An Effective Approach For Forest Fire Detection In Surveillance Video Using Rule-Based And Temporal Variations

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Abstract: Wild fires are actual risk to individual life, eco-friendly system as well as in infrastructure. There are many economical fire recognition sensor tools available, although all are different in their response time delay, require higher maintenance, high expenditure and additional problems to be applied in large open areas such as forests. In this paper, we propose forest fire detection along with the following phases. Initially, convert the video into frames. Secondly, these segmented moving regions (RGB) were converted into YCbCr color space and then seven fire finding rules were applied to separate candidate fire pixels. At last, temporal variation (motion detection) is used to distinguish among fire and fire like color objects. Nine internet video data sets are used in proposed method. Final result shows that up to 99 percent of true detection rates are achieved by the proposed method. Our result shows that the designed approach is more precise and also use in automated 'forest-fire-alarm' systems.

Keywords: Video based Fire Detection; color segmentation; image processing; False Alarm; Temporal variation; Rule based system; Computer vision

I. INTRODUCTION

Forest fire finding systems are taking more attention due to the continuing fire risk to cost-effective properties as well as community safety [1]. Every year, wildfires destroy hundreds of millions of areas [2] and over two lakhs forest fire incidents happen every year. A total approximate area of 3.5 - 4.5 million km^2 is destroyed by forest fires [3]. Increased forest fires have resulted in increased motivation to develop an early fire warning systems to detect wildfires [1]. Sensor tools were widely used in detecting fire basically depends on sensing physical features like pressure change, humidness and temperature change as well as in terms of chemical features like CO_2, CO and NO_2. Though, it is very difficult to apply this type of system in an uncovered area due to multiple reasons like huge expenditure, energy used in the sensors, the proximity of the sensor to recognize fire due to not accurate sensing as physical damage to the sensors [4]. Besides this, sensors have a heavy false alarming rate and their response time is also quite big [5]. There are various motivational factors for using a fire identification system depends on image processing. Firstly, rapid growth in digital camera technology, resulting in a rapid enhance in picture quality and a reduction in cameras' costs. Secondly, digital cameras can cover up large regions with outstanding outcomes. Third one, image processing models' response time is better as compared to present sensor. Lastly, the whole expenditure of image processing system is low as compared with present systems.

A. Related Studies

De Zhang et al., (2016) [6] proposed a new way to recognize the fire using single camera. Flames are processed by using 2 features, one is by using pixel color detection and other one is by using shape identification with respect to time. After this it uses the hidden markov model to differentiate flame flicker from the objects which have same color as the flame. This method uses 6 videos and gives total 97% correct result for fire detection. Enis Cetin et al., (2013) [7] provides video handling systems for identification and investigation of uncontrolled fire. We know that human can detect fire easily even from long distance but machine cannot understand it. Traditional point sensors have transport delay whereas VFD reduces the recognition time in both inside and outside on the grounds because cameras can screen "volumes". It is feasible to cover a zone of 100 km^2 with the help of a single tilt-zoom camera set on top of a peak for wildfire detection. A further advantage of the VFD association is; it provides significant information about the size and direction of smoke circulation. This system is used in high risk areas and in risky buildings. Despite not being fully automated systems, they are precious utensils for security point of view. The operator can check whether it is an actual fire or just a fire like image (false alarm) whenever the VFD system produces an alarm. T Wirayuda et al., (2013) [8] focused is on detecting fire based on the intensity of fire. For this, chromatic rule and color look up tables are used with histogram analysis i.e. value of pixel distribution. Histogram reduces the number of false fire which is used as input in temporal phase. First use color detection method then create Blob and after this apply histogram analysis using some rules. If fire is detected then apply temporal analysis. P. Patel et al., (2012) [9] proposed an approach which combine color, motion, and area for detecting fire. Firstly, it determines the fire on the bases of color, then finds whether the pixels are movable or not. If pixels are changing then find the area of pixels in a frame. This method converts the RGB to YCbCr so that it can recognize luminance and chrominance information separately and then apply some set of rules. After this motion can be detected by using frame differencing approach and remove noise with the help of Gaussian filter. At last find fire pixel region. T Tung et al., (2011) [10] follow four steps to detect smoke. In the first step it uses median method to separate moving areas from the video frame. Then use fuzzy c-means to cluster smoke area from other moving areas. Apply spatial-temporal approach to characterize the properties of smoke like surface roughness, motion vector and area of a smoke. At last, the outdoors from space-time is used as input for SVM to generate alarm if smoke was detected. This paper increases the accuracy of smoke detection on outdoor as well as indoor data set. This algorithm shows 89.5% average detection rate. Seong G. Kong et al., (2016) [11] proposed a method that analyze fire flames using logistic regression along with time based method. Using temporal modal it will reduce false alarm and maintain the accuracy to detect fire flame. This paper is used in both indoor and outdoor situations. The time require to detect fire is average. The logistic regression uses the features of fire like size, motion and color information to recognize fire region. Then apply temporal modal to reduce false alarm. This algorithm shows 98.2% average detection rate. S Rinsurongkawong et al., (2012) [12] proposed chromatic as well as dynamic features that represent real flame. Lucas-Kanade optical flow and growth rate are used to detect motion features which helps in differencing the object with same color and which are not fires. LKOF is used to track features in an image and helps in finding the distance of each moving pixel in different frame. It is based on brightness constancy, spatial coherence, and flow rate analysis. Some technique results in high false rate because when there are moving objects then it's not possible to detect fire. This limitation is avoided by using this approach. This algorithm shows 96.8% average detection rate. Thou-Ho et al. [13] proposed a method which is computationally simple but when there is moving fire like objects, it will generate false positive alarms. Its average detection rate is 87.75. Similarly Dios et al. [2] detect forest fire using optical modal but it require infrared cameras and sensors which are expensive. Yinglian et al. [14] proposed a method for fire prevention which depends on color of fire and smoke. As the smoke spreads, it increases false alarm rate due to the variation in color which depends on burning material. In this paper, we proposed an effective forest fire detection algo. YCbCr helps in spliting luminance from chrominance, also helps in identifying high temperature fire pixel. Our results point out that the proposed system is good in detecting fire as compared to [13], [14], [15]. Section 2 describes the intended approach; section 3 characterizing fire as surveillance object; section 4 summarizes the work and shows results.

II. PROPOSED APPROACH

Fire has several characteristics: color, movement, and region. The main objective is focusing on an object's movement in a sequence of frames. This system helps in decreasing false positives as we consider all the properties simultaneously. The algorithm suits for high intensity of visual color image of fire for the red portion of the RGB coordinates. The feature permits threshold norm for partitioning fire images in regular situations on the basis of red component of the color images. The ratio among the red component along with the blue and green component represent another characteristic to identify fire. Color detection system loads an image; apply the specific features of RGB pixels and generate result showing detected color region. Due to its simplicity and efficacy, predicated color methodologies were adopted and opted for this RGB and YCbCr. We used seven standards for detecting pixel as fire, and if these all seven rules were followed, mention this as a fire class pixel.

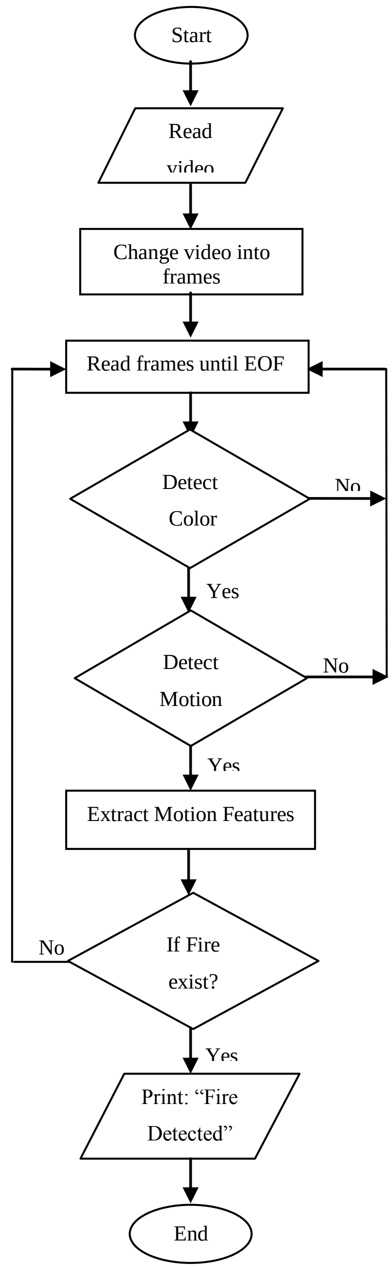


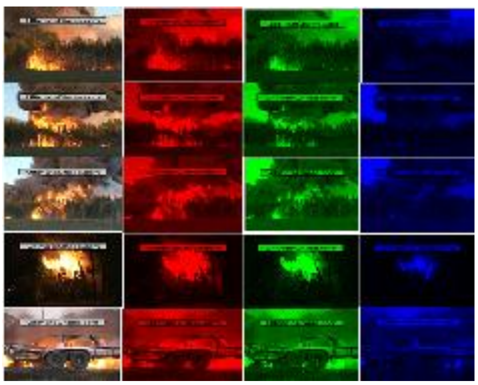
Figure 1: Proposed Approach for Detecting Fire

A. Color Based Detection

The details of the proposed fire pixel relegation algorithm are covered in this section. Figure 2 shows the projected algorithm flow. Due to its simplicity and efficacy, rule predicated color model and color space RGB and YCbCr be chosen. We identify seven rules for categorization of a pixel as fire. And if these 7 rules are satisfied for a pixel, then we can say, pixel belongs to fire group. There are three panels for colored image; these are red, green and blue (RGB), the mixture of these panels makes it possible to characterize a color in digital environment. Every color panel is quantified into distinct levels. Generally, for each plane, 256 quantization levels are used (8 bits/color plane), where white is [R, G, B] = [255, 255, 255] & black is [R, G, B] = [0, 0, 0]. Colored image contain pixels where each pixel describes spatial area with respect to rectangular grid (x, y) and a color vector (R(x, y), G(x, y), B(x, y)) related to the spatial area(x, y).

R1:

Red channel has high intensity value as compared with the green channel, in the same way the green channel has more intensity value than the blue channel as given below in Figure 2:



(A) (B) (C) (D)

Figure 2: Fire images- (A) RGB (B) Red channel (C) Green channel (D) Blue channel

Intensity (*Red*) > Intensity (*Green*) > Intensity (*Blue*)

Next we find out mean of channels *red*, *green*, and *blue* (Mean_R, Mean_G, Mean_B) in the actual images' segmented fire region. To recognize a fire at position $(\mathcal{X}_i, \mathcal{Y}_i)$ use:

$$\text{Rule1} = \begin{cases} 1, & R(\mathcal{X}_i, \mathcal{Y}_i) > G(\mathcal{X}_i, \mathcal{Y}_i) > B(\mathcal{X}_i, \mathcal{Y}_i) \\ 0, & otherwise \end{cases} \quad (1)$$

Table I: RGB image with Mean for figure 2

Y Mean	Cb Mean	Cr Mean
93.375	131.237	140.006
91.405	131.908	138.202
100.055	137.092	133.942
56.143	127.167	136.374
106.164	137.679	140.159

R2:

In order to classify the pixel as fire or not, we must apply threshold value after applying rule 1. This applies to RGB channels and helps to determine the fire's maximum and minimum value. On this basis, we are using:

Rule2

$$= \begin{cases} 1, & (R(\mathcal{X}_i, \mathcal{Y}_i) > 190) \;\&\&\; (G(\mathcal{X}_i, \mathcal{Y}_i) > 100) \;\&\& \\ & (B(\mathcal{X}_i, \mathcal{Y}_i) < 180) \\ 0, & otherwise \end{cases} \quad (2)$$

When we convert RGB into YCrCb, intensity and chrominance are easily distinguished. YCrCb helps in identifying the fire regions.

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} R \\ G \\ B \end{bmatrix} \begin{bmatrix} 0.41 & 0.36 & 0.18 \\ 0.21 & -0.72 & 0.07 \\ 0.02 & -0.12 & -0.95 \end{bmatrix} \quad (3)$$

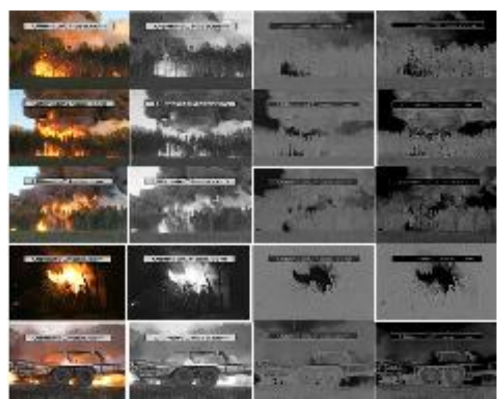
where Y is luminance, Cb and Cr are blue and red chrominance and RGB are red, green, blue respectively.

The mean value of Y, Cb, Cr is represented by Y_{mean}, Cb_{mean}, Cr_{mean} respectively and calculated as:

$$Y_{mean} = \frac{1}{N} \cdot \sum_{i=1}^{N} Y(X_i, Y_i) \quad (4)$$

$$Cb_{mean} = \frac{1}{N} \cdot \sum_{i=1}^{N} Cb(X_i, Y_i) \quad (5)$$

$$Cr_{mean} = \frac{1}{N} \cdot \sum_{i=1}^{N} Cr(X_i, Y_i) \quad (6)$$



(A) (B) (C) (D)

Figure 3: Fire images- (A) YCbCr (B) Y channel (C) Cb channel (D) Cr channel

Table II: YCbCr image with Mean for figure 3

Mean_R	Mean_G	Mean_B
109.169	85.405	63.974
104.005	84.027	64.568
107.291	95.764	84.108
59.790	43.719	26.913
124.36	98.586	87.341

R3 and R4:
Rules 3 and 4 are used to detect fire pixels on spatial axis $X_i, \mathcal{Y}_i$

$$\text{Rule3}(X_i, \mathcal{Y}_i) = \begin{cases} 1, & if\ Y(\mathcal{X}_i, \mathcal{Y}_i) \geq Cb\ (\mathcal{X}_i, \mathcal{Y}_i) \\ 0, & otherwise \end{cases} \tag{7}$$

$$\text{Rule4}(X_i, \mathcal{Y}_i) = \begin{cases} 1, & if\ Cr(\mathcal{X}_i, \mathcal{Y}_i) \geq Cb(\mathcal{X}_i, \mathcal{Y}_i) \\ 0, & otherwise \end{cases} \tag{8}$$

R5:
It has been observed that the value of Y component for the flame is high than the mean of Y component for the entire image, whereas the value of Cb is low as compared with mean value of Cb, and Cr value is higher when compared with the mean value of Cr component. So, flame region is one of the brightest regions with mean value of three panels Y_m, Cb_m and Cr_m having valid information. If a fire pixel exists, Rule5 becomes true.

$$\text{Rule5}(X_i, \mathcal{Y}_i) = \begin{cases} 1, & if\big(Y(\mathcal{X}_i, \mathcal{Y}_i) \geq Y_m(\mathcal{X}_i, \mathcal{Y}_i)\big)\ AND\ \big(Cb \leq Cb_m(\mathcal{X}_i, \mathcal{Y}_i)\big)\ AND \\ & \quad (Cr(\mathcal{X}_i, \mathcal{Y}_i) \geq Cr_m(\mathcal{X}_i, \mathcal{Y}_i)) \\ 0, & otherwise \end{cases} \tag{9}$$

R6:
We observed that the component Cb and Cr of the fire pixels are different. For any fire pixel, the Cb component is of 'low intensity' (black) and Cr component is of 'higher intensity' (white) as shown in equation 10:

$$\text{Rule6}(X_i, \mathcal{Y}_i) = \begin{cases} 1, & if\big(Cb(\mathcal{X}_i, \mathcal{Y}_i)\big) - \big(Cr(\mathcal{X}_i, \mathcal{Y}_i)\big) \geq \tau) \\ 0, & otherwise \end{cases} \tag{10}$$

Where τ is the range from 1 to 100 (more than 100 color images), achieved by the ROC curve (receiver operating characteristics).

Primarily, for each color frame, the fire pixel region is partitioned manually, then applied rule 1 to rule 5. The TP indicates that the frame contains a fire, while FP (false alarm) indicates that the frame contains "no fire" but classified as having fire. With the help of different threshold values, correct detection (True Positive) and false alarm rates (false positive) are computed as well as recorded. Correct identification is the one when the results matches with an actual image of fire, whereas false alarm is defined as an incorrect result when a img does not have fire but by mistake treated as having fire. Thus by picking the exact threshold τ, we get more relevant responses (TP).

R7
Some threshold values are considered for Cb-Cr, and don't consider the Y panel because of its luminance feature and also depend on the illumination (brightening) condition. The fire pixel detection at location $(X_i, \mathcal{Y}_i)$ is given by equation 11 following large number of datasets.

$$\text{Rule7}(X_i, \mathcal{Y}_i) = \begin{cases} 1, & if(Cb(X_i, \mathcal{Y}_i) \leq 120)\ AND\ (Cr(X_i, \mathcal{Y}_i) \geq 150) \\ 0, & otherwise \end{cases} \tag{11}$$

If all 1 to 7 rules are fulfilled, the pixel will be treated as fire, else not.

B. Motion Based Detection / Temporal Variation

Temporal detection is used among two back-to-back frames within a video to identify fire movement. One of the features of fire is that it is continuously changing; red-green color fluctuates very often. With the help of color detection, we obtain the fire pixel region, and then compare RGB value among consecutive frames (frame i-1 and frame i). If pixel values differ, it will display movement along with a message 'fire detected'.

III. CHARACTERIZING FIRE AS SURVEILLANCE OBJECT

One of the difficulties in tracking fire object is to select a suitable model which recognize and track the target object in a video. We all know that the boundaries of fire region are irregular in an image as compared with people or some regular object (having smooth boundaries). Our approach helps in detecting fire as surveillance object with the help of color-motion-flame movements. To identify flame color, predefined color values are compared with the color value of moving pixels. The output from color based detection is taken as input for motion detection which detects real fire situations. Our aim is to assess the performance in terms of sensitivity as well as in terms of specificity. The overall performance is increased with small effort. It can be integrated with surveillance system to monitor an indoor as well as outdoor region for early detection of fire. The fire thus detected can be a prominent surveillance object. Spatio-temporal relationship of fire object with other objects can play a key role in identifying the abnormal events in the scene.

IV. EXPERIMENTAL RESULTS

We are using multiple video which contain fires and our aim is to detect fire in those videos. The result shows the comparison between multiple image frames of multiple videos. This method is used for detecting fire in real time environment. We use it, for early detection of fire both in indoor as well as outdoor in surveillance system. We use two types of image sets with the dataset of UltimateChase.com. One set contain the images of fire and the other one contain the mixture of fire and non fire images. We tested our method on the 9 video clip containing total 3681 frames with image size 400 * 256 pixels. Our proposed approach gives better performance i.e. 99% accurate result. This corresponds to a fire detection rate of 1.0, where our method detection rate is 0.998 and false detection rate is little bit i.e. 0.0001 as shown in Table 4. Table 5 and figure 5 shows the comparison and performance results.

Video Clip	Filename	Frames	Resolution	Time duration (s)	Size	Database
VC1	Boat_Fire_Stream.wmv	715	400*256	51	2.35MB	UltimateChase.com
VC2	Burning_Vehicles_Stream.wmv	605	400*256	40	1.94 MB	UltimateChase.com
VC3	Controlled_Burn_Stream.wmv	539	400*256	36	1.59 MB	UltimateChase.com
VC4	Forest1.avi	199	400*256	13	598 KB	UltimateChase.com
VC5	Forest2avi	244	400*256	16	822 KB	UltimateChase.com
VC6	Forest4.avi	218	400*256	14	662 KB	UltimateChase.com
VC7	Oil_Refinery_Stream.wmv	589	400*256	39	1.85 MB	UltimateChase.com
VC8	Sparking_Wire_Stream.wmv	572	400*256	38	1.70 MB	UltimateChase.com

Table III: Test dataset description for Fire

Figure 4: Original and Fire detected images

We can measure the performance by:

1) Accuracy: Accuracy is the degree of nearness of a quantity's measurements to the actual (true) value of that quantity.

$$\text{Acc} = \frac{True\ Positive + True\ Negative}{Total\ number\ of\ frames} \quad (12)$$

2) Precision: In the field of information retrieval, the fraction of retrieved information relevant to the finding is precision:

$$\text{Prec} = \frac{True\ Postive}{(True\ Positive + False\ Positive)} \quad (13)$$

Precision takes into account all the documents that have been retrieved, but it can also be assessed at a given cut-off rank, taking into account only the top most of the system's results.

3) Recall: Recall in the retrieval of information is the fraction of documents that are suitable for the query that is retrieved successfully.

$$\text{Recall} = \frac{True\ Positive}{(True\ Positive + False\ Negative)} \quad (14)$$

For example, for searching for fire detection on a set of frames, recall is the number of correct fire detected divided by the number of returned results.

Where TP is true positive, region detected as fire is true fire, FP is false positive, region detected as fire is not fire, TN is true negative, region has no fire and has not been detected, FN is false negative, regions with fire but not detected.

Table IV: Performance comparisons with respect to detection rate and false rate

Videos Clips	VC1	VC2	VC3	VC4	VC5	VC6	VC7	VC8	Overall
Total Fire Frames	588	306	428	199	244	218	388	462	2833
Total Non Fire Frame	127	299	111	-	-	-	201	110	848
TP	600	306	428	199	244	218	386	462	2843
FN	05	-	-	-	-	-	02	-	07
FP	17	-	-	-	-	-	-	-	17
TN	93	299	111	-	-	-	201	110	814
TPR	.992	1	1	1	1	1	.995	1	.998
TNR	.85	1	1	-	-	-	1	1	.97
Accuracy	.97	1	1	1	1	1	.99	1	.995
Precision	.972	1	1	1	1	1	1	1	.997
Recall	.992	1	1	1	1	1	.995	1	.998

Table V: Comparison of methods with respect to recall, precision and F-score

Method	**Recall (%)**	**Precision (%)**	**F-score (%)**
Thou-Ho et. al. [13]	88.4	87.1	87.75
Yinglian et al. [14]	86.1	89	87.53
Mubarak A. I. et. al. [15]	93.13	92.59	92.86
Proposed method	99.8	99.7	99.75

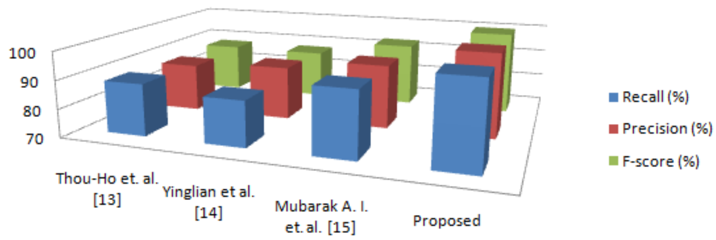


Figure 5: Performance evaluation of four methods

V. CONCLUSIONS

This approach proposed an effective method of forest fire detection that uses YCbCr color space to separate luminance from chrominance and has a good rate of detection. To detect the fire, seven rules for fire detection are applied. In this paper, the performance is measured on the dataset of 9 videos which are available on http://www.ultimatechase.com. The results show that the proposed method is more accurate and feasible in fully automatic fire-alarm systems in the forest. In future the system can be enhanced by means of combining the set of rules of different color spaces. Still, the challenge is to choose accurate rule based system from different color spaces to make the method more helpful.

REFERENCES

[1] B. Ko and S. Kwak, "Survey of computer vision based natural disaster warning systems", Optical Engineering, vol. 51, no. 7, 2012.

[2] J. R. Martinez-de Dios, B. C. Arrue, A. Ollero, L. Merino, and F. Gomez-Rodriguez, "Computer vision techniques for forest fire perception", Image and Vision Computing, vol. 26, no. 4, pp. 550-562, 2008.

[3] Y. Meng, Y. Deng, and P. Shi, "Mapping Forest Wildfire 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.

[4] P. M. Hanamaraddi, "A Literature Study on Image Processing for Forest Fire Detection", IJITR, vol. 4, pp. 2695-2700, 2016.

[5] P. Podrzaj and H. Hashimoto, "Intelligent space as a framework for fire detection and evacuation", Fire Technology, vol. 44, no. 1, pp. 65-76, 2008.

[6] De Zhang, Yahui Wang, "Real-Time Fire Detection Using Video Sequence Data", IEEE conference on 28th Chinese Control and Decision, 2016.

[7] Enis Cetin, Kosmas Dimitropoulos, Benedict Gouverneur, Nikos Grammalidis, Osman Günay, Y. Hakan Habiboglu, B. Ugur Toreyin d, Steven Verstockt e "Video fire detection – Review" 23 (2013) pp 1827–1843.

[8] T Wirayuda, F Sthevanie, "Fire Color Detection using Color Look Up and Histogram Analysis", International Conference of Information and Communication Technology IEEE, 2013.

[9] P. Patel, S Tiwari, "Flame Detection using Image Processing Techniques", International Journal of Computer Applications, Vol 58 – No. 18, Nov 2012.

[10] T Tung, J Kim, "An effective four-stage smoke-detection algorithm using video images for early fire-alarm systems", Fire Safety Journal ScienceDirect 46, 276-282, 2011.

[11] Seong G. Kong, D Jin, "Fast fire flame detection in surveillance video using logistic regression and temporal smoothing", Fire Safety Journal ScienceDirect 79, 37-43, 2016.

[12] S Rinsurongkawong, M Ekpanyapong, "Fire Detection for Early Fire Alarm Based on Optical Flow Video Processing", IEEE, 2012.

[13] C. Thou-Ho, W. Ping-Hsueh, and C. Yung-Chuen, "An early fire-detection method based on image processing", in proceedings of the 2004 International Conference on Image Processing, ICIP 04, vol. 3, pp. 1707-1710, 2004.

[14] Y. Wang and J. Ye, "Research on the algorithm of prevention forest fire disaster in the Poyang Lake Ecological Economic Zone", Advanced Materials Research, pp. 5257-5260, 2012.

[15] M. A. I. Mahmoud and H. Ren, "Forest fire detection using a rule based image processing", Mathematical Problems in Engineering, 2018. https://doi.org/10.1155/2018/7612487