Experimental study of video fire detection and its applications

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Abstract

Video fire detection makes a significant contribution to the effectiveness of fire detection systems, particularly as regards fire in large spaces such as Atria, Tunnels, Hangers, Warehouses and E&M Plant rooms, as traditional fire detection systems have been shown to be ineffective in large spaces. For the development of video fire detection systems, spatial, spectral and temporal indicators are important in the identification of a fire source. In the development of video fire detection systems, flame image segmentation, recognition, tracking and prediction are important areas of investigation. The multi-threshold algorithm of Otsu’s method and the Rayleigh distribution analysis method (modified segmentation algorithm) can be used in the segmentation of flame images. The modified segmentation algorithm, however, can be strengthened to extract the pool fire images making use of the optimum threshold values. Following such segmentation the pool fire images centroid analysis technique can be used to recognize pool fire images by means of the Nearest Neighbor (NN) algorithm. The objective of this paper is to examine the modified segmentation and the NN algorithms.

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Nomenclature

| Symbol  | Description                      |
|---------|----------------------------------|
| R,G,B   | Red, Green and Blue colour values|
| I       | Luminance                        |
| ω       | weight                           |
| μ       | mean                             |
| σ       | variance                         |
| λ       | parameter of Rayleigh model      |
| x       | x coordinate                     |
| y       | y coordinate                     |
| d       | distance between segmentation foreground images |
| k*      | threshold values                 |

1. Introduction

A building fire is a complex phenomenon the fire being affected by environmental factors such as wind speed and different types of fuel. In order to provide protection, it is important to detect fire at its earliest stages. Fire and smoke
spread within buildings can be affected by factors such as the building geometry, building dimensions, interior layout and type of usage of the building. Automatic flame image segmentation, image recognition, tracking flame movement directions and flame movement predictions are important areas needing solution in that they are essential to the development of video fire detection systems. The related software function has these four major sectors.

- Segmentation of foreground and background
- Recognition of foreground images
- Tracking the fire spread direction
- Prediction of flame movement

Three components: hardware, image data and software are required in the development of the video fire detection systems. Figure 1 gives the main components of a video fire detection and operation system.

The hardware includes camera lens, image sensors, a central processing unit (CPU) and a hard disk. Fire and smoke, if detected at an early incipient fire stage, can be easily be controlled by firefighters making escape by others to safety, not difficult. The traditional detection methods, however, have many significant drawbacks, including time delays especially in large spaces with high ceilings (such as atria, hanger and warehouses). Video fire detection systems can also be applied to detect forest fires. In addition, in order to protect historical buildings from fire damage and so maintain the historical characteristics of their architectural design, some video fire detection systems can be combined with existing closed-circuit television (CCTV) video surveillance system. As a consequence, use of a video flame detection system can be useful in complementing the protection of large spaces, forest and historical buildings both day and night.

The development of fire detection technologies, with video imaging is an important research and development field. A very useful and significant fire detection development would be the automatic detection by video images combined with the raising an alarm.

The video fire detection system hardware includes not only the lens and image sensor, but also the configuration of a computer platform is also important. The newly development algorithm runs on a PC platform with dual core 3.16Hz processor and 4G RAM.

The image data is represented in an appropriate image file format. Researchers have developed different image file formats, each depending on different objectives. In this investigation, Bitmap (BMP) file format has been used. The visual flame images are captured by camera at a resolution of 320(width) and 240(height) or a total of 76,800 number pixels. The range of RGB (red, green, blue) colour is from 0 to 255 so the intensity level is 256. This file format produces simple uncompressed images. The detection time is not increased as no encoding and compression processes are required when obtaining the image from the BMP file. As the BMP format was developed by Microsoft its format is compatible with the Microsoft operating system for the development of software. For the same reason of compatibility Microsoft Foundation Class (MFC) was used for fire image editing. Visual C++ and C++ are popular computer languages for developing algorithms and in this current study, the algorithm was developed using Microsoft Windows XP, Visual C++ and MFC.
2. Literature review

Following a review of the literature on codes of practice governing minimum fire service installations and equipment, the most common fire detection methods include smoke detection, heat detection, flame detection, beam detection, gas detection, dust detection and video image detection [1].

Fire detection methods are based on the use of fire signatures such as degree of obscuration, temperature change, toxic characteristics and dust particle and flame intensity (brightness). Video image detection methods make use of thermal images and general images. A thermal camera records thermal images for analyses of surface temperature profiles of viewed objects [2]. A general video camera records consecutive images enabling analyses of image changes. The literature since 1993, makes clear that researchers have developed different kinds of video fire detection algorithm [3] and many proposed different algorithms in their video fire detection system designs. It is clear, however that all relate to one of the three methodologies 1. Image processing, 2. Statistics and 3. Artificial Neural Network (ANN).

A lens is an optical device transmitting light to image sensors, including the Complementary Metal Oxide Semiconductor (CMOS) and the Charge - Coupled Device (CCD). CMOS and CCD are used to capture the images. CMOS and CCD image sensor technologies were developed in the late 1960s and early 1970s [4].

A video fire detection system must adhere to the relevant codes of practice and specified product standards. Codes and standards applying to fire detection products are illustrated in Table 1.

| Standard Number | Standard Topic |
|-----------------|----------------|
| NFPA 72:2010    | National Fire Alarm and Signaling Code 2010 Edition |
| ANSI/FM 3260:2004 | American National Standard for Radiant Energy – Sensing Fire Detectors for Automatic Fire Alarm Signaling |
| BS 5839-1:2002 + A2:2008 | Fire detection and fire alarm systems for buildings – Part 1: Code of practice for system design, installation, commissioning and maintenance |
| UL 268:2009      | Underwriters Laboratories Inc. Standard for Safety - Smoke Detector for Fire Alarm Systems |

A review of the literature relating to the colour analysis method, reveals that this method is very commonly applied in video fire detection systems. Table 2 gives the history of colour analysis method development.

| Years | Colour analysis method |
|-------|------------------------|
| 1994  | Temperature analysis for G/R ratio |
| 1999  | Flame colour analysis (HSV) |
| 2004  | Three decision rules for extraction fire pixels |
| 2005  | Flame colour analysis (RGB) |
| 2008  | Colour distribution |
| 2010  | Colour – Based Decision Rule |
| 2010  | Fire colour modeling algorithm |
| 2010  | Detection of fire coloured pixels |

From a review of the literature in 2004, it is clear that researchers have developed the fire pixels colour as Red ≥ Green ≥ Blue [5]. Video image detection systems have been designed for aircraft and engine components, but, such systems however were already in use by Simon Y. Foo [6]. He applied a rule – based machine vision approach using computer analysis to calculate the mean $\mu$, variance $\sigma$ and standard deviation $S$. 
2.1. Segmentation

Segmentation is the process of separating objects and regions from grayscale colour images. Segmenting pool fire images can make use of the specialized image processing toolbox (MATLAB). However, it must be noted that MATLAB cannot enable the building of different toolbox functions. It cannot be modified by the user. Because of the lack of flexibility of MATLAB in the respect, some researchers developed their own software to further develop video fire detection systems. Different algorithms are modified by computer program. Fig. 3. illustrates past segmentation approaches to image processing [7].

Otsu’s method is a threshold selection method. It was presented in 1979 by Nobuyuki Otsu [8]. The Otsu threshold method is fairly simple and powerful in processing the intensity of grayscale colour images [9]. Fig. 4. illustrates the traditional Otsu method for selecting a threshold value. When the flame image has been segmented successfully from the grayscale colour images, the colour distribution of the segmentation image consists of only 0 (black) and 1 (white). “0” (black) indicates image foreground (flame shape) and “1” (white) indicates background.
Before the foreground and background flame images are extracted by Otsu’s method, it is necessary to convert the grayscale colour image based on the weighted sum of the Red, Green and Blue (RGB) components \([10]\). Based on the study of the colour space analysis literature, the weighted sum of RGB components was derived using the Y components of the YIQ colour space format \([11]\). The domain “Y” is denoted by the term Luminance (I) \([12]\). The equation (below) is used to calculate different intensity values in accordance with the different RGB colour values.

\[
I = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B
\]  

(1)

Based on the traditional Otsu method, a threshold value can be obtained. However, the traditional Otsu’s method was not able to provide satisfactory segmentation images, so the selection of a suitable optimal threshold value was necessary.
value remains a big problem when segmenting flame images. In order to develop a satisfactory segmentation of images method, the Multi–threshold algorithm of Otsu’s method was integrated with the Rayleigh distribution analysis (modified segmentation algorithm) in the case of our experiment. Fig 4. illustrates the modified segmentation algorithm flow diagram.

START

Weight
Foreground $\Omega_f$; Background $\Omega_b$

Mean
Foreground $\mu_f$; Background $\mu_b$

Variance
Foreground $\sigma_f$; Background $\sigma_b$

Between Class Variance

\[
\sigma^2_B = \omega_b \left( \mu_b - \mu_f \right)^2 + \omega_f \left( \mu_f - \mu_T \right)^2.
\]

\[
\sigma^2_B = \omega_b \omega_f \left( \mu_f - \mu_b \right)^2.
\]

If $\sigma^2_B$ = $\sigma^2_B(k_1^*, k_2^*, k_3^*, k_4^*, k_5^*, k_6^*)$

It is max $\sigma^2_B(k_1, k_2, k_3, k_4, k_5, k_6)$

Threshold values $k_1^*, k_2^*, k_3^*, k_4^*, k_5^*, k_6^*$

Calculation the total pixels number from segmentation images, it is based on the threshold values by Otsu’s method

\[ OPnum \ (1.....6), \ 1 \leq n \leq 6 \]

Rayleigh distribution algorithm

Foreground $\lambda_f = \frac{\mu_f^2 + \sigma_f^2}{\omega_f}$

Background $\lambda_b = \frac{\mu_b^2 + \sigma_b^2}{\omega_b}$

Between Class Variance

\[ \lambda^2_B = \omega_b \left( \lambda_b - \lambda_f \right)^2 + \omega_f \left( \lambda_f - \lambda_T \right)^2. \]

\[ \lambda^2_b = \omega_b \omega_f \left( \lambda_f - \lambda_b \right)^2. \]

If $\lambda^2_B$ = $\lambda^2_B(k_1^*, k_2^*, k_3^*, k_4^*, k_5^*, k_6^*)$

It is max $\lambda^2_B(k_1, k_2, k_3, k_4, k_5, k_6)$

NO

YES

B
2.2. Recognition

In the recognition of flame images, the Nearest Neighbour (NN) algorithm is used. Calculation of the centroid following segmentation of the foreground images is required before the flame recognition process takes place. The x and y coordinates of the centroid are placed in the database. For flame image and non-flame image recognition purposes this centroid value is required by Nearest Neighbour (NN) algorithm. The Nearest Neighbour (NN) algorithm calculations are able to discriminate between those classes of foreground segmentation images which are close to each other (both flame images and non-flame images). The NN algorithm is based on Euclidean distances, as indicated in the equation (below). Fig 5. illustrates of Nearest Neighbour algorithm process.

\[ d_n(x, y) = \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2} \]  

(2)
3. Experimental results

3.1. Segmentation

The proposed method implemented the multi-threshold algorithm of Otsu’s method and Rayleigh distribution analysis (modified segmentation algorithm) and the Nearest Neighbour (NN) algorithm in experiment. Before segmentation and recognition of the images, it is necessary to capture the colour images. Fig 5. illustrates the original colour flame images.

![Original colour flame image](image1)

Fig. 5. Original colour flame image

The captured colour flame images were converted to grayscale colour images based on a weighted sum of the Red, Green and Blue (RGB) components. Fig 6. illustrates the converted colour flame image.

![Colour flame image convert to grayscale colour flame image](image2)

Fig. 6. Colour flame image convert to grayscale colour flame image (a) original colour flame image and (b) grayscale colour flame image

From the grayscale colour flame images, the intensity level histogram are obtained. The x-axis represents intensity levels from 0 to 255 (256 intensity levels). The y-axis represents pixel frequency. The function of the histogram is to depict the intensity / frequency characteristics of grayscale colour images including both fire images and non-fire images. Fig 7. illustrates this histogram.

![Histogram of intensity levels](image3)

Fig. 7. Histogram of intensity levels
From this histogram statistical data can be derived as illustrated by Fig 8. This data includes the maximum and minimum frequency, maximum intensity value, number of pixels, mean variance and standard deviation.

![Fig. 8. Statistical data of histogram](image)

After the flame colour images have been converted to grayscale images, segmentation of the foreground (flame images and non-flame images) from the background is required. Fig 9. illustrates the after segmentation images obtained from the traditional Otsu’s method. In this traditional segmentation results, flame brightness cannot be derived from the clear flame image.

![Fig. 9. Segmentation images by traditional Otsu’s method (a) grayscale colour images and (b) after segmentation flame images](image)

The multi-threshold algorithm of Otsu’s method, describe above, was used in this study to improve the segmentation results. Fig 10. illustrates the segmentation results derived using the modified segmentation algorithm. The results show a successful reduction of the effect of flame brightness on the grayscale flame images.

![Fig. 10. Segmentation results derived using the modified segmentation algorithm](image)
However, the multi-threshold algorithm of Otsu’s method can obtain deformed flame shape by over segmenting the images. The proposal, whereby the Otsu multi-threshold algorithm is combined with Rayleigh distribution analysis (i.e. the modified segmentation algorithm) to help overcome this over segmentation problem has proved able to obtain the optimum threshold value. It also reduces the flame intensity effect and minimizes segmentation deformation. Fig 11. illustrates the computer output following application of the modified segmentation algorithm. Based on experimental results, the optimum threshold value is considered to be 248 for a pixel number of 4222.

| Normal Threshold | Pixel | Rayleigh Threshold | Pixel |
|------------------|-------|--------------------|-------|
| 189              | 5684  | 108                | 5150  |
| 206              | 4937  | 306                | 4221  |
| 230              | 4002  | 230                | 4584  |
| 248              | 4222  | 248                | 4222  |
| 252              | 3984  | 252                | 3984  |
| 253              | 3914  | 253                | 3914  |

Fig. 11. Computer output following application of the modified segmentation algorithm

3.2. Recognition

After the successful images segmentation the next step in video fire detection is to identify the segmentation images by use of the Nearest Neighbour (NN) algorithm in connection with segmented flame image centroids. Fig 12. illustrates the centroid of flame images.
To distinguish between flame images and non-flame images, the database also requires another set of centroid coordinates. In this experiment, a swinging fluorescent tube was made use of. Fig. 13. illustrates the original images and the centroid of the fluorescent tube images.

![Original images of swing fluorescent tube](image1)

![Centroid of the fluorescent tube](image2)

*Fig. 13. Original images of swinging fluorescent tube and the centroid of the fluorescent tube images*

From the database of flame images and swinging fluorescent tube images, the Nearest Neighbour (NN) algorithm was used to identify the flame images and the fluorescent tube images. The experiment found that the calculated distances for the flame images centroid was close to the database centroid values. Similarly the calculated distance of the fluorescent tube centroid was not close to the flame images centroid. Thus based on the experimental results, the Nearest Neighbour (NN) algorithm centroid analysis approach is able to determine which are images of fire and which are images of non-fire items. Fig. 14. illustrates the calculation results.

![Calculation and analysis results of x and y coordinates](image3)

*Fig. 14. Calculation and analysis results of x and y coordinates*

**4. Future works and Conclusions**

One possible direction to improve the segmentation and recognition algorithm is to make use of flame characteristics such as flame colour, intensity of flame brightness, shape, height, and flicker frequency. This is to augment the accuracy of video fire detection recognition. Another direction lies in the tracking and prediction of the direction of flame spread. A video based system which could do this, would be of assistance to those seeking refuge. It should be noted that experimental work is necessary for the testing and validation of different algorithms.
This paper presents segmentation and recognition algorithms using video flame detection analysis. The Otsu multi-threshold algorithm integrated with Rayleigh distribution analysis (modified segmentation algorithm) can produce clear flame only images. The Nearest Neighbour (NN) algorithm can be used to detect specific image types (e.g. flame images, images other than those of flames). This aspect requires more experimental study because it is important that accuracy is achieved in a video fire detection system. This study points towards the prospects of further development of video fire detection systems of practical fire services installations.

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