Early Forest Fire Detection

M. Saritha Devi[1] | B. Ajith[2] | Ch.Himaja[3] | N.Sai Ram[4] | A.Vamsi Krishna[5]

[1,2,3,4,5] Department of Electronics and Communication Engineering, Godavari Institute of Engineering and Technology (A), Rajahmundry, Andhra Pradesh, India

Abstract: Forest fires represent a constant threat to human lives, ecological systems, and infrastructure. Many commercial fire detection systems exist, but the problem is they are very costly and difficult for maintenance and for considering forests like large areas it is very difficult to use. The approach for forest fire detection using image processing techniques is proposed. In this paper a forest fire detection algorithm is proposed, and it operates by converting the segmented moving regions from RGB to YCbCr color space and applying fire detection rules for finding out the fire pixels. The proposed method has both a higher detection rate and lower false rate. Since the algorithm is cheap in computation it can be used for real time forest fire detection..

Keywords— Forest fire detection, Image processing

Check for updates

DOI of the Article: https://doi.org/10.46501/GIETEC16

Available online at: https://ijmtst.com/icetee2021.html

As per UGC guidelines an electronic bar code is provided to seure your paper

To Cite this Article: M. Saritha Devi; B. Ajith; Ch.Himaja; N.Sai Ram and A.Vamsi Krishna. Early Forest Fire Detection. *International Journal for Modern Trends in Science and Technology* 2021, *7*, pp. 87-93. https://doi.org/10.46501/GIETEC16

Article Info. Received: 18 May 2021; Accepted: 25 June 2021; Published: 30 June 2021

INTRODUCTION

Forest fire detection systems have become very popular because of the continual threat from fire to both economic properties and public safety. Hundreds of millions of hectares are destroyed by wildfires each year and a huge number of forest fires happen every year in the world. Due to this temperatures have been rising very huge and a huge economic loss is happening all over the world. Increase in forest fires in forest areas around the world has resulted in an increased motivation for developing fire warning systems for the early detection of wildfires. Sensor technology has been widely used in fire detection, usually depending on sensing physical parameters such as changes in pressure, humidity, and temperature, as well as chemical parameters such as carbon dioxide, carbon monoxide, and nitrogen dioxide. However, it is hard to apply these systems in large open areas for a variety of reasons such as high cost, energy usage by the sensors, and the necessary proximity of the sensor to the fire for accurate sensing resulting in physical damage to the sensors. In addition, sensor methods have a high false alarms rate and their response time is quite big. The most frequently used fire smoke detection techniques are usually based on particle sampling, temperature sampling, and air transparency

testing. An alarm is not raised unless the particles reach the sensors and activate them.

1.1 SOME OF THE TRADITIONAL METHODS ARE MENTIONED BELOW:-

A. FIRE WATCH TOWER : In watch towers humans are made to observe the location throughout. If any fire occurs he reports it. Human observation may be limited by operator fatigue, time of day, time of year, and geographic location.

B. Wireless Sensor Networks: In a wireless sensor-based fire detection system, coverage of large areas in forest is impractical due to the requirement of regular distribution of sensors in close proximity and also battery charge is a big challenge.

C. Satellite and Aerial Monitoring: Satellites are used for monitoring over a large area but the resolution capacity is very less and due to the weather conditions it becomes more difficult in finding the fires.

Due to the rapid growth of image processing and also the availability of different softwares used for image processing has increased a lot and also due to the rapid decrease in the cost of electronics and costeless process and digital camera technology, they are obtaining high resolution and easily identifiable images and can be connected each other very easily and data can be transferred at a high speed.

The fire detection performance depends critically on the performance of the flame pixel classifier which generates seed areas on which the rest of the system operates. The flame pixel classifier is thus required to have a very high detection rate and preferably a low false alarm rate. There exist few algorithms which directly deal with the flame pixel classification in the literature.

STRUCTURE OF PAPER

The paper is organized as follows: In Section 1, The introduction of the paper is provided along with the structure, important terms and overall description. In Section 2 we discuss related work. In Section 3 we have the complete information about working and classification of fire fixels. Section 4 shares information about the experiment results and performance evaluation. Section 5 tells us about the future scope and concludes the paper with acknowledgement and references.

RELATED WORK

1. T. Celik and Hasan Demirel et al. further enhance a system that uses a statistical color model with Fuzzy logic for fire pixel classification. The proposed system develops two models; one based on luminance and second based on chrominance. Fuzzy logic uses the YCbCr color space for the separation of luminance from chrominance instead of using color spaces such as RGB. Existing historic rules are replaced with the Fuzzy logic to make the classification more robust and effective. This model achieves up to 99.00% correct fire detection rate with a 9.50% false alarm rate.

2. R. Gonzalez-Gonzalez et al. proposed a method to detect fire by smoke detection based on wavelets. In this smoke detection method, image processing on video

signals is proposed. The SWT transform is used for the area detection of ROI's. This method comprises three steps. In the first step, preprocessing is performed and the image is resized and transformed to grayscale image. Finally indexed the image using indexation. The second step involves high frequencies of an image being eliminated using SWT and reconstructing the image by inverse SWT. In order to group the intensity colors that are close to each other is the main purpose of image indexation.

3. Y. Habiboglu et al. proposed another method that uses covariance descriptors for fire detection. In this method, color, spatial and domain information are combined by using covariance descriptors for each spatio-temporal block. The blocks are generated by dividing the flame colored region into 3D regions. This method used a covariance matrix for the detection of flames. Background subtraction method is not used in this approach.

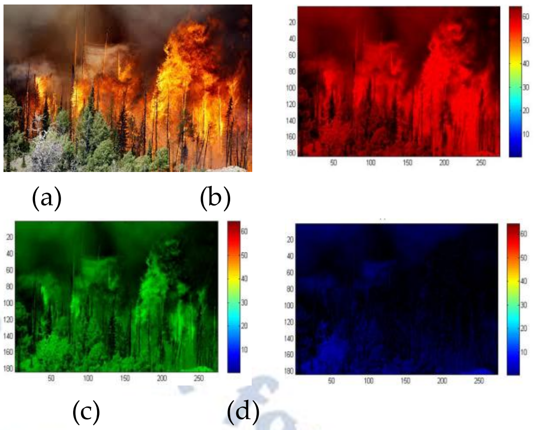
PROPOSED FOREST FIRE MONITORING SYSTEM :

In the proposed method, an image captured by the digital camera as input, processes the image and performs actions as shown in figure 1. In this paper we will discuss how fire regions are detected in the captured image.

WORKING :

CLASSIFICATION OF FIRE PIXEL :

This section covers the detail of the proposed fire pixel classification algorithm..Rule based color model approach has been followed due to its simplicity and effectiveness. For that, color space RGB and YCbCr is chosen as they are the most significant and widely used colour space models. For classification of a pixel to be fire we have identified different sets of rules to be followed .If a pixel satisfies all those rules, we say that pixel belongs to fire class. In a digital colored image, it has 3 planes: Red, Green and Blue(R,G,B) simply called the RGB color space model. By the combination of these colors we are able to represent the color in a digital environment. They will be in discrete values. In general there are 256(8 bits per color plane) quantization levels are used for each plane, plane, for instance white is represented by (R, G, B) = (255, 255, 255) and black is represented by (R, G, B) = (0, 0, 0). A color image consists of pixels, where each pixel is represented by spatial location in rectangular grid (x, y), and a color vector (R(x, y), G(x, y), B(x, y)) corresponding to spatial location (x, y).



(a) (b) (c) (d)

Fig 2 : (a) Original Image. (b) Red-Channel Image. (c) Green-Channel Image . (d) Blue-Channel Image.

It can be noticed from figure2 that for the fire regions, R channel has higher intensity values than the G channel, and the G channel has higher intensity values than the B channel. From that we can calculate the mean values of R, G and B planes in segmented fire regions of the original images.

It is clear that, on the average, the fire pixels show the characteristics that their R intensity value is greater than G value and G intensity value is greater than the B. So, for a pixel at spatial location (x, y) to be a fire pixel the below rule must be satisfied.

$$R1(x,y) = \begin{cases} 1, & \text{if } R(x,y) > G(x,y) > B(x,y) \\ 0, & \text{else} \end{cases}$$

------ (1)

The corresponding Mean values of the RGB colors for the image 2 are: :

Mean R = 252.5

Mean G = 210.3

Mean B = 83.1

CONVERTING RGB TO YCbCr COLOUR SPACE :

When the image is converted from RGB to YCbCr color space, intensity and chrominance is easily discriminated against. This helps to model the fire region easily in YCbCr color space.

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 0 \\ 128 \\ 128 \end{bmatrix} \quad \begin{matrix} Y \in [0,255] \\ C_b \in [0,255] \\ C_r \in [0,255] \end{matrix} \tag{F.15}$$

----- (a)

Relationship between YCbCr and RGB color space.

Where Y is luminance, Cb and Cr are Chrominance Blue and Chrominance Red components, respectively.
Given a RGB-represented image, it is converted into a YCbCr represented color image using the standard RGB-to-YCbCr.
The mean values of the three components Y, Cb, and Cr, denoted by Ymean, Cbmean and Crmean respectively are computed as follows:

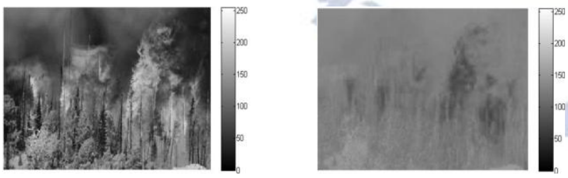
$$Y_{mean}(x,y) = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} Y(x,y)$$

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

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

------ (b)

where, (x,y) denotes the spatial location of pixels, M × N is the total number of pixels in the given image



(a) (b)

(c)

Fig 3 : (a) Y-Component corresponding to the original image in Fig (2). (b) Chrominance-Blue corresponding to the original image in Fig (2) (c) Chrominance-Red corresponding to the original image in Fig (2)

Mean values of Y, Cb, and Cr planes of fire regions for images given in Fig.3 :

Mean Y = 192

Mean Cb= 123

Mean Cr = 154

From the mean values we have developed the following rules to detect a fire pixel in any image.

RULE 1 : The rules for detecting a fire pixel at spatial location(x,y) :

R1(x,y) = 1 , if Ydash > Cb
0 , else

RULE 2 : The rules for detecting a fire pixel at spatial location .

R2(x,y) = 1 , if ((Dash> Y mean) and (Cr > Cmean))
0 , else

RULE 1 AND RULE 2: It is a combination of both rule 1 and rule 2. The flame region is generally the brightest region in the observed scene, the mean values of the three channels, in the overall image Y mean, Cbmean, and Crmean contain valuable information. From the figure 7 it can be observed that for the flame region the value of the Y(Ydash) component is bigger than the mean Y component of the overall image while the value of Cb component is in general smaller than the Y value of the overall image. Furthermore, the Cr component of the flame region is bigger than the mean Cr component. These observations which are verified over countless experiments with images containing fire regions are formulated as the following rule

R12(x,y) = 1 , if (Y dash> Cb) &(Y dash >Y mean)&(Cr>Crmean))
0 , else

RULE 3 : It states that in general the Y(Ydash) Component will be greater than the Cr and the Cb value will be greater than Cr **.**

$$R3(x,y) = \begin{cases} 1, & \text{if } ((Y\text{ dash} > Cr)\ \&\ (Cb > Cr)) \\ 0, & \text{else} \end{cases}$$

RULE 4 :

$$R4(x,y) = \begin{cases} 1, & \text{if } (Cr < 7.4{*}Crstd) \\ 0, & \text{else} \end{cases}$$

Here after testing various datasets the value 7.4 acts as a cross sectional value and at that point there will be more accuracy in finding the fire pixels in the image plane.

RULE 3 AND RULE 4 : From the histogram analysis of the fire location which is manually segmented. We have identified some threshold values for the pixel to be fired. We have threshold values for Cb and Cr planes, we are not considering Y plane because it is a luminance component and it depends on illumination conditions. We have tested these threshold values for hundreds of images from our data set. It is clear that, high true positive rate means a high false positive rate. Using this tradeoff, in our experiments the value of This picked such that the detection rate is over 95% and false alarm rate is less than 30% which corresponds to The = 7.4.

$$R34(x,y) = \begin{cases} 1, & \text{if } ((Y\text{ dash} > Cr)\ \&\ (Cb > Cr)\ \&(Cr < (7.4{*}Crstd))) \\ 0, & \text{else} \end{cases}$$

RULE 5 : It is the main rule of the program and it is the combination of the rule R12 and R34 , Adding the entire values of the obtained list by applying R12 and R34

f_f = imadd(Ir12 , Ir34)

Here imadd is a matlab function which adds the coordinates of the values obtained from the set of values. Here Ir12 and Ir34 are the set of relational values that are obtained by getting the rchannel , gchannel , b channel components . Here Ir is a 3d coordinate plane containing R, G, B values correspondingly.

A pixel is classified to fire class if all the Rules 1-5 is satisfied by that pixel. The process of segmentation can be easily understood with the help of figure 4 which explains step by step manner. As can be seen from figure 4 each rule alonge will produce false alarm, but their overall combination produces the result in finding out the fire region in the corresponding image. Figure 4 shows the experimental results for different input images.

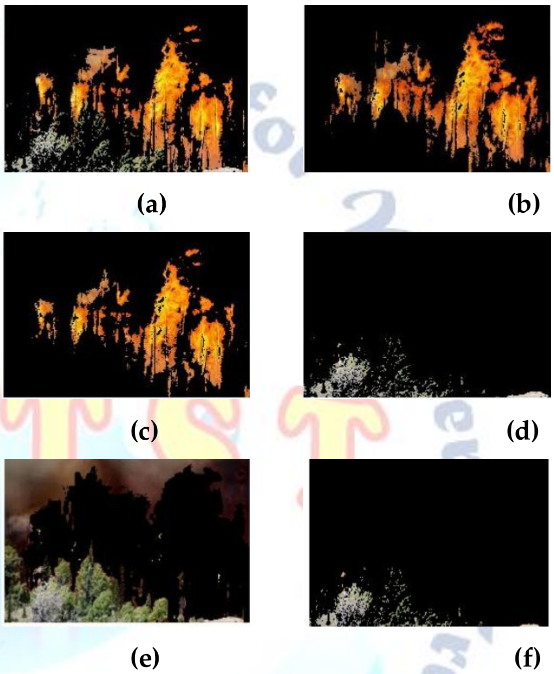


Fig 4 : Applying a different set of rules 1-5 which have stated above for the input image 2.

(a) Fire Segmen using only rule 1 .
(b) Fire Segmen using only rule 2 .
(c) Fire Segmen using only rule 1 & rule-2
(d) Fire Segmen using only rule 3
(e) Fire Segmen using only rule 4 .
(f) Fire Segmen using only rule 3 & rule -4

PERFORMANCE EVALUATION :

To evaluate the proposed method, comparison between some of the above-mentioned methods and the proposed one was carried out. All of these methods were tested in data sets consisting of 100 images, with diversity in fire-color and environmental illuminations. The other doesn’t contain any fire, but contains fire-colored regions such as sun, flowers, reddish objects, etc.

The following condition is used for declaring a fire region: if the model achieves to detect at least 10 pixels as fire, then it is assumed that the image has a fire region in it. For false alarm rate the same criterion is used with the non fire image set.

Experimental Results:

Classification error matrix is the relationship between known reference data and the corresponding classified result. In this matrix the diagonal elements represent the correctly classified result and non-diagonal elements give the number of misclassified results

Table I Classification Error Matrix for the Proposed Classifier..

Fire	No Fire
198(A)	28(B)
12(C)	172(D)
210 (C1)	210(C2)

(a) (b)

Fig 5 : Experimental Results :

(a) Input Images

(b) Corresponding Output Images.

FUTURE SCOPE AND CONCLUSION

In this research work a rule based color model for forest fire pixel classification is proposed. The proposed color model makes use of RGB color space and YCbCr color space. From this a set of seven rules were defined for the pixels to be classified as fire pixels.

The performance of the proposed algorithm is tested on two sets of images; one containing fire and the other with no- fire images. The proposed model achieves 85% flame detection rate and 14% false alarm rate.

The arithmetic operations of this model are linear with the image size. Also, the algorithm is cheap in computational complexity. This makes it suitable to use in real time forest fire monitoring systems.

The proposed system can be realized in future and can evaluate the performance of the system in a real time forest fire monitoring system.

Also, instead of using camera images if we go for videos, then we can calculate the spread of fire with time. Further, the flicker nature of fire can be utilized so as to reduce false alarm rate

REFERENCES

1. J.R. Gonzalez, M.Palahi, A.Trasobares, T. Pukkala, "A fire probability model for forest stands in Catalonia (north-east Spain)," Annals of Forest Science, pp.169-176, 2006.
2. E.Kuhrt, J.Knollenberg, V.Mertens. "An Automatic Early Warning System for Forest Fires". Annals of Burns and Fire Disasters, vol. XIV, pp.151-154, 2001.
3. L. Yu, N. Wang, X. Meng, "Real-time Forest Fire Detection with Wireless Sensor Networks", Proceedings of International Conference on Wireless Communication, Networking and Mobile Computing, vol.2, pp.1214-1217,2005.
4. Z. Li, S. Nadon, J. Cihlar, "Satellite detection of Canadian boreal forest fires: development and application of the algorithm," International Journal of Remote Sensing, vol. 21, no. 16, pp. 3057- 3069, 2000
5. T. J. Lynham, C. W. Dull, and A. Singh, "Requirements for space based observations in fire management: a report by the Wildland Fire Hazard Team, Committee on Earth Observation Satellites (CEOS) Disaster Management

Support Group (DMSG)," IEEE International Geoscience and Remote Sensing Symposium, vol. 2, pp. 762-764, June 2002.

6. W.Krull, I.Wıllms, R.R.Zakrzewskı, M.Sadok, J.Shırer, B.Zelıff, "Design and test methods for a video-based cargo fire verification system for commercial aircraft", Fire Saf. J. 41(4), pp. 290–300, 2006.