result of number frames detected as fire and performance time of method 1, 2 and 3.

Video sequences	Number of frames with fire	Number of frames detected as fire			Number of false positive frames			Performance time (ms/frame)			Description
		Method			Method			Method			
		1	2	3	1	2	3	1	2	3	
Video 1	345	345	125	162	0	220	183	15	34	25	Fire in room 1
Video 2	232	232	168	172	0	64	60	17	36	27	Fire in room 2
Video 3	0	0	2	0	0	2	0	12	27	33	Traffic 1
Video 4	255	255	76	22	0	179	233	16	37	21	Fire in garden
Video 5	0	0	22	0	0	22	0	13	34	22	Traffic 2
Video 6	0	0	12	0	0	12	0	19	28	28	Traffic 3
Video 7	0	1	1	12	1	1	12	14	30	21	Traffic 4
Video 8	0	0	5	0	0	5	0	11	40	22	Traffic 5

After analyzing the result, we found that there was one frame in the video sequences that transmitted a false alarm when treated with movement objects as fire objects. On another hand, there is only one fire sequence which system could not detect. The false alarm happened when natural movement objects contained as fast flicking as fire pixel. And our system did not raise any alarm with sequences that captured in a hight light environment, when fire movement couldn't be detected. But when tested in a not-too-bad environment, the system worked well.

IV. CONCLUSION

In our paper, an algorithm for fire detection in color video is developed. The algorithm not only used color and temporal variation information, but also analysis turbulent of fire to distinguish fire region and fire-like regions. Our method based on only color information and ordinary motion detection may produce false alarms in real scenes where no fires are taking place. The experimental results showed that false alarms can be drastically reduced by temporal and spatial wavelet analysis.

The method can be used for detection of fire in movies and video databases, as well as real-time detection of fire. It can be incorporated into a surveillance system monitoring an indoor or outdoor area of interest for early detection of fire.

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