Forest Fire Detection Using Image Processing

Bondili Laxmi Nitin Singh^{#1}, Venkatapuram Keshava Sai Kumar^{*2}, Guddilapalli Maurya Vardhan Reddy^{#3}

*SCOPE, VIT, Chennai Campus Kelambakkam -Vandalur Road, Rajan Nagar, Chennai, Tamil Nadu 600127, India

¹bondililaxmi.nitin2019@vitstudent.ac.in ²keshava.saikumar2019@vitstudent.ac.in ³mouryavardhan.reddy2019@vitstudent.ac.in

Abstract—Forest fires represent a true threat to human lives, ecological systems, and infrastructure. Several business fire detection device systems exist, however all of them are troublesome to use at giant open areas like forests as a result of their response delay, necessary maintenance required, high cost, and alternative issues. During this paper a fire detection algorithmic program is projected, and it consists of the subsequent stages. Firstly, background subtraction is applied to movement containing region detection. Secondly, changing the divided moving regions from RGB to YCbCr color house and applying 5 fire detection rules for separating candidate fire pixels were undertaken. Finally, temporal variation is then used to differentiate between fire and fire-color objects. The projected technique is tested employing a information set consisting of seven videos collected from the web. The final results show that the projected technique achieves up to 85.71%(i.e., 6 out of seven videos) of true detection rates. These results indicate that the projected technique is correct and may be employed in automatic forest fire-alarm systems.

Keywords— Temporal Variation, YCbCr, Background Subtraction, Fire Detection Rules.

I. Introduction

Forest fireplace detection systems are gaining tons of attention due to the continual threat from fire to each economic property and public safety [1]. many uncountable hectares are destroyed by wildfires every year [1] and over 200,000 forest fires happen once a year within the world. Forest fires destroy a complete space of three.5 to 4.5million km2 [1]. Increase in forest fireplaces in forest areas round the world has resulted in Associate in Nursing hyperbolic motivation for developing fire warning systems for

the first detection of wildfires [1]. Sensing element technology has been widely employed in fireplace detection, sometimes counting on sensing physical parameters like changes in pressure, humidity, and temperature, further as chemical parameters like carbonic acid gas, CO, and dioxide.

However, it's exhausting to use these systems in massive open areas for a spread of reasons like high value, energy usage by the sensors, and also the necessary proximity of the sensing element to the fireplace for correct sensing leading to physical injury to the sensors [4]. Additionally, sensing element ways have a high false alarms rate and their reaction time is sort of huge [5]. There are various motivating factors for the utilization of a picture process primarily based on the methodology of fireside detection. The primary issue is the fast development of camera technology and CCD or CMOS digital cameras, which has resulted during a fast increase in image quality and minimized value of the cameras. The second issue is that digital cameras will cowl massive areas with glorious results. Third, the reaction time of image process models is better than that of existing sensing element models. Finally, the value of image process systems is below existing systems.

II. Related Works

Several fireplace detection algorithms are projected by numerous researchers. Thou-Ho et al. [1] given a fireplace detection algorithmic program, which mixes Determination of the 2 thresholds RT

and ST is that the saturation channel of the HSV color and also the RGB color. This algorithmic program employs 3 rules ($R \ge G \ge B$), ($R \ge RT$), and ($S \ge RT$) ((255-R) *ST/RT). required. The bound values vary from 115 to 135 for RT and from 55 to 65 for ST supported several investigational results done by the technique authors. This is computationally straightforward compared to the opposite algorithms; but, it suffers from false-positive alarms just in case of moving fire-like objects. Dios et al. [2] given an associated optical model accustomed to discovering forest fires and living the properties of the fireplace like flame height, fire front, fireplace base dimension, and flame inclination angle. This method is extremely good; yet, it's terribly pricey as a result of it consists of infrared cameras and different technologies like GPS and mensuration sensors. Yinglian et al. [1] projected fire disaster bar algorithmic program supported image process. This algorithmic program depends on fireplace and smoke color properties to spot fire. Yinglian's algorithmic program is great, however the smoke spreads quickly and it hasmany totally different colors that depend upon the burning material; therefore, the warning rate rises.

III. Methods

This section presents the proposed fire detection rule. It consists of the subsequent main stages: the primary step receives the input video from the input device; the second step applies movement containing region detection supported background subtraction (MRDB); the third step converts the input image sequence from RGB to YCbCr color space; and also the fourth step applies the fireplace detection rules, and temporal variation. a fireplace alarm is activated if all detection conditions are good. The planned rule stages are delineated well.

Movement Containing Region Detection Based on Background Subtraction (MRDB). Detecting moving regions could be a key factor as most of the video based fire detection systems because fire boundaries endlessly fluctuate. Thus background subtraction is employed to pick candidate regions of fireside. A pixel settled at (x, y) is meant to be moving if the subsequent condition is met [1]. where Y_{mean} , Cb_{mean} , and Cr_{mean} are the mean values for the YCbCr channels; Y(x, y), Cb(x, y), and Cr

$$|I_n(x, y) - B_n(x, y)| > thr$$
 (1)

 $I_n(x, y)$ represents the intensity value of the pixel at location (x, y) in the nth gray-level for the current frame and B_n (x, y) represents the background intensity value at the same pixel location, and thr is a threshold value experimentally set to 3. The background is continuously updated using

$$B_{k+1}(x, y) = a * B_k(x, y) + (1 - a) * I_k(x, y),$$

Where $a \in (0, 1)$ (2)

Converting RGB images to YCbCr. thanks to the actual fact that totally different forms of moving objects is enclosed once applying background subtraction, like trees, animals, birds, and people, so pictures from the background subtraction stage ar reborn to YCbCr [1] to pick candidate fireplace regions victimization (3). The mean values of the YCbCr channel are then calculated victimization (4), (5), and (6).

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

$$+ \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix}$$
(3)

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

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

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

(x, y) are YCbCr channel values for pixel at specific location (x, y); and N*M is the total number of pixels.

Fire Color Pixel Detection Rules. In any fire image pixels, the red color value is larger than green and green is larger than blueThis fact is represented in RGB color space as R>G>B and can be converted to YCbCr using the following equations:

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

$$Cr(x, y) > Cb(x, y)$$
 (8)

Also, the Y component value is greater than the mean Y component of the same image and the Cb component is smaller than the mean Cb of the same image, while the Cr component is greater than the mean Cr mean component. This fact can be represented by the following:

$$\begin{split} F\left(x,y\right) \\ &= \begin{cases} 1 & if \ Y\left(x,y\right) > Y_{m}; \ Cb\left(x,y\right) < Cb_{m}; \ Cr\left(x,y\right) > Cr_{m} \\ 0 & Otherwise \end{cases} \end{aligned} \tag{9}$$

where F(x, y) can be any pixel on the image. Ym, Cbm, and Crm are the mean values for Y, Cb, and Cr, respectively. The Cb component as shown is predominantly "black" and the Cr component is "white". This idea can be represented by the following equations:

$$F(x,y) = \begin{cases} 1 & \text{if } |Cb(x,y) - Cr(x,y)| \ge \tau \\ 0 & \text{Otherwise} \end{cases}$$
 (10)

F(x, y)

$$=\begin{cases} 1; & (Cb(x, y) \le 120) \bigcap (Cr(x, y) \ge 150) \\ 0 & Otherwise \end{cases}$$
 (11)

where τ is a constant, specified in [10] using receiver operating characteristic (ROC), by applying different values of τ in the range [1, 100]. To measure the "true detection rate" and "false detection," data sets consisting of 500 images (300 of them being images of a forest fire, 200 nonfire images) collected from the Internet were used. Only (10) was used with

different values of τ in the range [1, 100] to detect binary images of the candidate fire region. τ was selected as $\tau = 70$ resulting in a true detection rate of more than 90% and false detection of less than 40%.

Temporal Variation. Using color models alone is not enough to identify fire correctly because there are several objects that share the same fire color such as red leaves, desert, and other red moving objects. The main difference between actual fire and the fire-color objects is the nature of their motion. Shape and size of the flame are totally changeable, because of burning materials and airflow; thus, it produces higher temporal variation. In contrast, rigid bodies' motion produces lower temporal variation. Therefore, it is possible to differentiate between the fire pixels and the fire color. To detect a fire movement, the difference between successive frames was analyzed. Suppose a video sequence consisting of n frames, and the average temporal variation is defined as [1].

$$\Delta(x, y) = \frac{1}{n} \sum_{i=1}^{n-1} |f_i(x, y) - f_{i+1}(x, y)|$$
 (12)

where $\Delta(x, y)$ is the average temporal variation, f i(x,y) is a pixel intensity at the location (x, y) in the ith frame. If $\Delta(x, y)$ >thr (experimentally determined threshold), then a moving pixel is fired.

Iv. Results and Performance Analysis

To measure the performance of the proposed model, 7 videos were collected from the Internet, 3 of them are available (http://www.ultimatechase.com/). Five of these videos actually had fire, and two were fire-color objects. The algorithm was implemented using MATLAB (R2020b) and tested on an Intel core i5 1.60 GHz PC 8GB-RAM PC. Table1 shows the variety of forest fire condition videos used in the test. A true-positive was counted if an image frame had fire pixels, and it was determined by the proposed model to be fire. In contrast, false-positive was counted, if the image frame has no fire, and the result was determined as a fire.

Table 1: Result of the proposed algorithm.

Sno.	Input Video Frame	Background Subtracted Frame	Frame after rule based detection	Output
1.	UltimateChase.com		, in the second	Forest Fire Detected
2.	UltimateChase.com			Forest Fire Detected
3.	NATURE ROOTAGE		5.47	Forest Fire Detected
4.				No fire Detected
5.	NATURE PROOTAGE			No fire Detected
6.				No Fire Detected









Forest Fire Detected

The results in Table 1 show that the proposed method has achieved average true-positive percentage (TTP) up to 85.71% in the tested forest fire videos and 14.29% false-positive rate. These results indicate the good performance of the proposed method in forest fire detection.

V. Conclusion

This study proposes an effective forest fire detection method by using image processing techniques including movement containing region detection based on background subtraction and color segmentation. The algorithm uses YCbCr color space which is better in separating the luminance from the chrominance and has a good detection rate. five fire detection rules are applied to detect the fire. The performance of the proposed algorithm is tested on a data set consisting of 7 videos collected from the Internet, five of which were actual fire videos, while two were fire-like objects videos. TP-rate and TN-rate were calculated. The results show that the proposed algorithm achieves good detection rates. These results indicate that the proposed method is accurate and can be used in automatic forest fire-alarm systems. For future work, the system could be improved by using a combination of rules of different color spaces; however, the challenge is selecting the right rules from different color spaces to build the method.

Data Availability

The data consists of 6 videos, 3 of them are available at (http://www.ultimatechase.com/) with license and the other 4 videos are collected from https://www.naturefootage.com/.

Acknowledgement

The work is done under the guidance of Dr. Geetha S (Professor and Associate Dean SCOPE at VIT Chennai)

References

- [1] Mubarak A. I.Mahmoud and Honge Ren, "Forest Fire Detection Using a Rule-Based Image Processing Algorithm and Temporal Variation" Hindawi Mathematical Problems in Engineering Volume 2018, Article ID 7612487, 8 pages https://doi.org/10.1155/2018/7612487
- [2] Y.Meng, Y. Deng, and P. Shi, "Mapping ForestWildfire Risk of the World," in World Atlas of Natural Disaster Risk, P. Shi and R. Kasperson, Eds., pp. 261–275, Springer Berlin Heidelberg, Berlin, Germany, 2015.
- [3] P. M. Hanamaraddi, "A Literature Study on Image Processing for Forest Fire Detection," IJITR, vol. 4, pp. 2695–2700, 2016.
- [4] A. D. Alzughaibi, H. A. Hakami, and Z. Chaczko, "Review of human motion detection based on background subtraction techniques," International Journal of ComputerApplications, vol.122, 2015.
- [5] C. E. Premal and S. S. Vinsley, "Image processing based forest fire detection using YCbCr colour model," in Proceedings of the 2014 International Conference on Circuits, Power and Computing Technologies, ICCPCT 2014, pp. 1229–1237, 2014.
- [6] L.-H. Chen and W.-C. Huang, "Fire detection using spatial temporal analysis," in Proceedings of the World Congress on Engineering, pp. 3–5, 2013.