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Fire Detection from Video based on Temporal Variation,Temporal Periodicity andSpatial Variance Analysis

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Abstract

Fire detection is an important issue in the modern security system. In this paper, a vision based fire detection system is proposed. The proposed method integrates both color and motion information to isolate the fire regions from the video frame. First, based on some training fire images,the color of each pixel is analyzed to locate the fire colored pixel. Temporal variation and temporal periodicity of each pixel are calculated to determine which of these fire colored pixels actually fire pixels are. Then, we analyzed the spatial variance of each fire colored region. And in this step, some spurious fire regions are eliminated. The fire has some center regions which are much brighter and relatively stationary than other regions. Extracting these regions is also a feature of this work.Finally, a region growing algorithm is applied to find the actual fire regions in the video. In the experimental result, we showed that the proposed method works in various environmental conditions and the number of false fire frames detection is very lowfor fire colored stationary or moving object.

Keywords:

YCbCr;
Color model conversion;
Standard deviation;
Temporal variance;
Spatial variance.

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1. Introduction

Nowadays fire accident causes a great loss of our lives and properties. Introducing an early fire detection system can minimize these human loses. The conventional methods require detecting equipments to be situated near to fire sources as they detect fire by fire generated particle analysis, temperature sampling, and air transparency checking. So, these methods are distance limited. Moreover, these methods can't detect the fire combustion; they detect the byproduct of fire combustion such as smoke, heat, etc. These methods can't detect the fire until these byproducts reach the sensors. As a result, these methods failed in open or large spaces. A solution to this limitation can be video-based fire detection system. Because video-based fire detection system detects the fire combustion itself, not its byproducts.

Video-based fire detection provides several advantages as compared to conventional system. First of all, there is no latency for fire's byproduct detection and fire information can reach the sensor at the speed of light, which makes it suitable to be implemented at the real time. Secondly, nowadays in all almost all public places, the CCTV (Closed Circuit Television) system is installed. The output of these CCTV cameras can easily be processed for video fire detection. Thirdly, the CCTV camera can monitor a large space, which makes video-based fire detection system suitable for open or large spaces. Fourthly, video detection system

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can not only detect fire or smoke, but also it canprovide additional information about location, size, the rate of growth, etc.

Several methods have been proposed for fire detection from images and videos. Almost all of the methods use motion, color information of the fire pixels and geometric characteristics of the flame region for fire detection.In [1], Zhou et al. presented a method for early fire detection in video based on flame contours. They use different selection rules to remove the unlikely frames from the suspicious fire frames and to detect the flame pixels in the candidate fire frames, and different decision rules based on area, perimeter, and roundness of flame contoursto determine whether a fire occurs in the video or not. Habiboglu et al. [2] proposed a method which uses only color characteristics of the fire region. Obviously, this method has a high false alarm rate not only for the moving objects but also for the stationary fire colored objects.

An improved approach was presented by Philips et al. [3] which makes use of motion information as well as color. This method used Gaussian color histogram model for isolating the fire colored pixels and temporal variance analysis. Finally, a region growing algorithm is applied to find complete fire region. In [4], a method is proposed which uses spectral, spatial and temporal features to detect fire. Here the spectral model describes the color probability density distribution of the fire pixels. The spatial behavior of fire region is described by the spatial model. The temporal model describes the change of spatial model over time.

Toreyin et al. in [5] proposed a method that analyzed temporal and spatial wavelet transformation to extract flicker and edge blurring characteristics of fire. Though the accuracy of their methodology was quite satisfactory for various sample data sets, they used many heuristic thresholds which could seriously undermine detection accuracy. In [6], Toreyinet al. implementedanothermethod to detect flames in video using the data generated from a camera and flame flicker process using a hidden Markov model. Markov models are used to distinguish flame flicker process from motion of flame colored moving objects.Celik et al. proposed a real-time fire detector that combines foreground object information along with pixel's color analysis [7]. An adaptive background subtraction algorithm was applied and the resultant was verified against a statistical fire color model.

Habiboglu et al. [8] also presented another video-based fire detection system, which uses color, spatial and temporal information, that divides the video into spatio-temporal blocks and uses covariance-based features extracted from these blocks to detect fire.In [9],Celik et al. proposed another model which uses different color models for both fire and smoke. The color models are extracted using a statistical analysis of samples extracted from a different type of video sequences and images. The extracted models can be used in complete fire detection system which combines color information with motion analysis. Pagar et al. in [10] presented a method using HSV color model for the smoke detection. Premalet al. in [11] used YCbCrmodel for fire detection from the image. Their proposed method also detects the central region of fire which is comparatively brighter than the remaining fire regions.

2. Research Method

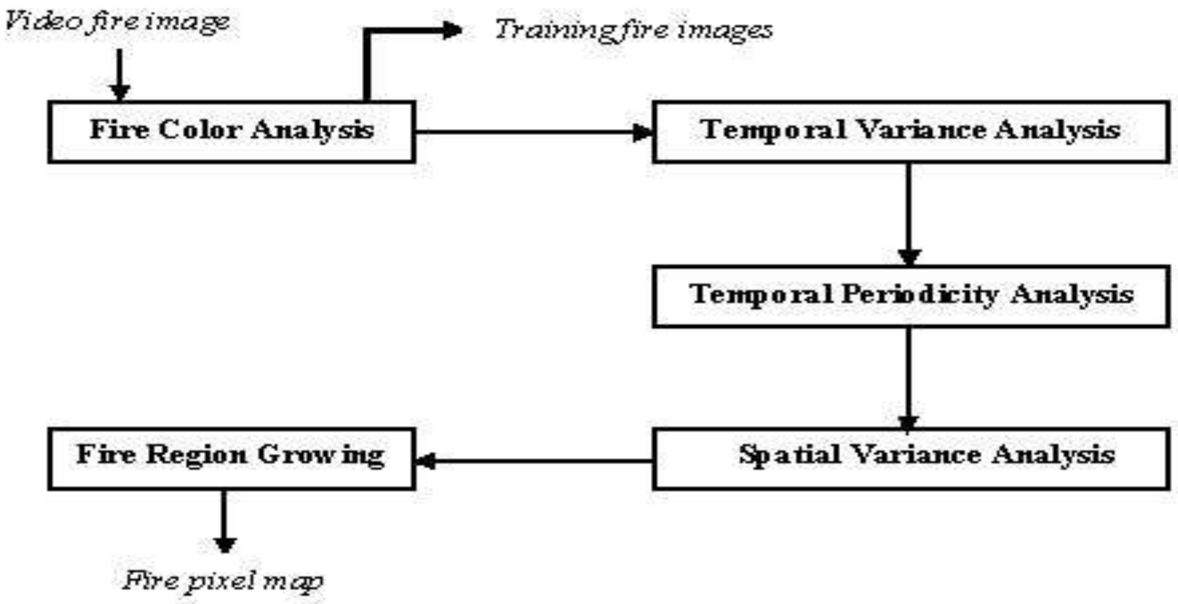


Figure 1.Steps for fire detectionfrom video

The developed system is divided into several steps of processing. Each step does a particular function which facilitates the requirements needed for the next step processing. The whole architecture of the developed system is shown in Fig. 1.

2.1. Fire Color Analysis

Generally, fire region in video images shows similar color. So we can isolate fire region in an image based on color properties of fire colored pixel. The primary detection of fire pixels is carried out using YCbCr samples. According to [11], in YCbCr samples, the greater the difference between Y and Cb components of a pixel is, the higher the likelihood that it is a fire pixel. Similarly, a higher discrimination between Cb and Cr componentsmeans thecorresponding pixel is more likely to be a fire pixel. So if *Th* is a threshold which if treated a minimum difference of Y and Cb or Cr and Cb, then we can summarize that $Cr - Cb > Th$.The value of *Th*is determined as 90 experimentally for video sequences.

Fire is gaseous and therefore, it may become transparent and undetected by the color predicate in some video frames. Therefore, it is necessary to average the fire color estimate over small windows of time proposed in [3] as follows:

$$FireColProb(x,y) = \frac{\sum_{i=1}^{n} FireColLo\ okup\ \left(I_i(x,y)\right)}{n} \tag{1}$$

$$FireColored(x,y) = \begin{cases} 1 & if\ FireColProb\ (x,y) \geq k_1 \\ 0 & if\ FireColProb\ (x,y) < k_1 \end{cases} \tag{2}$$

Where n is the total number of images in the subset andI_i is the i^{th} image in the subset,$I_i(x,y)$ is the RGB color value of the pixel at position (x,y) and k_1 is an experimentally determined constant. The *FireColProb* returns the probability of pixel at position x being fire. Finally, *FireColored* is a Boolean predicate used to mark a pixel as either fire colored or not. For our experiment, choosing n between 12 and 20 is sufficient. Experimentally, we have seen that a pixel must be detected at least 1/5 times by *FireColored*to be detected as fire. For this, we set constant k_1 to 0.2.

The color model can be converted from RGB to YCbCr. This conversion is linear. The conversion from RGB to YCbCr is shown in below.

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2568 & 0.5041 & 0.0979 \\ -0.1482 & -0.2910 & 0.4392 \\ 0.4392 & -0.3678 & -0.0714 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \tag{3}$$

Here ‘Y’ is luminance component, ‘Cb’ is the chrominance blue component, and ‘Cr’ is the chrominance red component. The range of ‘Y’ is [16 235] and the range of ‘Cb’ and ‘Cr’ is [16 240].

The mean values of these three components can be found using the following equations described in [13].

$$Y_{mean} = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} Y(x,y) \tag{4}$$

$$Cb_{mean} = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} Cb(x,y) \tag{5}$$

$$Cr_{mean} = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} Cr(x,y) \tag{6}$$

Here Y(x,y), Cb(x,y), and Cr(x,y) are Y, Cb and Cr components of the pixels at each location (x,y). Y_{mean}, Cb_{mean}, and Cr_{mean} are the mean value of luminance, chrominance blue and chrominance red components of pixels. M×N is the total number of pixels.Center regions are the brightest portion. In RGB color space, the rule to identify these regions is $R>G>B$ which is translated in YCbCr as shown in below.

$$Y(x,y) > Cb(x,y) \tag{7}$$

At high temperature,the center is white in color which means chrominance red component is very less and chrominance blue component is more at the fire center which gives us

$$Cb(x,y) > Cr(x,y) \tag{8}$$

Following equation described in [13] gives the standard deviation of Cr plane:

$$Cr_{std} = \sqrt{\left(\frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} (Cr(x,y) - Cr_{mean})^2\right)} \tag{9}$$

Some of the white colored regions are segmented during segmenting the fire center. To overcome this problem, the texture of the fire region is also incorporated. The texture of the fire region can be defined by the statistical parameters such as mean, median, and standard noitaived. Taking *Cr* plane Cr_{std} can be used as

$$Cr < \tau \, Cr_{std} \tag{10}$$

The value of 'τ' is determined as 6.4 experimentally for video sequences.

2.2. Temporal Variation Analysis

Color alone is not sufficient for fire region detection. Ordinary fire colored objects, such as the sun, the man with fire colored clothes can be detected as fire if we use color alone. The key to distinguish between fire and fire colored object is to use the motion characteristics of fire pixels. Between consecutive frames, fire regions move significantly than fire colored object. Fire pixels generally have high temporal variation because they change their intensity level at a much higher rate. Fire colored rigid objects do not show that kind of high temporal variation. In order to use this features, we calculate the temporal variations of the intensity values of each fire colored pixels over a small window. For this purpose, we calculated the average pixel by pixel intensity difference of fire colored pixel over a consecutive set of frames. Considering global temporal variation in sequential video frames due to for instance for camera noise we calculated a normalized temporal variation for fire pixels by taking global non-fire pixels' temporal variation into account as described in [3]. The pixels that do not exhibit high temporal variations are eliminated in this step. So the overall process can be summarized as follows:

i) Calculate *FireDiffs* of fire colored pixel.

ii) Find the average change in intensity *AverageNonFireDiffs* of all non-fire pixels.

iii) Subtract this average value from the value in *FireDiffs* at each location.

For *n* consecutive video frames, temporal variation may be defined as:

$$FireDiffs(x,y) = Diffs(x,y) - AverageNonFireDiffs \tag{11}$$

Diffs(x,y) and *AverageNonFireDiffs(x,y)*are calculated as follows:

$$Diffs(x,y) = \frac{\sum_{i=2}^{n} |I(F_i(x,y)) - I(F_{i-1}(x,y))|}{n-1} \tag{12}$$

where, *Fi* is the i^{th} frame in a sequence of *n* images, and *I* is a function that given an (R,G,B) triple, returns the intensity (which is (R+G+B)/3).

$$AverageNonFireDiffs = \frac{\sum_{x,y,color\ (x,y)=0} Diffs\,(x,y)}{\sum_{x,y,color\ (x,y)=0} 1} \tag{13}$$

The denominator represents the number of non-fire pixels computed. Pixels for which *FireDiffs (x)*<k_2(≈5) are eliminated from the binary fire pixels map developed in the first step.

2.3. Temporal Periodicity Analysis

If an object moves in front of a fire colored background or for a dynamic fire colored object, the previous steps may result in false detection of fire. In that particular case, some non-fire pixels will be classified as fire because these pixels a)will demonstrate color characteristics of fire colored pixels, and b) will show significant temporal variation because of the motion of the object. In order to avoid such spurious detection, we look at the oscillatory behavior of the *FireColLookup* of a pixel over a small window of time. The flickering characteristics of turbulent flames cause higher frequency content. That is, boundary pixels in a flame could appear and go away several times in a short time period. So, *FireColLookup*'soscillation at a higher rate indicatesthe significant probability of the presence of fire in the video.

$$TemporalFreq = \frac{\sum_{2}^{n} |FireColLookup\ _i(x,y)| - |FireColLookup\ _{i-1}(x,y)|}{n} \tag{14}$$

For true fire pixels,*TemporalFreq* is greater than k_3Hz, where $k_3$is an experimentally determined constant(≈3Hz). Pixels that show lower temporal frequency are removed from the fire pixel map generated by the previous steps.

2.4. Spatial Variance Analysis

Another important characteristic that can be used to separate fire from fire colored object is spatial variance. Fire regions exhibit larger spatial variance compared to fire colored ordinary objects.In order to calculate the spatial variance, we first need to calculate the average intensity of each pixel over a set of consecutive video frames. Then we need to find the isolated fire regions. This is accomplished by applying the connected component algorithm to the fire pixel map.

For the connected component algorithm, we can apply breath first search or depth first search algorithm. Let $R = \{p_1, p_2, \ldots, p_n\}$ be a fire region consisting of n pixels. The spatial intensity variance for this fire region R is calculated as follows:

$$SpatialVariance = \frac{\sum_{i=1}^{n}(I(pi) - SpatialMean\ )^2}{n} \tag{15}$$

where *SpatialMean* is defined as below:

$$SpatialMean = \frac{\sum_{i=1}^{n} I(p_i)}{n} \tag{16}$$

For actual fire region,*SpatialVariance* is greater than k_4, where $k_4$is an experimentally determined constant (≈ 60*)*. The regions for which this calculated spatial variance are less than the threshold $k_4$are eliminated from fire pixels map in this step.

2.5.Fire Region Growing

Above steps may eliminate some true fire pixels that do not fulfill all the above criteria. So we applied a region growing algorithm to find the actual fire region. In order to obtain the exact fire region, we grow the output of previous steps. We check the *FireColProb(x, y)* of each neighbor of each fire colored pixel with a smaller threshold as described in [3]. If this pixel passes this test we set the corresponding entry for this pixel as fire in the fire pixel map. The threshold increases as we go far from fire pixel. This region growing algorithm is a modified version of breadth first search technique.

Finally, fire regions and center of fire regions are shown in the output using white and green colors respectively.

3.Results and Analysis

3.1. Environment

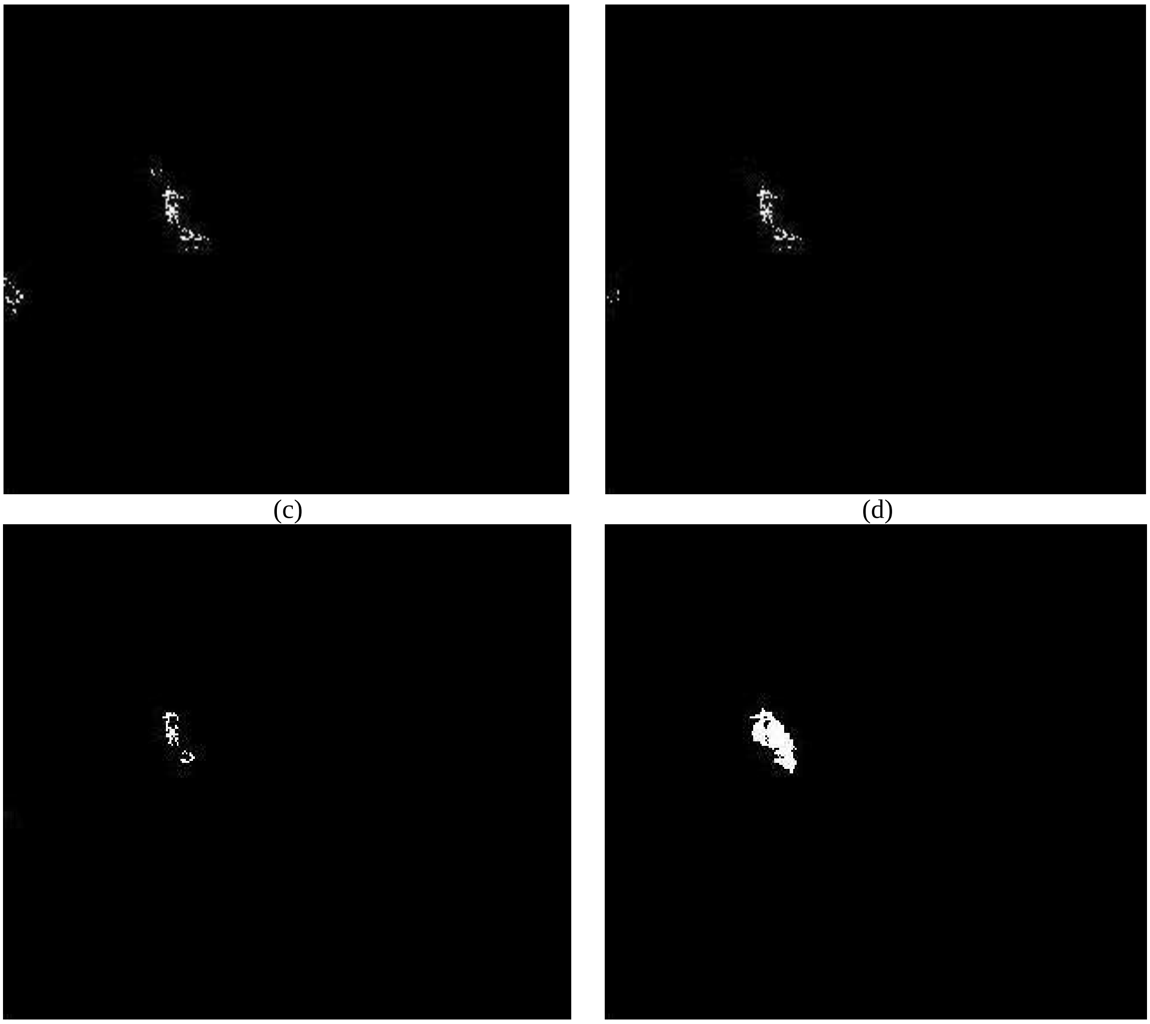
The proposed system has been tested in various environments. We test the system for both videos containing the fire and videos having ordinary fire colored objects. We run the system on a personal computer with the processor: Intel Core i3 2.40 GHz, RAM 2GB. For simulating the system, MATLAB 7.5.0 was used. We analyzed 12-15 consecutive video frames to detect the presence of fire in these video frames.

3.2. Experimental Results

We tested the proposed system for videos containing true fire or fire colored regions. These videos are taken in different environments. Following figures, from Fig. 2(a) to Fig. 2(f), show the output of different phases of the proposed system for a video taken in the outdoor environment.

(a) (b)

Figure 2. (a) Video frame with fire, (b) Fire pixel map after color analysis*(continued…)*

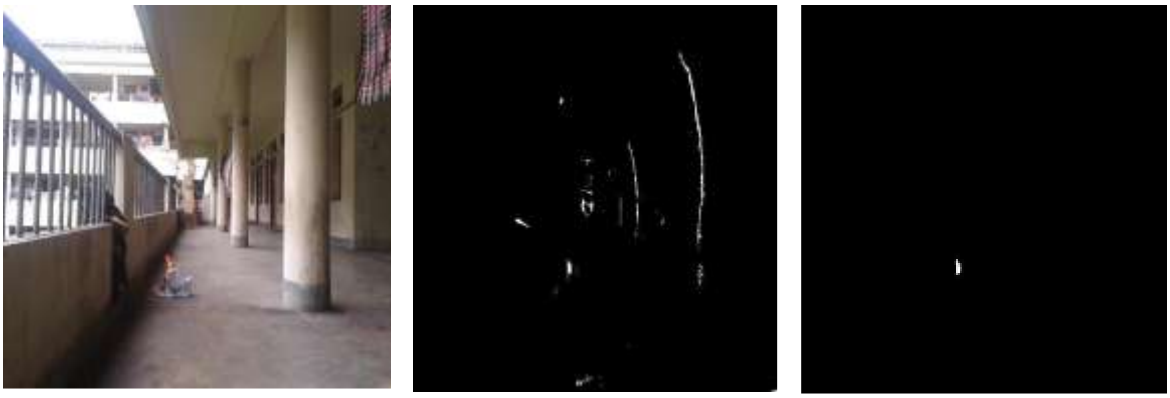


(c) (d)

(e) (f)

Figure2.(c) Fire pixel map after temporal variation analysis, d)Fire pixel map after temporal periodicity analysis, (e) Fire pixel map after spatialvariance analysis, and (f) Final fire pixel map

From the figures, it is clear that after temporal variation and temporal periodicity analysis, some spurious fire pixels remain in the fire pixel map, but spatial variance analysis removes those spurious fire pixels. Finally, we obtain the final fire pixel map after applying region growing algorithm.Fig. 3 shows the outputs for an input video taken in semi-indoor environment containing fire regions. From the resultant image it is seen that using only color information, a lot of non-fire pixels are detected as fire. But after motion analysis of fire pixel, these non-fire pixels are removed.



(a) (b) (c)

Figure 3.(a)Video frame with fire, (b)Fire pixel map after color analysis, and (c) Final fire pixel map after temporal variation, temporal periodicity, and spatial variance analysis

The system is tested for video having fire colored background and a moving object in front of this background as shown in Fig. 4(a)(i) and the result shows that the proposed method doesnot detect any fire region. Similarly, it is tested with the video having fire colored moving object as shown in Fig. 4(a)(ii) and the output represents that this method doesnot detect ordinary fire colored moving objects as fire.

(i) (ii)

(a) (b) (c)

Figure 4. (a) Video frame with (i) fire colored background,(ii)firecolored moving object;(b) Fire pixel map after color analysis, and (c) Final fire pixel map after temporal variation, temporal periodicity, and spatial variance analysis

3.3. More Experimental Results

The system is tested by a lot of videos of different situations and environments, such as a video frame of (i) a fire accident at night, (ii) a burning forest, (iii) a fire and fire colored still object, (iv) a fire accident in outdoor, and (v) a fire in dark environment, etc. It shows robustness and consistency through all the situations. The results for some more videos are depicted in Fig. 5. The system has successfully detected the fire regions in these videos. The detected fire regionsare shown in Fig.5(b).

(i)

(ii)

Figure 5. (a) Input video frames; (b) Output of fire regions with centers/no center*(continued...)*

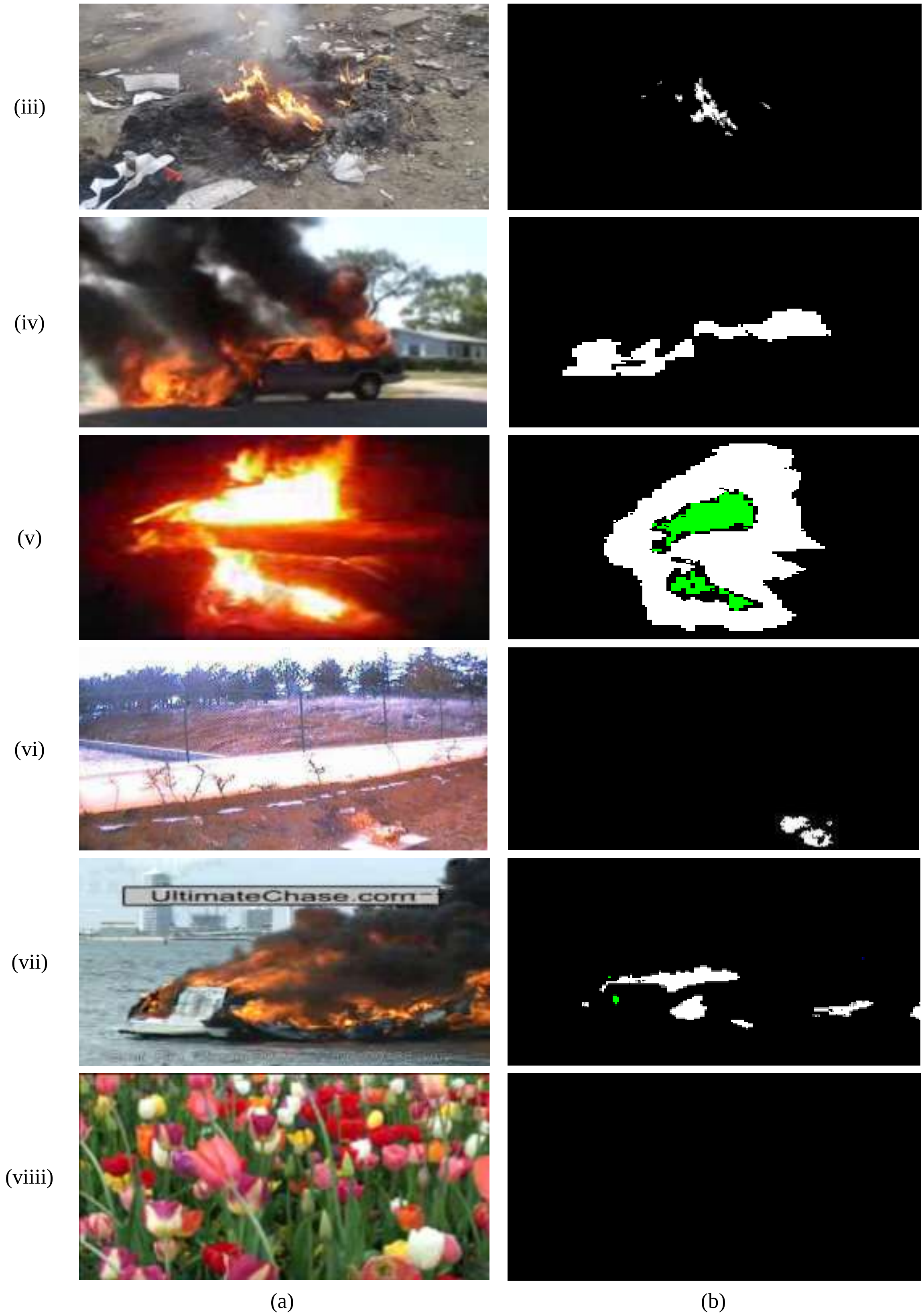


Figure 5.(a) Input video frames of different situations and environments; (b) Output of fire regions with centers/no center or no fire region

In Fig. 5(i)(a), the fire region is not every section of the frame, mostly concentrated in an area and scattered in other places of the frame. After analyzing, Fig. 5(i)(b) gives the final result. The green regions specify the most burnt places and are considered as the center. The rest of the regions, i.e., the white regions are mostly fire regions with low temperate and spaces with movable fire flame.The sample shown in Fig.

5(iii)(a) has a red colored still object similar to fire color. This still object is not detected as fire and the output gives the fire region, but not any center.The input in Fig. 5(iv)(a) shows a car is on fire in daylight. The whole fire region is selected in the output image. No center region is in the output as not seen in the input frames.

In night environment, only fire is in the input frames of Fig. 5(v)(a). In the output, a very large center compared to previous inputs is detected due to its brightness and rest of the area is white.The sample input of Fig. 5(vii)(a) shows a burning watercraft in sharp daylight. Each portion of the fire regions is almost same in color and bright center region is not visible sharply. The output in Fig. 5(vii)(b) shows the fire region and a small, unstable center.Fire colored moving objects is given in the sample input of Fig. 5(viii)(a). Some flowers of red and yellow colors are moving because of air flow is in the input video. These moving objects are not detected as fire in the output given in Fig. 5(viii)(b).

3.4. Performance Analysis

For performance analysis, we analyzed several sample video clips. The test videos include several events under a variety of conditions like outdoor environment, semi-outdoor environment, low light condition, fire colored moving objects, etc. Test videos also include videos having fire colored moving object and videos having moving object in front of fire colored background. The developed system is compared with one of the previous fire detection systems [3]. Here the number of false detection is used as a metric for performance analysis. The comparative experimental result for these two methods is given in Table 1.

Table 1. Performance comparison of fire detection systems

Video Name	**Number of Frames**	**Number of Frames with Fire**	**Frames Detected as Fire**	
			The Proposed Method	**Phillps et al. [3]**
Video1	218	218	218	218
Video2	708	708	708	708
Video3	1134	0	0	60
Video4	967	967	967	967
Video5	260	260	260	260
Video6	330	0	0	40
Video7	472	0	48	360
Video8	208	208	208	208
Video9	346	0	0	270

From the result, we see that the proposed system can successfully detect in several environments. And the number of false detection for the proposed system is much less than the previous system [3]. Some false detections can mainly be caused due to sharp daylight, an outdoor environment where the center region is not easily detected but the fire is detected there , fire colored moving object running too quickly, for example, a red color car moving at high speed are detected as fire. But fire colored object moving at normal speed such as red or yellow colored flowers are not detected as fire.

4. Conclusion

Here a robust and computationally efficient method is proposed for detecting fire region from a color video. Both Color and motion characteristics of the fire have been used to detect flame in video. For motion analysis, we used temporal variation, temporal periodicity, and spatial variance properties of fire region. The method based on only color information or method using only ordinary motion information like temporal variation may have high false alarm rate. The experimental result shows that the proposed method drastically reduces the number of false detection. Also, computational complexity is low in this system. The proposed method can be used for fire detection in movies and video databases. It can be incorporated into a surveillance system monitoring an indoor or outdoor environment for the interest of early fire detection.

Through the tests, this method has shown promise for detecting fire in real world situations, and in movies. One possible direction for future work is to implement this algorithm in hardware for cheap commercial use. Because of the low computational demand necessary for this algorithm, it is also possible to use this algorithm as part of a robust, real-time system for fire detection. Another direction would be to distinguish between different types of fires. Predicting fire’s path in video would be interesting for fire prevention. Finally, the proposed algorithm can be extended to incorporate the smoke in the video sequences, which may be used as faster fire alarm detection in some special condition where smoke is seen first before fire is visible.

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