COMPUTER VISION BASED METHOD FOR FIRE DETECTION IN COLOR VIDEOS

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ABSTRACT

This paper presents a computer vision based system for automatically detecting the presence of fire in stable video sequences. The algorithm is based not only on the color and movement attributes of fire but also analyzes the temporal variation of fire intensity, the spatial color variation of fire and the tendency of fire to be grouped around a central point. This method is effective at detecting all types of uncontrolled fire in various situations, lighting conditions and environments.

***Index Terms*—** Video fire detection, color analysis, computer vision.

1. INTRODUCTION

The effects of smoke, fire and flames are one of the leading hazards affecting everyday life around the world. This is true to such an extent that fires and burns are the second most common cause of death to children under 10 in the United States of America, second only to automobile crashes. [1] While many of these deaths occur because of faulty smoke detectors, smoke detectors are only useful to an extent. They can not be used reliably to detect fires in large spaces . This means that they are unreliable at best in auditoriums, warehouses, and outdoor spaces.

Further failings of the point particle detectors include the fact that they are easily set off by ordinary particles, such as hairspray or cigarette smoke, whereas a video fire detection system would not.

Other reliable systems of fire detection include the use of infrared cameras. These systems are rather reliable, but involve expensive cameras. However, with the increased popularity and use of standard surveillance cameras, a fire detection system that was reliable and capable of utilizing these already installed cameras could be invaluable.

The most reliable systems currently proposed have focused on isolated environments where there would be few false positives. Such methods include that proposed by Gottuk et all.[2] for shipboard use. This method is highly reliable by specifying the type of environment it will be used in.

A significant amount of research seeking a reliable environment ambiguous system has been done in the area of fire detection in video. Some methods, such as the one proposed by Healey et all. [3], rely on identifying fire on movement and color alone. Other methods, such as those proposed by Liu et all. [4] and Marbach et all. [5], add an analysis of temporal variations of fire to allow for the fact that fire flickers. These methods lack the detection of one of fire's most distinguishing characteristics – its spatial color variation. The method proposed by Töreyin et al. [6] includes 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 and analyzes the grouping of fire regions to eliminate further false alarms.

The method proposed by this paper is highly flexible and can be used in almost any condition as long as the camera is fixed and stable. This method is reliable in all lighting conditions and is fairly apt at not detecting moving fire-colored objects, allowing it to be used in a multitude of environments.

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

2. METHOD

The proposed fire detection algorithm consists of five steps (i) detecting areas with a high frequency luminance flicker using a cumulative time derivative matrix, (ii) analysis of the fire color of each frame culminating in a cumulative color matrix, fall within the range of fire colored, (iii) the fire colored moving regions are then dilated to combine them if they are closely located, regions satisfying the three previous conditions are then analyzed for (iv) temporal variations and (v) spatial variations. Each step is explained in detain in the following subsections.

2.1. Flicker Detection

One of the most prominent properties of fire that separates it from other objects is its tendency to flicker with a frequency between 1-10 Hz [7].

Regions with a high frequency luminance flicker are detected by using a cumulative time derivative method developed by Marbach et al. [5]. For this stage of fire detection the video is represented in YUV color space and the luminance component is represented by $Y_{ik}(t)$ where t is the time and i, k are the horizontal and vertical pixel position.

The time derivative of the luminance, $Y_{ik}(t)$, will track a moving object because the time derivative for a moving object is a non-zero while it is zero for a static environment. To analyze not only motion, but also tendency for fire to periodically flicker around a region, the sum of the absolute value of the derivatives throughout the video clip. Because fire flickers around a region, the value of these regions will be greatly higher than non-flickering moving objects, thus making the flickering regions of the fire the strongest values. The cumulative time derivative matrix $A_{ik}(t)$ is expressed by the formula:

$$A_{ik}(t)=\alpha A_{ik}(t\text{-}1)+(1\text{-}\alpha)D_{ik}(t), \text{ [5]}$$

where α represents the cumulative strength calculated by (N-1)/N where N is the number of frames being analyzed. D

Figure 1. Typical fire video image (a) and its cumulative matrix (b).

is the time derivative for that frame. D is expressed by the formula:

$$D_{ik}(t)=|Y_{ik}(t)\text{-}Y_{ik}(t\text{-}1)|. \text{ [5]}$$

To further improve robustness and eliminate more false alarms the time the time derivative matrix is multiplied by a weight matrix $W_{ik}(t)$:

$$A_{ik}(t)=\alpha A_{ik}(t\text{-}1)+(1\text{-}\alpha)D_{ik}(t)W_{ik}(t). \text{ [5]}$$

where $W_{ik}(t)$ is calculated to be proportional to the luminance of D. $W_{ik}(t)$ is expressed by:

$$\text{if } Y_{ik}(t) \geq \delta \text{ then } W_{ik}(t) = Y_{ik}(t), \text{ else } W_{ik}(t) = 0 \text{ [5]}$$

where $\delta(\lambda_1,\lambda_2)$ depends on the constants λ_1 and λ_2. These constants ensure that the luminance threshold is always between the mean luminance and the maximal luminance. This removes most of the non-fire pixels of the scene.

In a fire scene, the borders of the flame region will have high values in the cumulative matrix $A_{ik}(t)$ and will otherwise have values that are near zero. The center of the fire, as the luminance is highly saturated, have a time derivative of zero and do not contribute to $A_{ik}(t)$. [5]

2.2. Color Detection

Previous methods of color detection in visual flame recognition, such as those proposed by Marbach et all. [5], Töreyin et all. [6], Liu C. et all. [4], and Phillips III et all. [9], focused only on the pigmentation values of the color to determine what is fire colored. However, the color detection method proposed by this paper focuses not only on the pigmentation values of the fire's color, but also the saturation and the intensity properties of fire. For this method color space is represented in both RGB and HSV.

Fire colored regions are calculated per frame and are then are combined to create a cumulative fire color matrix $F_{ik}(t)$, which is akin to the cumulative time derivative matrix. The cumulative fire color matrix $F_{ik}(t)$ is expressed by the formula:

$$F_{ik}(t)=\alpha F_{ik}(t\text{-}1)+(1\text{-}\alpha)C_{ik}(t),$$

where $C_{ik}(t)$ is the color mask of the current frame and α is the same as previously defined. $C_{ik}(t)$ is calculated in several steps as follows.

Initially a mask, called Rmask(t), is created to focus only on the values within the red to yellow range, as conventional fire always falls within this range. The definition used is that defined by Chen et all. [8]:

$$R_{ik}(t)>R_{T\ ik}(t) \,\&\, R_{ik}(t)>G_{ik}(t) \,\&\, G_{ik}(t)>B_{ik}(t) \text{ [8]}$$

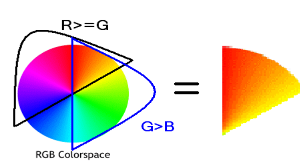

Figure 2. The red to yellow colorspace.

where R_T is an experimentally defined threshold.

The $Rmask_{ik}(t)$ is then multiplied by $S_{ik}(t)$, which is the saturation values of the frame, creating $S2_{ik}(t)$, thus allowing the method to analyze only the pixels contained within the red to yellow range.

$S2_{ik}(t)$ is then tested to see if the average level of the saturation of the red levels are high or low. This is important because the saturation levels of fire are either very low or very high depending on whether or not the fire is the main source of light within the video. Therefore, for further calculations, if the average saturation level is very low,

$$S2_{ik}(t) = 1-S2_{ik}(t).$$

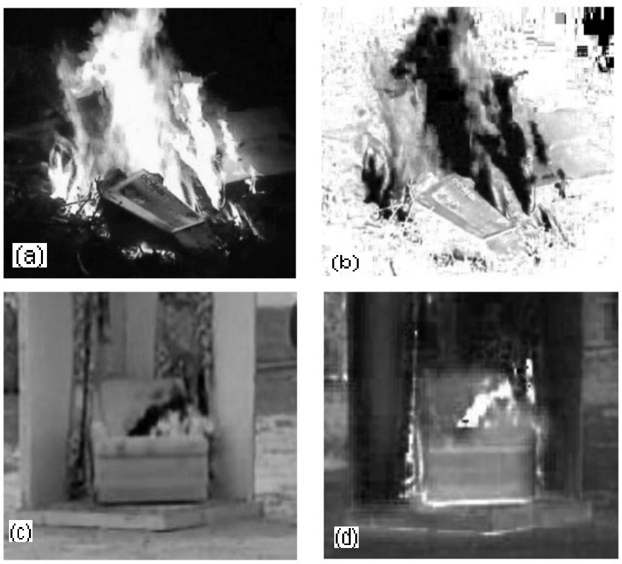

Figure 3. A typical fire at night (a) and its saturation values (b) A typical fire in the day (c) and its saturation values(d)

Areas with an intensity that is either greater than an experimentally determined threshold greater than .5 or the average value of the intensity in that frame, whichever is greater, are then found. These areas are defined as $V_L(t)$. $V_{Lik}(t)$ and $S2_{ik}(t)$ are then multiplied together to create $C_{ik}(t)$, so that the pixels associated with strong intensity and saturation are considered more likely candidates to be fire colored.

The final step of color detection is to eliminate all pixels in $F_{ik}(t)$ that are less than the average of $F_{ik}(t)$ so as to suppress those pixels which are not as strongly fire colored.

The highly likely fire areas as of this point are defined as $M_{ik}(t)$ which is expressed as

$$M_{ik}(t) = F_{ik}(t) * A_{ik}(t).$$

2.3. Region Merging

M(t) is composed of several areas that are considered to have a high likelihood of being fire. However, to further eliminate false positives a method of growth and erosion is used. $M_{ik}(t)$ is then dilated to combine the areas with a high likelihood of being fire. Then the areas that remain one or two pixels before dilation are then eliminated from M(t) as

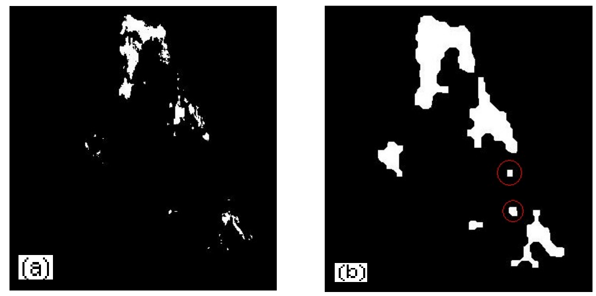

Figure 4. A typical mask M(t) before dilation (a) and after dilation (b), the circled regions in (b) are those to be removed.

they are often non-fire outliers. M(t) is then eroded back to its original size before dilation.

2.4. Temporal Color Variation

The next step in the fire detection algorithm is to keep track of the temporal color changes of each of the pixels in the fire colored region, or non-zero elements of M(t), and to analyze the number of changes that occur between fire colored pixels. This helps to eliminate items such as leaves blowing in the wind in front of a brick building or during a sunset. This is done by adding up the R, G, and B values of every pixel in every frame of the sample. Then each non-zero pixel, $P_{ik}(t)$, in $M_{ik}(t)$ is tracked throughout the frame, subtracting the previous value from the current color value of that pixel. If the absolute value of the difference between the pixel at the two different times is greater than a threshold then it is regarded as a change, which is added to the change value of $P_{ik}(t)$, $Ch_{ik}(t)$. If if it is also fire colored, for when a fire flickers parts of the background are also seen, then if

$$abs(P_{ik}(t) - P_{ik}(f)) > P_T$$

where f is the last fire colored pixel and P_T is an experimentally determined threshold, then it is regarded as a fire colored change, which holds more weight in the final calculation, and the recognition of the fire colored change, is added to the fire colored change value of $P_{ik}(t)$, Fc_{ik}.

Once the changes for every pixel has been calculated, the two are combined in the following expression:

$$T_{ik} = Ch_{ik}(t) * 2Fc_{ik}(t).$$

Then any element in T_{ik} that is less than a threshold, determined in part by the number of frames in the sample, are eliminated from T_{ik}.

2.5. Spatial Color Variation

The final elimination of non-fire elements is to analyze the spatial color variation between the fire-colored pixels remaining in T_{ik}. Fire is unique in that it does not remain a steady color. It is composed of several varying colors within a small area. This helps to eliminate objects with a solid flame-color, such as shirts in consistent lighting.

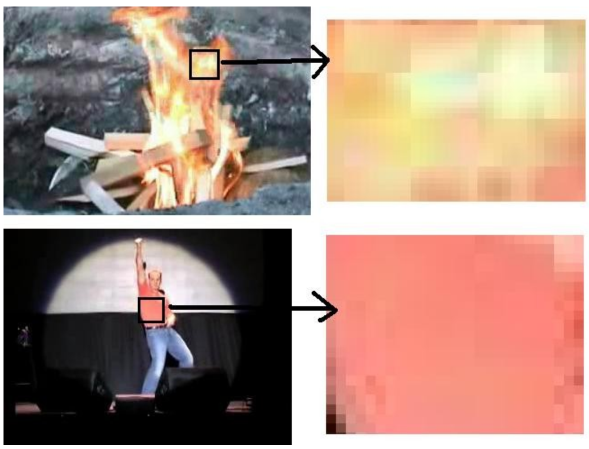

Figure 5. Spatial variation in fire and in a typical fire colored object.

For this step, T_{ik} is transformed into a binary mask Bw_{ik} which is then applied to every frame in the original video so as to keep the colors true. This makes a new dataset $Mf_{ik}(t)$. Then a range filter is applied to each frame of $Mf_{ik}(t)$. The range filter outputs the range value (maximum value - minimum value) of the 3-by-3 neighborhood around the corresponding pixel. There is a range value for the red, green, and blue, aspects of the frame. Only values with a large green range are considered to be fire pixels. This is because the red value of fire has a fairly limited range of change while the green value varies greatly.

2.6. Final Verdict

The presence of fire is finally determined by the ratio of fire colored pixels to the number of non-fire colored pixels. If the ratio is greater than a determined threshold then fire is considered present and an alarm is issued.

3. EXPERIMENTAL RESULTS

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	14	0	No	Fire truck with lights on
Movie 10	32	0	No	American flag waving
Movie 11	48	0	No	A swinging light bulb
Movie 12		0	No	A mall with pink floors
Movie 13	142	142	Yes	Armchair burning.
Movie 14	104	104	Yes	3 dog houses burning.
Movie 15	34	0	No	A boy dancing in front of a window with a neon orange blanket and red clothing.

Figure 6: Results for some of the sequences tested.

The proposed method is effective for a large number of conditions and was tested on a large and varied database (which is not publicly available). All of the clips within the database have a minimum resolution of 320x240 and the minimum viable frame rate used with this method is 25 frames per second. The database consisted of over 80 videos with a broad range of situations and content. Several of the videos in the database were designed to throw the system off and induce false positives. While we did indeed detect a few false positives, all within videos designed to trick the system, such as Movie 1 in Figure x, all forms of fire were 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 and at the same rate as uncontrolled fires.

The false positive represented by Movie 1 is a typical error in our detection system. Movie 1 is of a Yellow lit fountain at night with several arches of water and a bit of yellow lit mist. The fountain exhibited all the characteristics of fire utilized by this system and could only be conceivably eliminated through the use of shape analysis.

In many cases this system performed with a higher accuracy and resulted in smaller regions of false positives, when false positives were present, than the fire detection system suggested by Töreyin et all. [6], when tested on our database.

4. FUTURE WORK

Possible improvements on the current system include increasing the run time efficiency in order for the system to run in real time, thus making it practical as a preventative fire detection system. Further research is needed to eliminate the current false positives detected by the system, such as those in Movie 1. This may be achieved by adding a method that analyzes the shape of the fire.

Another possible improvement to this system occurs once it has been made to run in real time. This is to incorporate it with a grid system to allow the location of the fire to be known thus enabling automatic fire extinction.

5. CONCLUSION

This paper presented a novel system for automatically detecting the presence of fire in stable video sequences. The algorithm is based not only on the color and movement attributes of fire but also analyzes the temporal variation of fire intensity, the spatial color variation of fire and the tendency of fire to be grouped around a central point. Experimental results indicate

6. REFERENCES

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