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Fire Detection in Still Image Using Color Model

Hira Lal Gope*[1], Machbah Uddin[2], Shohag Barman[3], Dilshad Islam[4], Dr. Mohammad Khairul Islam[5]
[1]Assistant Professor, Department of CSE, Sylhet Agricultural University, Sylhet-3100, Bangladesh
[2]Lecturer, Department of CSM, Bangladesh Agricultural University, Mymensingh-2202, Bangladesh
[3]Department of CSE, University of Chittagong, Chttagong-4331, Bangladesh
[4]Lecturer, Dept. of PMS, Chittagong Veterinary and Animal Sciences University, Bangladesh
[5]Professor, Department of CSE, University of Chittagong, Chttagong-4331, Bangladesh
*Corresponding author, e-mail: hlgope@sau.ac.bd

Abstract

Fire incidence is one of the major disasters of human society. This paper proposes a still image-based fire detection system. It has many advantages like lower cost, faster response, and large coverage. The existing methods are not able to detect fire region adequately. The proposed method overcome and addresses the issue. A binary contour image of flame that is capable of classifying fire or no fire in image for fire detection is proposed in this study. The color of fire area can range from red yellow to almost white. So, here it is challenges the detected area is actually fire or no fire. Our propose method consists of five parts. Firstly, the digital image is taken from dataset and the digital image is sampled and mapped as a grid of dots or picture elements. We convert image to separate RGB Color range Matrix. We define some rules to select yellow color range of the image later on converted the image to binary range. Finally, binary contour image of flame information that detect the fire. We have analyzed different types of fire images in different varieties and found accuracy 85-90%.

Keywords*: dataset, digital image, binary range and matrix, binary contour image, fire detection*

1. Introduction

Fire is one of the biggest disasters for human begins. It is very challenging for detecting fire, environmental disasters or serious damage to human life. In particular, accidents involving fire and explosion have attracted interest to the development of automatic fire detection systems. Existing solutions are based on ultraviolet and infrared sensors, and usually explore the chemical properties of fire and smoke in particle samplings [1]. However, the main constraint of these solutions is that sensors must be set near to the fire source, which brings complexity and cost of installation and maintenance, especially in large open areas.

Several methods regarding to fire detection on videos have been proposed in the last years. These methods use two steps to detect fire. First, they explore the visual features extracted from the video frames (images); second, they take advantage of the motion and other temporal features of the videos [2]. In the first step, the general approach is to create a mathematical/rule-based model, defining a sub-space on the color space that represents all the fire-colored pixels in the image.

2. Literature Review

There are several empirical models using different color spaces as RGB [1], YCbCr [3], CIE Lab [4] and HSV [5]. In these cases, the limitation is the lack of correspondence of these models to fire properties beyond color. The problem is that high illumination value or reddish-yellowish objects lead to a higher false-positive rate. These false-positives are usually eliminated on the second step through temporal analysis. In contrast to such methods, our proposal is to detect fire in still images, without any further (temporal) information, using only visual features extracted from the images. To overcome the problems aforementioned, we propose a new method to detect fire in still images that is based on the combination of two approaches: pixel-color classification and texture classification. The use of color is a traditional approach to the problem; whilst, the use of texture is promising, because fire traces present

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particular textures that permit to distinguish between actual fire and fire-like regions. We show that, even with just the information present in the images, it is possible to achieve a high accuracy level in such detection.

Fire detectors are one of those amazing inventions that, because of mass production, cost practically nothing. Recently, several methods have been proposed, with the aim to analyze the videos acquired by traditional video surveillance cameras and detect fires or smoke, and the current scientific effort [6, 7] focused on improving the robustness and performance of the proposed approaches, so as to make possible a commercial exploitation. Although a strict classification of the methods is not simple, two main classes can be distinguished, depending on the analyzed features: color based and motion based. The methods using the first kind of features are based on the consideration that a flame, under the assumption that it is generated by common combustibles, such as wood, plastic, paper, or others, can be reliably characterized by its color, so that the evaluation of the color components in RGB (Red, Green, Blue), YUV (Luminance, Chrominance) or any other color space is adequately robust to identify the presence of flames. This simple idea inspires several recent methods: for instance, in [8] and [9], fire pixels are recognized by an advanced background subtraction technique and a statistical RGB color model: a set of images have been used and a region of the color space has been experimentally identified. So that if a pixel belongs to this particular region, then it can be classified as fire.

Generally, current residential fire detection research focuses on upholstered furniture/mattress fires. The fire losses from residential furniture fires may decrease due to the development of new regulations; therefore it is imperative to evaluate the new detection approaches with the next most significant fire losses in residential fires.

The existing method cannot detect fire region properly; however, many other features have to be taken into consideration. In our research, our propose method that can overcome these issues. A novel feature extraction method that is capable of classifying an object as fire or no fire in video frame for fire detection is propose in this study. The color of fire area can range from red yellow to almost white. So, here it is challenges the detected fire is actually fire or not. Irregularity of the boundary of the fire-colored region is taken into consideration and image is converted to gray scale image. Eventually, our approach can identify more relevant concepts for detecting fire by utilizing system especially, the techniques of convert images to binary images.

In our paper we have worked with a sample image in Figure 1.

Figure 1. Sample Input Image to Detect Fire

Our proposed method detects not only the fire but also it can detect the intensity of fire like low fire, medium fire and no fire. When the flame is getting more violent, flame change their shapes more rapidly. Therefore, the variation of flame is needed to measure the intensity of flames. Here, contour information of the binary image is needed.

Since, the contour information of the flame is needed, the corresponding binary image, b(x, y), of a contour image, c(x, y), is defined as follows:

$$b(x,y) = \begin{cases} \text{black}, & \text{if} c(x,y) = \text{black} \\ \text{white}, & \text{otherwise} \end{cases}$$

In the contour image, set the remaining fire color is white and it is called the binary contour image. Now, the difference $d(x,y)$, of two binary contour image, $\mathrm{b_p(x,y)}$ and $\mathrm{b_q(x,y)}$ is as follows:

$$\mathrm{d(x,y)} = \left|\mathrm{b_p(x,y)} - \mathrm{b_q(x,y)}\right|$$

The image $d(x,y)$ is called the difference contour image. After obtaining a contour difference image, it is time to measure the intensity of fire by using the amount of white pixels. White pixels ratio, $\mathrm{r_{white}}$ can be defined as follows:

$$\mathrm{r_{white}} = \frac{\mathrm{n_{white}}}{\mathrm{n}}$$

Where, $\mathrm{n_{white}}$ is the amount of white pixels and n is the total number of pixels in the contour image $\mathrm{d(x,y)}$.

The ratio is higher it means the more intensity of fires. Here, we consider three types of fires such as small fire, medium fire and big fire.
If the ratio is equal to 0 it means no fire is detected in the image.

$$\mathrm{r_{white}} = 0$$
$$\mathrm{Threshold_1} > \mathrm{r_{white}} > 0$$
$$\mathrm{Threshold_2} > \mathrm{r_{white}} > \mathrm{Threshold_1}$$
$$\mathrm{Threshold_2} < \mathrm{r_{white}}$$

Second condition confirms that small fire is recognized. Similarly, third condition tells that the medium fire is detected. And finally, fourth condition is assumed that the big fire is detected. In our research, we exploit the hierarchical structure and their relations together with binary images order to identify and predict more specific concept for fire detection.

This test image shows the area of contour fire pixels.

Figure 2. Detected Fire Area

In our experimental result we see that the accuracy rate is nearly 90%

3. Proposed Method

This section covers the detail of the previously proposed fire detection methods. It is assumed that the image capturing device produces its output in RGB format. During an occurrence of fire, smoke and flame can be seen. With the increasing in fire intensity, smoke and flame will be visible. An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it. So, in order to detect the occurrence of fire, both flame and smoke need to be analyzed. Many researchers used unusual properties of fire such as color, motion, edge, shape. Lai, et al., [10] suggested that features of fire event can be utilized for fire detection in early stages. Han, et al., [11] used color and motion features while Kandil, et al., [12] and Liu, et al., [13] utilized shape and color features to detect an occurrence of fire.

The main aspects of this research are to develop system with good accuracy. The research is ongoing, and some proposals are under consideration as complements to the currently planned approach. Using fire detection basic algorithm we are:

a) At first find out digital image from image dataset

b) After finding digital images then convert these images to RGB (Red, Green, Blue) color range matrix

c) Select yellow color range of photo from RGB color range matrix and convert image to binary range

d) After converting to binary image then count how much set pixel inside the image

e) Take the decision from set count value, fire is present or not.

The proposed fire detection method can be divided into five major parts: (1) Collected Image from video frame.(2) Convert the image to RGB color, (3) Selection of yellow color range of the image, (4) convert image to binary range, and (5) Detect the intensity of fire by contour binary image, as depicted in Figure 3.

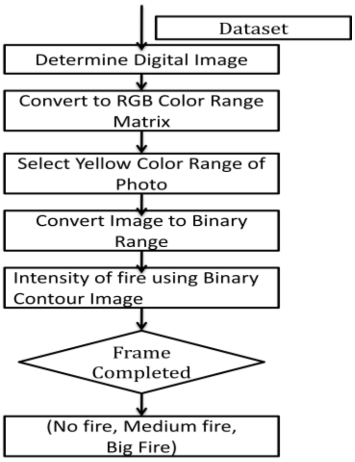


Figure 3. Flow Chart of Proposed Algorithm for Fire Detection in Image Sequences

Table 1. Summary For Fire and No Fire Images

Image Name	Height	Width	Test bit	Ratio	Comments
fire4444	669	1000	75007	0.1121	High Range
fire14	1200	1600	282	0.00014	Actually no fire
fire3	2896	1944	342869	0.0609	High Range
fire	335	423	4209	0.0297	Medium Range
fire10	533	517	154321	0.56	High Range
fire444	211	239	0	0	No fire
fire4	282	425	32091	0.2678	High Range
fire6	2592	3872	22006	0.0022	Low Range
fire805	300	400	11860	0.0988	Medium Range
fire7	823	1291	0	0	No fire

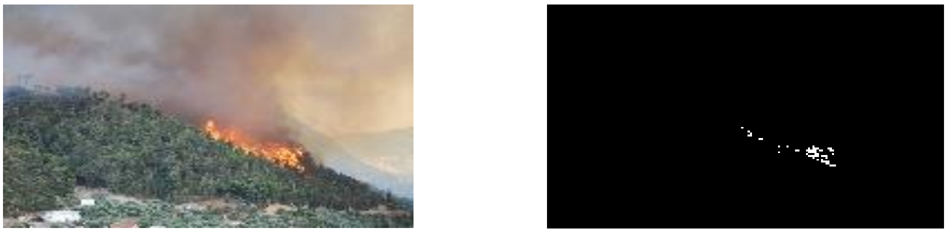
4. Experemental Result and Discussion

We performed experiments using a dataset of fire images. It consists of different images with various resolutions. Also, it was divided in two categories: some images containing fire, and some images without fire. The fire images consist of emergency situations with different fire incidents, as buildings on fire, industrial fire, car accidents, and riots. These images were manually cropped by human experts. The remaining images consist of emergency situations with no visible fire and also images with fire-like regions, such as sunsets, and red or yellow objects.

We have taken two RGB image frames then algorithm is applied on it, and result is shown as in Figure 4(a), Figure 4(b) and Figure 4(c). Sample RGB image frames having fire, it contains sub images of different steps in algorithm: 1st image frame, 2nd image frame having flame, red component of fire pixel according to condition as mentioned above, motion is detected between these two frames, and last sub image shows the fire pixel detected in image.

(a) First Image Shows the Intermediate Result of Processing, and Second Image Shows the Contour Fire Pixels

(b) First Image Shows the Intermediate Result Of Processing, and Second Image Shows the Contour Fire Pixels



Low Range

Medium Range

High Range

(c) These Images Show the Result of Different Ranges
Figure 4. Analytical View for Different Images

5. Results

In our research there are 2 classes of image. At first step we have applied folding method on two classes of images that classes are Fire and No Fire class and we see that our proposed method based fire detection gives a good result. Each of the classes contains 10 images with different verities. The result is in Table 2.

Table 2. Number of Class Accuracy

Class Name	Number of Image	Fire Detected	Not detected
Fire	10	8	2
No Fire	10	3	7

Table 3. Results per Class Success

No. of image	Classes Name	No. of images	Fire Detected	Fire Not Detected	Accuracy
10	Fire	10	8	2	80.00%
10	No Fire	10	1	9	90.0%

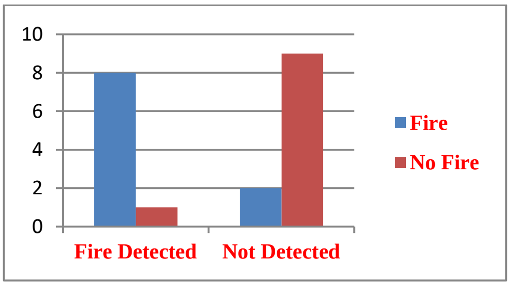


Figure 5. Success and Failure per Class

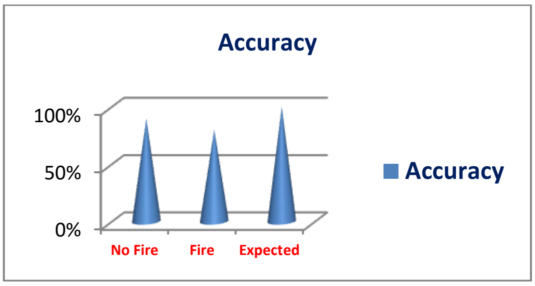


Figure 6. Accuracy Graph of Different Class

Cross-validation, sometimes called rotation estimation, is a technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. One round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the validation set or testing set). To reduce variability, multiple rounds of cross-validation are performed using different partitions, and the validation results are averaged over the rounds.

K-fold cross-validation, the original sample is randomly partitioned into k equal size subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k-1 subsamples are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds then can be averaged (or otherwise combined) to produce a single estimation. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. 10-fold cross-validation is commonly used, but in general k remains an unfixed parameter.

5.1. K-Fold Cross-Validation

In stratified k-fold cross-validation [14, 15], the folds are selected so that the mean response value is approximately equal in all the folds. In the case of a dichotomous classification, this means that each fold contains roughly the same proportions of the two types of class labels.

2 fold-cross validation, this is the simplest variation of k-fold cross-validation. For each fold, we randomly assign data points to two sets d0 and d1, so that both sets are equal size (this is usually implemented as shuffling the data array and then splitting in two). We then train on d0 and test on d1, followed by training on d1 and testing on d0. This has the advantage that our training and test sets are both large, and each data point is used for both training and validation on each fold.

Now 2 folding method applied on ten classes of image, that means 50 percent image of a class are in training set and 50 percent images of that class are on test, that started 2 class, 3 class. The results are given on Table 3. Per class success and failed rate chart in Figure 5.

The next section that describes the accuracy rate of two classes and the expected class in below chart Figure 6.

6. Conclusion

In this paper, image processing based fire detection system using color model was proposed. We have collected a number of sequential frames from original video, which consists of fire and non fire images. The proposed method consists five main stages: - collected Image from video frame, convert the image to RGB color, selection of yellow color range of the image, convert image to binary range, and detect the intensity of fire by contour binary image. The proposed method is applied on video sequences and detected fire is classified into three groups such as small fire, medium fire and large fire based on the threshold values.

7. Future Directions

To accomplish more valuable and more accurate video fire detection, this paper points out future directions. We will improve the result for the step of intensity of fire by contour binary image. Feature extraction method will be included before step five and we will use machine learning algorithms like SVM, and KNN as a classifier to detect the fire more accurately by replacing step five.

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References

[1] TH Chen, PH Wu, YC Chiou. An early fire-detection method based on image processing. *ICIP.* 2004; 3: 1707-1710.
[2] AK Yoon-Ho Kim, HY Jeong. Rgb color model based the fire detection algorithm in video sequences on wireless sensor network. *International Journal of Distributed Sensor Networks*. 2014: 10.
[3] TC Elik, H Demirel. Fire detection in video sequences using a generic color model. *Fire Saf. J.* 2009; 44(2): 147-158.
[4] C Ha, U Hwang, G Jeon, J Cho, J Jeong. *Vision-based fire detection algorithm using optical flow*. CISIS. 2012: 526-530.
[5] J Zhao, Z Zhang, S Han, C Qu, Z Yuan, D Zhang. SVM based forest fire detection using static and dynamic features. *Computer Science and Information Systems*. 2011 8(3): 821-841.
[6] AE Çetin, et al. Video fire detection-Review. *Digit. Signal Process.* 2013; 23(6): 1827-1843.
[7] Z Xiong, RE Caballero, H Wang, AM Finn, PY Peng. Video fire detection—Techniques and applications in the fire industry. In: A. Divakaran. *Editor*. Multimedia Content Analysis (Signals and Communication Technology). New York, NY, USA: Springer-Verlag. 2009: 1-13.
[8] T Celik, H Demirel, H Ozkaramanli, M Uyguroglu. Fire detection using statistical color model in video sequences. *J. Vis. Commun. Image Represent*. 2007; 18(2): 176-185.
[9] 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.
[10] CL Lai, JCY. *Advanced Real Time Fire Detection in Video Surveillance System.* IEEE International Symposium on Circuit and Systems (ISCAS). 2008: 3542-3545.
[11] D Han, Byoungmoo Lee. Flame and Smoke Detection method for early real-time detection of a tunnel fire. *Fire Safety Journal.* 2009; 44: 951-961.

[12] M Kandil, M Salama. *A New Hybrid Algorithm for Fire-Vision Recognition*. IEEE Eurocon. 2009: 1460-1466.
[13] CB Liu, N Ahuja. *Vision based fire detection.* Proceedings of the 17th International Conference on Pattern Recognition (ICPR' 04). 2004; 4: 134-137.
[14] http://www.cs.cmu.edu/~schneide/tut5/node42.html.
[15] Kohavi, Ron. *A study of cross-validation and bootstrap for accuracy estimation and model selection.* Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence. 1995; 2(12): 1137-1143.