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SMOKE DETECTION BASED ON IMAGE PROCESSING BY USING GREY AND TRANSPARENCY FEATURES

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ABSTRACT

In this study, we improve smoke detection approach based on frame movement by analyzing the characteristics of early smoke. Background and different modeling methods are used to detect moving objects in every frame accurately. Sequentially, the image was converted to binary mode, and while undesirable lightness pixels are removed from the image. Smoke was detected by using two features, namely, gray and transparency. The first feature depends on the standard deviation of the object, and the second one measures image transparency. Experimental results show that the suggested algorithm can achieve a high detection rate of smoke approach to 92%. These results were observed by using accuracy scale as a mathematical base for classification.

Keyword: *Motion Detection; Smoke Detection; Standard Deviation; Transparency.*

1. INTRODUCTION

Smoke detection some time represents an early sign of most fires. It is important to monitor air infection and its effects on human health and nature; therefore, an effective method to detect smoke is necessary [1] The Early detection of fires is important to reduce fire damage. The flame or smoke usually represents the first alarm that a fire or forest fire gives it. Flames may not be visible at monitoring cameras if the flames appear at along distance far away or they are obscured by obstacles, such as mountains or buildings. Smoke is an effective indicator of a forest fire, but identifying smoke in images is difficult because it lacks a specific shape or color pattern [2].

Celik et al. pro[3] proposed a method for smoke detection using image processing. They used color and saturation information in order to detect smoke in images. In general, a grayish color of smoke is reasonably reliable. Smoke information is used for early fire detection systems; therefore, smoke features are detected when smoke exhibits low heat and low saturation. Chen [4] proposed a smoke detection algorithm based on video processing for early fire alarm systems. The algorithm depends on a chromatically effect which is based on static decision rule, while diffusion-affected by dynamic decision criterion. The static decision relies on the grayish color of smoke, and the dynamic decision rule is based on the spreading attributes of smoke, such as smoke disorder and growth rate. The grayish color is described using the intensity component of the HSI color system. Kopilovic et al. [5] observed that irregularities occur in the motion of the objects because of the non-hardness of smoke. They applied a multilevel optical flow computation and the entropy of the motion distribution in the Bayesian classifier to detect the special motion of smoke. Yuan [6] proposed a fast orientation model that effectively finds the motion characteristics, thereby saving computational time. Although significant advances have been made in the development of this area, the adoption of these methods in general monitoring systems is not widely reported. Appearance-based approaches are also used to detect smoke. Simone Calderara [7]proposed a system able to smoke detecting by using means of the motion segmentation algorithm and both Wavelet Transform energy coefficients and image color properties were used to detect process.

Where the energy is analyzed using the wavelet Transform coefficients evaluating its temporal evolution. The color properties of the objects are analyzed accordingly to a smoke color model to detect if color changes in the scene are due to a natural variation or not and the adoption of a two contributions likelihood measure solves most of the emerged problems of each chosen feature and

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boosts up significantly the detection process Here, we propose new techniques to implement in video to provide optimized results in smoke detection. The remainder of the paper is structured as follows. Objects motion detection and the difference in regions are defined in Section (2). Image analysis and feature extraction in each region are presented in Section (3). In Section (4), we used a morphological method for smoke detection by accounting average standard deviation to object color and applied Fourier transform to distinguish transparent smoke and track objects.

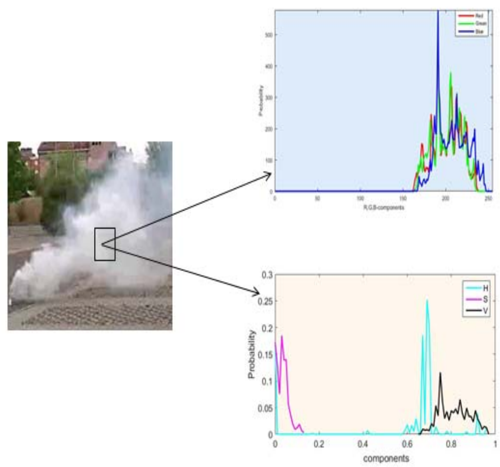

Figure 1. Histogram Of The RGB And HSV Color Spaces For The Smoke Region.

2. COLOR MODELS AND SMOKE FEATURE ANALYSIS.

Determining the color model for smoke and analyzing the images that consist of smoke samples are important in the smoke detection [8]. HSV color space is chosen intentionally because of its capability to separate light (or luminosity) information from chrominance more effectively compared with other color spaces. Smoke pixels do not show colonization properties, such as fire pixels, in which the smoke is mostly gray and contains a few color details. Thus, the luminance information is much larger than the achromatic information. Figure 1 shows the histogram of the RGB and HSV components for the smoke region. Notably, the histograms of the RGB components are approximately equal. In the case of HSV, the light component is distributed equally with RGB and it presents a large distribution. Thus, we can formulate smoke pixels as follows:

$$R(x,y) - G(x,y) <= \alpha \qquad (1)$$

$$R(x,y) - B(x,y) <= \alpha \qquad (2)$$

$$B(x,y) - G(x,y) <= \alpha \qquad (3)$$

where α is a global threshold that ranges from 0 to1.

3. PROPOSED SYSTEM

The system consists of video given by a fixed camera to detect smoke by video analysis. The video data are converted to a series of frames, and each frame is analyzed. As fires begin, the characteristics of smoke or flame are difficult to identify; however, as the intensity of fire increases, the identification of properties becomes easy. Determining the characteristics of smoke is performed by image analysis. All the objects in the image are identified by changing the movement. The next step, each object is tested in the image to determine the smoke behavior on the basis of the following steps.

3.1.Smoke Detection Algorithm

Smoke detection is essential in defining the early detection of a fire. Smoke can be determined by the characteristics of its five main parts. First, we convert input video into a sequence of frames and determine objects of moving areas in an image by subtracting the frames to find all objects in each frame. Motion detection is also used, In addition to converting the image to HSV color, we also use models to analyze color and
intensity smoke candidate features. Furthermore, we remove or reduce undesirable lightness pixels and track the objects that meet the threshold and conditions. The standard deviation was calculated for each color component (RGB) of The colors of the resulting object. We adopt the highest values and compare them with the characteristics of smoke to determine whether smoke is present. Finally, Fourier transform was used to calculate the transparency of all objects during the smoke, thereby the accuracy of the system increases.

3.1.1 Convert video to frame

The pre-processing video is converted to a sequential frame on the basis of resolution, thereby, enabling comparison between fires and determining the differences in processing methods. This process may increase the performance of the proposed detection algorithm and reduce false alarms. The algorithm includes motion detection and conversion of the frame to

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binary, thereby decreasing undesirable lightness pixels.

3.1.2. Motion detection and color transform

Motion detection is a necessary step for extracting objects in each frame. In this process, the first frame will be stored as a background and the difference between the sequential frames will be found. We used the subtraction method between sequential frames on the basis of a specific step to increase speed processing and reduce time, thereby detecting the differences between the frames and determining the resulting objects for each frame were easy. The tracking mechanism for each object will be applied to determine and store its coordinates and label it as follows:

$$d_{1,i+1} = abs(C_1(x,y,n) - C_{i>1}(x,y,n)) \quad (4)$$

Where (C) represent image number , i=1,2,3…n, (n) is number of the frame.

$$If\ d > t\ (extract\ object) \quad (5)$$
$$Else\ i = i + 1\ \ (next\ operation)$$

where the value should be **d > t** to extract the object. For example, if the two successive images are similar, then their **d** values will be close to **(0);** if they are not the same, then their **d** values will be large.

In the proposed algorithm, each object will be tested inside the frame. The frame will be converted to the HSV color space, thereby determining the value from the intensity of all objects within the frame as possible. V value can be obtained by:

$$\boldsymbol{V} = max\ (r(x,y), g(i,j), b(i,j)) \quad (6)$$

where V is the maximum value among the RGB color values.

The frames are converted to binary in order to identify objects clearly. Small regions and undesirable pixels are also removed

3.1.3. Remove undesirable lightness pixels and labeling objects

The change in the level of lighting plays a key role in determining the properties of the object. The properties of each object were determined and tested to determine whether the object is smoke or not. An algorithm is suggested to delete undesirable pixels of lightness and small objects of binary images by using threshold lightness pixel. In the algorithm, any pixel of a lightness value less than the threshold was deleted as Figure 3.

The morphological closure process that includes dilation and erosion are used to fill the hole and delete undesirable small object and lightness pixel for determining the object accurately and all objects are tracked within the frame. The Figure 2 flowchart represent main steps to detect and track object .

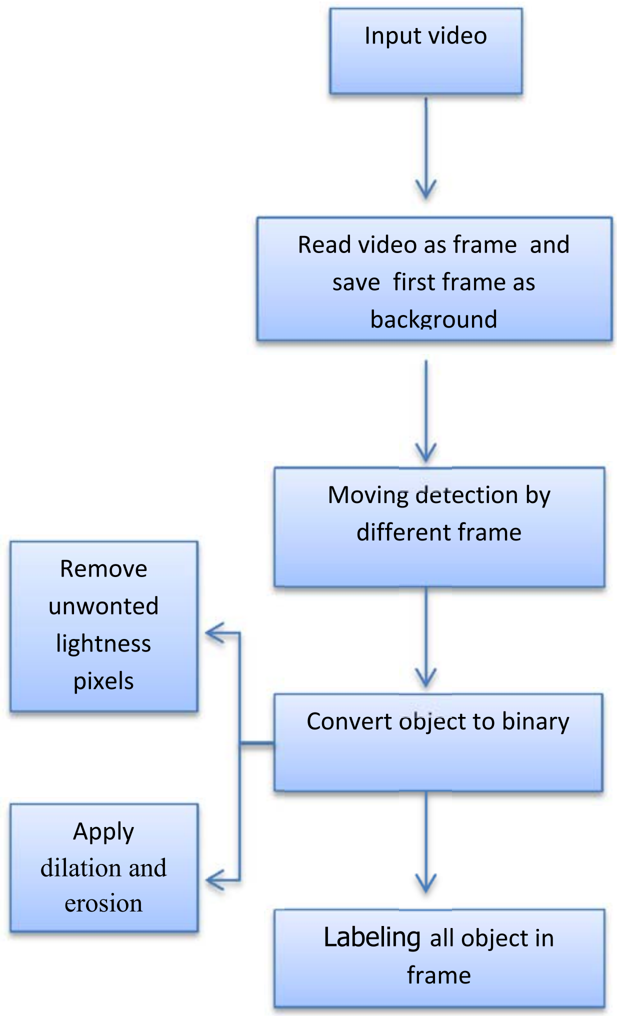

Figure 2. Flow chart to object detection and tracking steps.

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(a)

(b)

(c)

(d)

(e)

(f)

Figure 3. Group (1) Representing Background Images In (A,B), State Smoke Image In (C,D), And Binary Image For Motion Detection Object By Subtracting Two Images In (E,F).

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This process is shown in Eq. (7) and leads to increased accuracy and speed detection. We used a morphological closure process that includes dilation and erosion to fill the hole for determining the object accurately and all objects are tracked within the frame.

Morphological dilation and erosion areas of small undesirable pixels of lightness and small objects are obtained by:

$$d(x,y) = \begin{cases} 0 & > th \\ 1 & \text{other wise} \end{cases} \qquad (7)$$

If more than one object meets the threshold, then the coordinates of each object are stored and labeled. Then, the coordinates in the background image to select the object clearly were used, well as applying statistical calculations by using the following Algorithm1

labeling region Algorithm 1 :

1: binary image; V(x, y) = 0: background, V(x, y) = 1: foreground

The image V is labeled (destructively modified) and returned.

2: Let m ← 2 … value of the next label to be assigned

3: for all image coordinates (x, y) do

4: if V(x, y) = 1 then

5: Set V(x, y) ← label

6: Check all pixels neighbors: V(x+1,y), V (x, y+1), V (x-1, y), V (x, y-1)

7: m ← m + 1.

8: return the labeled image V.

9. End

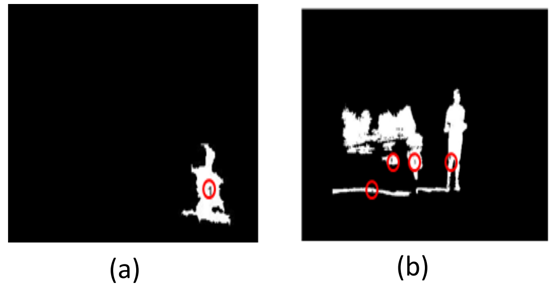

Figure 4 Group (2) Representing Extracted Objects After Removing Unwanted Pixels To The Images In (a,b).

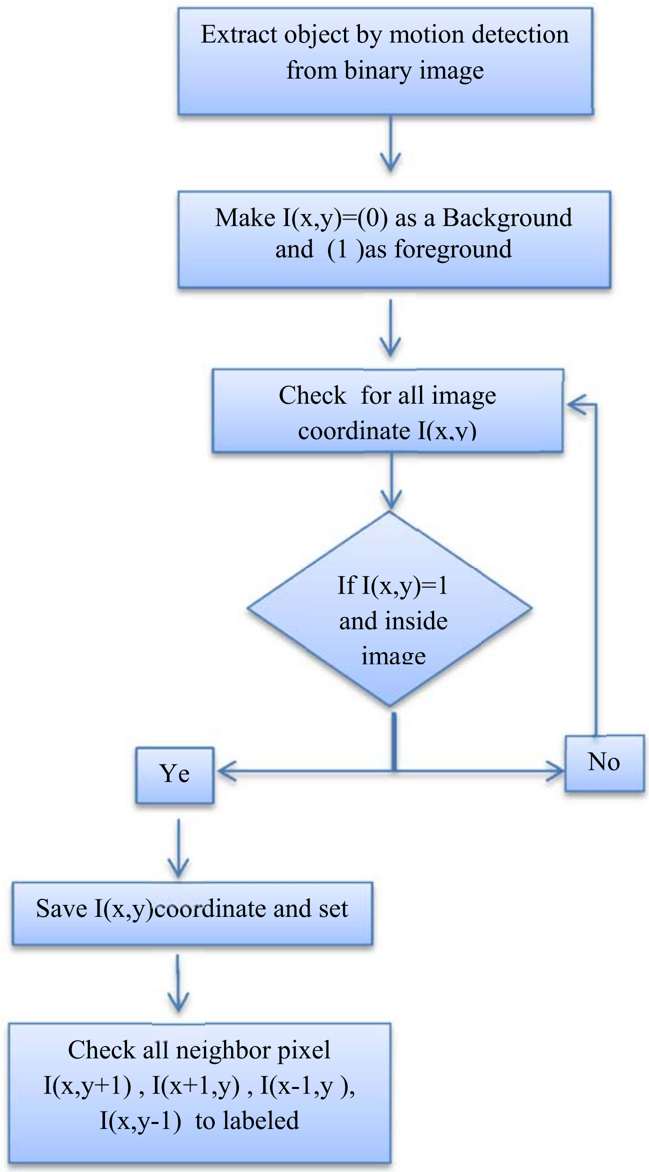

Figure 5. Labeling algorithm for object detection .

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3.1.4 Smoke detection by standard deviation value

After object extraction is completed, a separate process is needed for smoke detection.
Smoke can change its brightness–color performance in an extremely wide range of values, from transparent grayish colors to grayish–blue. Thus, we analyzed areas of intensity. In the analysis of the smoke object [11], the smoke color value in the RGB color space is obtained by the condition R± a= G ±a =B ±a. The rule implies that three components (RGB) of smoke pixels are equal.
Tracking technology was applied to each object to locate and store coordinates for all objects.
To determine the chromatic properties of each object, we calculated the standard deviation of each component (R, G, and B) by using Eq. (8) to measure the approximation between the values. We also calculate the maximum (**std**) values of the color components (RGB) by using Eq. (9) for testing based on the threshold value. Accordingly, the colored smoke object is identified, as in below Eq.

$$std(x_i) = \sqrt{\sum \frac{x_i^2}{n} - \sum(\mu_i^2)} \qquad (8)$$

where (X) is the vector, (i) represents RGB components, and μ is the average value.
The maximum of the standard deviation in RGB components is obtained by.

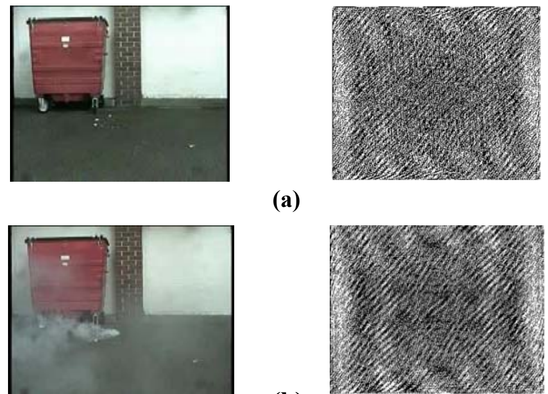
$$Std_{\max} = \max(std(r), std(g), std(b)) \qquad (9)$$

where, if the difference in standard deviation is small, the object will represent smoke properties. and the next step, the threshold value was applied when the following condition is satisfied. and the object is represented the interested region where that region contains grayscale gradients for gray smoke and non-gray ones for a colored smoke.

$$feature1\text{: } if\ Std_{\max} < th\ then$$
$$the\ object\ is\ significant\ regeion \qquad (10)$$

- **Fourier transform :**

Fourier analysis is used in data analysis usually because it breaks the signals into the sinusoidal components of different frequencies. The Fast Fourier Transform (FFT) is considered an effective algorithm .It is especially useful in areas such as image processing and signal, where its uses range from convolution, filtering, and frequency analysis to the power spectrum, estimation. Discrete Fourier Transform (DFT) usually is known in working with the Fourier Transform on a computer where that involves a form of the transform
Figure represent First Fourier Transform for two image



(a)

(b)

Figure 6: (a) *Fast Fourier Transform (FFT) for image without smoke, (b) Fast Fourier Transform (FFT) for image with transparency smoke.*

3.1.5 Measure transparency smoke by using Fourier transform :

Fourier transform is important in transparency detection. In Figures 7,8 we noted that the presence of certain colors (chromatic information) in the smoke images indicates transparency. The algorithm was used to apply Fourier transform to the largest value of each chromatic component for each channel (RGB) by using Eq. (11), thereby calculating the transparency factor. Thus, the accuracy and detection of transparent smoke are increased in this study. Transparency was detected by using Fourier transform in accordance with (12, 13).

$$I = max(r, g, b) \qquad (11)$$

The property in the Fourier domain is shown as follows:

$$I_f = FFT(I) \qquad (12)$$

$$p(I_f) = \sum_{j=1}^{k} nj/k \qquad (13)$$

Where nj is the frequency j =1,2,3… k , K being the number of frequency.
where is the frequency j =1,2,3… K and K is the frequency number.
We can use two factors as features in determining the transparency of objects. The first is the value of the maximum peak of the histogram and the second is the value of the change in the shifting between two images (a,b). If the value of the maximum peak to the image (b) is larger than that of the image (a), then the value of the shift will be as small as possible.

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This object can be regarded as smoke, as shown in Figure 7,8 and Table 1 .

(a) (b)

Figure 7. Contain Group (3) Changes In Shifting Value And Maximum Peak For Identifying Transparent Objects;.

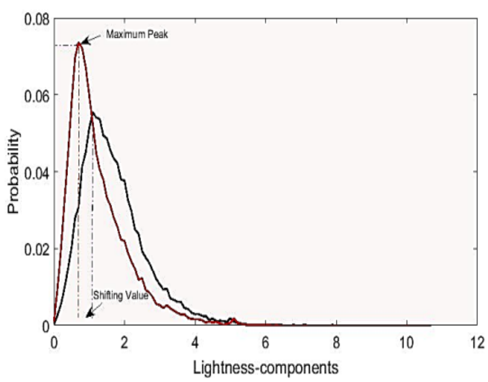

Figure 8. Show Change Value Shifting And Maximum Peak To Identify Transparency Object .

Where the greater proportion transparency is less maximum peak value and greater shifting value represents the maximum probability is obtained by using Eq. (14):

$$M(X_{shift}) = max(p(x))$$
$$feature2 = M\ (Xshift(n+1)) < M\ (X\ shift(n))\ \ or\ \ max\ ((P(xn+1) > max(P(xn)$$
$$If\ feature1\ satisfied\ then \qquad (14)$$
$$if\ feature2\ \ satisfied\ then:$$
The object is smoke or color smoke
End

Feature 1 represents smoke, colored and non-colored areas, which may contain only gray gradients in accordance with Eq. (11). Given that smoke possesses a transparency feature, the second characteristic must always be satisfied to identify the object as smoke.as Table 1.

Table 1. Two Features ,Highest Peak And Shifting Value After Apply Fourier Transform To Compare Image (Group1(A,B) And Group4(B)) With Background Image E(Group1(C,D)And Group4(A)) To Determined Transparency Object.

No.	Highest Peak	Shifting value	No.	Highest Peak	Shifting value	Total max Peak	Total shifting
Image group 1(a)	0.0525	1.8000	Image group 1 (c)	0.0480	1.7000	0.0045	0.1
Image group 1(b)	0.0596	1.2000	Image group 1 (d)	0.0556	1.2000	0.004	0
Image group 3(b)	0.0737	0.7000	image group 3 (a)	0.0554	1.1000	0.0183	0.4

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4. Object tracking and boundary

Object tracking is a critical task in computer vision. Three important steps are used in video analysis, namely, detection of interested moving objects, tracking of such objects by frame, and analysis of object tracks to recognize their behavior. The complexity of object tracking is due to image noises, scene illumination changes, complex object motion, and partial and full object occlusion. Most tracking algorithms assume that the motion of the object moves smoothly and indicates no sudden change [9].
We rely on tracking of such objects by frame to track our object after attaining every condition and drawing boundaries around the object, as shown in Figure 9.
where A and X_{shift} is the value of x with p(x) and (n) is the number of frames

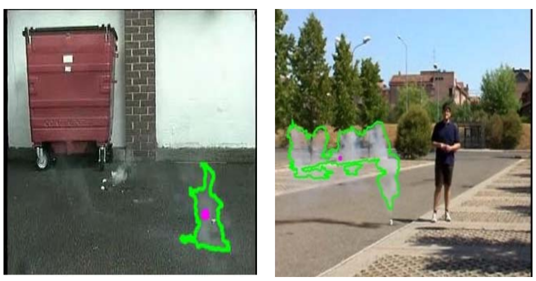

Figure 9 Contain Group (4) ,Representing The Tracked Smoke Objects And Drawn Boundaries

The preceding steps can be summarized by using the Algorithm 2:

Algorithm 2: suggestion methods detect smoke and object tracking

1. *Input video $C_i(x,y,n)$. i is the number of frem x,y position cordinate n =1,2,3 red ,green and blue components.*

2. *Read first image frame from the video $C_1(x,y,n)$ and other images at i=2,3,... $C_{i>1}(x,y,n)$.*

3. *Find the difference between the first image and other images by using*

$d_{1,i+1} = abs\big(C_1(x,y,n) - C_{i>1}(x,y,n)\big)$.

$If\ d < th\ \ i = i + 1$

Go to step 2

Else Go to the next step

4. *Convert $C_i(x,y,n)$ to binary image $Cb_i(xb,yb)$ and delete undesirable eara ,where xb, yb Represent the coordinates where the body exists $Cb_i = 1$.*

5. *using labeling region algorithm to detect number of object N in the frame $C_i(x,y,n)$ to get $Cb_{iN}(xb,yb)$.*

6. *Match the coordinates of the binary image $Cb_{iN}(xb,yb)$ to the original image $C_i(x,y,n)$ to get $C_{iN}(xb,yb,n)$.*

7. *find feature in the image $C_{iN}(xb,yb,n)$ If the feature exist, make a colored border around the body and end else go to step 2.*

8. *End .*

And in the next chart represent the suggestion methods steps to detect smoke and object tracking

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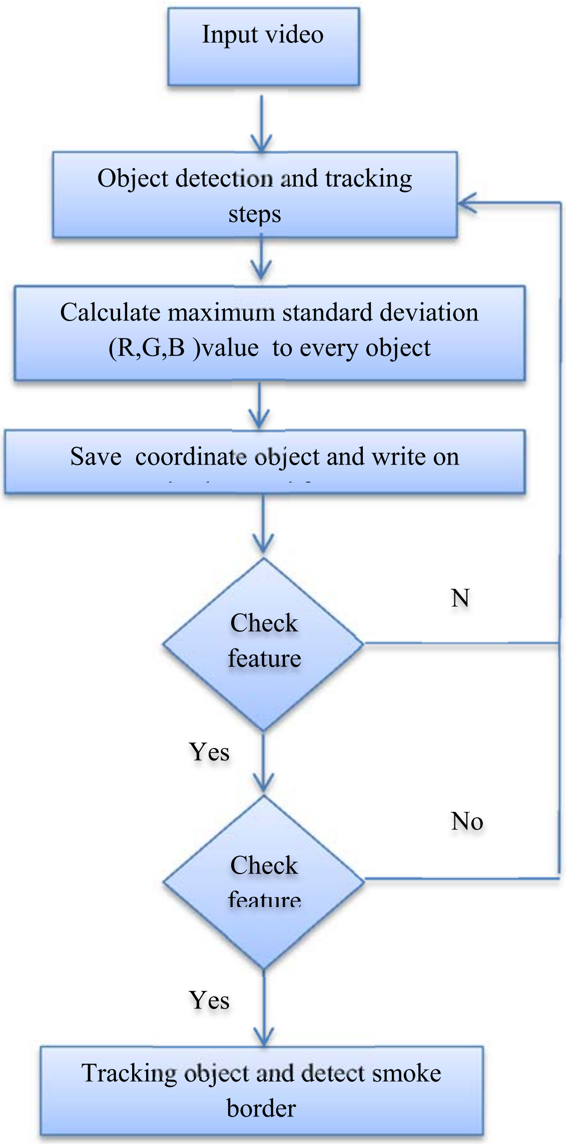

Figure 10 Flow Chart Of Suggestion Methods.

We test our method on selected videos by using MATLAB, some of which are provided by the fire detection from [14, 15] in Figure 11.
The computation can operate at a speed of 25 frames per second, and all videos are normalized to 320 pixels by 240 pixels. The smoke object is shown in a green border. The calculation accuracy results [10]are obtained by.

$$\text{Accuracy} = \text{TP}/(\text{TP} + \text{TN}) \ldots\ldots(16)$$

Table2. Smoke Detection State Of The Method.

Video sequence	Smoke detect state	description
Video1	Y	Only smoke
Video2	Y	Only smoke
Video3	Y	Smoke and person
Video4	N	Moving Car
Video5	Y	Only smoke
Video6	N	Moving man in office
Video 7	Y	Smoke bomb
Video8	Y	Fire and smoke

5. RESULT AND DISCUSSION

In this study, we improve a smoke detection approach based on frame movement by analyzing the characteristics of early smoke. Background and different modeling methods are used to detect moving objects in every frame. After motion detection, the image is converted to binary mode, and undesirable lightness pixels are removed from the image. Smoke is detected using two features, namely, gray and transparency features. We reveal the transparent smoke by Fourier transform and gray smoke by calculating mean and standard deviation. The proposed method is tested on several videos, as shown in Figure10.and the result inTable 3 explain a feature of every video in term number of frame video convert and a number of the frame that present frame smoke and first smoke frame detect in the system and the result appear is 92.6 % in Table 3

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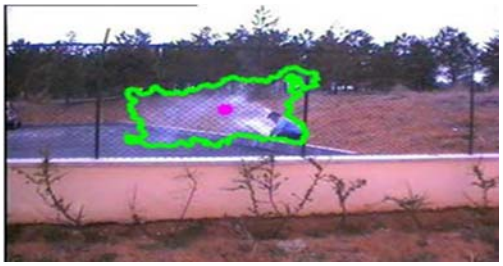
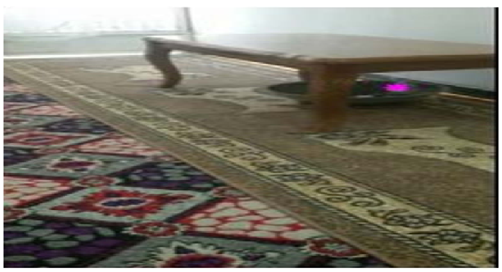


Video (1)

Video (2)

Video (3)

Video (4)

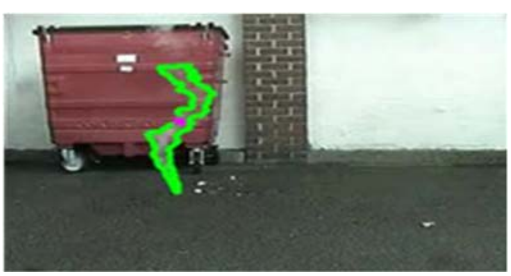


Video (5)

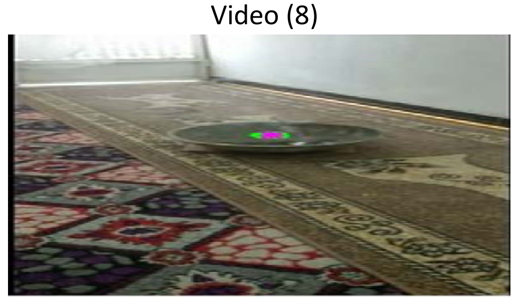
Video (6)

Video (7)

Video (8)



Video (9)



Video (10)

Figure 11. Group (2) Representing Snapshots Of The Proposed System Working On Several Online Videos In Different Conditions. The Selected Area In The Images Is Detected As Smoke.

Table 3. Explain Tested Video Information And Frame Detection To Every Video

Video name	Total frame	Smoke frame No	First present to smoke frame	First frame detect system	No. of smoke true detect	Nonsmoke true detect	Nonsmoke false detect	Total detect
Video1	630	615	15	20	610	15	5	99.2
Video2	1835	1378	457	489	1346	457	32	98.2
Video3	552	156	396	512	40	396	116	78.8
Video4	168	0	0	0	168	0	0	100
Video 5	629	629	1	14	615	0	13	97.7
Video6	356	0	0	0	356	0	0	100
Video7	68	51	17	17	51	17	0	100
Video8	1168	1168	1	322	846	0	321	72.4
Video9	900	850	1	34	827	50	23	97.4
Video10	619	619	1	105	514	0	104	82.9

6. CONCLUSIONS

The proposed approach obtains an accuracy of 92.6%. The results of the proposed method are compared with those of the methods in[11] [12] [13], Table 4 shows that the proposed method obtains the highest percentage of detection among the compared methods. Therefore, the proposed method is superior in terms of detection accuracy.

Table 4. Explain Average True Detection Rate For Our Method With Other Methods.

Method in Literature [13]	Method in Literature [12]	Method in Literature [11]	our Method
83.05%	84.08%	87%	92.6%

REFERENCES:

[1] Memane, S. and V. Kulkarni. (2015)." A review on flame and smoke detection techniques in video's". Int. J. of Advanced Research in Electrical, Electronics and Instrumentation Engineering. 4(2): p. 885-889.
[2] Kim, D. and Y.-F. Wang.(2009)."Smoke detection in video". in Computer Science and Information Engineering, WRI World Congress on. 2009. IEEE.
[3] Celik, T.,et al (2007). "Fire detection using statistical color model in video sequences". Journal of Visual Communication and Image Representation. 18(2): p. 176-185.
[4] Chen, T.-H., et al(2006). "The smoke detection for early fire-alarming system base on video processing". in Intelligent Information Hiding and Multimedia Signal Processing. IIH-MSP'06. International Conference on. 2006. IEEE.
[5] Kopilovic, I., B. Vagvolgyi, and T. Szirányi.(2000)." Application of panoramic annular lens for motion analysis tasks: surveillance and smoke detection". in Pattern Recognition,. Proceedings. 15th International Conference on. 2000. IEEE
[6] Yuan, F., A(2008)." fast accumulative motion orientation model based on integral image for video smoke detection".Pattern Recognition Letters. 29(7): p. 925-932.
[7] Calderara, S., P. Piccinini, and R. Cucchiara, Vision based smoke detection system using image energy and color information. Machine Vision and Applications, 2011. 22(4): p. 705-719.
[8] Çelik, T., H. Özkaramanlı, and H. Demirel.(2007). "Fire and smoke detection without sensors: image processing based approach". in Signal Processing Conference, 15th European. 2007. IEEE.
[9] Shantaiya, S., K. Verma, and K. Mehta.(2015). "Multiple object tracking using kalman filter and optical flow". European Journal of Advances in Engineering and Technology,. 2(2): p. 34-39.
[10] Kong, S.G., et al.(2016). "Fast fire flame detection in surveillance video using logistic regression and temporal smoothing". Fire Safety Journal,. 79: p. 37-43.

[11] Ye, S., et al.(2017)." An effective algorithm to detect both smoke and flame using color and wavelet analysis". Pattern Recognition and Image Analysis. 27(1): p. 131-138.

[12] Avgerinakis, K., A. Briassouli, and I. Kompatsiaris.(2012.). "Smoke detection using temporal HOGHOF descriptors and energy color statistics from video". in International Workshop on Multi-Sensor Systems and Networks for Fire Detection and Management.

[13] Lee, C.-Y., et al(2012)." Smoke detection using spatial and temporal analyses". International Journal of Innovative Computing, Information and Control,. 8(7): p. 4749-4770.

[14] http://signal.ee.bilkent.edu.tr/VisiFire/Demo/SampleClips.html

[15] http://imagelab.ing.unimore.it/visor/video_videosInCategory.asp?idcategory=8