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Machine Vision-based Indoor Fire Detection Using Static and Dynamic Features

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Abstract

In this paper, an effective machine vision-based fire detection technique is proposed. In the earliest stage, color segmentation is carried out to separate potential fire areas using the red component of RGB. Moving pixels are identified using the frame differences from a reference frame followed by de-noising. In the next phase of the proposed model, the growth of the segmented regions of the current frame is compared with later frames and based on the fact that a hazard expands with time, regions with no or decreasing growth are removed. The complex boundary of a fire (rotundity) is valuable information that aids in detection. In the last step, a feature vector is created with rotundity information and trained using a neural network. The proposed model is tested using a dataset containing a wide range of indoor lighting conditions and is compared to a state of the art fire detection technique to confirm its effectiveness. The experimental results show that the proposed model performs better compared to the state of the art model in terms of accurate detection and computation time, yielding an average accuracy of 99.1%.

Keywords: *Fire detection, static features, dynamic features, neural network*

1. Introduction

Fire is a calamitous phenomenon that occurs without warning. Fire accidents cause non-compensable damage to human lives and the environment. According to a survey conducted by the World Health Organization, middle income countries are more vulnerable to burn casualties. In Bangladesh, there were more than 10 fire incidents in 2016 alone, which included textile factories, houses, slums and malls. In 2017, two major incidents have already occurred in Dhaka, subsequently ending lives, costing millions, and resulting in severe aftermath. Hence, early detection of a fire is critical and has become a subject of great importance.

Most current fire detection systems use heat and smoke sensors, but they tend to have disadvantages, including having a small area coverage, requiring the fire to be in proximity of the sensors for early detection, and failing to provide additional information such as the location of the occurrence or the size and growth rate of the fire [1]. To overcome the aforementioned drawbacks of conventional systems, a vision-based approach has been brought into focus as an alternative [1, 2]. Besides its higher accuracy, the proposed method can be easily incorporated into CCTC cameras, eliminating the need for installing additional hardware.

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Fire has discernible features such as color, perimeter, area, and rotundity [3, 4] and it is both a temporal and spatial occurrence. Therefore, evaluation of the changes of these characteristics over frames is crucial. This paper employs a changing growth of a fire as a dynamic feature, along with the color information and rotundity as static features for an effectual fire detection system.

The rest of the paper is organized as follows. Section 2 presents related works. Section 3 describes the implementation of the proposed model. Section 4 validates the efficiency of the suggested approach in terms of the accuracy and computation time. Finally, the conclusions of the study are discussed in Section 5.

2. Related Works

Several studies show that almost all image/video-based applications use the color information of flames as the foundation of detection. This is because the color range is the most prominent visual property of fire, and thus several techniques based on vision have exploited this property. Chen *et al.* [1] developed a set of rules to identify fire pixels based on RGB. Celik and Huseyn *et al.* [5] expanded this research to other color spaces and developed novel equations based on YCbCr, which were further modified and used [6-8]. Color is a prime aspect of a fire, but it is not sufficient to conclude that a region is actually a fire. Color segmentation frame differencing has been conducted to identify moving pixels followed by analyses of the growth rate and disorder of captured regions over a number of frames to reduce false regions [1,9]. A statistical color model on RGB was proposed that is independent of saturation [10,11]. They used a mixture of three Gaussians to extract the foreground and examined the changes in the spatial average and area of detected blobs for further verification. According to a survey [12], the Gaussian mixture model has a high computation time and a larger memory requirement, making it unsuitable for real time applications. Moreover, whether thresholds used for the dynamic properties (spatial average and area) are adaptive or fixed was not considered. An approach similar to previous works [10,11] was conducted, except the distribution of two Gaussians was considered [13]. Lianghua *et al.* [14] used a Gaussian to model HSV and analyze the temporal and spatial factors of flames. Nevertheless, the problem mentioned previously in [12] was sustained, and the analysis was also vague. Jarareet *et al.* [15] proposed segmentation using a combination of rules based on HSV and YCbCr. This would make the system perform extra conversions from one color space to another. The most alarming fact about their work was that it was completely based on static color values, making it highly vulnerable to false positives. In another work [3], 11 static and 27 dynamic features were trained using SVM and then employed for the final analysis. Qingfeng *et al.* [4] performed unnecessary work when carrying out experiments regarding changing features used previously [3], and determined that only similarity and rotundity provide good results. Similarity is analogous to blob area comparison and rotundity is the measure of the complexity of an object boundary. While defining the periphery of flames, rotundity is an immensely useful characteristic in distinguishing fires from other luminous sources. As a result, in this study, rotundity was incorporated along with region growth.

3. Proposed Model

The work flow of the proposed model is presented in Figure 1 and a comprehensive explanation is given in subsections 3.1–3.5.

3.1. Color Segmentation on the RGB Color Space

Fire samples with different flame colors were first tested using the decision rules put forward in modified works on the YCbCr platform [7,8]. Surprisingly, some fire regions went undetected, as shown in Figure 2. The reasons for this error are due to two proposed conditions that are not true for flames that have a bright yellow color: i) for a pixel to be classified as fire, its Cr component must be greater than that of Cb and ii) the difference between Cr and Cb has to be at least 40. In addition, there is some extra computational cost associated with converting an RGB frame to YCbCr.

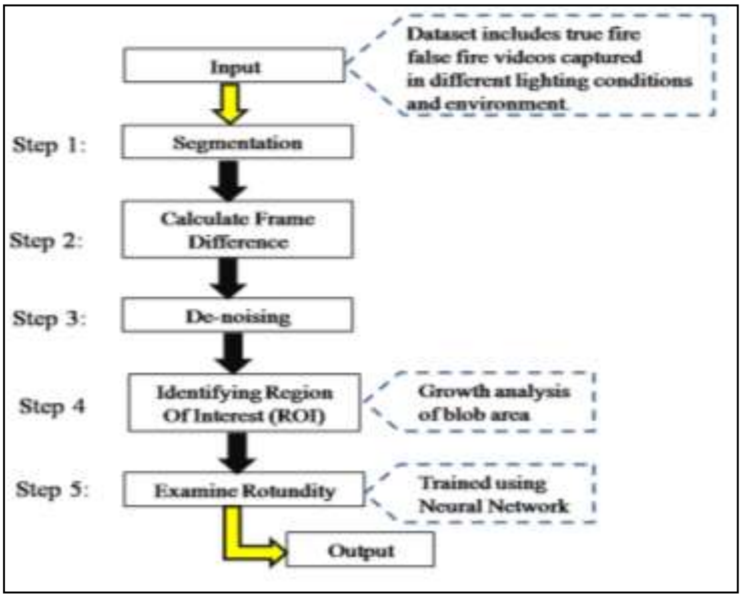
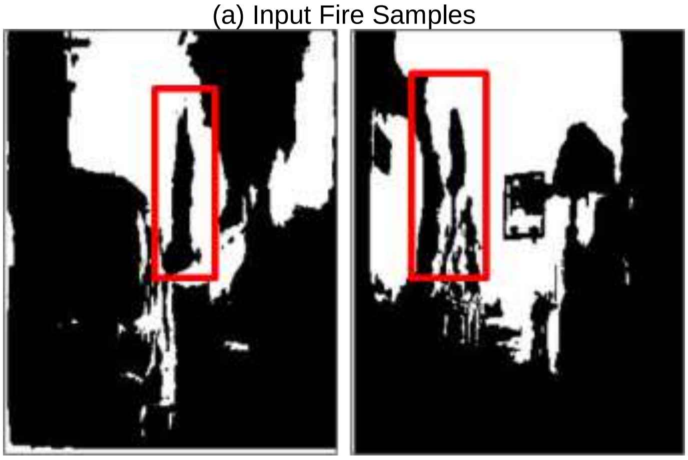


Figure 1. Block Diagram of the Proposed Model

(a) Input Fire Samples



(b) Color Segmentation output using YCbCr

Figure 2. Undetected Fire Regions Marked by Red Squares

The RGB model developed previously in [1] uses the saturation measure of each pixel along with two other conditions described by the following equations. Saturation is the measure that defines the purity of the color.

$$R > R_T \tag{1}$$
$$R \geq G > B \tag{2}$$
$$(S \geq ((255\text{-}R)*ST\,/\,RT)) \tag{3}$$

S_T and R_T denote the thresholds for saturation and the red component, respectively. Jing *et al.* [16] came up with a two-step simple rule for RGB, independent of saturation, which can be defined as follows.

$$F_R(x\ ,y) = \begin{cases} F_{ori}(x, y), & F^R_{ori}(x, y) >= 250 \\ 0, & \text{Otherwise} \end{cases} \tag{4}$$

If the red component of a pixel from the original image is equal to or greater than 250, then it is considered as a potential flame pixel in the first stage. A second step is added to remove white and other spurious fire pixels from $F_R(x, y)$. The resulting equation can be stated as follows.

$$F_{RGB}(x, y) = \begin{cases} F_R(x,y),\ F^R_R(x, y) \neq F^G_R(x, y\ ) \\ \quad \text{or } F^R_R(x, y) \neq F^B_R(x, y) \\ \quad \text{or } F^R_R(x, y) \neq F^B_R(x, y) \\ 0, \quad \text{Otherwise} \end{cases} \tag{5}$$

The algorithm proposed in this work for segmentation is similar to a previous algorithm in [16] that saves the threshold value. After experimenting with a number of different fire images with dark and bright backgrounds and different burning materials, we determined that the condition $R \geq G$ used previously [1] is not always true. In addition, computing the saturation for each pixel consumes a significant amount of time, as shown in Table 4. The measure of the R component of flames ranges from 190 (the thin flares at the top) to 255 (the core). Choosing the minimum results in too much noise, whereas choosing the maximum can result in overlooking true pixels. In order to deal with this issue, we chose the median of the range, which is 222. The outputs with different thresholds are shown in Table 1 and Figure 3, which demonstrate the execution of color segmentation on a sample frame using the formulas proposed in this work. Thus, the set of formulas can be described as follows.

$$R >= 222 \tag{6}$$
$$R > B \tag{7}$$

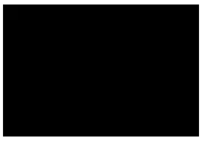
3.2. Frame Differencing

Frame differencing was carried out in order to identify the moving pixels. A reference frame, F_{Ref}, is selected at T_0 seconds. Then, a couple of test frames, F_1 and F_2, are chosen at T_2 and T_3 seconds, respectively, after careful observation of consecutive frames after T_0 seconds. Subtractions are carried out for each of the test frames (F_1 and F_2) from the reference frame. Working with two test frames allows us to analyze the change in growth of the subtracted regions. Subsection 3.4 provides a detailed explanation of this approach. The following formulas illustrate the procedure.

$$F_{Difference1} = F_1 - F_{ref} \tag{8}$$
$$F_{Difference2} = F_2 - F_{ref} \tag{9}$$

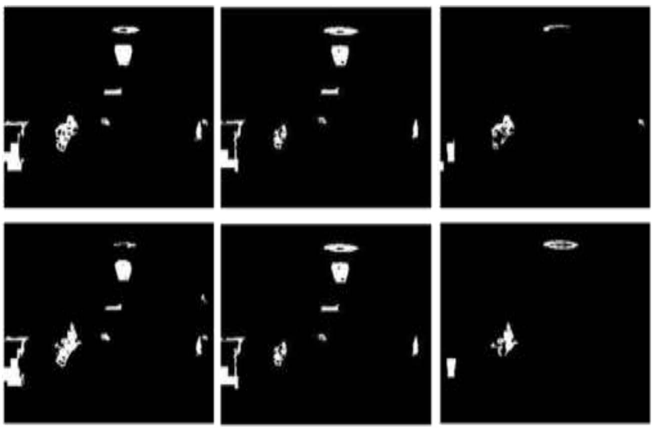
The ultimate decision of whether a fire has been detected or not is based on the change of features between $F_{Difference1}$ and $F_{Difference2}$. Figure 4 illustrates the detailed procedure and the output of different sampling frames.

Table 1. Color Segmentation Using Different Thresholds for the R Component

(a) Threshold	(b) A Test Frame	(c) Output
R>=190		
R>=222		
R>=250		

(a) A Test Frame (b) Output

Figure 3. Color Segmentation on a Sample Frame Using Rules (6) and (7)

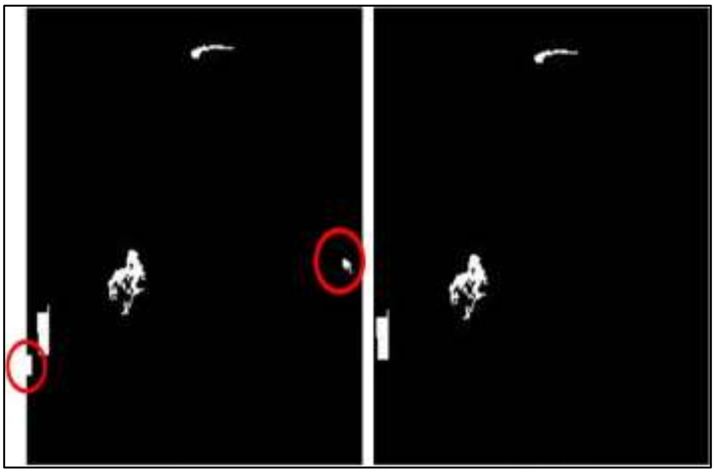


(a) (b) (c)

Figure 4. (a) F_1 and F_2, (b) F_{ref} , and (c) $F_{Difference1}$ and $F_{Difference2}$

3.3. De-noising

Only one of the white regions obtained from step 2 are not fire regions. Moreover, there could be true fire regions which should not be detected such as a burning candle, stove, and other non-accidental small fires. The output from the previous step will contain such non-desirable white marks and to discard them, we set a rule that the fire area should match a certain threshold, *T*, before it is termed dangerous. The value of *T* is selected after running an empirical study over sample fire videos under diverse conditions and surroundings. Figure 5 demonstrates a sample frame being subjected to de-noising.

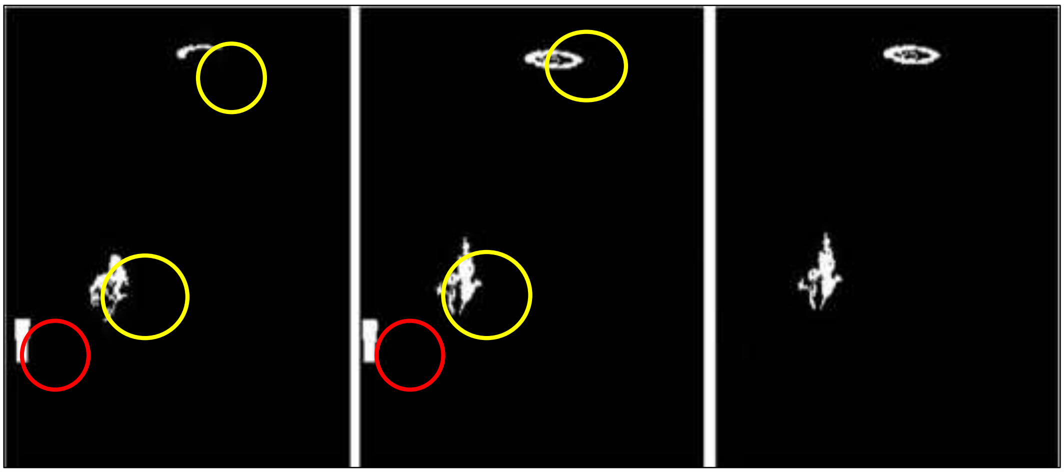


(a) Sample Frame (b) Output

Figure 5. (a) Unwanted Regions Circled in Red and (b) Output after De-noising

3.4. Identifying a Region of Interest

The temporal growth of a fire is a natural truth, making it a key dynamic factor that dominates during fire detection. In this phase of the work, corresponding blobs between $F_{Difference1}$ and $F_{Difference2}$ are examined. Regions whose area measurements are not increasing in the latter frame are eradicated. Figure 6 illustrates the process of finding a region of interest.



(a) $F_{Difference1}$ (b) $F_{Difference2}$ Output

Figure 6. Identifying a Region of Interest

Figures 6(a) and Figure 6(b) show $F_{Difference1}$ and $F_{Difference2}$, respectively, resulting from de-noising. Both of these frames have three identical blobs corresponding to each other and if carefully analyzed, the area of the blob circled in red remained constant while the areas of the blobs circled in yellow increased. Figure 6(c) is the output of the current step where the non-increasing region is eliminated. The algorithm is given in Algorithm 1.

Algorithm 1. Algorithm to Find a Region of Interest

```
Algorithm find_region_of_interest (F_Difference1, F_Difference2):

  for each blob u in F_Difference1
    for each blob v in F_Difference2
      if u and v have a common pixel then
          u and v are corresponding blobs
          if area(v) > area(u)
            fire_regions = v
```

3.5. Analysis of the Rotundity of the Remaining Blob(s) using a Neural Network

As depicted in Figure 6(c), a faulty region (a circular object) still exists. Thus, for reassurance, this final step of analyzing rotundity is conducted. Rotundity, as mentioned before, measures the complexity of a region's boundary. The values range from 0 (the most complex boundary) to 1 (the smoothest). The formula for calculating rotundity [4] is as follows.

$$C = \frac{4\pi S}{L^2} \tag{10}$$

In this equation, S is the area of the region and L is the perimeter. The area of a region is the number of white pixels in it and the perimeter [4] is computed as follows.

$$L = \sum_{i=0}^{n} \sqrt{\left(x_{(i+1)}-x_i\right)^2 + \left(y_{(i+1)}-y_i\right)^2} \tag{11}$$

Here, (x, y) and (x_{i+1}, y_{i+1}) are the coordinates of adjacent pixels on the boundary of the connected region. About three hundred images under various conditions were collected from the internet and their extracted rotundity values were trained using a neural network. Figure 7 shows the output after the final test, where the real fire region was successfully identified.

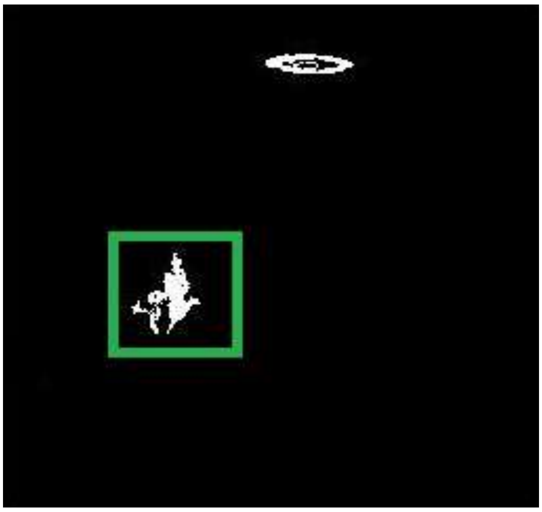


Figure 7. The Real Fire Region is Identified

4. Experimental Results

In order to evaluate the robustness, the proposed system was tested with videos collected from a data set used previously in [17] and YouTube. The data set consists of two types of scenarios. The first type contains a real fire displaying flame colors ranging from very bright yellow to red, while the other type is characterized by luminous non-fire objects such as sunlight and electric bulbs. These scenarios are explained in Table 2 and Table 3, respectively.

Table 2. Description of Fire Videos

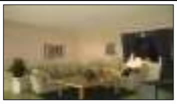
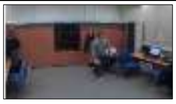
Video No.	Frames	Fire	Scene Description	Sample Scenes
1.	2,558	Yes	Fire ignited in a bedroom having a bright background and luminous objects such as a lamp, light, and sunrays from the window.	
2.	1,995	Yes	Fire ignited in a living room. It has a yellow flame very similar to the background.	
3.	1,791	Yes	A kitchen fire.	
4.	2,718	Yes	Warehouse fire showing a very bright yellow flame.	
5.	3,250	Yes	Industrial fire simulation covering multiple areas.	

Table 3. Description of Non-fire Videos

Video No.	Frames	Fire	Scene Description	Sample Scenes
1.	342	No	Sunrays through the window with smoke present.	
2.	1,920	No	A person walking with a red book and an orange ball.	
3.	1,485	No	A person walking with an orange ball. This video has a reddish background.	

The performance obtained using the intended approach with the enhanced segmentation rule and added rotundity scrutiny was compared with the technique modeled by Chen *et al.* [1]. Two types of comparisons were carried out to correct fire blob detection and evaluate the computation time. For correct blob(s) detection, if either of the methods succeeds to identify some portion of it, then it will be declared as an accurate detection.

(a) Input video frames (b) Final Output

Figure 9. Experimental Results

Table 4. Comparison of the Proposed Model with a State of Art Technique [1] Using a Dataset Containing True Fire Instances

Video	# of Fire Frames Tested	# of Fire Frames Correctly Detected		Avg. Exec Time per Frame		Accuracy	
		[1]	Proposed	[1]	Proposed	[1]	Proposed
1.	300	285	293	1.07	0.73	95.3%	97.7%
2.	300	280	295	1.17	0.82	93.3%	98.5%
3.	300	300	300	1.10	0.78	100%	100%
4.	300	273	290	1.12	0.77	91%	96.7%
5.	300	295	295	1.19	0.83	98.3%	98.3%
Average Accuracy						95.5%	98.2%

The comparisons of the results are tabulated in Tables 4 and 5. Table 4 displays the results when the models were tested with real fire situations, which revealed that the proposed model yielded an average accuracy of 98.2% for positive instances. Moreover, the projected approach outperformed the state of the art technique in terms of computation time. Examining the accuracy against individual videos, it seems that the state of the art model is weak when exposed to situations when the flame exhibits a yellowish flame (Videos 2 and 4) and when the background contains other luminous fire-like objects (Video 1). The reason behind the slowness is the calculation of the saturation value. Table 5 shows the results when the models were tested with scenarios containing fire-like objects but no true fire, with both techniques achieving a precision of 100%. In this case, the proposed method was faster. In order to summarize the results, the accuracy combining the positive and negative samples was calculated. The model proposed in this paper achieved an overall precision of 99.1%, which is better than Chen's model with a combined accuracy of 97.75%. Figure 9 shows some visual examples of our experiments.

Table 5. Comparison of the Proposed Model with a State of the Art Technique [1] Using a Dataset Containing False Fire Instances

Video	# of Non-fire Frames Tested	# of Non-fire Frames Correctly Detected		Avg. Exec Time per Frame		Accuracy	
		[1]	Proposed	[1]	Proposed	[1]	Proposed
1.	150	150	150	1.18	0.85	100%	100%
2.	150	150	150	0.86	0.61	100%	100%
3.	150	150	150	0.85	0.59	100%	100%
					Average Accuracy	100%	100%

5. Conclusion

To achieve a reliable and fast fire detection system, this paper proposed a new feature-based model composed of a new segmentation rule for RGB plus rotundity analysis using a neural network. Fire colored pixels were first identified followed by frame differencing to separate the moving pixels. Unwanted pixels were then removed and the spatial growth of the remaining blobs was compared with the equivalent blobs in a later frame. For the final step, the complexity of the region boundary was examined. The experimental output demonstrated that the model proposed in this paper surpassed the previous approach, yielding an average accuracy of 99.1%.

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