FIRE DETECTION IN COLOR VIDEO

Jennie Shipley, Jessica Ebert

Utah State University, Connecticut College

ABSTRACT

This paper proposes a novel method to automatically detect fire in video sequences. While the underlying algorithm is based mainly upon the color and motion properties of fire, further specificity is derived from temporal and spatial wavelet transforms.

Index Terms-- Video fire detection, spatial color analysis, computer vision, image processing

1. INTRODUCTION

Every day, many people die from the effects of smoke, fire and flames. In fact, fires and burns are the second most common cause of death to children under 10, next to automobile crashes. [1] What can be done about this? Smoke detectors are useful in detecting fires, but cannot be used in large spaces, posing a threat for auditoriums, parks and forests alike. Point particle detectors are also set off by ordinary particles, such as hairspray or cigarette smoke, whereas a video fire detection system would not. Fire detection in video is fairly simple when infrared cameras are used; however, these are much less common than ordinary cameras. Surveillance cameras are becoming increasingly prevalent, and so it would be convenient if they could also be used to detect fires.

A significant amount of research has been done in the area of fire detection in video. Some methods are based solely on the color of fire [2], the temporal variation of fire[3], or a combination of the two. These methods lack the detection of one of fire's most distinguishing characteristics – its spatial color variation. Toreyin et al. [5] include this vital step; however, their method for color detection is too specific and does not detect all fire. The method presented here corrects that problem. It also is robust in that there can be other moving objects in a variety of environments and lightings, and it detects both fires during the day and fires at night. The only requirement is that the camera must remain stable and motionless.

The proposed method should work with a constant video stream, extracting a short clip, analyzing it for fire, and then extracting another clip. If a fire is detected, an alarm is issued.

2. PROPOSED APPROACH

This approach to fire detection utilizes the same basic structure as the method proposed by To¨reyin et all [5], with improvements leading to better detection of fires and increased performance. The first step is to detect moving pixels. Next, we detect the pixels that are fire-colored. Third, we determine if the temporal variance (flicker) is at the proper levels. Fourth, we analyze the spatial variation to see if the variance is similar to the variance in fire.

2.1. Detection of Moving Pixels

Pixels in fire are always moving, always changing. To eliminate motionless pixels, we implemented a background subtraction method based upon hybrid background estimation. [6]

The method of determining moving objects by subtracting the background relies heavily on determining what is background and what is not. The background is determined by the function:

$$B_{n+1}[k,l] = \begin{cases} aB_n[k,l] + (1-a)x_n[k,l] & \\ \quad \text{if } [k,l] \text{ is non-moving} & \\ B_n[k,l] & \\ \quad \text{if } [k,l] \text{ is moving,} & \end{cases} \qquad [5]$$

where n is the number of frames in the video sequence, $x_n[k,l]$ is the intensity of the pixel at position [k,l], and $B_n[k,l]$ is the previous estimate of the pixel at position [k,l]. Alpha is an update parameter close to 1. The value of a determines how much the background is updated per frame. Moving and non-moving mean whether the pixel has changed at all (more than a threshold) since the previous frame.

The first frame of a video sequence will always be ignored, as there is no basis for comparison. If there is fire in the scene, it is assumed the fire will persist for more than a single frame. Otherwise it is not a threat.

2.2 Detection of Fire-Colored Pixels

Most color detection models in fire detection work well under ordinary circumstances and with typical fires. However, there are certain instances where these models do not identify fires, such as fires during the day, or large, very hot, very white fires. Here we propose four color conditions to include not just typical fires, but all uncontrolled flame. The conditions are as follows:

1. The red-value of the pixel must be greater than an experimentally defined threshold

2. Red>=green and green>blue (or, the red-yellow spectrum)[7]

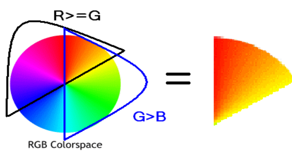

Figure 1. The red to yellow colorspace.

3. Saturation is either greater than 80% or less than 20%

Figure 2. Two fires, at night and during the day, and their saturation components.

4. Intensity must be greater than 40%.

Figure 3. The intensity of a fire

We determined that a fire should always be in the range of red to yellow, except in controlled fires such as blowtorches, which burn different colors. Fires are often white because the quality of the video camera cannot always detect color differences in such an intense light.

As fire is a light source, the intensity should always be fairly high, regardless of the average intensity of the frame.

Saturation of fire is either very high or very low, depending on whether the fire in question is the primary source of light. If it is, the fire appears brighter, and will have very low saturation. If it is not the fire appears more colorful, with a high saturation.

2.3 Temporal Wavelet Analysis

Fire flicker frequency is typically between 1 and 10 Hz. [8] To determine if a pixel is flickering, we take an array of the pixel throughout all frames and perform a discrete wavelet transform (dwt) . This returns the wavelet subsignals from the low- and high-pass filters, e_n and d_n, respectively. We then perform another dwt on e_n. If the pixel is flickering, there will be changes in the wavelet subsignals, whereas the values of a non-flickering pixel will remain close to zero. To eliminate non-fire pixels, it was determined that to be considered as fire, the following formula must apply:

(Xn=max(Xn[k,l])/2 + st. dev(Xn[k,l])>=Num. of frames/4

So the low-low filter wavelet subsignal must cross a certain range at least once per four frames to be flickering at the proper rate. This range is within one standard deviation of half of the tallest peak. This differs from the original approach [5]. Their approach used zero-crossings instead of the range. This proposed method works better, as everything varies slightly, crossing zero several times, whereas a car driving by would result in only one tall spike.

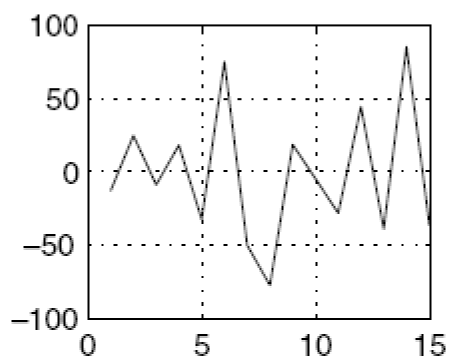

Figure 4. A plot of the high-high wavelet subsignal

2.4 Spatial Wavelet Analysis

The color of fire is never uniform. Spatially, it varies greatly. To detect this, two 2-D discrete wavelet transform were performed on regions of potential fire candidate pixels. If fewer than 10% of the pixels in the region were potentially fire, the pixels were eliminated. Otherwise the dwt was performed. Then pixels were eliminated according to the following equation:

$$v_4 = \frac{1}{M \times N} \sum_{k,l} |x_{lh}[k,l]|^2 + |x_{hl}[k,l]|^2 + |x_{hh}[k,l]|^2 \quad [5]$$

where x_{lh}, x_{hl}, and x_{hh} are the wavelet subsignals. This equation adds the squares of the subimages to see if the spatial variation is high enough to be that of fire. If the value of v4 was less than an experimentally determined threshold, then the region is not fire.

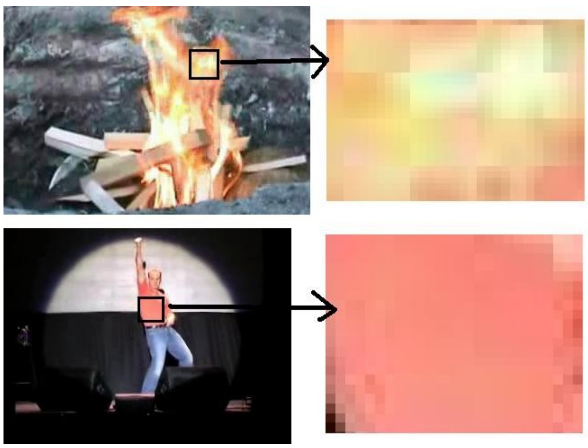

Figure 5. Comparison of the spatial color variation in fire and non-fire objects.

2.5 Decision

A binary mask for each step is created. Each step only considers the pixels identified as potential fire by the binary mask created in the previous step. A combined mask for all stages and frames is created and updated with every step.

If a pixel is not eliminated as fire by any of the steps, it is determined to be fire. If there are more than a set number of "fire" pixels in a video's combined final mask, the video is determined to contain fire and an alarm is issued.

3. EXPERIMENTAL RESULTS

The proposed method was tested on our extensive data set (which is not publicly available), of which the following table is a sample. While we did detect a few false positives, almost every instance of fire was detected. The only fire that was not consistently detected was that of the flame on small candles, as they do not tend to flicker consistently at the same rate as uncontrolled fire.

Movie 1 is one of the false positives we detected; however, it must be noted that the clip is of a yellow and red lit fountain at night, which displayed all the characteristics of fire, including flicker and spatial color variance.

Sequence	*Length*	*Frames with fire*	*Fire detected ?*	*Description*
Movie 1	41	0	yes	Lit fountain at night
Movie 2	37	0	no	White birds taking off
Movie 3	618	401	yes	Tan couch on fire
Movie 4	49	49	yes	People holding candles
Movie 5	48	0	no	Street intersection
Movie 6	98	98	yes	Campfire in the day
Movie 7	108	108	yes	Cardboard fire at night
Movie 8	93	93	yes	Campfire at night
Movie 9	32	0	no	American flag waving
Movie 10	33	0	no	Cars on an icy road
Movie 11	48	0	no	Swinging light bulb
Movie 12	66	66	yes	Armchair on fire
Movie 13	142	142	yes	Another armchair, fire
Movie 14	104	104	yes	3 dog houses burning

Table 1. The experimental results.

In every case, this system showed a marked improvement in regards to accuracy of fire detection when compared with the method proposed by To¨reyin et all (we'll call this "Method 2".) Also, the regions of false positives detected were smaller in size when both methods were tested using the same database. The proposed method detected all instances of fire; however, Method 2 did not detect one of the three flaming doghouses from Movie 14. Also, Method 2 detected the taillights on the cars in Movie 10 as fire, whereas our method did not.

4. FUTURE WORK

Possible improvements on the current system include increasing the efficiency so it is capable of performing in real-time, thus making it practical as a preventative fire detection system. Further research is necessary to eliminate the current false positives. There is also potential, utilizing the binary mask that results from the program, to determine the location of the fire for automated extinction.

5. CONCLUSION

This method is an innovative approach to video detection in fire, and can be used on short, stable video clips to determine is there is fire present. This paper proposes a novel method to automatically detect fire in video sequences. While the underlying algorithm is based mainly upon the color and motion properties of fire, further specificity is derived from temporal and spatial wavelet transforms.

11. REFERENCES

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