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Efficient Fire Pixel Segmentation Using Color Models in Still Images

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Abstract— Forest Fire causes more disasters to the environment. Detecting the fire in the early stage will play a crucial role to prevent the risky effects. The vision-based approaches have gained more impact than the conventional fire detection methods with respect to accuracy and less false alarms. A reliable and efficient computer vision based technique to retrieve fire-colored pixels in still images is proposed in this article. It adopts both RGB and L*a*b* space for segmenting the fire-colored pixels on colour feature. The proposed results are compared with the current methods. The results of proposed method bring satisfactory results than the existing techniques.

Keywords—Object detection, Color Spaces, Thresholding, Segmentation

I. INTRODUCTION

Fire and flames causes economic losses and severe damages to human lives. In addition, it modifies the forest's structure, atmosphere and environment. Forest fire shows evidence of the irregular, brutal, severe movement and the dynamic changes in the texture of the fire region. The characteristics and intensity of forest fire would be wild and different from other fires like building fire, vehicle fire etc. [1]. It is expected that the detection method, alarms about the fire in the early stage to get recovery rapidly. Conventional detection systems were more expensive with low efficiency. These conventional fire detector systems make use of smoke, temperature, photosensitive characteristic to detect the fire, which is complicated to use in large places, tough environment or outdoor surroundings. Due to rapid developments in digital image processing technology, broad range of computer vision based approaches methods are come into existence to overcome the problems with conventional systems [2].

Numerous methods are available in the literature for fire detection in the video sequences. But sufficient methods are not available for still images. Detecting forest fire on mobile platforms will become difficult at the absence of motion information [3]. The Mobile platforms systems face the challenges when there is rapid change in illumination and visibility of fire become extinct within a short period of time. So still images would help in these situations. Forest fire recognition in still images is a risky task when shadows, illumination and noise occurs. Usually color plays an important part to identify fire in the image. The initial step in detecting fire is finding fire-colored pixels. Because there is a sort of existing fire like pixels with the same color can also be erroneously interpreted as fire, eg. Sun, Red Objects, Orange etc. So discrimination between fire and non fire pixels is a rigid task. This proposed method utilizes both RGB color space and CIE LAB color space to acheive better results.

Since RGB color space has high correlation between red, green and blue colors, it cannot overcome the problems when there exists high illumination and noise. There is a requirement to employ the other color spaces for better separation between colors to identify the fire. Since fire has more illumination, CIELAB space would play better role in discrimation between pixels.

LAB color space describes all the colors which are visible to human and it is a device independent space. By regulating the values of a and b component, or by using L component to adjust the lightness contrast, precise color balance corrections can be achieved. This characteristics motivates to use the LAB space to acquire the better results in fire detection [12] [18].

Existing methods commonly use color, shape, and motion to detect fire [12] [13]. Since the unavailability of motion details in mobile platforms, more specifically this paper considers only the still images with color feature. Color feature extraction methods are computationally less expensive [4]. Color makes simpler the object detection and extraction from a scene.

Normally the fire in the image can be represented by its visual properties. In general fire color is nearly in red and its illumination will be high, so the range of fire color can be defined as an interval of color values between red and yellow [9].

This property can be used to define measures to detect fire existence in the image. Each technique has its own pros and cons. But still there is a scope for improving the efficiency of fire detector and to lessen the false alarms.

This paper is structured as Section II briefs the existing approaches in the literature; Section III overviews about RGB and LAB color spaces; Section IV presents the color modelling to detect the fire-like colored pixels. ; Section V discusses the experimental results.

II. RELATED WORK

Chen et al proposed a rule based fire detection method [14] with the combined approach of the RGB and the HSI color models. Toreyin and others [3] proposed a method with a mixture of Gaussian models in RGB space to find the fire pixels. Daniel Y. T. Chino et al. [4] proposed method on still images for fire detection on color and texture features.

Arjun Santhosh E et al. [1] detected moving pixels of fire by optical flow estimation method by using CIE L*a*b* space. Turgay celik [16] a developed a technique to identify fire pixels by using only color with CIE lab space. Hira Lal et al. [6] uses only RGB image for fire detection in still images by creating RGB color matrix without using any temporal information. Kumarguru et al [9] has proposed a method by using RGB color space by finding the growth of the fire and applying color based segmentation.

Celik et al. [12] proposed a technique to make statistical analysis on rg, rb and gb planes with normalized (rgb) values reduce the effects of changing illumination. Here the fire pixels are recognized when it is found on the triangular region of rg, rb and gb planes with normalized (rgb) values reduce the effects of changing illumination. Here the fire pixels are identified when it lies on the triangular region of rg, rb and gb planes.

Phillips and others [17] proposed a refined method for recognizing fires in color video. The motion and color feature information was selected by them. A look-up table would be generated at the early stage. This brings the drawback in segmenting fire pixels in video sequences. Moreover, this approach is not suitable in real-time applications because it is more complicated.

Vipin V [18] proposed a method with combination of RGB and YCbCr color space to partition the fire from the given input image. But this method is not effectual under all circumstances.

Emmy Prema et al [19] suggested a method a to detect fire with static and dynamic features of the flame in YCbCr color space from videos. Dynamic feature played a major advantage to identify the fire pixels.
Pasquale Foggia et al [20] proposed a method to segment fire pixels in video sequences based on color, shape variation and motion analysis.

However existing methods [2] [10] [11] outputs a lot of false alarms due to more illumination and noise. Because the illumination of the fire will be high in range at night and less at day. So, there is a necessity to fine-tune the existing methods to meet the above challenges to detect the fire in terms of accuracy and false alarms in still images.

The major complications encountered by the detection systems are due to the fire color. There is a possibility of existing the other objects in mixture of red, orange, white, yellow. Those pixels will also be captured as fire-like-colored pixels.

This method employs both RGB and CIE L*a*b* color space to retrieve enhanced results. The motive to adopt CIE *L*a*b** color space is since it is perceptually homogeneous color space, i.e. it illustrates all the colours are evident to the human eye and was designed to serve as a device-independent model [12] thus making it possible to represent color information of fire better than other color spaces. The initial step of the proposed approach is detecting fire-like-coloured pixels. Since fire color is in close proximity to red with high illumination, the color feature is used to extract the pixels related to fire. So, then discrimination between actual fire pixels and fire-like pixels can be done.

III. COLOR SPACES

The intention of the color model is to make ease of specification of colours in some standards. There are numerous color models are in use in image processing applications like RGB, HSV, HSI, YUV, YCbCr, CIE L*a*b*[5]. This method utilizes both RGB and CIE L*a*b* color spaces for achieving good results.

A. RGB Colour space

In this space color pixels will be separated into Red, Green and Blue color components. Figure 1 shows the primary colours of RGB space. The fire pixels are close to red and it can be segmented from the image. RGB is device dependent. Usually there will be high correlation between red, green and blue colours. Changes in one color will affect the other one.

This space will not be suitable for fire detection. RGB color model does not detect fire effectively when more illumination and noise is present in the image [18]. The Red, green and blue color values can be expressed as $R_I(x, y)$, $G_i(x, y)$ and $B_i(x, y)$ at spatial location (x, y) respectively.

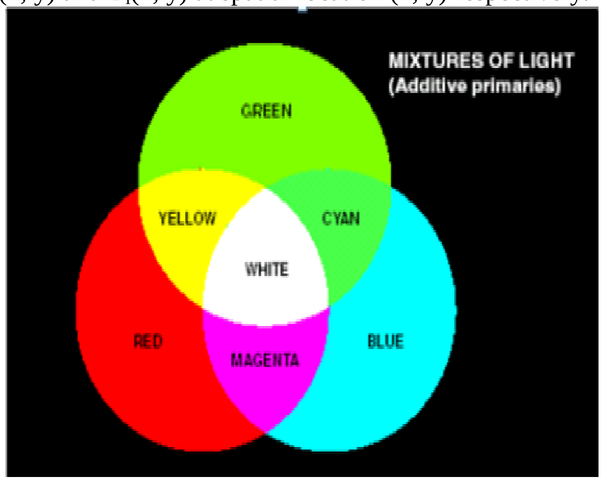

Figure 1 Primary colours of RGB

*B. CIE L*a*b Color Space*

This color space is initially defined by CAE and specified by the International Commission on Illumination. In this colour space, the lightness or Luminance or Brightness *L** represents the darkest black at L* = 0, and the brightest white at *L** = 100. The* and b* color channels, will correspond to neutral gray values when a* = 0 and b* = 0. In the* axis the red color is represented as positive values and green as negative values [16]. Similarly, in b* axis, blue color is at negative side and yellow at positive side as shown in Figure 2. L*, a* and b* values at spatial location can be represented as $L^*_i(x, y)$ $a^*_i(x, y)$, and $b^*_i(x, y)$ respectively. For the meantime, the data ranges of L*, a*, and b* components are [0, 100], [–110, 110], and [–110, 110], respectively. Most important feature of this color space is that this is device independent [5]. The Color Components of CIE LAB color modes is depicted in Table 1.

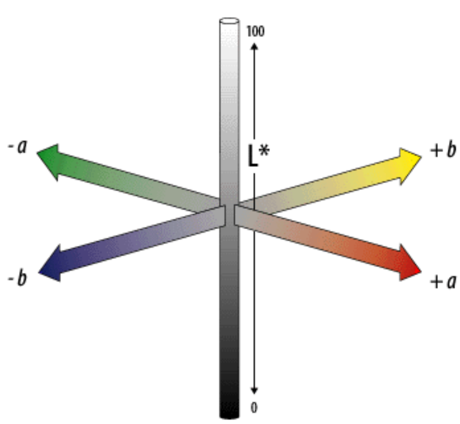

Figure. 2 LAB colour values

Table 1: Colour components of LAB Model

Colon	L	A	B
Black	0	0	0
White	100	0.00526	-0.0104
Red	53.23288	80.10930	67.22006
Green	87.73703	-86.18463	83.18116
Blue	32.30258	79.19666	-107.86368
Cyan	91.11652	-48.07961	-14.13812
Magenta	6.31993	96.25421	-60.84298
Yellow	97.13824	-21.55590	94.48248

IV. COLOR MODELLING FOR FIRE DETECTION

Figure 3 shows the flowchart of proposed system. In this proposed system both RGB and CIE L*a*b* color pigmentation values are used to detect the fire. The subsequent operations are carried out to estimate the fire-like colored pixels.

Firstly, finding the fire color mask using the associations among red, green, and blue components in RGB space by the assumption that fire potentially falling into a red to yellow range with high illumination.

Secondly, estimate new L*a*b* fire membership matrices by thresholding the image with statistical measures of high possibility of being fire.

Thirdly, fire-like-colored pixels are retrieved based on the combinations of new L*a*b*.

Finally, the highly likely strong fire-colored pixels will be derived by combining the results of RGB and L*a*b* space Thus, to define a fire pixel, the proposed color detection algorithm follows the steps*:*

Find Ri(x, y), $G_i(x, y)$, $B_i(x, y)$, $a^*_i(x, y)$, $b^*_i(x, y)$ and $L^*_i(x, y)$ represents the red, green, blue, a*,b* and L* value components at each *x*-row and *y*-column in RGB and LAB color spaces, respectively.

Thus, to define a fire pixel, the proposed color detection algorithm follows the steps*:*

a) Find $R_i(x, y)$, $G_i(x, y)$, $B_i(x, y)$, $a^*_i(x, y)$, $b^*_i(x, y)$ and $L^*_i(x, y)$ represents the red, green, blue, a*,b* and L* value components at each *x*-row and *y*-column in RGB and LAB color spaces, respectively.

b) For Each Position (x,y) in RGB space, perform the subsequent procedure

Create a Fire color Mask $FCM_i(x,y) =$

$$\begin{cases} 1, \text{ if} R_i(x,y) > Th \ \&\&\& \ \& R_i(x,y) > G_i(x,y) \\ \qquad \&\& \ G_i(x,y) > B_i(x,y) \\ 0, \text{ otherwise} \end{cases} \quad (1)$$

Here Th is a global threshold value. In general, red component will be dominating the other colors in RGB space. This does more favour in fire detection since fire is in red color

c) Create a new matrix $N_i(x, y)$ to retrieve only Fire-colored pixels.

$$N_i(x,y) = \begin{cases} N_i(x,y), if FCM_i(x,y) = 1 \\ 0, Otherwise \end{cases}$$

(2)

An interval of colour values between red and yellow classify the fire color in range. To define measures to detect the fire existence in an image we can use the color as feature since fire prone to red and with more illumination.

d) Create Fire Color Matrix considering the pixel values L*, a*, b* which are above to their respective threshold values to keep strong the fire colored region.

$$NewL_i(x,y) = \begin{cases} 1, & L*(x,y) > LTH \\ 0, & otherwise \end{cases}$$

(3)

$$Newa_i(x,y) = \begin{cases} 1, & a*(x,y) > aTH \\ 0, & otherwise \end{cases} \quad (4)$$

$$Newb_i(x,y) = \begin{cases} 1, & b*(x,y) > bTH \\ 0, & otherwise \end{cases} \quad (5)$$

Here LTH, aTH and bTH are threshold values to segment the image based on the statistical measures of color channels L*, a* and b* respectively.

New values of L*, a* and b* are calculated as $NewL_i(x, y)$, $Newa_i(x, y)$, $Newb_i(x, y)$ values. Since L* shows the brightness, a* contains red color at the positive axis and b* contains yellow at positive axis.

The Probability of likelihood pair for fire detection is calculated with all the three combinations p (NewL*, Newa*), p (NewL*, Newb*) and p (Newa*, Newb*).

By the investigational results the chances of color pixels can be detected as fire pixel by using the combinations of the pairs (L*, b*) and (a*, b*) with their new values with thresholding by performing mathematical operations on the pairs.

$$Fire(x, y) = (NewL_i(x, y), Newb_i(x, y), (Newa_i(x, y), Newbi(x, y)) \quad (6)$$

Finally combined results of RGB thresholded image and segmented images of Lab by using Equations (1) (3) (4) (5) and (6) to get the strong fire -colored pixels.

V. EXPERIMENTAL RESULTS

Several existing methods are efficient either at day or smoke. But the projected method is aimed to be efficient for a detecting fire like pixels at day, night and also with smoke. Variety of images with smoke, high illumination are tested on the basis of finding fire colored pixels The Dataset contains the images with the presence of fire coloured pixels and non-fire coloured pixels

The Figure 4 shows the segmented results by using both RGB and CIE L*a*b* space

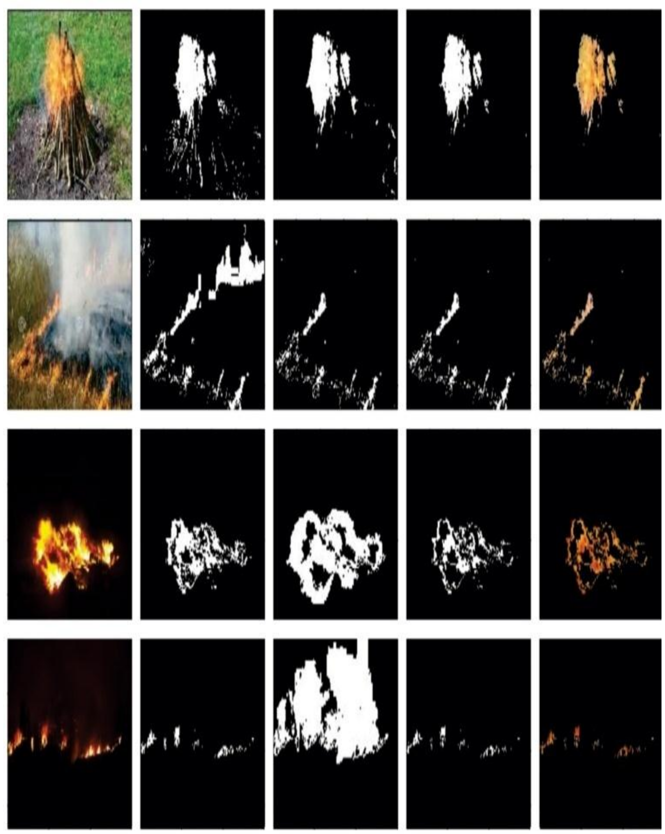

Figure 4 (a) Original RGB image, (b) RGB thresholded image using (3), (c) LAB thresholded image using (3-5), (d) binary image using (6) (e) combining results of (b)(c) and (d) by binary AND operator

VI. PERFORMANCE EVALUATION

Performance of the proposed fire detection system is measured up with the few existing methods. 100 set of images are used for Comparison. Table 2 shows the true positive rates and false positive rates for both proposed and existing methods. True positive rates are defined that number of pixels which are accurately identified as fire color pixels above the total number of pixels .False positive rates are the number of non-fire pixels which are wrongly detected as fire pixels.

True Positive rate (TP) (%)

$$= \frac{No.of.correctly\,\det ected.pixels}{Total.no.of.fire.pixels} ..$$

False Positive rate (FP) (%)

$$= \frac{No.of.incorrectly.\det ected.non.fire - pixels}{Total.no.of.fire.pixels} ..$$

Chen at el [13] defined rules to detect fire color with RGB color space. The Model defined by Celia at el [12] uses normalized rob values to segment the region. Vipin [18] uses RGB and Ycbcr to segment the fire.

Table 2: Performance evaluation of Proposed and Existing method with Original Images

Methods	True Positive rate	False Positive rate
Chen at l[13]	0.92	0.52
Celik at el[12]	0.942	0.50
Vipin V[18]	0.97	0.23
Proposed-RGB and CIE LAB	0.98	0.12

The below graph clearly shows the true positive and false positive rate of all the methods. Proposed method results are more compromising

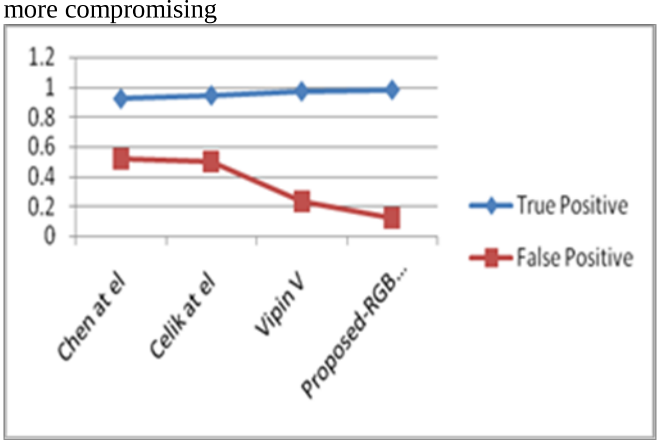

Figure 5.

There is a gradual increase in accuracy of detecting total number of true fire pixels in the proposed method. The non-fire color pixels like apple, orange, yellow rose in the image can be wrongly detected as fire pixels. But the rate of false positives are reduced in the proposed results. The overall of above results shows that the proposed method has higher detection rate with the original image than existing results

VII. CONCLUSIONS

Detecting fire is a hard progress especially when there is more illumination, noise and smoke. Normally smoke prones to high false detections, so detecting and removing smoke at early stages will improve the performance. First step is detecting super pixels of fire. In this Paper a new method is proposed for detecting fire-like coloured pixels in the still images by combining both RGB and CIE L* a* b* color models to improve the efficiency of the detector at high difficulties. The results achieved are better than the existing algorithm. The proposed method will be further enhanced to include texture features to classify from similar non-fire pixels such as sunset and sunrise.

REFERENCES

[1] Arun and Santhosh, "Lab Color Space Model with Optical Flow Estimation for Fire Detection in Videos ", IOSR Journal of Computer Engineering, 2014, pp 23-28.

[2] B.U. Toreyin, Y. Dedeoglu, and A.E. Cetin, “Computer Vision Based Method for Real-Time Fire and Flame Detection”, Pattern Recognition Letters, vol. 27, no. 1, 2006, pp. 49-58.

[3] B.U. Toreyin, Y. Dedeoglu, and A.E. Cetin, “Flame Detection in Video Using Hidden Markov Models”, Proc. IEEE Int. Conf. Image Process. 2005, pp. 1230-1233, 2005.

[4] Daniel Y. T. Chino, Letricia P. S. Avalhais, Jose F. Rodrigues Jr., Agma J. M. Traina BoWFire: Detection of Fire in Still Images by Integrating Pixel Color and Texture Analysis, Proceedings of the 28th SIBGRAPI Conference on Graphics, Patterns and Images, 2015.

[5] Habiboˇglu, Y.H., G¨unay, O., C¸ etin, A.E., “Covariance matrix-based fire and flame detection method in video”, Machine Vision and Applications 23(6), 11031113 (2011).

[6] Hira Lal Gope*1, Machbah Uddin2, Shohag Barman3, Dilshad Islam4, Dr. Mohammad Khairul Islam5, "Fire Detection in Still Image Using Color Model " ,Indonesian Journal of Electrical Engineering and Computer Science Vol. 3, No. 3, September 2016, pp. 618 ~ 625.

[7] J. Zhao, Z. Zhang, S. Han, C. Qu, Z. Yuan, and D. Zhang, “Svm based forest fire detection using static and dynamic features,” Computer Science and Information Systems, vol. 8, no. 3, pp. 821–841, 2011.

[8] J.Liu, W, "Early fire detection in coalmine based on video processing" Advance in Intelligent Systems and Computing, vol.181,, 239-245, 2013.Kumarguru Poobalan1 and Siau-Chuin Liew2, "Fire Detection algorithm using Image Processing Techniques" , Proceeding of the 3rd International Conference on Artificial Intelligence and Computer Science (AICS2015), 12 - 13 October 2015 pp 160-168.

[9] Rossi, L., Akhloufi, M., Tison, Y, " On the use of stereovision to develop a novel instrumentation system to extract geometric fire fronts characteristics", Fire Safety Journal 46, 920 (2011).
[10] Rudz, S., Chetehouna, K., Hafiane, A., Laurent, H., Sero-Guillaume, O., " Investigation of a novel image segmentation method dedicated to forest fire applications" , In: Measurement Science and Technology 24(7), pp.075403 (2013).
[11] T. Celik et al., "Fire Detection Using Statistical Color Model in Video Sequences," J. Visual Commun. Image Representation, vol. 18, no. 2, Apr 2007, pp. 176-185.
[12] T. Celik, H. Demirel, and H. Ozkaramanli, "Automatic Fire Detection in Video Sequences," Proc. European Signal Process. Conf., Florence, Italy, Sept. 2006.
[13] T.-H. Chen, P.-H. Wu, and Y.-C. Chiou, "An early fire-detection method based on image processing," in ICIP, vol. 3, 2004, pp. 1707–1710.
[14] Tom Toulouse, Lucile Rossi, Turgay Celik, Moulay Akhlou, "Automatic fire pixel detection using image processing: A comparative analysis of Rule-based and Machine Learning-based methods", Signal Image and Video Processing, 2015, pp.1863-1703.
[15] Turgay Celik, "Fast and Efficient Method for Fire Detection Using Image Processing ", ETRI Journal, Volume 32, Number 6, December 2010.
[16] W. Phillips III, M. Shah, and N. da Vitoria Lobo, "Flame Recognition in Video," Proc. 5th Workshop Appl. Computer Vision, 2000, pp. 224- 229.
[17] YH Kim, A Kim, HY Jeong, "RGB color model based the fire detection algorithm in video sequences on wireless sensor network ", Int. J. Distrib. Sensor Netw. 2014.
[18] V. Vipin. "Image Processing Based Forest Fire Detection", IJETAE, 2(2012) 87-95.
[19] C. Emmy Prema*,S. S. Vinsley, S. Suresh," Efficient Flame Detection Based on Static and Dynamic Texture Analysis in Forest Fire Detection", Fire Technology Journal , 54, 255–288, 2018
[20] Pasquale Foggia," 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 ·, pp 1-12, January 2015.

