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FIRE DETECTION BY STATIC IMAGE CHARACTERISTICS OF THE LIGHT BLUE FLAME USING ROI-BASED COLOR INTENSITY COMPOSITION DETECTION ALGORITHM

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Abstract. *In this paper, a new ROI-based fire detection method by using the static image characteristics of the light blue flame is proposed. The images are simply received by using a USB CCD camera in real time. The image is grabbed in the memory and fire-suspected regions are defined by using the region of interest (ROI) technique. The blue flame character pixels which are commonly found in gas fire are then checked in each ROI by using color intensity composition detection algorithm. If at least one ROI has the threshold amount of blue flame character pixels, this ROI is assumed to have a fire breakout. Furthermore, the average light intensity of the whole image is also calculated in order to use different threshold values of the blue flame for different background lights. This method was successfully tested with the gas fire flame and it worked well under different background lights in various experiments. While checking for the fire character pixels, the algorithm also checks the pixels that may not exist in the light blue flame while it checks those that would certainly exist, and therefore leading to a less number of false alarms.*

Keywords: Blue flame recognition, Fire detection algorithm, Fire RGB color model, ROI-based fire detection, Static image processing

1. **Introduction.** Although fire is very advantageous to human civilization and social progress, it can cause disasters once it is out of control having such negative effects as soil erosion, water and air pollution, damage to properties and hazard to human life. In order to reduce the risks of fire, there are two fundamental ways to deal with it: fire prevention and firefighting. Fire detection which is the information source for fire fighting is essential as it can immediately alert people once the fire breaks out and facilitate containment.

The traditional fire detection techniques (temperature, humidity, ultraviolet, infrared, air transparency, smoke sensors, etc.) are not activated until the particles actually reach the sensors as they only detect the byproducts of combustion and their responses are very slow. They must be set in close proximity to the fire so they are impractical for covering large areas. Besides, they are unable to provide any additional information such as the location, size and burning degree of the fire. Furthermore, they are not always reliable because the energy emission of non-fires may be detected by misadventure, which results in false alarms. Therefore, more robust fire detection techniques are still under high demand.

Recently, vision sensor-based fire detection systems are becoming popular because of their low equipment cost, faster response time, monitoring a large area and being able to confirm the existence of a fire through the surveillance monitor without visiting the location. Based on the fire information detected by such system, the most effective fire fighting method can be chosen and applied properly.

Most of the vision-based fire detection systems first construct the spatial, spectral or temporal variation models of fire region and then apply some recognition algorithm to detect the presence of fire in those models. Ko et al. proposed the detection of candidate fire regions by applying the probabilistic models to nodes of hierarchical Bayesian Networks used for the final fire-pixel verification [1]. In their second algorithm, a luminance map was made and used to remove non-fire pixels; a temporal fire model with wavelet coefficients was created and applied to a two-class support vector machines (SVM) classifier with a radial basis function (RBF) kernel [2]. Celik et al. proposed the extraction of the foreground object information by using adaptive background subtraction algorithm, and verified by the statistical fire color model [3]. In their second algorithm, a set of rules defined on the Y, Cb and Cr color components together with the developed chrominance model on the Cb-Cr color plane was used to detect the fire pixels [4]. Toreyin et al. proposed the detection of color variations in flame regions by computing the spatial wavelet transform of moving fire-colored regions [5]. They also proposed Markov models representing the flame and flame colored ordinary moving objects to distinguish temporal flame flicker process from motion of flame colored moving objects [6]. Marbach et al. proposed the extraction of the characteristic fire features from the candidate flame region and combined them to determine the presence of fire patterns [7]. Phillips III et al. proposed an approach that was based upon creating a Gaussian-smoothed color histogram to detect the fire-colored pixels. The actual fire pixels were determined by using the temporal variations of the pixels [8]. Yu et al. proposed a mathematical tool based on fractal dimensions, along with the chromatic features, to make a raw localization of fire regions. The dynamic features of the early fire in video were considered to improve the fire detection performance [9]. Yu et al. proposed a set of quaternion Gabor wavelets to establish an analysis tool for local spectral, spatial and temporal characteristics of fire regions. Their quaternion Gaussian kernels were used to represent the spectral distribution of fire pixel clusters [10]. Lu et al. proposed that the logistic regression method in which some spurious fire-like regions were removed by the image difference method and the color masking technique, and then the burning degree of the fire flame was estimated to generate a proper warning alarm [11]. Xie and Wang proposed the method in which the parameters of an autoregressive (AR) model of each extracted region were estimated and used as features for fire classifier [12]. Yuan and Zhang proposed the static and dynamic state detection in which two successive images are subtracted from one another and the fire character pixels are counted in the resultant image [13].

In this paper, a new ROI-based flame recognition algorithm is proposed. First, the fire-suspected regions are constructed by using ROI method so that they can later be used as candidate fire regions. If at least the threshold amount of blue flame character pixels is found in a candidate fire region, it is assumed that there is a fire breakout. Besides, in order to assure the detection performance, different threshold values are used under the four different background light intensities.

Except the white color flame, the blue flame which is produced from the complete combustion due to the pre-mixing of sufficient oxygen and fuel is the hottest and it has more heat energy than any other colors in a flame. For example, the temperature of more bluish oxyacetylene flame is about 3000°C while that of the candle flame is about 1400°C. Early detection of the more dangerous blue flame is essential for choosing a proper fire fighting method, and hence, the vision-based blue flame detection was carried out in this research. According to the experiments, the results found that about 92% of the static blue flames are correctly identified except less than 10% errors for no detection of flames and false detection of non-fire objects. The average rate of correct detections can be compared with the 86.1% of SVM method by Ko et al. [2] and the 95.28% of quaternion method by Yu et al. [10].

2. Structure of Fire Detection System. In this fire detection system, a USB camera was used as the fire sensor. In order to cover the wider view, the camera is set up at the upper corner of a fire ignition box which is specially built with steel and glass. The tested fire is ignited using a gas oven and the flame produced is mainly light blue in color. The overall fire detection system is shown in Figure 1. The hardware system includes a USB digital camera (Logitech V-UAR33 CCD) and a PC computer which has Intel® Core™ 2 Duo E7500 CPU with 2.93 GHz speed, DDR3 1.96 GB SDRAM with 1066 MHz and Intel® G-41 Express video memory with 1024 MB. The software system is composed of three modules; video acquisition and image sampling, image recognition and audio-visual alarm modules implemented by using DirectShow and Visual C++ programming. Image recognition module calculates the RGB color values of the image and then returns whether the image has fire character or not. Audio-visual alarm module raises a warning alarm when the image with fire character is returned from the image recognition module.

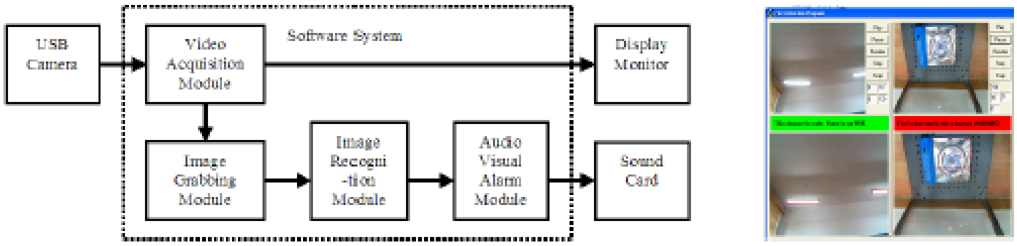


FIGURE 1. The structure of overall fire detection system and the detection software view

3. ROI-Based Color Intensity Composition Detection Algorithm. In this experiment, the proposed ROI-based color intensity composition detection algorithm uses the advantages of RGB color intensity properties. First, the received video stream is sampled at the rate of 15 images per second and the first 3 images are stored in the memory. The algorithm has four steps: (1) selecting the candidate fire-suspected ROIs, (2) calculating the composition of color intensities within the selected regions, (3) calculating the different background light intensities, and (4) determining whether the candidate ROI has actual fire or not.

In this research, the fire-suspected ROI is first defined as a brightest region of the image containing the pixels which have the RGB color intensities that satisfy Equation (1).

$$ROI_{fire\text{-}suspected} = \{RGB \mid (R > 215) \cap (G > 215) \cap (B > 215) \tag{1}$$

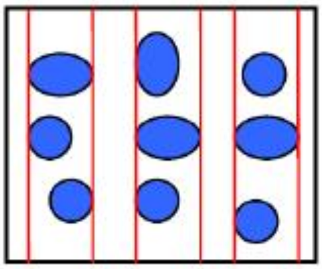
where, R, G and B stand for the intensity values of red, green and blue color channels of each pixel. Then the fire-suspected ROIs are constructed bounding within each rectangle by using ROI detection algorithm including vertically downward detection, horizontally leftward detection and final confirmation of the region boundaries as shown in Figures 2(a)-2(c) with the blue shapes depicting the fire-suspected bright light regions.

The algorithm flowcharts of selecting the candidate fire-suspected ROIs and that of color intensity composition detection algorithm are shown in Figures 3 (a) and 3(b).

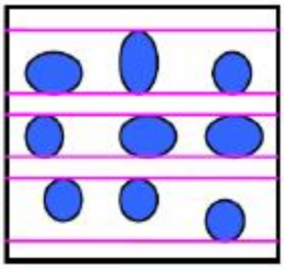
In the first stage, $ROI_{fire\text{-}suspected}$ are searched vertically downward from top to bottom. Once a predefined suspected pixel is detected, the column number of that pixel is supposed as the left column number ($left[ROI_{row}][ROI_{col}]$), where

$$ROI_{row} = n \quad (n = 0, 1, 2, \ldots, 9); \quad ROI_{col} = n \quad (n = 0, 1, 2, \ldots, 9) \tag{2}$$

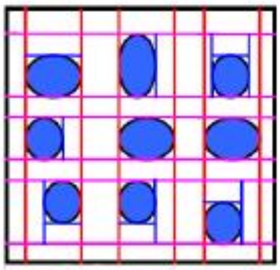
Here in this research, the maximum expected number of ROIs in each row and in each column is assumed not to exceed 10 which can constitute up to 100 ROIs in a static image.



(a) Vertical check



(b) Horizontal check



(c) Final confirmation of ROI

(d) Detected fire-suspected ROIs

FIGURE 2. (a)-(c) diagrams showing the step by step construction of ROIs; (d) detected fire-suspected ROIs in the images containing fire-like luminance

In order to find the right column number of the ROI, total number of column-wise $ROI_{fire\text{-}suspected}$ pixels are collected as fire-suspected pixel count (*fpcount*) as shown in Equation (3).

$$fpcount = \begin{cases} \sum\limits_{i=upper}^{lower} ROI_{fire\text{-}suspected}, & \text{for column-wise checking;} \\ \sum\limits_{j=left}^{right} ROI_{fire\text{-}suspected}, & \text{for row-wise checking} \end{cases} \tag{3}$$

As long as $fpcount > 0$, the checking counter is flagged to continue checking for the next time. Once $fpcount = 0$, the checking counter is flagged to stop checking and the last recorded column value becomes the right column number ($right[ROI_{row}][ROI_{col}]$) of the ROI. In the second stage, $ROI_{fire\text{-}suspected}$ are searched horizontally forward from left to right, and the upper number ($upper[ROI_{row}][ROI_{col}]$) and the lower row number ($lower[ROI_{row}][ROI_{col}]$) of the ROI are searched by using the similar way as in the first stage. The left, right, upper and lower numbers of ROIs found in the above two stages are only the estimated values, and the enveloped regions may also include the extra non-fire-suspected regions which are then removed in the third stage, final confirmation of ROIs.

All of the ROIs or candidate fire-suspected regions, stored in each memory array are checked for the blue flame character pixels which are commonly found in the gas fires. The gas fire flame is supposed to include RGB color intensity characters of white and light blue pixels with the limited amount of black color pixels. According to the experiments,

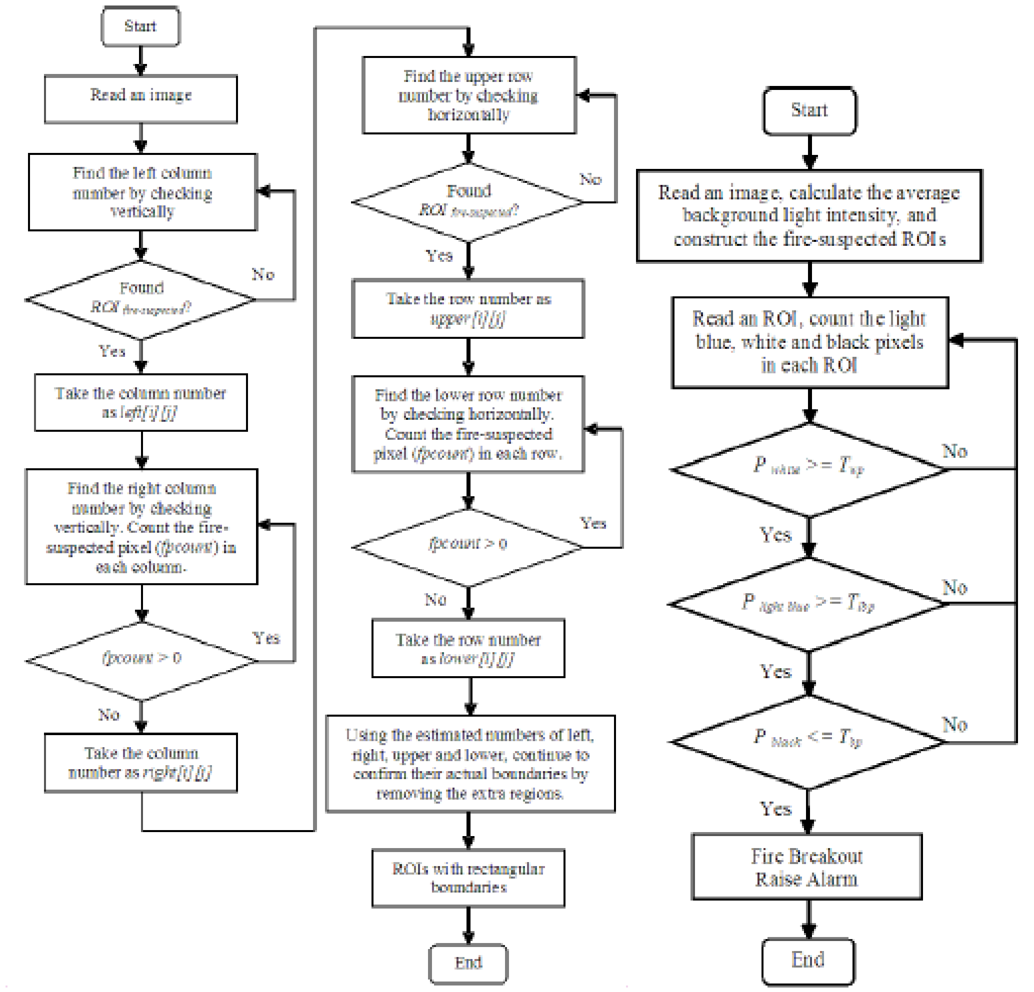


Figure 3. (a) Construction of ROIs with rectangular boundaries; (b) ROI-based color intensity composition detection algorithm

the blue flame fire has the specific RGB characteristics as shown in Equations (4)-(6).

$$RGB_{light\ blue} = \{RGB \mid (70 < R < 175) \cap (110 < G < 215) \cap (200 < B < 255) \quad (4)$$

$$RGB_{white} = \{RGB \mid (R \geq 250) \cap (G \geq 250) \cap (B \geq 250) \quad (5)$$

$$RGB_{black} = \{RGB \mid (R \leq 50) \cap (G \leq 50) \cap (B \leq 50) \quad (6)$$

RGB values of pixels are checked counted in each ROI according to Equation (7).

$$RGB_{light\ blue} = \begin{cases} 1 & \text{if satisfy Equation (4)} \\ 0 & \text{otherwise} \end{cases};$$
$$RGB_{white} = \begin{cases} 1 & \text{if satisfy Equation (5)} \\ 0 & \text{otherwise} \end{cases}; \quad (7)$$
$$RGB_{black} = \begin{cases} 1 & \text{if satisfy Equation (6)} \\ 0 & \text{otherwise} \end{cases}$$

Then, the numbers of light blue, white and black pixels in each ROI are counted and the percent composition of light blue, white and black pixels in each ROI is again calculated according to Equation (8), where, $ROI(x, y)$ is a fire-suspected ROI with x row and y

column. The symbol *color* represents *light blue*, *white* or *black*.

$$N_{color}(ROI(x,y)) = \sum_{i=upper}^{lower} \sum_{j=left}^{right} RGB_{color} \in ROI(x,y);$$
$$P_{color}(ROI(x,y)) = \frac{N_{color}(ROI(x,y))}{Area\ of\ ROI} \times 100\% \tag{8}$$

The average background light intensities are calculated using Equation (9).

$$Blue_{avg} = Blue_{total}/(240 \times 320); \quad Green_{avg} = Green_{total}/(240 \times 320);$$
$$Red_{avg} = Red_{total}/(240 \times 320); \quad Gray_{avg} = (Blue_{avg} + Green_{avg} + Red_{avg})/3 \tag{9}$$

where

$Blue_{total}, Green_{total}, Red_{total}$ = the total channel intensity of each color channel;

$Blue_{avg}, Green_{avg}, Red_{avg}$ = the average channel intensity of each color channel;

$Gray_{avg}$ = the average background light intensity.

Different background light intensities are considered in the preprocessing stage. The average RGB color channel intensities for the four different background light intensities are grayavg $<= 50$ for dark, grayavg > 50 and grayavg $<= 80$ for dim, grayavg > 80 and grayavg $<= 115$ for normal and grayavg > 115 for bright backgrounds.

According to the experiments, it was found that there are both white and light blue color pixels together in the blue flame. Black spots may not exist totally or may exist only in very small amounts so it is assumed that it is not a fire region if such spots are found to be more than the threshold values. The threshold values vary with the different background light intensities and the general equations for various different background light intensities are as shown in Equation (10).

$$ROI_{fire} = \begin{cases} P_{light\ blue} | P_{light\ blue}(ROI(x,y)) \geq T_{lbp}; \\ P_{white} | P_{white}(ROI(x,y)) \geq T_{wp}; \\ P_{black} | P_{black}(ROI(x,y)) \leq T_{bp} \end{cases} \tag{10}$$

where, ROI_{fire} is a specific ROI in which fire is detected, T_{wp}, T_{lbp} and T_{bp} represent the threshold values of white pixel, light blue pixel and black pixel respectively. The minimum threshold values for the white and light blue pixels, and the maximum threshold values for the black pixels are 5, 3 and 5 for bright; 3, 3 and 5 for normal; 2, 2 and 5 for dim; and 1, 1 and 5 for dark. Finally, in the decision stage, if a suspected fire region has at least the threshold amount of blue flame character pixels, it is determined that there is a fire breakout.

4. **Results and Discussion.** Fire detection experiments were carried out under the four different background light intensities: bright, normal, dim and dark. The values of background light intensities were thoroughly adjusted by turning on and off the ceiling lights and by drawing the window curtains. Besides, the experiments were carried out in the daytime and nighttime respectively. Similarly, the amount of fire flame to be detected was also adjusted by turning the gas outlet valve. The efficiency of the fire detection system (η) was evaluated according to Equation (11).

$$\eta = \frac{N - E}{N} \times 100\% \tag{11}$$

where, N is the total number of trials and E is the number of incorrectly identified trials. The number of incorrectly identified trials (E) is the sum of the number of trials in which non-fire objects were incorrectly detected and the number of trials in which the actual fire was not detected. A total of 50 trials were carried out under each of the background light. The detection efficiencies were found to be 88% for bright, 90% for normal, 94% for dim and 96% for dark background lights which constitute an average detection efficiency of

92%. There are some detection errors because of false detection of non-fire objects and no detection of the actual fire. The efficiency is decreased when the background light becomes brighter because of more false detections to brighter non-fire objects. Experimental results obtained under four different background light intensities are as shown in Figure 4.

5. **Conclusion.** The proposed fire detection algorithm has been successfully tested using the ROI-based color intensity composition detection algorithm which is composed of two main steps: construction of fire-suspected ROIs by bounding with the rectangles and detection of light blue flame character pixels within each ROI. The method can distinguish well between the fire and non-fire objects as the detection of fire character pixels is considered under the four different background lights: dark, dim, normal and bright. While collecting the fire character pixels, the algorithm not only detects the white and light blue colored pixels that would certainly exist in the blue flame but also checks the black pixels that may not exist at all or may exist as only a very few amounts, so there is a less number of false alarms. This ROI-based fire detection algorithm checks only within the selected ROIs and it does not check the whole image for fire character pixels. The method is expected to be applied for fire detection in the large indoor areas or open outdoor spaces.

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(a) No fire detected in bright background ($Gray_{avg} = 135$)

(b) Fire detected in bright background ($Gray_{avg} = 135$)

(c) No fire detected in bright background ($Gray_{avg} = 102$)

(d) Fire detected in bright background ($Gray_{avg} = 102$)

(e) No fire detected in bright background ($Gray_{avg} = 63$)

(f) Fire detected in bright background ($Gray_{avg} = 63$)

(g) No fire detected in bright background ($Gray_{avg} = 36$)

(h) Fire detected in bright background ($Gray_{avg} = 36$)

FIGURE 4. Fire detection results after using ROI-based color intensity composition detection algorithm under the four different background light intensities