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Fire Detection Using Multi Color Space and Background Modeling

*Adnan Khalil, Sami Ur Rahman, Fakhre Alam and Irshad Khalil, Department of Computer Science and Information Technology, University of Malakand, Chakdara, Pakistan

Iftikhar Ahmad, Department of Computer Science and Information Technology, University of Engineering and Technology, Peshawar, Pakistan

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Abstract. Emergency incidents and events of fires can be dangerous and required quick and accurate decision-making need quick and correct decision-making. The use of computer vision for fire detection can provide a efficient solution to deal with these situations. These systems handle the usual data, provide an automated solution, and discard non-relevant information without discarding relevant content. Researchers developed many techniques for fire detection in videos and still images by using different color-based models. However, for videos, these methods are unsuitable because of high false-positive results. These methods use few parameters with little physical meaning, which makes fire detection more difficult. To deal with this, we have proposed a novel fire detection method based on Red Green Blue and CIE $L*a*b$ color models, by combining motion detection with tracking fire objects. We have eliminated the moving region and calculate the growth rate of the fire to reduce false-alarm and calculate the risk. The proposed method operates on a reduced number of parameters compared to the existing methods. Experimental results demonstrate the effectiveness of our method of reducing false positives while keeping their precision compatible with the existing methods.

Keywords: Fire detection, Fire growth, Static object tracking

1. Introduction

In everyday life, various abnormal events (accidents, medical emergency, disaster, fire, and flood, etc.) occur which require early detection and effective strategies to combat. Early detection of such abnormal events can significantly decrease the chance of massive disasters [1]. Fire poses a constant threat to the ecosystem, human life, and infrastructure [2]. The recent past has witnessed multiple instances of fire causing the catastrophe and resulting in loss of precious human lives and property [3]. For example, in September 2015, three major fires ravaged the state of California at the same time. The valley fire burned over 73,000 acres in the counties of Lake and Napa, killing one person and devastating almost 600 homes [3]. A series of devastating bushfires have struck Australia's southeastern state of

* Correspondence should be addressed to: Adnan Khalil, E-mail: adnanpk44@gmail.com

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Victoria, wrecking several plots of land and forcing thousands of people to flee their homes [4]. Besides human lives and valuable properties, fire is also endangering biological communities in forests. Thus, concentrated and directed efforts are required for timely detection of fire to minimize its spread and save human lives, biological communities, and properties. The traditional method to detect fire is based on the deployment of vulnerable inspectors to identify the spread of fire, which remains an expensive and inefficient process. An efficient and reliable method is to properly use Information and Communication Technology (ICT) for the accurate detection of suspicious fire [5]. These ICT based methods use smoke and temperature sensors and photographic features to detect smoke and distinct change in temperature [5] to reliably detect fire.

The Internet of Things (IoT) plays a significant role in quickly and early fire detection. In IoT based method, different sensors are typically deployed which is responsible to detect different fire criteria. However, IoT based fire detection methods are prone to error, primarily concerning the excessive amount of heat detected by fire sensors [6]. Surveillance cameras also play an important role in the monitoring processing and most of the researchers use these methods for fire detection. In this method, the fire event can be accurately detected by properly analyzing the captured video footage [7]. Computer vision-based techniques address the shortcomings of sensor-based methods and therefore replace conventional fire detection approaches. Modern computer vision-based fire detection currently remains a well-explored area, and existing studies are useful in the detection of unusual fire, its behavior, and the spread/growth rate [8]. These methods are comparably more efficient as they do not depend upon the mobilization of sensor nodes and can properly monitor a vast area. However, in computer vision-based systems, researches have been done to sufficiently reduce false positive and false negative values by modifying their specific thresholds.

The fire detection method based on computer vision depends on the accuracy and robustness of the candidate fire area segmentation. The selection of a good color model for fire segmentation is important because a fire in the images uses a consistent color space. In this article, we combine two different color space i.e. Lab and RGB color space to segment the fire like region more accurately and reduce false alarms. These color spaces are used due to the fact that it represents the image more uniformly than any other space. Further moving pixels are accurately detected by applying a GMM subtraction algorithm in a unique way with the growing object tracking algorithm for fire detection and precise calculation of the fire growth. Contribution of the paper are

1. Due to the fact that the fire area uses a consistent color space and identifies candidate fire regions, two different color spaces (RGB and Lab) are combined and different rules for fire region segmentation are proposed.
2. Unlike other existing methods, we use GMM with segmented fire images to detect only moving objects with fire-like colors. This step will only detect moving fire pixels and skip any other moving objects.

3. The third contribution of the paper is the development of a simple method for tracking growing objects and discarding moving objects. This step will improve accuracy and reduce false alarms in fire detection methods.

The rest of the paper is arranged as follows: In Sect. 2, we properly present a recent literature review of fire detection using modern CCTV cameras. Section 3, introduces the proposed architecture for the initial detection of visible flames in surveillance videos. Section 4 contains experimental evaluation and discussion. Conclusion and future directions are listed in Sect. 5.

2. Literature Review

A computer vision-based approach for fire detection (VFD) is a modern technique based on pattern recognition and machine vision. This modern method preserves many advantages over traditional methods, like the ease of deployment, fast response rate and there is no limitation of space. VFD can scarcely detect fires at their initial stage. This automated system can be broadly divided into three fundamental categories which include pixel-level, blob-level, and patch-level [9].

The pixel-level recognition methods are remarkably fast as compare to blob and patch level [10] as these approaches are based on pixels features, however, their detection performance is unattractive. Blob level detection approaches show better performance than pixel-level as these methods carefully considered blob level candidates region for fire detection. The primary limitations of blob level detection techniques experience the political difficulty in training classifiers due to the unusual shape of the fire blob. In patch level, color is critically analyzed using background segmentation to merely improve performance against the previous algorithms. However, the patch-level method also produces false alarm due to fire in a video frame are too far from the capturing location [11]. All types of fire detection systems usually include fire pixel classification, moving object detection and analysis of the detection area [5, 12].

Color remains a primary feature to correctly classify fire pixel and are utilized in almost all detection methods. Traditionally, the RGB (Red Green Blue), HSV (Hue Saturation Lightness), HSI (Hue Saturation Intensity) and YCbCr (Luminance Chrominance Blue Chrominance Red) are carefully applied for detection of fire [10]. Segmentation of fire pixels involves a color analysis of the images using one or more decision rules in various spaces. For instance, RGB and HSV models are utilized to create three decision rules for the detection of the candidate region [5, 13]. YCbCr color space is used for a generic model and proposed various rules for accurate detection [14]. The currently published paper [15] uses multi-color feature rules to detect fire pixels in the video sequence. RGB color space rules are

$$R_{GRB} = \begin{cases} Rule1 : R \geq G \geq B \\ Rule2 : R > R_T \\ Rule3 : S > (255 - R) * S_T / S_R \end{cases} \tag{1}$$

where, R, G, B are components of RGB image and R_T represent the threshold whose values are empirically defined and S_T represents the threshold value of R and S components respectively of HSV color space. *Rule*1 specify that in any video frame in which red color is not dominant will be discarded. Any pixel in the video frames can be viewed as fire pixel they meet criteria according to Eq. 2. Similarly, Han et al. [15] utilized the *HSI* and *YUV* color space and proposed the following rules.

$$R_{HSI} = \begin{cases} Rule4 : 0 \leq H \leq 60 \\ Rule5 : 20 \leq S \leq 100 \\ Rule6 : 100 \leq I \leq 255 \\ Rule7 : Y \geq Y_T \\ Rule8 : |U - 128| \leq U_T \\ Rule9 : |V - 128| \leq V_T \end{cases} \tag{2}$$

where H, S, and I are the hue, saturation and intensity component and Y, U and V are the luminance and chrominance values of *HSI* and *YUV* color space respectively. Similarly, RGB, HSV, and YCbCr color space are utilized [16] to propose the rules to segment the fire region in a video sequence. The proposed rules are combined with the background subtraction and morphology operations. Shidik et al. [16] analyze the segmented region by updating the current condition of frame time by time to sufficiently reduce the false alarm. The heuristic features for fire detection, the author [17] use RGB, LAB color space to form decision rules, and use dynamic analysis. This efficient method calculates the position of the pixels in the video frame. However, the method fails to define the growth rate since it is based on blob counter per unit time.

Recently, by using different types of feature vectors and classifiers, a fire detection method based on machine learning has been successfully developed. The popular fire detection classifier is the SVM classifier, which is mainly used for radial basis Kernels. The use of classifiers in fire detection further improves the accuracy of false alarm. Other types of classification used in fire detection are the Adaboost method, neural network methods, hidden Markov model, and rule-based methods. Many researchers have extracted the characteristics of candidate regions used in fire detection, that is, the local distribution of fire colors in the scene and the specific characteristics of fire areas. These represent shapes, geometric, or contours to identify specific features that help predict the presence of flames. For example, statistical movements i.e. color, area size, surface coarseness, boundary roughness, and skewness are analyzed in video frames to detect candidate regions [18]. Rafiee et al. [19] combine the energy and shape of the detected region with the statistical movements to reduce the false alarms. Toreyin et al. [20] proposed a method to track the history of the red channel for each pixel that is part of the firing contour in a relatively short time. They considered it as input to the wavelet method. Apart from the change of the fire area and the flicker, Hu et al. [21] implemented the change in the roundness of the fire region. This describes the complexity of the shape to filter the regions with regular shape. Ko et al. [22] extracts spatial-temporal features (static and dynamic) from video frames and used random forest classifier to detect fire. Two stage fire detection method [23] based on spatial and temporal properties of fire region are feed to the SVM classifier to identify the fire in a video frame.

In short, these methods are based on features extraction that require additional execution time and pre-processing, thereby reducing real-time performance. In machine learning techniques, these features perform well in some scenes but produce invalid results due to high smoke and moving objects. To improve fire detection accuracy, we first modify the ideas from the previous studies, i.e., foreground and fire pixel detection. We used the motion detection technique to extracts the candidate fire regions that reduce the number of false alarms and meet the real-time requirements. Then, the tracking growth object (TGO) method is used together with motion detection for fire detection in video frames to distinguish between fire areas and motion areas. In this paper, color features along with growing object tracking are applied for fire detection to minimize miss detection, determine the size of fire and growth rate. The proposed method used fewer parameters than previous fire detection methods, which leads to a more intuitive process of fine-tuning the automated detection. The result is compared with other state-of-the-art fire detection methods [10, 15, 16].

3. Proposed Method

Over the past decade, many studies have focused on the traditional methods of extracting elements for flame detection. The main problem with this method is that its development process is long and its performance in fire detection is not satisfactory. Such method will generate many false alarms, especially when observing with visible shadows, unusual lighting conditions, and brightly colored objects. To overcome these problems, we examined fire detection methods, motivated by recent improvements in multi-color models for image representation. We carefully explore Lab and RGB color models to extract color features with motion detection, to improve the accuracy of fire detection and calculate the growth rate of the fire. Unlike other studies in the literature, the goal of the paper is to detect the fire in the video and calculate the growth rate of the fire. Figure 1 show the block diagram of the proposed fire detection method using multi-color space and background modeling. In step 1, pre-processing and color filtering in the RGB and LAB color spaces are applied to segment the flame area in the input image. This area contains both the fire area and unknown objects with similar fire characteristics. In step 2, the position of fire is tracked to find whether the object is moving or in a fixed position. If the detected region does not change its position, we can measure the growth rate. This step effectively reduces the false alarm and predicts the segmented region as a fire or non-fire object in the video.

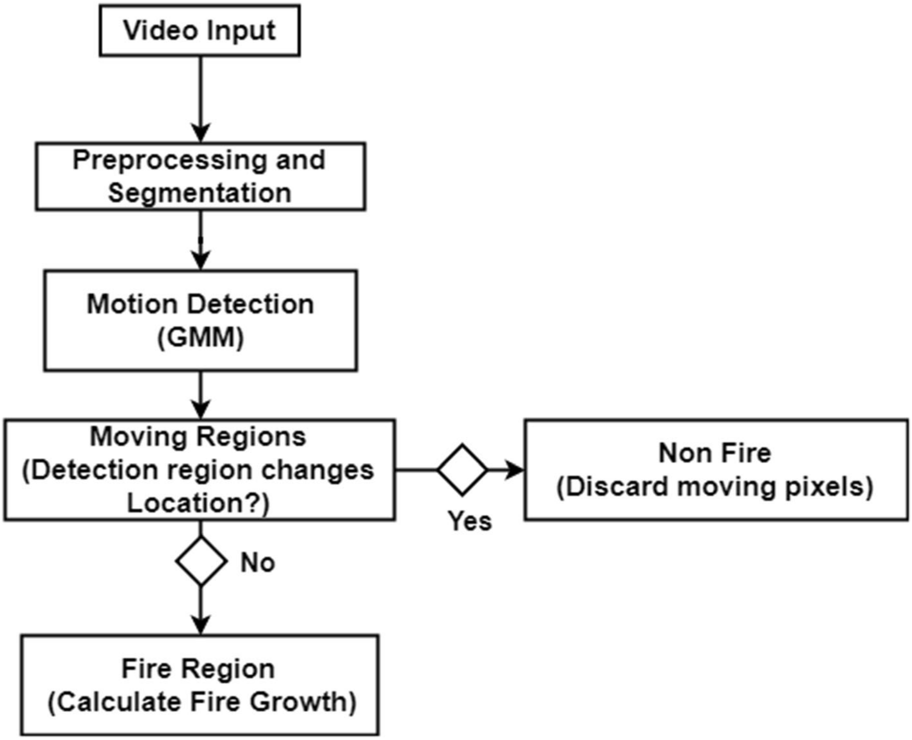

Figure 1. Flowchart summarizing the fire detection method and fire growth rate calculation.

3.1. Pre-processing and Segmentation Using Multi Color Space

In order to correctly segment the fire area, first, the Eq. (3) is used to enhance the image.

$$l_c = R^{1.5}G^{0.7}B^{0.9} \tag{3}$$

After enhancing the image, RGB and LAB color space is used to segment the fire region. For correct region segmentation, a simple threshold in RGB color space and rules developed by Celik et al. [14] are used to classify a pixel x as a fire pixel or nonfire pixels. The rules of segmentation are given below (4).

$$R_{RGB} = \begin{cases} I_R(x) > R_{mean} \\ I_R(x) > I_G(x) > I_B(x) \\ I_S(x) > (255 - I_R(x))\frac{S_T}{R_T} \end{cases} \tag{4}$$

where R_{Mean} is the mean of the red channel values of all the image pixels: $R_{Mean} = 1\frac{1}{N}\sum_{x\epsilon I} I_R(x)$ with N is the number of pixels in the image. S is the saturation channel and R_T, S_T are the threshold respectively. This step divides the fire area and non-fire area from the video frame. To further enhance accuracy and reduce false positives, we converted the image to LAB color space to continue to the segmentation process. This step divides the fire area and non-fire area from the video frame. LAB color model is independent of the device and can precisely define color correctly without the direct influence of device capability. To convert an RGB image to LAB color space the following equation can be used.

$$\begin{aligned} L =& 116 \times (0.299R + 0.587G + 0.144B^{\frac{1}{3}}) - 16, \\ a =& 500 \times [1.006 \times (0.607R + 0.174G + 0.201B)^{\frac{1}{3}} \\ & - (0.299R + 0.587G + 0.114B)^{\frac{1}{3}}], \\ b =& 200 \times [(0.299R + 0.587G + 0.114B)^{\frac{1}{3}} - 0.846 \\ & \times (0.066G + 1.117B)^{\frac{1}{3}}]. \end{aligned} \tag{5}$$

To propose a set of rules on the CIE Lab color space segmentation, the following rules must be satisfied to label a pixel x as a fire or non-fire pixels.

$$R_{LAB} = \begin{cases} I_{L*}(x) \geq L*_{Mean} \\ I_{a*}(x) \geq a*_{Mean} \\ I_{b*}(x) \geq b*_{Mean} \\ I_{b*}(x) \geq I_{a*}(x) \end{cases} \tag{6}$$

where $L*_{mean}$, $a*_{mean}$, $b*_{mean}$ are the mean values of $l*, a*$ and $b*$ color channels respectively. These rules successfully segment the fire area from the images. Finally, RGB and LAB color spaces are combined by using Union operation to form a multicolor model to identify fire region and mathematically can be expressed as:

$$Rcolor(i,j,n) = R_{RGB} \bigcup R_{lab} \tag{7}$$

The result of multicolor fire detection is illustrated in Fig. 2.

3.2. Motion Detection

Detecting moving objects in the video sequence is a basic task in the computer vision application. Mostly, three various methods are utilized for the detection of moving objects. The Gaussian mixture model GMM [24] is a standard method for performing background modeling and foreground detection and detecting moving objects. Other methods have been developed for object detection, such as Li el al. [25] have proposed two on-line Expectation-Maximization (EM) algorithms to improve learning the background in the form of a GMM. Rubio et al. [26] adopted a novel background model based on probabilistic self-organizing maps for foreground detection. Even though most background learning approaches are sta-

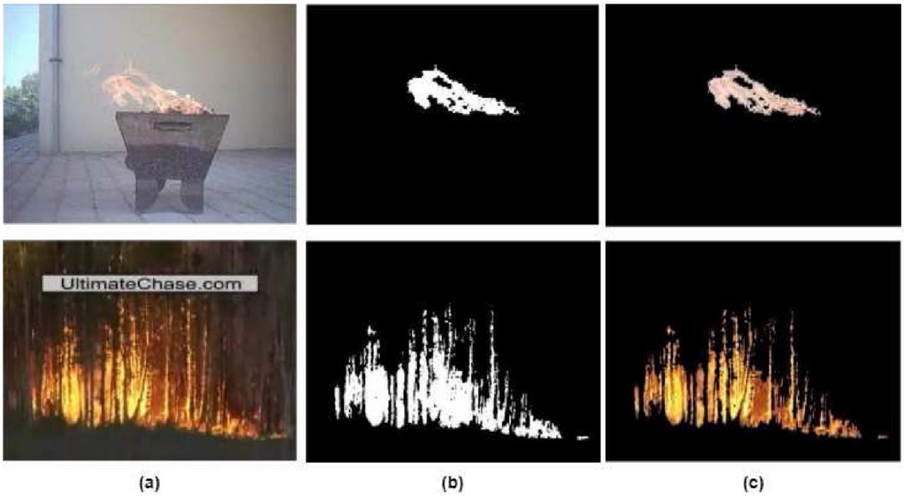

Figure 2. Detected fire region using multicolor space rules. (a) shows orignal image and (b) and c are the black and white and RGB segmented images respectively.

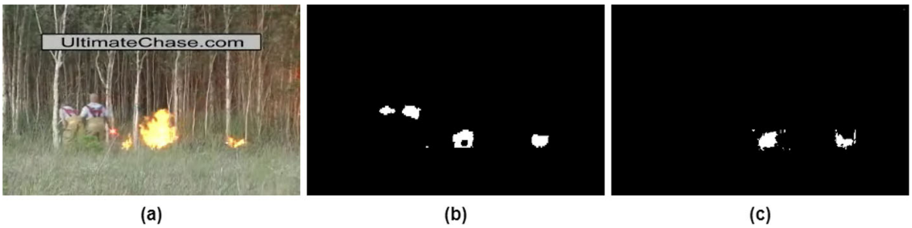

Figure 3. Candidate region detection results. (a) is the original image in RGB (b) and c shows the detected region with with segmentation and without segmentation respectively.

tistically based, some non-statistical and heuristic methods are also reported to obtain desirable results. However, we have used the state-of-the-art GMM method to detect the fire region. GMM models the values of each pixel as a mixture of K Gaussian distributions. This algorithm has a high performance than any other background modeling algorithms in terms of effectiveness, robustness and adaptability. "Unlike previous studies [15] the input image (i) is segmented into GMM to detect the foreground area. With the help of this, GMM only detects the fire region, and discard all other moving objects in the scene.

$$O(I,K) = \{Gmm_i \mid 0 \leq i < K\}. \tag{8}$$

This equation uses the image I and return K detected fire region, where *Gmm* is the Gaussian Mixture Model algorithm. Figure 3 shows the results of the motion detection using GMM with segmentation and without segmentation. It is clear from the figure that segmentation steps improve the accuracy of the fire detection region. With segmentation, the GMM considered only moving fire pixels as foreground regions, while without segmentation GMM consider all moving pixels as foreground regions.

3.3. Tracking Object

Video analysis has three important steps in object recognition, identify and track areas of interest, analyze objects and detect behavior. The complexity of moving region tracking relies on image noise, changes in scene lighting, complex object movement, and partial and complete object occlusions. Most algorithms assume the motion of the region is smooth and shows no sudden change. We rely on the tracking frame by frame to follow detected objects after attaining every condition and drawing boundaries around the object. We consider the object which is detected using Eq. 8 as a moving pixel and Eq. 9 is used to detect a candidate fire region (F) as below.

$$F(x, y, t) = O(x, y)^{\wedge} S(x, y) \tag{9}$$

where ^ is a binary AND operator.

A fire area in the binary image is further analyzed in the successive frames. Let FRO (t) get the set of all fire areas in F at time t. We track the FRO in time to produce a more isolated decision by considering the behavior of the region. A fire region grows and remains fixed at its position. To quantify this behavior, FRO is analyzed in consecutive frames. The counter NFR(t) is generated for FRO (t) in the video scene.

$$NFR(t) = \begin{cases} FRO(t-1) + 1 & ifFRO(t) \geq FRO(t-1) \\ FFO(t-1) & otherwise \end{cases} \tag{10}$$

Equation 10 counts the number of pixels in the fire region appears at time t. It shows that the $FRO(t-1)$ has equal or greater pixels at time t. To analyze the fixed position (PFR) behavior of the fire region, we calculate the overlapping of the previously detected object with the newly detected object in the consecutive frames,

$$OV = \frac{area(FRO(t) \bigcap area(FRO(t-1))}{min(area(FRO(t)), area(FRO(t-1)))} \tag{11}$$

where OV is the overlapping of the detected fire regions in consecutive frames. The above function calculates the area of the fire region at the specified interval and min identity the fire region with minimum area. If $FRO(t)$ and $FRO(t-1)$ overlaps, the value of the OV can be greater than value 0.5, and the $FRO(t)$ is considered as the same as $FRO(t-1)$. If the OV value is less than 0.5 then it is considered as the moving pixels. This process continues every frame and the detected object positions are compared with the previous objects and the moving objects are discarded. If an object continues to overlap in the consecutive 15 frames, then the detected region is considered as fire region (Fig. 4).

3.4. Rate of Fire Growth

In a personal safety analysis that assesses the occupier's ability to escape from the source of the fire, only the start and growth phases of the fire are important [26]. In general, the fire increases and spreads in proportion to the time and is calculated using low-power equations. In video surveillance applications, the growth rate of fire depends on the accuracy of the classification fire pixels in the video. For improving the accuracy of detection, we use the growth of fire pixels to check if it is an actual fire and to calculate the intensity of the fire. We calculate the fire pixels (FP) between two consecutive frames using the following equations.

$$FP_f = F(P(s))_{i+1} - F(P(s))_i \tag{12}$$

Where F is the frame from the video and P (s) is the number of fire pixels. This equation shows the fire is increasing or decreasing. Similarly, to find the fire pixel difference between two frames at different times intervals, we use the following equation.

$$FP_t = F(P(s))_{f(r)+i} - F(P(s))_i \tag{13}$$

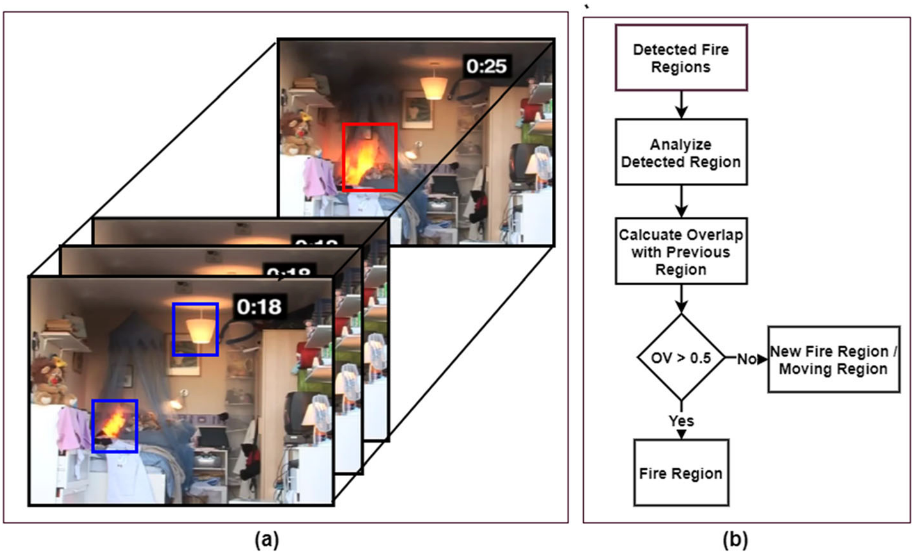

Figure 4. Block diagram of proposed growing region and moving object detection method.

where f(r) is the frame rate of the video and P(s) is the segmented fire like pixels in the successive images. The growth of the fire typically depends on the air-flow direction and fuel type. Because of the flow of air, the size of the flame of the fire can change, but it will continue to develop toward increasing, especially for the initial burning flame. The growth rate can be positive, negative, or zero. If the rate of change in FP regarding time is linear, then the fire grows uniformly. If the rate of change in FP is increasing and the growth rate is not uniform, then the intensity of the fire is high. We can calculate the intensity of fire mathematically by calculating the slope of the FP at two various times.

$$\text{Intensity } = \frac{FP_n - FP_{n-1}}{t_n - t_{n-1}} \tag{14}$$

3.5. Fire Detection Algorithm

The distinct steps of the proposed fire-detection algorithm can be concluded in Fig. 1. First, image enhancement is performed, then two different color model is used to get color features and get a segmented image from the enhanced image. The segmented image is used to get only the fire region in the video sequence and other non-fire like regions. Fire growth is used to remove the moving pixels from the video sequence. It should be pointed out that if these fire-pixels show dynamic motion features, there is an immense fire. Finally, fire-alarm raising conditions are inspected simultaneously to check if the fire is going to spread out and the intensity of the fire is calculated.

4. Experimental Evaluation and Discussion

This section contains details on the data sets, with experimental evaluation and a comparison of our method with the latest fire detection method. The next step is to evaluate the robustness of our system to existing methods, by discussing the parameters of the system and their feasibility in uncertain surveillance environments. We present all the experimental details and comparisons in this section. We carried out experiments from different perspectives using videos from different sources. The proposed method is based on the combination RGB and LAB color model and region growing algorithm detection, to detect fire region and calculate the growth rate of the fire. To test the performance of the proposed method, we have checked it on different videos downloaded from the link [27] including different environmental parameters. Besides these, we have compared our obtained results with other fire detection methods, i.e. [10, 15, 16] to evaluate the accuracy. We have developed the proposed method in MATLAB 2018.

4.1. Data Set

All videos in our experiments are downloaded from the link [27] having different resolutions. These videos have different scenes including different fire types and background environmental conditions. These different varieties of the environment and conditions make it easier to evaluate system performance. The data set video details are shown in Table 1. To evaluate the performance of the proposed method on the data set, a comprehensive empirical assessment of the proposed method is performed, using over 6808 numbers of frames extracted from 15 positive and negative video clips collected from the Internet. The frames are manually labeled to fire, or non-fire frames to create ground truth with the help of a video labeler using MATLAB. To calculate the performance metrics, the frames with fire and fire-like disturbances are used. Table 1 shows the data set video detail and a number of fire frames and non-fire frames as a ground truth. Figure 5 shows frames from the videos tested using the proposed fire detection technique.

4.2. Performance Evaluation with State-Of-Art Methods

This section compares the performance of our proposed method based on the results collected from the data sets [27] with the existing methods. Two various sets of evaluation metrics are used to evaluate the performance of each method from all prospective. The first metrics of measurements obtain accuracy, false negative, and false-positive results (also known as false alarm rates) [17]. These metrics parameters compare the proposed system with the most related work [10, 15, 16]. The second metrics of measurements are precision and recall and used with the cost of false-positive are extremely high. Mathematically

Table 1
Empirical Analysis of the Data Set Used

Video sequence	Total frames	Fire frames	Non Fire frames	Video description
Video 1	439	433	6	Barbeq
Video 2	260	260	0	Controlled Environment 1 320 × 240
Video 3	246	201	0	Controlled Environment 2 320 ×240
Video 4	208	997	7	Controlled Environment 3 320 ×240
Video 5	1201	704	204	Backyard
Video 6	708	200	0	Fire 1 400 × 256
Video 7	200	245	0	Forest 1 400 × 256
Video 8	245	255	0	Forest 2 400 × 256
Video 9	255	219	0	Forest 3 400 × 256
Video 10	219	216	0	Forest 4 400 × 256
Video 11	216	216	0	Forest 5 400 × 256
Video 12	218	218	0	Forest 6 400 × 256
Video 13	789	625	164	Highway 640 × 360
Video 14	1201	1129	72	Field 320 × 240
Video 15	402	390	12	Farm 320 ×240
Video 16	357	0	357	Fire moving color car 320 ×240
Video 17	306	0	306	Person with fire colored shirt 320 ×240
Total	7401	6434	1128	

Figure 5. Extracted frames from the used dataset.

Table 2
Empirical Result of Proposed Method with State-Of-The-Art Methods

Method Name	True Positive	True Negative	False Positive	False Negative	Accuracy (%)
Chen et al. [10]	5791	643	382	746	85.08
Han et al. [15]	6278	189	431	697	92.59
Shidik et al. [16]	5167	1267	347	791	78.68
Proposed Method	6293	137	1087	41	97.42

$$\text{Precision} = \frac{Truepositive}{True\,positive + false\,positive} \tag{15}$$

$$\text{Recall} = \frac{True\,negative}{True\,positive + false\,negative} \tag{16}$$

The experimental evaluation was performed using 15 videos collected from multiple sources. Some videos in the collection (video 1, 5, 13, 14, and 15) contain non-fire frames that are not visible to the naked eye. Video 16 and 17 consist of moving objects with no fire frame and the rest videos contain a fire in each frame. The video data frame rate varies from 20 to 25 fps, and the image resolution is 400×256 and 320×240. Table 1 describes the videos used in the simulation. Here, videos 1 to 15 contain both indoor and outdoor fire, and videos 16 and 17 contain moving objects with fire like region to evaluate the accuracy of the proposed method. Low false alarm rate and the detection rate is an essential criterion for the extensive evaluation of the proposed method. Table 2 compares the true negative, false-negative rate, and accuracy of the proposed method with state-of-the-art methods. This table depicts the average value of the obtained results of all the methods. In this table, the correct positive rate is the rate at which an actual fire is correctly identified as a fire, and the false positive rate is the rate at which no fire is identified as a fire. In the table, accuracy is calculated using formulas.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}. \tag{17}$$

It is clear from the Table that proposed method perform better in term of accuracy and other parameters than the existing methods.

Experimental results show that the accuracy of the method is 97.42%, which proves that our proposed method has higher accuracy and good performance in various scenes. To further investigate the performance of the proposed method, we use performance evaluation metrics which are widely used. These metrics include precision and recall (which are further investigated in [28]). From Table 3 it is clear that the precision and recall of the proposed method show the most satisfactory performance over the existing methods.

Figures 6 and 7 illustrate the qualitative evaluation of the proposed method. These figures show the segmented fire region of different video frames in BW and RGB. Figure 7 shows the obtained results of the proposed method of two different videos. It shows the original image of the scenes, (a) is the segmented black and white fire region image while (b) is the RGB segmented fire regions. Figure 6 also shows the comparison of the proposed method with the state-of-the-art methods, this figure shows only the segmented image in RGB of all the methods. From Figs. 6 and 7 , it is clear that using the proposed method fire pixel segmentation is better than the existing methods [10, 15, 16].

These existing methods have not used the growth rate of fire. To demonstrate the fire growth rate of the proposed method, we have checked our proposed method on all the videos in which only one video, the fire is increasing while in other videos there is fire, but the fire regions are not increasing (Figs. 8, 9).

These existing methods do not use the growth rate of fire. To demonstrate the fire growth rate of the proposed method, we have checked our proposed method on all the videos in which only one video, the fire is increasing while in other videos there is fire, but the fire regions are not increasing. According to the experimental results, the correct rate of the proposed method is close to 97.1%, which proved that our proposed new method has higher accuracy and stability. How-

Table 3
Precision and Recall of the Proposed Method

Method name	Precision	Recall
Chen et al. [10]	0.9381	0.8859
Han et al. [15]	0.9802	0.9358
Shidik et al. [16]	0.8031	0.9371
Proposed method	0.9803	0.9967

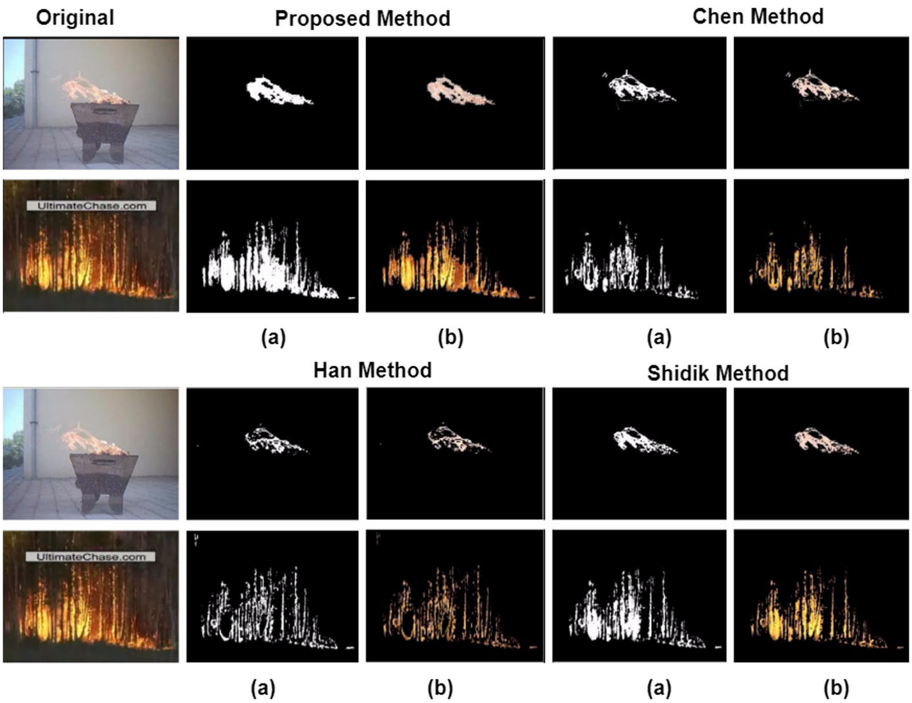

Figure 6. Segmentation Result using proposed method and existing methods. Original shows the candidate fire image from different videos, (a) shows the segmented image in black and white, while (b)shows the RGB segmented image from the frame.

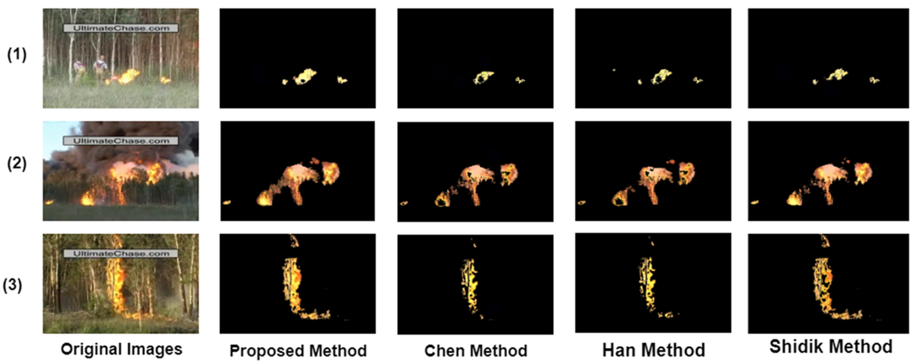

Figure 7. Segmentation result of three different videos using proposed method and existing methods.

ever, our algorithms also have certain limitations, such as when the staff dressing in clothes, which look like the fire is coming towards the camera, this condition is in line with our proposed fire motion detection, so it may cause false positives. In

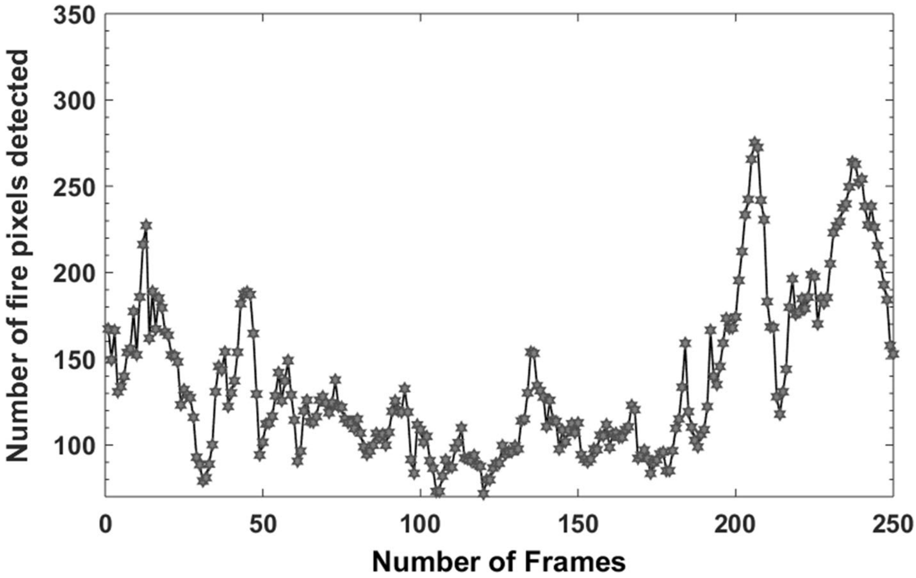

Figure 8. Fire detected and the fire size is not increasing with respect to time.

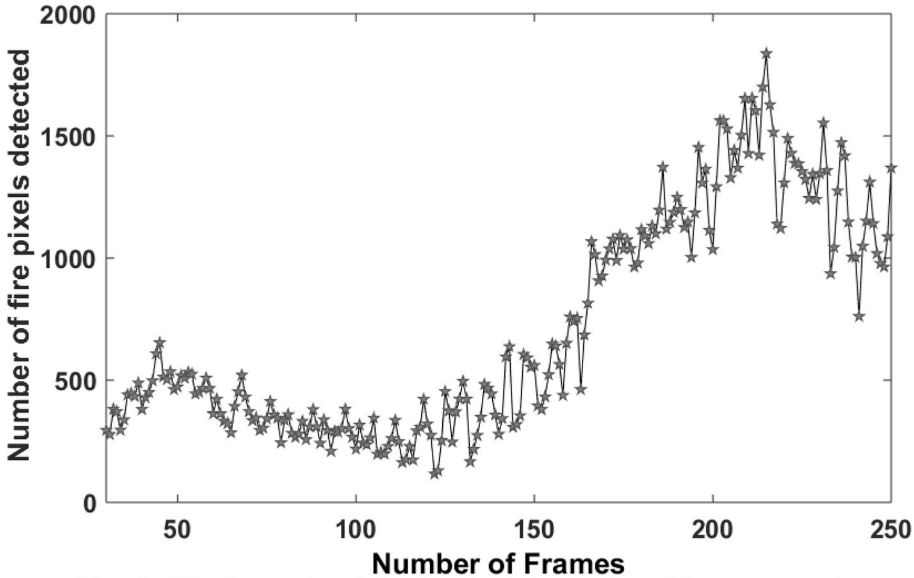

Figure 9. Fire detected and the fire size is increasing with respect to time.

the future, more advanced segmentation of fire pixels should be carried out while trying to use more advanced methods to solve the problems faced by the actual environment.

5. Conclusion

In this paper, we proposed a new fire detection method based on multi-color space with background modeling and candidate region tracking in video. The key difference between the proposed method and existing state-of-the-art methods is that the proposed method first performs segmentation to detect fire-like pixels, then the segmented image is provided to the GMM to capture only the moving region in the video. Finally, the proposed method calculates the fire growth rate in the video. This method has been tested on various video streams. Experimental results show the proposed method achieves an average detection rate of about 97.1%, demonstrating its effectiveness, adaptability and robustness. Please note that the proposed method provides the best results in all cases. The computational requirements of the proposed method are higher compared with those of the to the existing algorithms based on motion detection modeling. However, the proposed method is still considered suitable for early fire alarm systems. However, the average frame rate of the algorithm is still considered adequate for an early fire warning system. While this work has improved the accuracy of fire detection, it still has a large number of false alarms and requires further investigation in this direction to handle more complex real-world situations. In addition, the proposed flame detection method can be intelligently adjusted to detect both smoke and fire.

Compliance with Ethical Standards

Conflict of interest The authors declares that there is no conflict of interest regarding the publication of this article.

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