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Fire Detection Using Multi-Channel Information and Gray Level Co-occurrence Matrix Image Features

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Abstract
Recently, there has been an increase in the number of hazardous events, such as fire accidents. Monitoring systems that rely on human resources depend on people; hence, the performance of the system can be degraded when human operators are fatigued or tensed. It is easy to use fire alarm boxes; however, these are frequently activated by external factors such as temperature and humidity. We propose an approach to fire detection using an image processing technique. In this paper, we propose a fire detection method using multi-channel information and gray level co-occurrence matrix (GLCM) image features. Multi-channels consist of RGB, YCbCr, and HSV color spaces. The flame color and smoke texture information are used to detect the flames and smoke, respectively. The experimental results show that the proposed method performs better than the previous method in terms of accuracy of fire detection.

Keywords
Color Features, Fire Detection, Texture Features

1. Introduction

Fires are frequent at this time of the year; there have already been some reported fires, making the current situation extremely dangerous [1,2]. Fires will become a great danger if we are not careful. Many people have lost their homes after a fire. Carelessness is often the cause of many fires. Fire prevention is a matter of great urgency. It is easy to use fire alarm boxes; however, such boxes are frequently activated by external factors such as temperature, and humidity conditions. Hence, there is a need for a reliable and efficient vision-based fire detection algorithm.

There are several works published in relation to fire detection that suggest using RGB color models and background subtraction methods. The method used in [3] has two major advantages, namely modest computational load and fast processing. However, the downside is the quality of fire detection. Another method uses HSV and YCbCr color models with conditions to separate the brightness of a fire from the background and ambient light [4]. The method described in [5] extracts the flame objects using iterative adaptive threshold techniques. In [6], fire was detected using a method focused on adaptive edge detection and classification of the flame level; this method was shown to be resilient, as it

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was based on neural networks.

The method described in [7] detected the flame and smoke in order to apply the Gaussian mixture model to the difference image. The features used in the method described in [8] are the intensity mean, intensity skewness, wavelet energy mean, wavelet energy skewness, and orientation of the movement. These methods [7,8] are efficient, which is good; however, the detection speed has to improve. We propose a fire detection method using the flame color and smoke texture information to achieve a high detection accuracy.

This paper is structured as follows. In Section 2, we explain our method of fire detection using multi-channel information and gray level co-occurrence matrix (GLCM) image features. In Section 3, the results of the testing and evaluation of this method are presented. In the conclusion, we reflect on our findings.

2. Proposed Method

This section describes the details of the proposed fire detection algorithm. Fig. 1 shows a flowchart of the proposed algorithm. We use the flame detection model and smoke detection model for fire detection. The flame and smoke detection models consider the flame color and smoke texture, using a machine learning system. It makes use of the learning stage of each feature through the algorithm. The proposed method detects the fire using the results of each model.

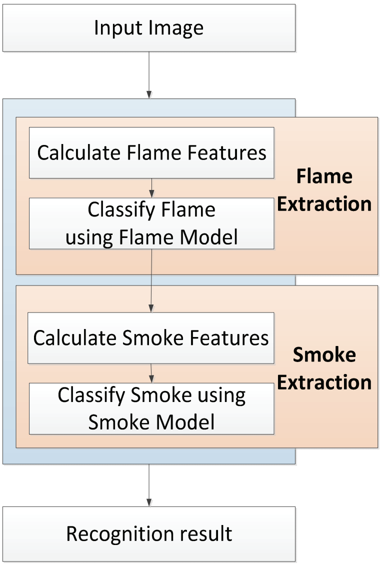

Fig. 1. Proposed method.

The fire detection method is as follows. In Fig. 2, the flame feature extraction block is chosen from the RGB, YCbCr, and HSV color spaces. The RGB features consist of the mean values of the three components R, G, and B, denoted by R_{mean}, G_{mean}, and B_{mean}, respectively, which are calculated as follows:

$$R_{mean}(i,j) = \frac{1}{I_B \times J_B} \sum_{i=1}^{I_B} \sum_{j=1}^{J_B} R(i,j) \tag{1}$$

$$G_{mean}(i,j) = \frac{1}{I_B \times J_B} \sum_{i=1}^{I_B} \sum_{j=1}^{J_B} G(i,j) \tag{2}$$

$$B_{mean}(i,j) = \frac{1}{I_B \times J_B} \sum_{i=1}^{I_B} \sum_{j=1}^{J_B} B(i,j) \tag{3}$$

where, (i,j) denotes the spatial locations of pixels and $I_B \times J_B$ is a 4×4 block in a given image.

Given an RGB-represented image, it is converted into YCbCr and HSV represented color images using the standard RGB-to-YCbCr and RGB-to-HSV approaches, respectively. The YCbCr and HSV features consist of the mean values of each of their components. RGB features are numbered F_1 to F_3, YCbCr features are numbered F_4 to F_6, and HSV features are numbered F_7 to F_9. Each feature is computed using formulae (1) to (3), as given above.

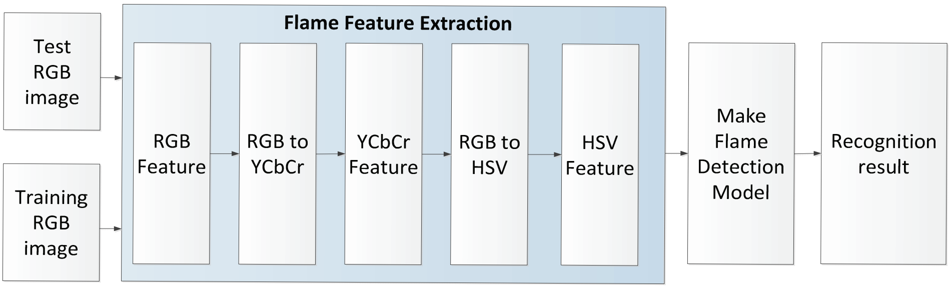

Fig. 2. Flame detection method.

We can establish a method for detecting a flame pixel at the spatial location (i,j) in RGB color space (F_{10}):

$$F_{10} = \begin{cases} 1, if (R(i,j) > 190) \cap (G(i,j) > 100) \cap (B(i,j) < 140) \\ 0, otherwise \end{cases} \tag{4}$$

In the YCbCr color space, the two features (F_{11} and F_{12}) for detecting a flame pixel at spatial location (x,y) are given by:

$$F_{11} = \begin{cases} 1, if \;\; Y(x,y) \geq Cb(x,y) \\ 0, otherwise \end{cases} \tag{5}$$

$$F_{12} = \begin{cases} 1, if \;\; Cr(x,y) \geq Cb(x,y) \\ 0, otherwise \end{cases} \tag{6}$$

The flame detection model is constructed using a support vector machine. In the learning stage, we calculate features F_1 to F_{12} after receiving the inputs of the training images. The learning data consist of features F_1 to F_{12}, a portion of which is shown in Fig. 3. The flame detection model utilizes features F_1 to F_{12}. In the recognition stage, upon receiving the image data and calculating features F_1 to F_{12}, the method classifies the input as a flame image or a normal image.

```
1 1:253.355469 2:219.265625 3:63.941406 4:24.652344 5:190.699219 6:253.355469 7:0.096298
8:0.744919 9:0.989670 10:1 11:1 12:1
1 1:252.992188 2:214.296875 3:55.257813 4:24.187500 5:199.449219 6:252.992188 7:0.094482
8:0.779099 9:0.988251 10:1 11:1 12:1
-1 1:88.011719 2:110.226563 3:118.937500 4:98.546875 5:66.414063 6:118.937500 7:0.384949
8:0.259430 9:0.464600 10:0 11:0 12:0
-1 1:105.000000 2:111.062500 3:114.812500 4:101.375000 5:22.687500 6:114.812500 7:109.812500
8:124.687500 9:130.750000 10:0 11:0 12:0
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Fig. 3. Flame features F_1 to F_{12}.

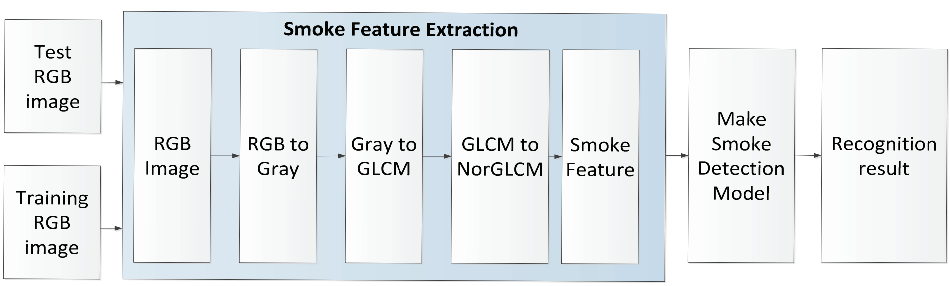


Fig. 4. Smoke detection method.

The smoke detection model builds the GLCM features as shown in Fig. 4. The definition of GLCM is given in [9]. Suppose that an image to be analyzed is rectangular and has I columns and J rows. The gray levels appearing at each pixel are quantized to N levels. Let $I = \{1,2,\ldots,I\}$ be the columns, $J = \{1,2,\ldots,J\}$ be the rows, and $G = \{0,1,\ldots,N\text{-}1\}$ be the set of N quantized gray levels. The set $I \times J$ is the set of pixels of the image ordered by their row-column designations.

45	64	44	150
43	151	68	35
201	180	35	36
50	35	145	203

(a)

0	1	0	2
0	2	1	0
3	2	0	0
0	0	2	3

(b)

2	1	3	0
2	0	0	0
1	1	0	1
0	0	1	0

(c)

0.16	0.08	0.25	0
0.16	0	0	0
0.08	0.08	0	0.08
0	0	0.08	0

(d)

Fig. 5. Gray-level co-occurrence matrix computation. (a) Original image, (b) four level image, (c) GLCM image, and (d) normalized GLCM image.

The GLCM and normalized GLCM are presented in Fig. 5. In the first step, the grayscale version of the original image (Fig. 5(a)) is reduced to a four-level image (Fig. 5(b)). In the second step, each pixel value in the GLCM image calculates the GLCM value by using the four-level image. The probability value in the normalized GLCM is computed by dividing each of the GLCM values by the sum of all values in the GLCM image (Fig. 5(c)). The normalized GLCM image is shown in Fig. 5(d).

Different features are calculated based on the probability values computed from the GLCM pixels. These consist of the angular second moment (ASM) (F_{13}), contrast (F_{14}), entropy (F_{15}), variance (F_{16}), correlation (F_{17}), inverse difference moment (IDM) (F_{18}), sum average (F_{19}), sum variance (F_{20}), sum entropy (F_{21}), difference variance (F_{22}), difference entropy (F_{23}), where each feature is computed respectively as follow:

$$F_{13} = \sum_{i=0}^{I_B-1} \sum_{j=0}^{J_B-1} NorGLCM(i,j)^2, \quad F_{14} = \sum_{i=0}^{I_B-1} \left\{ \sum_{i=0}^{I_B-1} \sum_{j=0}^{J_B-1} NorGLCM(i,j) \right\} \tag{7}$$

$$F_{15} = \sum_{i=0}^{I_B-1} \sum_{j=0}^{J_B-1} NorGLCM(i,j) log NorGLCM(i,j) \tag{8}$$

$$F_{16} = \sum_{i=0}^{I_B-1} \sum_{j=0}^{J_B-1} (i-\mu)^2 NorGLCM(i,j) \tag{9}$$

$$F_{17} = \sum_{i=0}^{I_B-1} \sum_{j=0}^{J_B-1} NorGLCM(i,j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y} \tag{10}$$

$$F_{18} = \sum_{i=0}^{I_B-1} \sum_{j=0}^{J_B-1} \frac{1}{1+(i-j)^2} NorGLCM(i,j), \quad F_{19} = \sum_{i=0}^{2(I_B-1)} i \times P_{x+y}(i) \tag{11}$$

$$F_{20} = \sum_{i=0}^{2(I_B-1)} (i - F_{19})^2 \times P_{x+y}(i), \quad F_{21} = \sum_{i=0}^{2(I_B-1)} P_{x+y}(i) log P_{x+y}(i) \tag{12}$$

$$F_{22} = \sum_{i=0}^{I_B-1} \left(i - \sum_{i=0}^{I_B-1} i \times P_{x-y} \right)^2 \times P_{x-y}(i), \quad F_{23} = \sum_{i=0}^{I_B-1} P_{x-y}(i) P_{x-y}(i) \tag{13}$$

The smoke detection model is established using a support vector machine. In the learning stage, we calculate the smoke features F_{13} to F_{23} using the inputs received from the training images. The learning data consist of features F_{13} to F_{23}, a portion of which is shown in Fig. 6. A fire detection model is constructed by utilizing features F_{13} to F_{23}. In the recognition stage, upon receiving image data and calculating features F_{13} to F_{23}, the method classifies the image as a smoke image or a normal image.

```
1  1:253.355469  2:219.265625  3:63.941406  4:24.652344  5:190.699219  6:253.355469  7:0.096298
8:0.744919 9:0.989670 10:1 11:1 12:1
1  1:252.992188  2:214.296875  3:55.257813  4:24.187500  5:199.449219  6:252.992188  7:0.094482
8:0.779099 9:0.988251 10:1 11:1 12:1
-1  1:88.011719  2:110.226563  3:118.937500  4:98.546875  5:66.414063  6:118.937500  7:0.384949
8:0.259430 9:0.464600 10:0 11:0 12:0
-1  1:105.000000  2:111.062500  3:114.812500  4:101.375000  5:22.687500  6:114.812500  7:109.812500
8:124.687500 9:130.750000 10:0 11:0 12:0
```

Fig. 6. Smoke features F_{13} to F_{23}.

3. Experimental Results

In this section, we will evaluate the performance of our fire detection method. The test images included 400 fire images and 600 normal images. To measure the performance of the proposed method, we used the positive rate, negative rate and average rate, which are defined as follows:

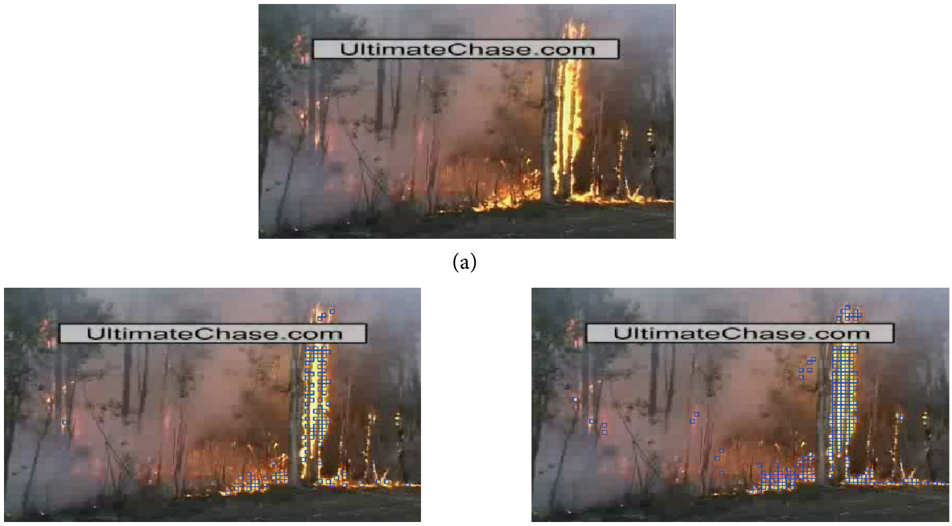
- Positive rate: The number of determined fire images in the set of fire images divided by the total number of fire images.
- Negative rate: The number of determined fire images in the set of normal images divided by the total number of normal images.
- Average rate: The sum of the positive rate and negative rate, divided by two.

Table 1. Comparison of each method

Method	Average rate (%)
Method in [10]	86.6
Proposed method	92.8

Table 1 shows the results of the average rate using each method. The method proposed in [10] achieves an average rate of 86.6% while the currently proposed method achieves an average rate of 92.8%. Our method's average rate is 6.2% higher than that of the method described in [10].

Fig. 7 shows the experimental comparison of flame detection using the proposed method and the method described in [10]. The method described in [10] uses the bag-of-words model as well as color filters of RGB and HSL that use color threshold parameters and color conditions as detection methods. Fig. 7(b) shows the detection of the flame using the method described in [10]; however, many flame blocks remain as normal blocks. Fig. 7(c) shows the detection of the flame block when the suggested method using the flame model is used. The experimental results show that the proposed method performs better than the method described in [10] in terms of flame detection.



(a)

(b) (c)

Fig. 7. Experimental comparison of flame detection using the proposed method and the method described in [10]. (a) Original image, (b) the method in [10], and (c) proposed method.

Fig. 8 shows the experimental results using the proposed method: in the set region of interest (ROI) in Fig. 8(b), the small blue rectangle represents the detected flame block; the small green rectangle is the detected smoke block. The large red rectangle on the outside represents a fire state.

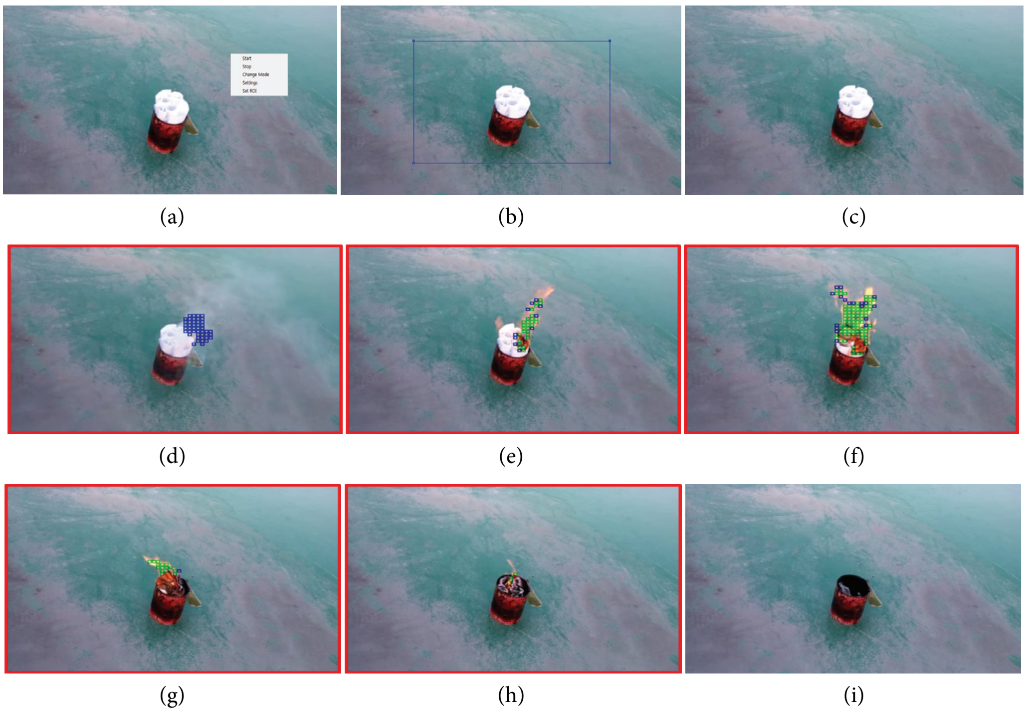


Fig. 8. Proposed method results. (a) 1 frame (setting menu), (b) 1 frame (set ROI), (c) 100 frame, (d) 200 frame (detect fire), (e) 300 frame (detect fire), (f) 400 frame (detect fire), (g) 500 frame (detect fire), (h) 600 frame (detect fire), and (i) 700 frame.

4. Conclusion

In this paper, we proposed a fire detection method using multi-channel information and GLCM image features. Our method includes flame and smoke detection, which are sensitive to flame color and smoke texture information. The average detection rate of our method is higher than that of the previous method. In the future, we plan to consider other features in order to obtain an even higher recognition rate.

Acknowledgement

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