Real-Time Fire Detection Based on Feature Analysis Using Enhanced Color Segmentation and Novel Foreground Extraction

By

Rubayat Ahmed Khan
15166005

A thesis submitted to the Department of Computer Science and Engineering in partial fulfillment of the requirements for the degree of
Master of Science in Computer Science and Engineering

Computer Science and Engineering
BRAC University

July 2017

© 2017. Rubayat Ahmed Khan
All rights reserved.

Declaration

It is hereby declared that

1. The thesis submitted is my own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. I have acknowledged all main sources of help.

Rubayat Ahmed Khan
15166005

Approval

The thesis titled "Real-Time Fire Detection Based on Feature Analysis Using Color Segmentation and Novel Foreground Extraction" submitted by

1. Rubayat Ahmed Khan (15166005)

Of Spring, 2015 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of M.Sc. in Computer Science and Engineering on 27.07.2017.

Examining Committee:

Supervisor:
(Member)

Dr. Jia Uddin
Associate Professor, Department of Computer Science and Engineering
BRAC University

Program Coordinator:
(Member)

Dr. Amitabha Chakrabarty
Associate Professor, Department of Computer Science and Engineering
BRAC University

External Expert Examiner:
(Member)

Dr. Md. Rashedul Islam
Associate Professor, Department of Computer Science and Engineering
University of Asia Pacific

Internal Expert Examiner:
(Member)

____

Dr. Md. Ashraful Alam
Assistant Professor, Department of Computer Science and Engineering
BRAC University

Hossain Arif

Internal Expert Examiner:
(Member)

____

Hossain Arif
Assistant Professor, Department of Computer Science and Engineering
BRAC University

Departmental Head:
(Chair)

____

Dr. Sadia Hamid Kazi
Associate Professor, Department of Computer Science and Engineering
BRAC University

Abstract

This research proposes two effective real time fire detection techniques, based on video processing. The former technique is restricted to indoor conditions only while the later does not have such constraints. Both the proposed methods utilize prominent features such as flame color information and spatiotemporal characteristics to identify fire areas. For the first technique, color segmentation is carried out in the earliest stage to separate potential fire areas using the red component of RGB. Moving pixels are identified using frame differences from a reference frame followed by de-noising. In the next phase of the model, the growth of the segmented regions of the current frame is compared with later frames and based on the fact that a hazardous fire expands with time, regions with no or decreasing growth is removed. The complex boundary of fire (rotundity) is valuable information that aids in detection. In the last step, a feature vector is created with rotundity information and trained using a neural network. The proposed model is tested using a dataset containing a wide range of indoor lighting conditions and compared to a state of the art fire detection technique to confirm its effectiveness. The experimental results show that the proposed model performs better compared to the state of the art model in terms of accurate detection and computation time, yielding an average accuracy of 99.1%.For the second technique, the initial stage of the work extracts fire colored pixels using a set of enhanced rules on RGB. Fire pixels are dynamic and to detect these moving pixels a novel method is proposed in this approach. The final verification is done by examining the area of the extracted regions. A harmful fire will grow over time, thus if the area happens to increase, the region under focus is declared as fire. Experimental results show that the model put forward outperforms other state of art models yielding an accuracy of 97.7%.

Keywords: Fire Detection; Static and Dynamic Features; Color Segmentation; Foreground Extraction

Dedication

I would like to dedicate my thesis to my beloved family members.

Acknowledgement

Firstly, all praises and thanks to Almighty ALLAH, the Creator and the Owner of this universe, the most Gracious and most Merciful; who guided me and gave me the strength to complete this research.

I am especially thankful to my supervisor and co supervisor Dr. Jia Uddin and Ms. Sonia Corraya respectively, for their help and support throughout.

Table of Contents

List of Tables

List of Figures

List of Acronyms

RGB	Red Green Blue
YCbCr	
NN	Neural Network
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative
FD	Correct Fire Detection
WFD	Wrong Fire Detection

Chapter 1

Introduction

1.1 Motivation

Fire is a calamitous phenomenon which occurs without a warning leaving irreversible damages to human lives and environment. According to a survey conducted by the World Health Organization, middle income countries are more vulnerable to burn casualties. In Bangladesh, there were more than 10 fire incidents in 2016 alone, which included textile factories, houses, slums and malls. In 2017, two major incidents have already occurred in Dhaka, subsequently ending lives, costing millions, and resulting in severe aftermath. Hence, early detection of a fire is critical and has become a subject of great importance. Hence an early and effective fire detection system is crucial in the field of surveillance, hence making it a matter of great concern. The conventional sensor based systems carry huge drawbacks such as short area coverage, for an early detection fire must be at a close proximity of the sensors, fail to provide any additional information such as location, growth rate, etc. [1-3]. Moreover these sensor based devices require additional installation labor and cost. Therefore to overcome the aforementioned disadvantages, vision based approach is put forward as an alternative which can be easily incorporated in CCTV cameras, which now a days are extensively used almost everywhere[4].

Flames exhibit discernible characteristics such as color, non-uniform perimeter, area [2, 3] and the change of these properties over time occurs to be vital in the vision based detection. This paper employs the static RGB values for color based segmentation, the dynamic behavior of these values to extract moving foreground and lastly the growth of fire area for a powerful fire detection system.

1.2 Contribution Summary

In this work two models of fire detection are proposed. Firstly, an indoor fire detection model is presented. It consists of a 4 step process which includes color segmentation, frame differencing, region growth and rotundity analysis. Color segmentation is conducted initially to select the fire like pixels followed up by frame differencing to detection moving pixel. The area of the regions detected is inspected between frames based on the fact that a dangerous fire grows over time. Lastly the rotundity (complexity of the shape) of the regions is evaluated using Neural Network. This model yielded an accuracy of 99.1%.

A second model is developed to work on a wide environmental domain unlike the previous model. It is implemented on both indoor and outdoor conditions, different lighting conditions, static and dynamic backgrounds and also forest fire. Like the first model it starts off with color segmentation, followed by foreground extraction using Neural Network. Both these steps use the static and dynamic properties of color and produced great results. At the last step it uses the same algorithm to inspect the growth of detected regions used in the previous model. This approach has produced an accuracy of 97.7%.

1.3 Thesis Goals

1. Study the state of art techniques and identify the advantages and the disadvantages
2. Develop simpler and more effective color segmentation rules. Color segmentation is the vital step in this work as the later phases work on the pixels identified through segmentation.
3. Come up with simpler and more accurate foreground extraction. This is to reduce false positives, which is considered to the limitation of vision based fire detection approach.
4. Compare proposed models with the state of art models.

1.4 Thesis Outline

The rest of the paper is organized as follows

1. Chapter 2: Literature review
2. Chapter 3: Overview and description of the proposed models
    - Sub Chapter 3.1: First Model- Indoor Fire Detection using static and dynamic features
    - Sub Chapter 3.2: Second Model- Fire Detection using Enhanced Color Segmentation and Novel Foreground Extraction
3. Chapter 4: Experimental Analysis of the proposed models
    - Sub Chapter 4.1: Experimental analysis of the first model
    - Sub Chapter 4.2: Experimental analysis of the second model
4. Chapter 5: Conclusion and future works

Chapter 2

Literature Review

Numerous investigations have utilized the color range of flame as a key feature for identifying fire from still image/video frames. Color is the most noticeable property of fire thus making it central to vision based methods. Chen et al [1] were among the first to list out a set of formulas for recognizing fire pixels dependent upon RGB. Celik and Demirel later presented and recommended statistical color model for RGB in [5, 6]. These formulas were further investigated in different color spaces. Celik and Huseyn et al [7] developed new rules based on YCbCr which were later altered and utilized in [8-10]. Lianghua et al [11] implemented their work on HSV and Jareerat et al [12] employed their technique on both HSV and YCbCr. Videos and images acquired use RGB hence working with other color spaces requires extra conversion time.

Although the color property is a primary aspect but it alone is not adequate for confirming a region as an actual fire. This is because there are other luminous sources exhibiting similar color range. Fire is a spatiotemporal phenomenon and this natural characteristic is used as the next fundamental step in the detection process. In [1, 13] frame differencing has been carried out for detecting moving pixels followed growing rate and continuity analyses of the suspected regions. In the work of [4, 5, 6 and 11] Gaussian mixture models are used to separate moving foreground from the background. The drawbacks of using Gaussian mixture model, as stated by a study [14], are high time and space complexities making it infeasible for real-time applications.

Besides color information and continuous flickering, features such as growth of area, shape, periphery complexity play a vital part in the vision based detection of fire. In a study [2], 11 static and 27 dynamic features were marked and trained using SVM for detection. Qingfenget al [3], conducted a vigorous study on the features used in [3] and proved that only similarity and rotundity produced good results. Similarity is practically comparing blob area over time and rotundity is measuring the degree of complexity of object boundary.

Chapter 3

Proposed Models

3.1 Indoor Fire Detection Using Static and Dynamic Features

The work flow of the proposed model is presented in Figure 1 and a comprehensive explanation is given in subsections 3.1.1–3.1.5.

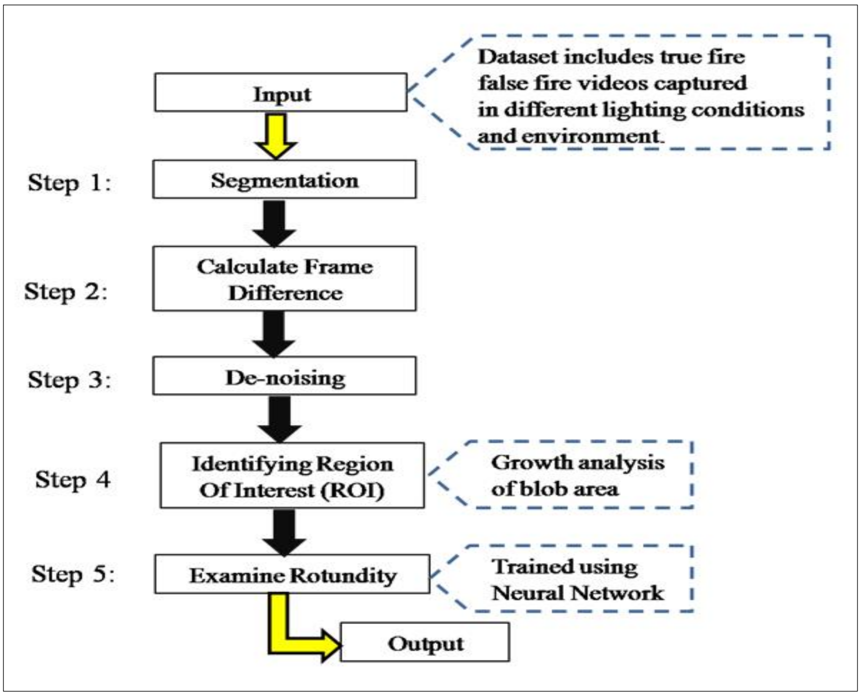

Figure 1: Block Diagram of Model 1

3.1.1 Color Segmentation on RGB Color Space

Flames display a distinctive range of red-yellow colors depending on its temperature [13] and this property makes color segmentation one of the most fundamental steps. The later decisions based on shapes and other features depend on how accurately true fire pixels are segmented out. Fire samples with different flame colors, and backgrounds are collected and initially tested with the rules proposed in [1] on RGB, equations (1-3), and with the ones proposed by Celik in [9, 10] on YCbCr, equations (4-8).

$$R > R_T \tag{1}$$

$$R \geq G > B \tag{2}$$

$$(S \geq ((255-R)*S_T / R_T)) \tag{3}$$

R, G and B stand for the red, green and blue values for particular pixels. R_T and S_T denote the threshold set for red component and the threshold set for saturation, respectively.

$$Y(x, y) > Cb(x, y) \tag{4}$$

$$Cr(x, y) > Cb(x, y) \tag{5}$$

$$F(x, y) = \begin{cases} 1, \text{ if } Y(x, y) > Y_{mean}, Cb(x, y) < Cb_{mean}, Cr(x, y) > Cr_{mean} & \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$F(x, y) = \begin{cases} 1, \text{ if } |Cb(x, y) - Cr(x, y)| \geq \tau & \\ 0, & \text{otherwise} \end{cases} [\tau = 40] \tag{7}$$

$$F_{CbCr} = \begin{cases} 1, \text{ if } Cb(x,y) \geq fu(Cr(x,y)) \cap Cb(x,y) \leq fd(Cr(x,y) & \\ \qquad \cap Cb(x,y) \leq fl(Cr(x,y) & \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

$Y(x, y)$, $Cb(x, y)$ and $Cr(x, y)$ denote the luminance, blue difference and red difference chrominance values, respectively, at the pixel position x, y. Y_{mean}, Cb_{mean} and Cr_{mean} stand for the average value of the components of a particular frame. Lastly fu, fd and fl denote the polynomials used to model the Cb-Cr plane.

Figure 2: Color Segmentation Results Using Equations 4-8

Surprisingly, experiments using YCbCr failed to segment out true fire regions on a few occasions where the flame inherited a bright yellow color as shown in Figure 2. After some vigorous analysis it is found that the condition in (5), where Cr component of a pixel must be greater than that of Cb, and in (7), where the difference between Cr and Cb has to be at least 40, are not true for flames with bright color. In image processing the computation complexity of RGB is less than that of other color models [1]. Jing et al [15] came up with a two-step simple rule on RGB stated in equations (9) and (10).

$$F_R(x,y) = \begin{cases} F_{ori}(x,y), & F^R_{ori}(x,y) >= 250 \\ 0, & \text{Otherwise} \end{cases} \tag{9}$$

The above equation is broken down as, if the R component of a pixel at x, y is greater or equal to the threshold 250, the pixel is considered as potential fire pixel else discarded. Equation 10 was added to remove any white and spurious regions resulting from the previous step.

$$F_{RGB}(x,y) = \begin{cases} F_R(x,y), & F^R_R(x,y) \neq F^G_R(x,y) \\ & \text{or } F^R_R(x,y) \neq F^B_R(x,y) \\ & \text{or } F^R_R(x,y) \neq F^B_R(x,y) \\ 0, & \text{Otherwise} \end{cases} \tag{10}$$

The algorithm proposed in this work for segmentation, equations (11) and (12), is similar to equations (9) and (10) with an enhancement of the threshold value. After experimenting with a number of different fire images with dark and bright backgrounds and different burning materials, we determined that the condition $R \geq G$ used previously [1]is not always true. In addition, computing the saturation for each pixel consumes a significant amount of time, as shown in Table 4. The measure of the R component of flames ranges from 190 (the thin flares at the top) to 255 (the core). By experimenting it is found that choosing the minimum results in too much noise, whereas choosing the maximum result in overlooking true pixels. In order to deal with this issue, we chose the median of the range for the threshold, which is 222. The outputs with different thresholds are shown in Table 1.The execution of color segmentation on a sample frame, using the formulas proposed in this work, is shown in Figure 3. The set of formulas can be described as follows.

$$R >= 222 \tag{11}$$

$$R > B \tag{12}$$

(a) Threshold	(b) A Test Frame	(c) Output
R>=190		
R>=222		
R>=250		

Table 1: Experimental Results using model 2. Column (a) contains sample fire frames, (b) final output of [1] and (c) final output of the proposed work. Column (b) shows false regions in the first two instances while the last one got completely undetected.

Figure 3: Color Segmentation Results Using Equations 11-12

3.1.2 Frame Differencing

Frame differencing was carried out in order to identify the moving pixels. A reference frame, F_{Ref}, is selected at T_0 seconds. Then, a couple of test frames, F_1 and F_2, are chosen at T_2 and T_3 seconds, respectively, after careful observation of consecutive frames after T_0 seconds. Subtractions are carried out for each of the test frames (F_1 and F_2) from the reference frame. Working with two test frames allows us to analyze the change in growth of the subtracted regions. Subsection 3.1.4 provides a detailed explanation of this approach. The following formulas illustrate the procedure and Figure 4 illustrates the detailed procedure and the output of different sampling frames.

$$F_{Difference1} = F_1 - F_{ref} \tag{13}$$

$$F_{Difference2} = F_2 - F_{ref} \tag{14}$$

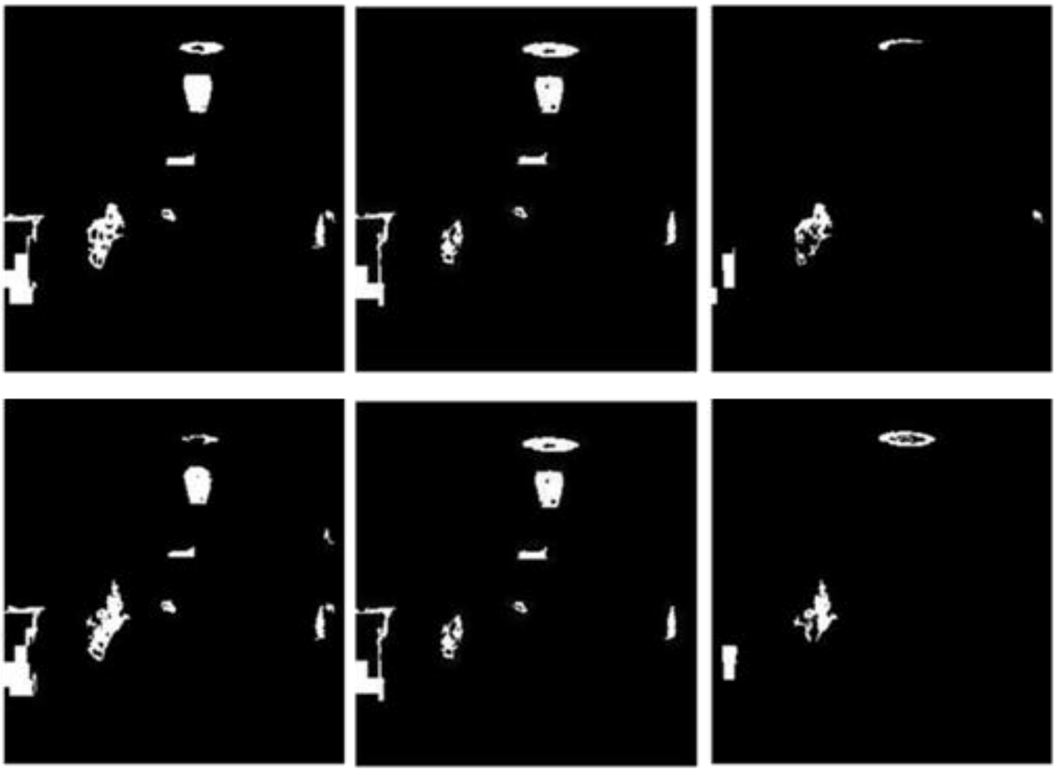

Figure 4: Moving Pixel Detection Using Frame Differencing. Images in the third column are the output images.

3.1.3 Denoising

It is not necessary that all the segmented regions obtained from frame differencing are fire regions. These could be other luminous sources or even true fire regions which should not be detected such as a burning candle, stove, and other non-accidental small fires. The output from the previous step will contain such non-desirable white marks and to discard them, we set a rule that the fire area should match a certain threshold, T, before it is termed dangerous. The value of T is selected after running an empirical study over sample fire videos under diverse conditions and surroundings. Figure 5 demonstrates a sample frame being subjected to de-noising.

Figure 5: Denoising

3.1.4 Identifying Region of Interest

The temporal growth of a fire is a natural truth, making it a key dynamic factor that dominates during fire detection. In this phase of the work, corresponding blobs between $F_{Difference1}$ and $F_{Difference2}$ are examined. Regions whose area measurements are not increasing in the latter frame are eradicated. Figure 6 illustrates the process of finding a region of interest and the algorithm is given in Algorithm 1.

3.1.5 Analysis of Rotundity

As depicted in Figure 6(c), a faulty region (a circular object) still exists. Thus, for reassurance, this final step of analyzing rotundity is conducted. Rotundity, as mentioned before, measures the complexity of a region's boundary. The values range from 0 (the most complex boundary) to 1 (the smoothest). The formula for calculating rotundity [4] is as follows.

$$C = \frac{4\pi S}{L^2} \qquad (15)$$

In this equation, S is the area of the region and L is the perimeter. The area of a region is the number of white pixels in it and the perimeter [4] is computed as follows.

$$L = \sum_{i=0}^{n} \sqrt{\left(x_{(i+1)} - x_i\right)^2 + \left(y_{(i+1)} - y_i\right)^2} \quad (16)$$

Here, (x, y) and (xi+1, yi+1) are the coordinates of adjacent pixels on the boundary of the connected region. About three hundred images under various conditions were collected from the internet and their extracted rotundity values were trained using a neural network. Figure 7 shows the output after the final test, where the real fire region was successfully identified.

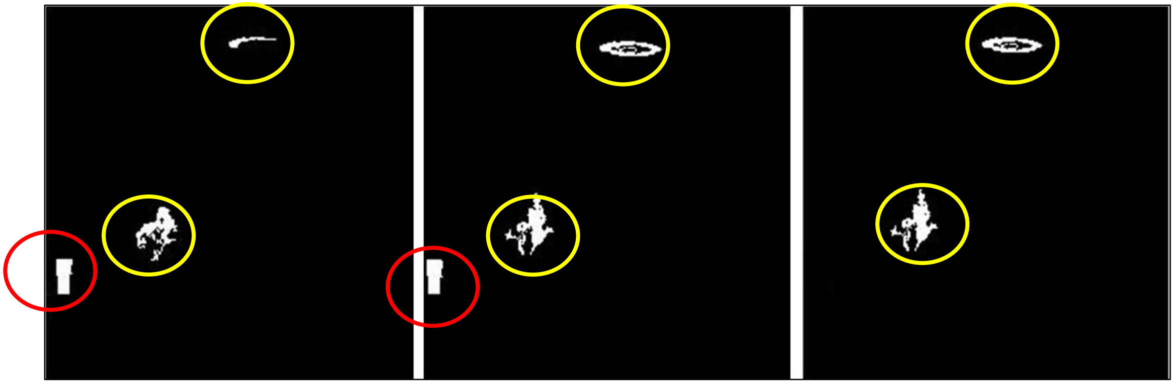

Figure 6: Identifying Region of Interest Based on Temporal Growth. (a) and (b) are FDifference1 and FDifference2 respectively. (c) The output. The blob marked with red circle in (a) did not increase in (b), hence it was eradicated.

1: Algorithm find_region_of_interest($F_{Difference1}$, $F_{Difference2}$):
2: *for each blob u in* $F_{Difference1}$
3: *for each blob v in* $F_{Difference2}$
4: *if u and v have a common pixel then*
5: *u and v are corresponding blobs*
6: *if area(v) > area(u)*
7: *fire_regions = v*

Table 2:The algorithm used in 3.1.4

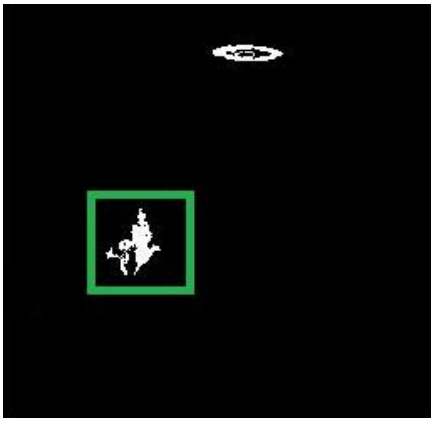

Figure 7: Final Output after Rotundity Analysis

3.2 Fire Detection Using Enhanced Color Model and Novel Foreground Extraction

The work flow of the proposed model is demonstrated as a block diagram in Figure 8 and the comprehensive explanation of each step is given in subsections 3.2.1 – 3.2.3.

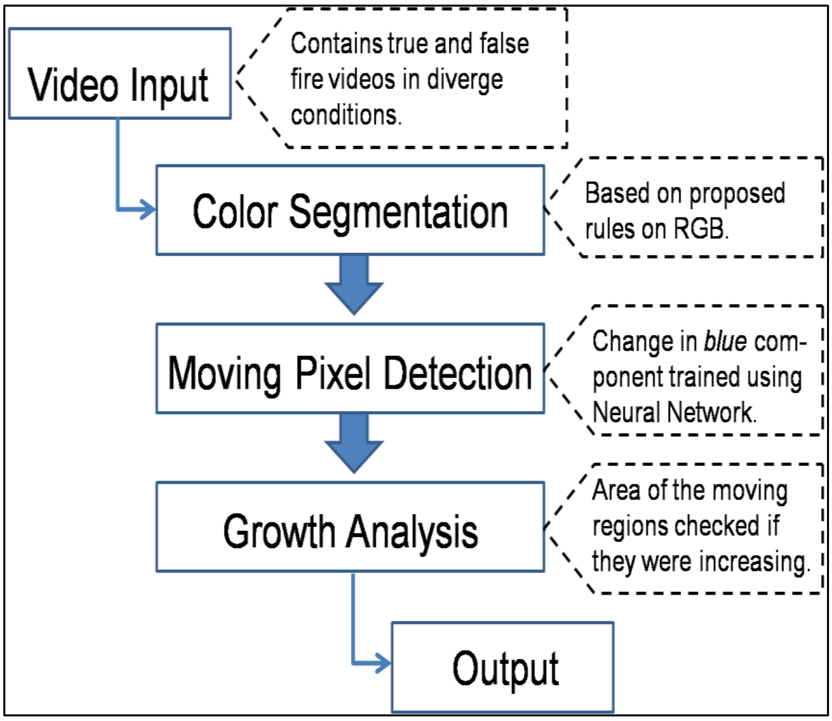

Figure 8: Block Diagram of Model 2

3.2.1 Color Segmentation Using RGB Color Space

The proposed rules for color segmentation are modified from phase 1 and they happen to prove more efficient in removing non fire pixels. The equations are given in (17) and (18).

$$R(x, y) >= \tau \quad (17)$$

$$G(x, y) > B(x, y) \quad (18)$$

R(x, y) is the value of the red component at the coordinate x, y which has to be greater or equal to a threshold and the value of the green component at x, y has to be greater than the blue component at the same pair of coordinates. The values of R component in fire pixels

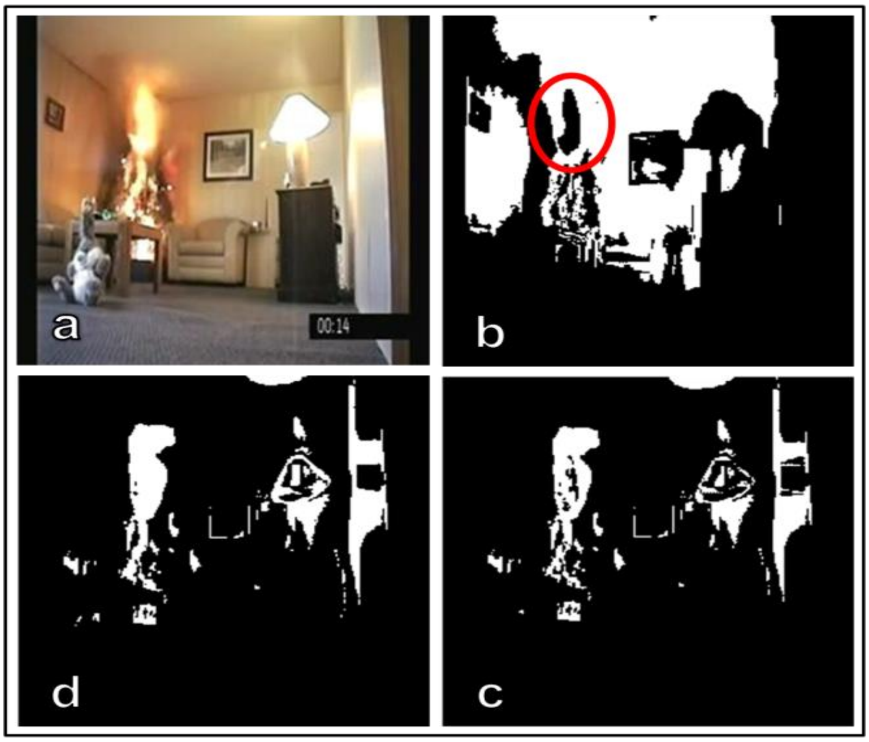

Figure 9: Color Segmentation Output by the Proposed Rules in and the State of Art Models. (a) Sample frame (b) Color Segmentation on YCbCr Using Equations (4-7) (c) Color Segmentation on RGB Using Equations (1-3) (d) Segmentation Using Proposed Equations.

range from 190 to 255. This led the value of τ to be decisive as choosing the minimum will result in too much noise and choosing the maximum will cause to ignore true fire pixels. In order to capture the best picture possible the median of 190 and 255 is chosen which 222 is. Figure 9 shows the different output of color segmentation using the approaches proposed by [1], [9 and 10] and in this phase.

Figure 10: Variation of Blue Component Values in the Static Objects and Fire between Frames.

3.2.2 Foreground Extraction using Moving Pixel Detection

The resulting image from color segmentation will contain objects displaying fire like color, thus lights and bulbs, sunlight and candles are likely to be present. Fire is a spatiotemporal occurrence, flickering at a frequency of 10Hz [16]. The continuous movement of fire means the pixel values are not constant over frames. This information is exploited in identifying moving objects and eventually extracting out the real fire regions. The change in R, G and B components over consecutive frames is thoroughly examined using both true and false fire videos. The variation of Blue component of RGB showed a promising pattern. In case of fire, the change is drastic whereas in case of static luminous objects the component value is almost constant. Figure 10 demonstrates an example explaining the distinctive variation in values.

Feature Extraction and Training: The characteristic behavior of the B component of corresponding pixels over three consecutive frames is used to create the feature vector for training. This is done through a two-step process. At first, B component values of true and false fire pixels are extracted from video frames. About three thousand unique features are pulled out and tabulated where each column represents an instance of three frames and each row holds the B measure of each frame at the same pair of coordinates. Figure 11 gives a clear understanding of the tabular representation. As the second and the final step to create the feature vector, the absolute difference of B is calculated, first frame from the second and the second frame from the third. The difference table is shown in Figure 12. This difference table is the feature vector that is trained using a neural network. The reason behind training the subtracted results is that these are the numbers that hold the degree of dissimilarity, in other words how much the B change for fire versus other radiant sources. The feature vector is trained along with its target vector. This is created by assigning a value of 1 to the differences belonging to true fire cases and a value of 2 to the differences belonging to false fire cases. Once the data is trained and the network created, our data set is tested with a clustering threshold of 1.5 and the results are astonishing. Figure 13 shows some of the samples and their output.

Instance 1	Instance 2
187	162
205	163
207	164

Figure 11: Tabulating the Change in Blue Component Values. (a), (b), (c) are three consecutive frames of one instance and similarly (d), (e) and (f) are consecutive frames of a second instance. Each column belongs to an instance and the three rows hold the Blue Component measures of the three frames respectively.

Instance 1	Instance 2
187	162
205	163
207	164

Difference 1	Difference 2
18	1
2	1

Figure 13: Creating Feature Vector. (Difference 1) and (Difference 2) hold the corresponding differences of (Instance 1) and (Instance 2). This difference matrix is the feature vector that is trained using NN.

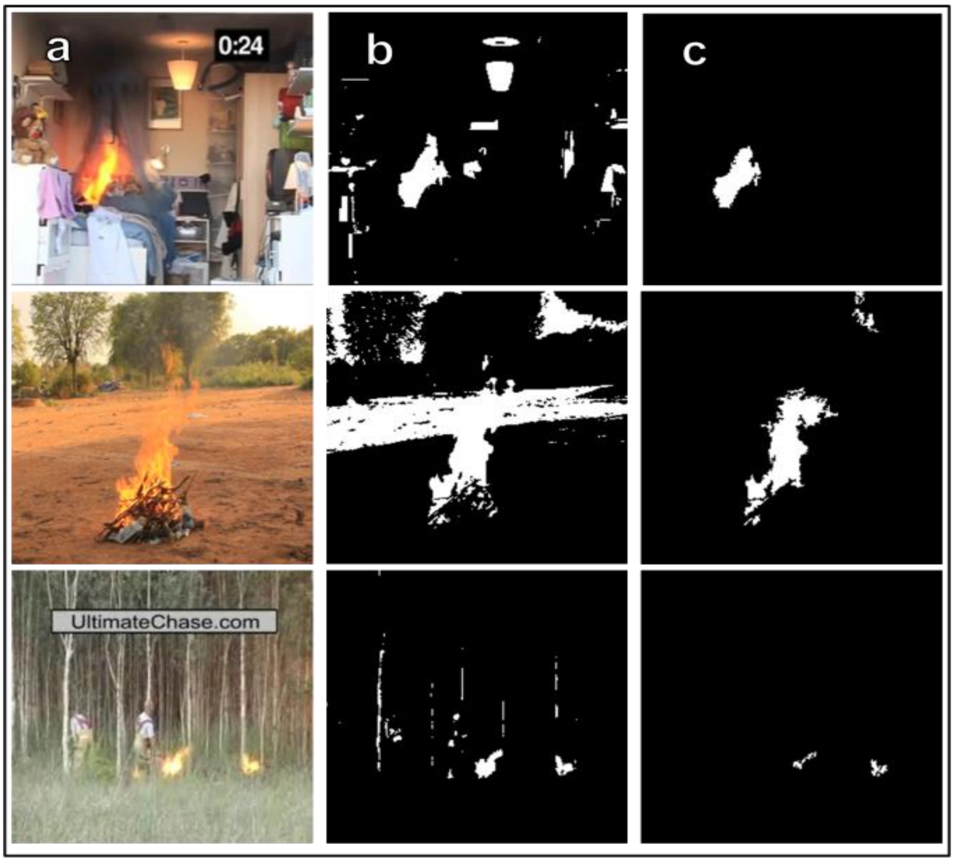

Figure 12: Results after Color Segmentation and Foreground Extraction. Column (a) shows frames of test videos. Column (b) shows the results of color segmentation applying the rules proposed in this work, equations (17) and (18). Lastly column (c) shows the output

3.2.3 Detection of Region of Interest Based on Growing Area

The final phase of the work is carried out to remove spurious moving foreground. This is done by measuring the area of the regions extracted in the previous step. The area of fire is expected to increase basing on the fact that a hazardous fire grows over time. As mentioned before, three consecutive frames are a used as one instance to identify the moving foregrounds. In this stage, the resultants of two consecutive instances of a video (six consecutive frames) are used to distinguish the true fire region(s). Let a, b and c be three consecutive frames of a video and Output1 be the binary image, containing moving objects, resulting from a, b and c. Similarly, let d, e and f be the next three consecutive frames after c and let Output2 be the second binary image resulting from d, e and f. Corresponding white blobs between Output1 and Output2 are measured. The white regions whose area measurements are not increasing are eradicated. Figure 14 explains the full process.

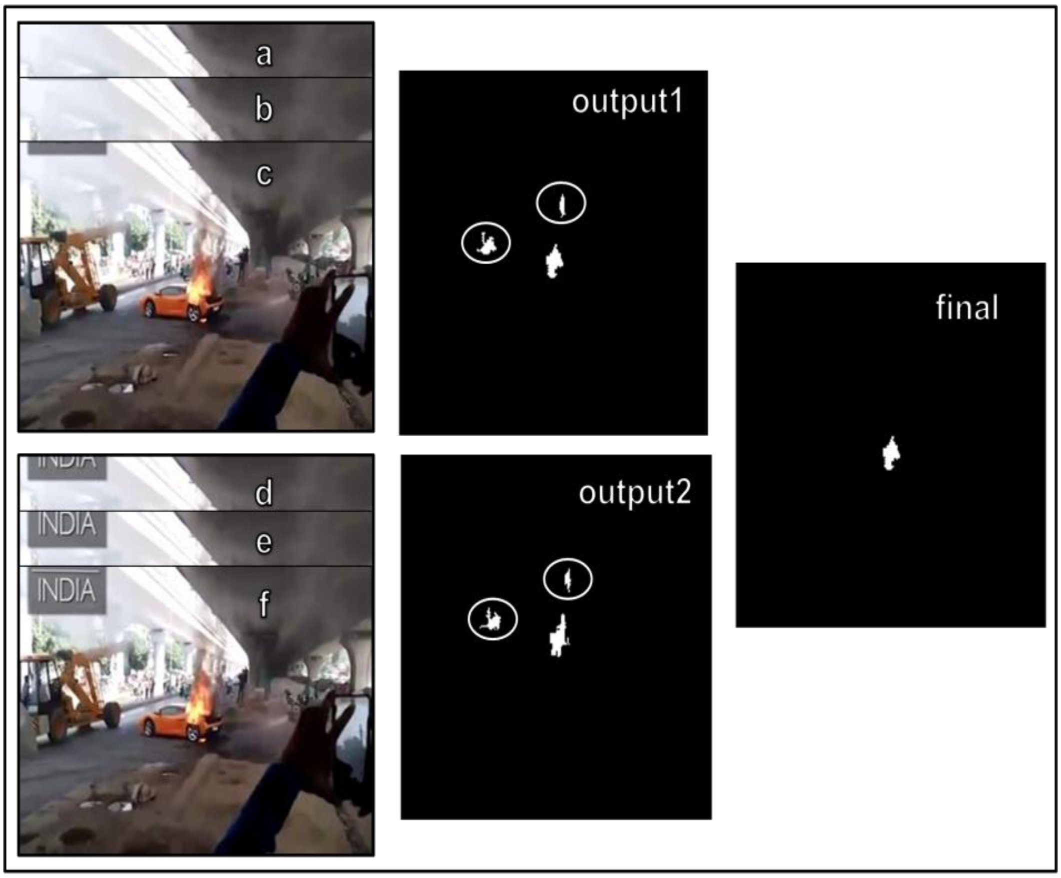

Figure 14: Final Output after Region Growth Analysis. (a), (b) and (c) are three consecutive frames and (output1) is the corresponding result from step 3.2. Similarly (output2) is the output of (d), (e) and (f). Each contain three blobs equivalent to each other a

Chapter 4

Experimental Analyses of the Proposed Models

Two different types of models have been proposed in this research – the first model being focused to indoor conditions while the latter covers any background and surrounding. In order to assess the robustness, the proposed model is tested with videos containing both true and false fire scenes in a diverse range of environmental conditions and illumination.

4.1 Result of Model 1

Video No.	Frames	Fire	Scene Description	Sample Scenes
1.	2,558	Yes	Fire ignited in a bedroom having a bright background and luminous objects such as a lamp, light, and sunrays from the window.	
2.	1,995	Yes	Fire ignited in a living room. It has a yellow flame very similar to the background.	
3.	1,791	Yes	A kitchen fire.	
4.	2,718	Yes	Warehouse fire showing a very bright yellow flame.	
5.	3,250	Yes	Industrial fire simulation covering multiple areas.	

Table 3: No of Frames and Scene Description of True Fire Video used in Model 1

Video No.	**Frames**	**Fire**	**Scene Description**	**Sample Scenes**
1.	342	No	Sunrays through the window with smoke present.	
2.	1,920	No	A person walking with a red book and an orange ball.	
3.	1,485	No	A person walking with an orange ball. This video has a reddish background.	

Table 4: No of Frames and Scene Description of False Fire Videos used in Model 1

The performance obtained using the intended approach with the enhanced segmentation rule and added rotundity scrutiny was compared with the technique modeled by Chen *et al.*[1]. Two types of comparisons were carried out to correct fire blob detection and evaluate the computation time. For correct blob(s) detection, if either of the methods succeeds to identify some portion of it, then it will be declared as an accurate detection.

The comparisons of the results are tabulated in Tables 5 and 6. Table 5 displays the results when the models were tested with real fire situations, which revealed that the proposed model yielded an average accuracy of 98.2% for positive instances. Moreover the projected approach outperformed the state of the art technique in terms of computation time. Examining the accuracy against individual videos, it seems that the state of the art model is weak when exposed to situations when the flame exhibits a yellowish flame (Videos 2 and 4) and when the background contains other luminous fire-like objects (Video 1). The reason behind the slowness is the calculation of the saturation value. Table 6 shows the results when the models were tested with scenarios containing fire-like objects but no true fire, with both techniques achieving a precision of 100%. In this case, the proposed method was faster. In order to summarize the results, the accuracy combining the positive and negative samples was calculated. The model proposed in this paper achieved an overall precision of 99.1%, which is better than Chen's model with a combined accuracy of 97.75%. Figure 15 shows some visual examples of our experiments.

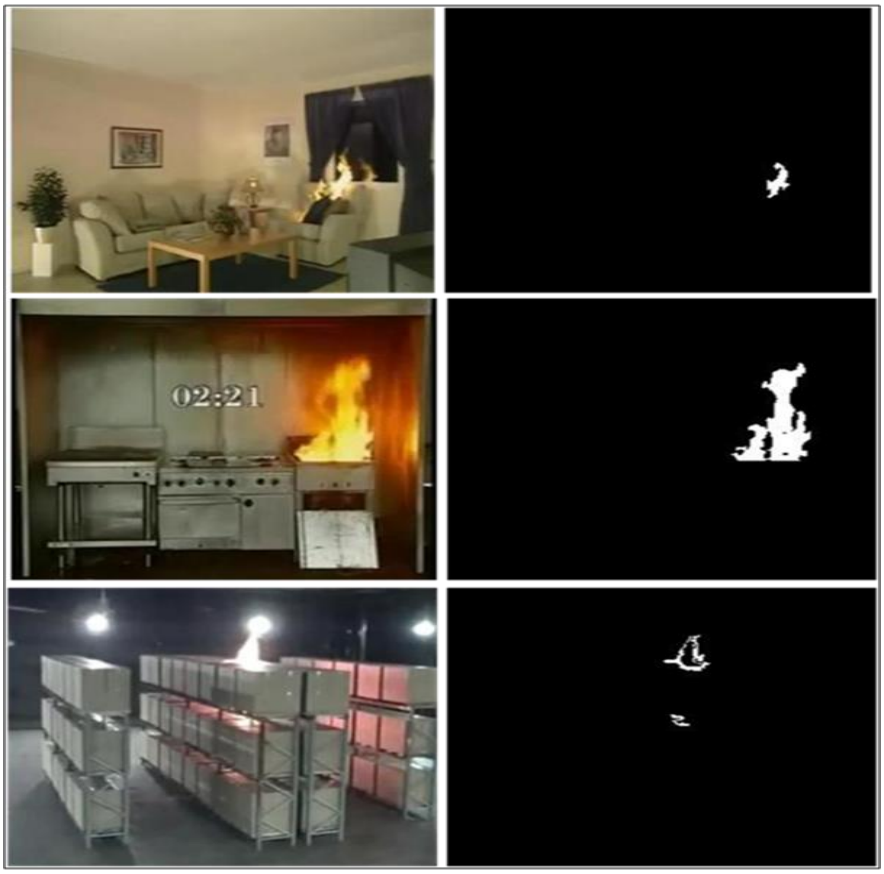

Figure 15: Some Experimental Results using Model 1

Video	**# of Fire Frames Tested**	**# of Fire Frames Correctly Detected**		**Avg. Exec Time per Frame**		**Accuracy**	
		[1]	Proposed	[1]	Proposed	[1]	Proposed
1.	300	285	293	1.07	0.73	95.3%	97.7%
2.	300	280	295	1.17	0.82	93.3%	98.5%
3.	300	300	300	1.10	0.78	100%	100%
4.	300	273	290	1.12	0.77	91%	96.7%
5.	300	295	295	1.19	0.83	98.3%	98.3%
					Average Accuracy	95.5%	98.2%

Table 5: Comparison Table between Model 1 and State of Art Approach using True Fire Videos

Video	**# of Non-fire Frames Tested**	**# of Non-fire Frames Correctly Detected**		**Avg. Exec Time per Frame**		**Accuracy**	
		[1]	Proposed	[1]	Proposed	[1]	Proposed
1.	150	150	150	1.18	0.85	100%	100%
2.	150	150	150	0.86	0.61	100%	100%
3.	150	150	150	0.85	0.59	100%	100%
					Average Accuracy	100%	100%

Table 6: Comparison Table between Model 1 and State of Art Approach using False Fire Videos

4.2 Result of Model 2

The performance of the intended approach with improved color segmentation rules and a novel foreground extraction technique is compared with the model put forward by Chen *et al.* in [1]. The comparison is based not just on detecting fire regions correctly but also how effectively the false regions are eliminated. The evaluation perimeters are given below and the results are shown in Table 7 and Table 8.

- TP (true positive): regions detected as fire are true fire
- FP (false positive): regions detected as fire are not fire
- TN (true negative): non fire regions are not detected
- FN (false negative): true fire regions are not detected
- FD (fire detection): percentage of correctly detected frames

$$\text{FD} = \frac{\text{TP x 100}}{\text{Total Fire Frames}} \qquad (13)$$

- WFD (wrong fire detection): percentage of false fire detection, the lower the number the better.

$$\text{WFD} = \frac{\text{(FP+FN) x 100}}{\text{Total Frames}} \qquad (14)$$

- Overall (Overall accuracy)

$$\text{Overall} = \frac{\text{(TN+TP) x 100}}{\text{Total Frames}} \qquad (15)$$

While comparing to the technique proposed in [1], the model put forward in this paper has yielded an accuracy of 95.2% for detecting the true fire regions correctly. Moreover it has a much lower rate of detecting false positives, 4.8%. Examining the detections from Table 6, it seems that Chen's method performs poorly when exposed to conditions where there are multiple luminous sources present. In order to summarize the overall accuracy is calculated. The model put up in this paper achieved an overall precision of 97.7% which aces over

Chen's which has gained 92.5%. Figure 16 shows some visual examples of our experiment versus Chen's.

Vid. No.	**Fire Frames**	**Non Fire frames**	**TP**		**FP**		**TN**		**FN**		**Description**
			(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	
1	100	100	100	100	0	0	100	100	0	0	Bedroom fire
2	100	100	40	90	0	0	100	100	60	10	Living room fire
3	50	50	50	50	0	0	50	50	0	0	Kitchen Fire
4	50	0	50	50	48	5	0	0	0	0	Outdoor Fire
5	30	10	30	30	16	2	10	10	0	0	Living room fire
6	20	10	20	20	0	0	10	10	0	0	Forest Fire
7	0	20	0	0	0	0	20	20	0	0	Car Headlights
8	20	10	18	10	0	10	10	10	2	10	Living room fire
9	10	10	7	10	0	0	10	10	3	0	Car crash
10	20	0	20	20	8	0	0	0	0	0	Outdoor fire
11	0	10	0	0	0	0	10	10	0	0	Smoke and red background
12	0	30	0	0	0	0	30	30	0	0	Smoke in outdoor
13	0	50	0	0	0	0	50	50	0	0	Red background, moving objects
14	0	50	0	0	0	0	50	50	0	0	Red objects
15	15	0	15	15	15	5	0	0	0	0	Car crash

Table 7: No. of Videos used, No. of Frames Tested and Experimental Output Comparison between Model 2 and State of Art Approach. (1) is the algorithm proposed by Chen et al. and (2) is the proposed model.

Proposed Model	**FD**	**WFD**	**Overall**
(1)	84.3%	17.5%	92.5%
(2)	95.2%	4.8%	97.7%

Table 8: Accuracy Comparison between Model 2 and State of Art Approach. (1) is the algorithm proposed by Chen et al. and (2) is the proposed model.

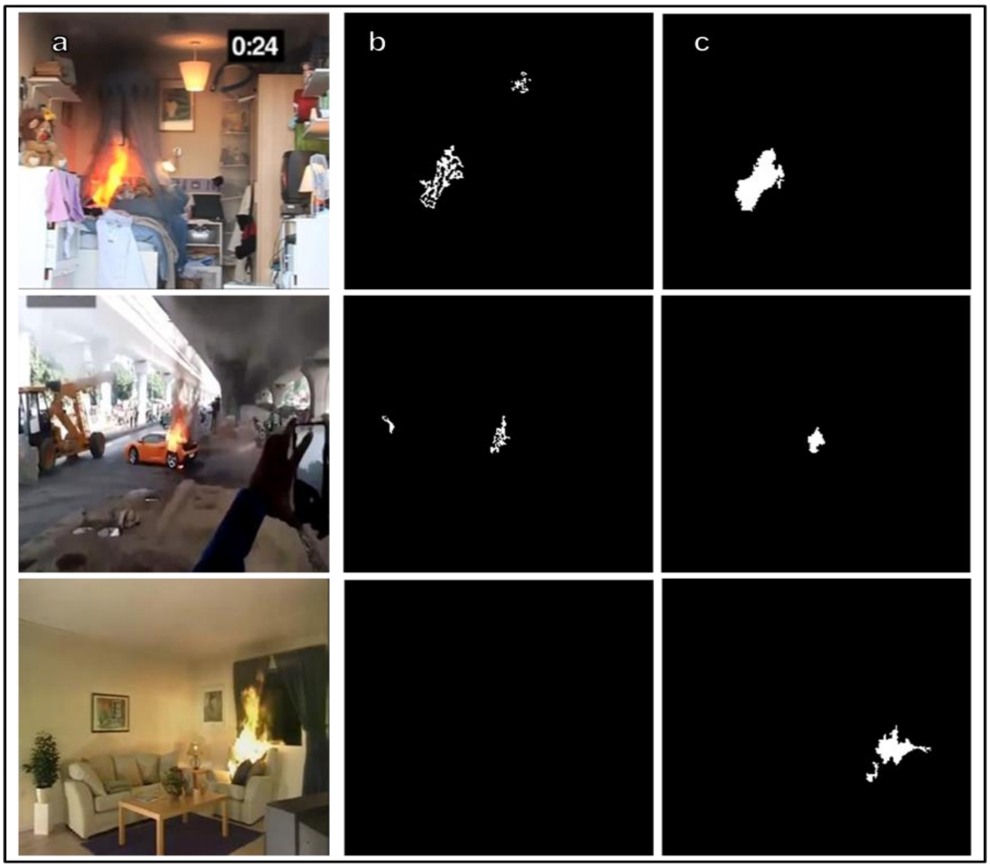

Figure 16: Experimental Results using Model 2. Column (a) contains sample fire frames, (b) final output of [1] and (c) final output of the proposed work. Column (b) shows false regions in the first two instances while the last one got completely undetected.

Chapter 5

Conclusion

This thesis proposed 2 models to detect fire. The former one focusing on indoor conditions whereas the later one covers diverge circumstances both indoor and outdoor. In the first model proposed a new segmentation rule on RGB plus rotundity analysis using Neural Network. Fire colored pixels was first identified followed by frame differencing to separate the moving pixels. Unwanted pixels were then removed and the spatial growth of the remaining blobs was compared with the equivalent ones in a later frame. For the final step the complexity of the region boundary was examined. The experimental output showed the model put forward in this paper has surpassed the other approach, yielding an average accuracy of 99.1%. The second model is composed of simple and developed color segmentation rules on RGB and a brand new tactic for identifying moving fire pixels with the help of neural network. Fire-colored pixels were first identified followed by foreground extraction to separate the moving objects. As the final step of the process, unwanted regions were removed through analyzing their spatial growth over frames. The experimental output showed the model put forward in this paper has surpassed the other state of approach, yielding an average accuracy of 97.7%.

References

[1]	T. Chen, C. Kao and S. Chang, “An Intelligent Real-Time Fire-Detection Method Based on Video Processing,” IEEE 37th International Carnahan on Security Technology, Taipei, Taiwan, October 2003 pp. 104-111
[2]	J. Zhao, Z. Zhang, S. Han, C. Qu, Z. Yuan and D. Zhang, “SVM Based Forest Fire Detection Using Static and Dynamic Features,” Journal of Computer Science and Information Systems, vol. 8, 2011, pp. 821-841.
[3]	Q. Zhou, X. Yang and L. Bu, “Analysis of Shape Features of Flame and Interference in Video Fire Detection,” IEEE Chinese Automation Congress, Wuhan, China, November 2015 pp. 633-637
[4]	Y. Kim, A. Kim and H. Jeong, “RGB Color Model Based The Fire Detection Algorithm in Video Sequences on Wireless Sensor Network,” International Journal of Distributed Sensor Networks, vol. 10, 2014
[5]	T. Celik, H. Demirel, H. Ozkaramanli and M. Uyguroglu, “Fire Detection in Video Sequences Using Statistical Color Model,” IEEE International Conference on Acoustics, Speech and Signal Processing, Toulouse, France, May 2006 pp.213-216
[6]	T. Celik, H. Demirel, H. Ozkaramanli and M. Uyguroglu, “Fire Detection Using Statistical Color Model in Video Sequences,” Journal of Visual Communication and Image Representation, vol. 18, 2007, pp. 176-185
[7]	T. Celik, H. Ozkaramanli and H. Demirel, “Fire Pixel Classification using Fuzzy Logic and Statistical Color Model,” IEEE International Conference on Acoustics, Speech and Signal Processing, Honolulu, HI, USA, April 2007 pp.1205-1208

[8]	T. Celik, H. Ozkaramanli and H. Demirel, "Fire and Smoke Detection Without Sensors: Image Processing Based Approach," 15th European Signal Processing Conference, Poznan, Poland, September 2007 pp.1794-1798
[9]	T. Celik and K. Ma, "Computer Vision Based Fire Detection in Color Images," IEEE Conference on Soft Computing in Industrial Applications, Muroran, Japan, June 2008 pp.258-263
[10]	T. Celik and H. Demirel, "Fire Detection in Video Sequences Using a Generic Model," Fire Safety Journal, vol. 44, 2009, pp.147-158
[11]	L. Chen and W. Huang, "Fire Detection Using Spatial-temporal Analysis," World Congress on Engineering, London, UK, 2013 pp. 2222-2225
[12]	J. Seebamrungsat, S. Praising and P. Riyamongkol, "Fire Detection in the Buildings Using Image Processing," IEEE 3rd ICT International Student Project Conference, Nakhom Pathon, Thailand, March 2014 pp.95-98
[13]	T. Chen, P. Wu and Y. Chiou, "An Early Fire-detection Method Based on Image Processing," Proceedings of the IEEE International Conference on Image Processing, Singapore, Singapore, October 2004 pp.1707-1710
[14]	Y. Benezeth, P. Jodoin, B. Emile, H. Laurent and C. Rosenberger, "Comparative Study of Background Subtraction Algorithms," Journal of Electronic Imaging, vol. 19, 2003 pp.33003-33003-12
[15]	J. Shao, G. Wang and W. Guo, "An Image-Based Fire Detection Method Using Color Analysis," IEEE International Conference on Computer Science and Information

	Processing, Xi'an, Shaanxi, China, August 2012 pp.1008-1011
[16]	J. Chen, Y. He , J. Wang, "Multi-feature Fusion Based Fast Video Flame Detection, " Journal of Building and Environment, Vol. 45, 2010 pp. 1113-1122
[17]	P. Foggia, A. Saggese and M. Vento, "Real-time Fire Detection for Video Surveillance Applications using a Combination of Experts Based on Color, Shape and Motion", IEEE Transactions on Circuits and Systems for Video Technology, vol. 25, 2015, pp.1545-1556.