An Enhanced Vision-Based Approach to Detect Fires

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Abstract

This project will be used in teaching course "Engineering Computational Methods" course offered by Engineering and Physics Department of Oral Roberts University. The project will affect the research activity associated with computer engineering, electrical engineering, and mechanical engineering. It will transform the teaching strategy and redesign the course through the application of Matlab toolbox for the video image processing. With the image processing technology used and Matlab toolbox, more experiments and projects will be introduced to complement theoretical knowledge gained in the classes, with the goal of enhancing learning and increasing student enthusiasm and retention. Students will gain a deeper understanding of the material through hands-on experiences that emulate real life fire detection situations. The project will include the development of a research environment for both faculty and students based on video image processing on the fire detection using Matlab toolbox, resulting in more research achievements and applications on Matlab language learning and video image processing technology.

This paper describes the methodology to detect fire using image processing technology. All the experiments were implemented using Matlab image processing toolbox. In this paper, authors proposed an enhanced video image processing applied to the fire detection. The enhanced system is based on previous work done by the authors and which has been described in paper [5]. The previous work has been proven to be insufficient as many false alarms are generated in various cases. In this paper, additional features are added to it in order to eliminate the false alarms in several cases.

The additional features are: *sudden change detector*, *foreground mean colour computation* and *foreground colour element ratio computation* in order to eliminate the false alarms in several cases. Two additional features: *foreground bounding box* and *three-level alarm trigger* aim to improve the efficiency and sensitivity of the system.

Several experiments were conducted to verify the performance of the enhanced system. At the end of the paper, conclusions and possible further improvements are discussed.

1. Introduction

Video analysis has improved significantly in recent years. Since the introduction of digitalization to images (both motion and still), the analysis has become simpler and less time-consuming. Its usage also ranges greatly in various implementation areas.

A popular area of video processing implementation is security, which includes fire detection. Its recent implementation includes hydrocarbon fires detection and fire detection in aircraft dry bays [1]. A more general implementation which is able to work under various environments is discussed in [5]. [5] introduces three basic features which are sufficient in detecting growing fires. However, in several cases, such as background object removal, those basic features prove to be insufficient as the system generates false alarms where no fire exists in the monitored environment.

Many video-based image processing techniques have been applied to the fire detection [1-5]. In the system discussed in [5] there are three basic features which are sufficient in detecting growing fires. However, in several cases, such as background object removal and flickering controllable fire, those basic features have proven to be insufficient as the system generates false alarms. This paper introduces additional features: *sudden change detector*, *foreground mean colour element computation*, *foreground colour element ratio computation* and *three-level alarm trigger* to enhance the performance of the system.

2. Methodology

Using a camera to monitor the target area, images are sampled in frequency f and fed into the system. The images act as input, which further calculation and process are done to determine the existence of fire in the environment.

2.1 Background Learning Algorithm

A background image, symbolised by Ψ, is a collection of pixels that have slow intensity change and do not belong to any moving objects. Background learning is a process for a fire alarm system to learn from an environment to build up a background image which consists of all the non-mobile objects and no fire present in the scenario. Such a background image is not always available in practical, for example, in a airport or in a MRT (Mass Rail Transportation) station, there is always a constant movement of crowd -- people walking about at all times of the day. Hence it is difficult to obtain a static background image in this scenario. This is where the background learning algorithm comes in. The background learning algorithm extracts the background image, even when there are mobile objects or people moving around the target area continuously.

Illumination is an another important issue in video and image processing since different illumination may produce difference images. Background updating algorithm is introduced to make sure that the obtained background image is able to response to changing environment dynamically such as light changing due to sunset and sunrise. Figure 2.1a are samples of 100 crowd sequential images. The figure 2.1b is the background image obtained through the background learning algorithm. In the background image, only background (non-moving part) is extracted from the crowd sequential images.

Figure 2.1a: Sampled crowd images

Figure 2.1b: Background image

2.2 Three Basic Features

A foreground image, symbolised by *X*, is a collection of pixels that have rapid intensity change and belong to moving objects. In [5] three features, *foreground pixels, foreground intensity* and *colour temperature*, were employed to detect the existence of fire through video image processing. The features are calculated using a foreground image.

2.2.1 Foreground Pixels

At given time t, the foreground pixels P_t from an image frame f can be defined as:

$$P_t = \sum_{(x,y)\in\chi} P[f(x,y)] \qquad (1)$$

where (x,y) represents the coordinate of a pixel in the image frame. $P[f(x,y)]$ returns 1 when $f(x,y)$ is part of the foreground image and 0 otherwise.

2.2.2 Foreground Intensity

The system recognises the existence of a growing fire through increment in the image intensity. Let I_t be the foreground intensity of an image at time t, then we can define I_t as follows:

$$I_t = \sum_{(x,y)\in\chi} I[f(x,y)] \qquad (2)$$

where *I[f(x,y)]* returns the intensity value of a pixel coordinate in the image if *f(x,y)* is part of the foreground image.

2.2.3 Foreground Colour Temperature

Ishii et al in [4] estimated thermal values by obtaining colour element of fire images taken by a colour Charged Coupling Device camera. Hence we can use G/R ratio in determining the temperature of a foreground image. This computation result is called *colour temperature* R_t and is defined as follows

$$R_t = \sum_{(x,y)\in\chi} \frac{G[f(x,y)]}{R[f(x,y)]} \qquad (3)$$

where *G[f(x,y)]* returns the green element value of the pixel coordinate *(x,y)* in the image and *R[f(x,y)]* for the red element value if *f(x,y)* is part of the foreground image.

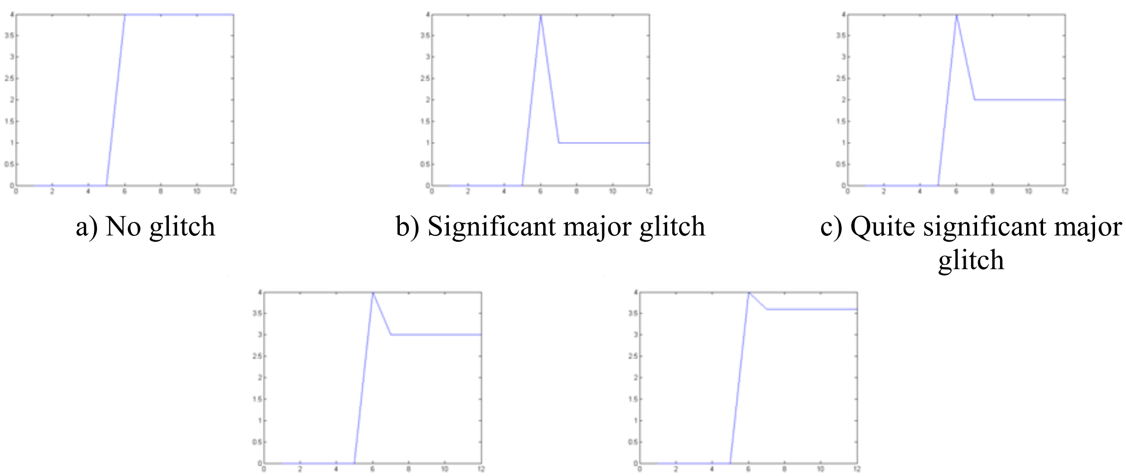
2.3 Additional Features

Even though the basic features are sufficient in detecting a possible fire threat, false alarms are generated by the systems in various special cases. In order to eliminate the false alarms, additional features are introduced to the system.

2.3.1 Sudden Change Detector

A sudden existence of objects (e.g. people walking by, etc.) may trigger false alarm in the system. This is due to sudden rise in the three basic features, which may cause the alarm level indicator to go beyond the threshold value. *Sudden change detector (glitch detector)* feature is introduced to tackle the false alarm problem. The activation of feature is triggered when any of the features' value changes beyond the *change-limit threshold* values. These glitches are categorized as *major glitches*, and are further categorized into:

- Significant major glitches
  Value drops/rises suddenly then rises/drops to ≤ 25% of the sudden change.
- Quite significant major glitches
  Value drops/rises suddenly then rises/drops to ≤ 50% of the sudden change.
- Insignificant major glitches
  Value drops/rises suddenly then rises/drops to ≤ 75% of the sudden change.
- Minor glitches
  Value drops/rises suddenly then rises/drops to ≤ 95% of the sudden change.



a) No glitch b) Significant major glitch c) Quite significant major glitch

d) Insignificant major glitch e) Minor glitch

Figure 2.3a: Types of glitches

Each feature is assigned a single counter (*variable glitch counter*). Each of these glitches contributes a different value towards the respective *glitch counter*. At the end, each counter is compared to its respective *variable glitch threshold* during *decision-making phase*. Figure 2.3a shows the types of glitches.

2.3.2 Foreground Mean Colour Element Computation

At time t, M_R, M_G and M_B define the mean values of red, green and blue colour element of the foreground object in the image respectively and are defined as:

$$M_Z = \frac{\sum_{(x,y)\in\chi} Z[f(x,y)]}{\sum_{(x,y)\in\chi} f(x,y)} \qquad (4)$$

,

where Z = R, G and B for red, green and blue element. *R[f(x,y)], G[f(x,y)] and B[f(x,y)]* returns the red, green and blue colour element values of pixel coordinate in the image respectively if *f(x,y)* is part of the foreground image.

For a red-flame fire, M_R, M_G and M_B fall within certain range of values, i.e.

$$M_{R(min)} < M_R < M_{R(max)} \qquad (5)$$
$$M_{G(min)} < M_G < M_{G(max)} \qquad (6)$$
$$M_{B(min)} < M_B < M_{B(max)} \qquad (7)$$

Using this colour element range of fire image, i.e. *if [(5) ∩ (6) ∩ (7)] = true,* the possibility of fire existence in the monitored environment increases.

Foreground Bounding Box: Since the algorithm involves a lot of computation on the foreground image, there comes a necessity to limit the area which need to be focused on to minimise the computation time. It is where the *foreground bounding box* feature comes in to provide the ability to create a border surrounding the foreground part, so that the system may ignore the unnecessary part during the execution of other features.

The creation of the bounding box is done by automatically checking the foreground image pixel-by-pixel and determining the X_{min}, X_{max}, Y_{min} and Y_{max} values of the current foreground image. An image with foreground bounding box is shown in Figure 2.3b.

Left - Image without foreground bounding box
Right - Image with foreground bounding box

Figure 2.3b: Foreground bounding box

2.3.3 **Foreground Mean Colour Ratio Computation**

In the enhanced system, other colour ratios are taken into consideration in determining the existence of fire and thus, increase the sensitivity of the system. The colour ratios used are

- Blue-green colour element ratio: $\frac{M_B}{M_G}$
- Blue-red colour element ratio: $\frac{M_B}{M_R}$
- Green-red colour element ratio: $\frac{M_G}{M_R}$

For a red-flame fire, $\frac{M_B}{M_G}$, $\frac{M_B}{M_R}$ and $\frac{M_G}{M_R}$ fall within certain range of values, i.e.

$$\frac{M_B}{M_G}_{\min} < \frac{M_B}{M_G} < \frac{M_B}{M_G}_{\max} \qquad (8)$$
$$\frac{M_B}{M_R}_{\min} < \frac{M_B}{M_R} < \frac{M_B}{M_R}_{\max} \qquad (9)$$
$$\frac{M_G}{M_R}_{\min} < \frac{M_G}{M_R} < \frac{M_G}{M_R}_{\max} \qquad (10)$$

Using this colour element ratio range of fire image, i.e. *if [(8) ∩ (9) ∩ (10)] = true,* the possibility of fire existence in the monitored environment increases.

2.3.4 **Three-level Alarm Trigger**

Another additional feature is the implementation of three-level alarm trigger. The aim of this alarm system is to provide the flexibility to the user in taking the best possible actions necessary depending on the current alarm level (threat level) posed by the possible fire existence in the monitored environment. The *three-level alarm trigger* is defined as

- Green-level alarm (GA): no possible growing fire detected
- Yellow-level alarm (YA): possible growing fire detected
- Red-level alarm (RA): highly possible growing fire detected

2.4 Decision Making Phase

Consider an foreground image $f_t(x,y)$ with time index t = (0, 1, 2, …). With the assumption that the images are taken at a constant rate with i and j as the time indices where $j = i + 1$, the three counters: *p.counter, i.counter* and *r.counter* (referring to the counter used by *foreground pixels*, *foreground intensity* and *foreground colour temperature*) are defined as follows:

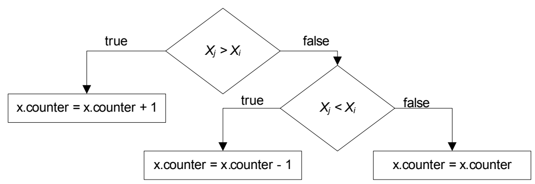


Figure 2.4a: Three features growth counter

In *Figure 2.4a*, x = p represents foreground pixels, x = i for foreground intensity and x = r for foreground colour temperature. The alarm level counter C_{total} is determined using the combination of the 3 counter values defined as follows:

$$C_{total} = w_p * p.counter + w_i * i.counter + w_r * r.counter \qquad (11)$$

where w_p, w_i and w_r represents the multiplication factor of *p.counter*, *i.counter* and *r.counter* respectively and $w_p + w_i + w_r = 1$.

The C_{total} value calculated is then compared with the *alarm threshold value* – a constant value to determine the level of sensitivity of the system in the environment. The additional features act as a monitor to the basic features. This is done so since the basic features are *sufficient* in detecting the fire existence but *insufficient* to prevent false alarm in some cases. The additional features indicate whether any possible errors, such as glitches, have occurred during the calculation of C_{total}. As for the monitors, *colour mean factor* returns 2 if (5), (6) and (7) in *section 2.3.2* is hold and zero otherwise. *Colour ratio factor ratio* returns 2 if (8), (9) and (10) *in section 2.3.2* is hold and zero otherwise.

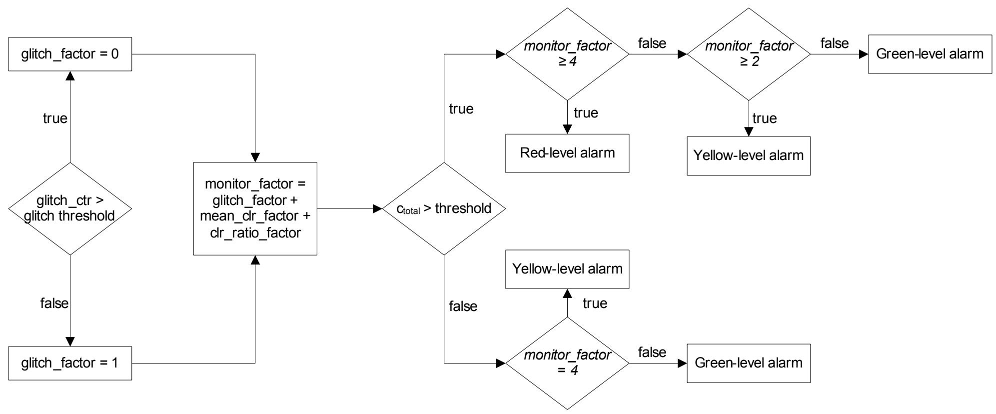


Figure 2.4b: Final decision making process

3. Experiment

Several experiments using *Matlab 6.5* were conducted to test the new enhanced fire detection system. For these experiments (*day time fire images, static controllable fire images, sudden object removal images)*, image sampling rate is 3 images/sec., decisions were made every 5 frames. w_p= 0.2, w_i = 0.2 and w_r = 0.6. Alarm threshold value = 1.5.

3.1 Day Time Fire Images

100 sequential images showing a growing fire during daytime were fed into the system.

Figure 3.1a: Day time fire 5th, 50th, 60th and 90th images

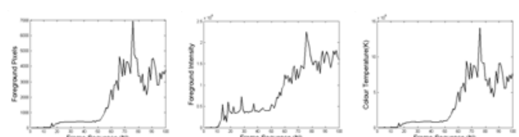


Figure 3.1b: Three features for daytime fire images

Frame sequence	**5th**	**50th**	**60th**	**90th**
C_{total} / *monitor_level*	1/1	4/2	7.8/4	6.6/5
Alarm triggered	**GA**	**YA**	**RA**	**RA**

Table 1: Daytime fire images experiment result

As shown in *Figure 3,* the fire started to grow rapidly in the 50th frame. Since the system is designed to be quite sensitive (*alarm threshold value* =1.5), the system directly triggered *yellow-level alarm.*

3.2 Sudden Background Object Removal

60 sequential images showing immobile objects were fed into the system. An object (bottle) was placed in front of the camera and was recorded with the surrounding objects. After some time, the bottle was removed in upward direction from the sight of the camera.

Figure 3.2a: Sudden background object removal, 20th, 40th, 50th and 60th images

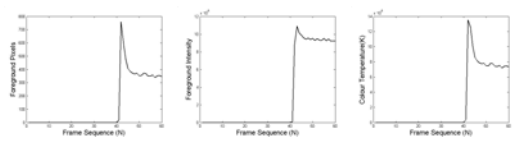


Figure 3.2b: Three features for sudden background object removal images

Frame sequence	**20th**	**40th**	**50th**	**60th**
C_{total} / *monitor_level*	0/1	0/1	0.2/1	0.2/1
Alarm triggered	**GA**	**GA**	**GA**	**GA**

Table 2: Sudden background object removal images experiment result

As shown in *Figure 3.2b,* starting from the 40th frame, each graph shows a major glitch due to the removal of object from the sight of camera (sudden change).

3.3 Static Controllable Fire Without Wind

45 sequential images showing immobile objects were fed into the system. A lit candle was placed in front of the camera. During the experiment, no external disturbance (wind) was introduced to the system.

Figure 3.3a: Controllable fire without wind, 5th, 15th, 30th and 45th images

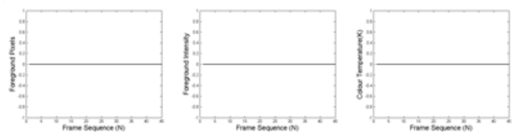


Figure 3.3b: Three features for controllable fire without wind

Frame sequence	**5th**	**15th**	**30th**	**45th**
C_{total} / *monitor_level*	0/0	0/0	0/0	0/0
Alarm triggered	**GA**	**GA**	**GA**	**GA**

Table 4: Static controllable fire (without wind) images experiment result

All three graphs in *Figure 3.3b* do not show any change in its value. This happens when the environment is stabile (no object movements in the monitored environment).

3.4 Static Controllable Fire With Wind

A similar experiment with the previous experiment was conducted. However, in this experiment an external disturbance factor (wind) was introduced.

Figure 3.4a: Controllable fire with wind, 5th, 20th, 30th and 50th images

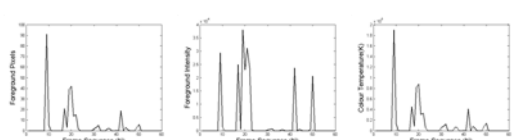


Figure 3.4b: Three features for controllable fire with wind

Frame sequence	5th	20th	30th	50th
C_{total} / *monitor_level*	0/1	1.6/2	1/1	2.2/3
Alarm triggered	**GA**	**YA**	**GA**	**YA**

Table 3: Static controllable fire (with wind) images experiment result

The graphs' glitches in *Figure 3.4b* happen due to the flickering of fire. Due to the sensitivity of the system, *yellow-level alarm (warning,* not false alarm) was triggered by the system. This problem can be tackled by raising the *alarm threshold value*.

4 Conclusion

Based on the three basic features in [5], additional features are added on the system to enhance the performance of the system. Three new features *sudden change detector*, *foreground mean colour element computation* and *foreground colour element ratio computation* introduced to minimise the possibility of *false alarm* occurrences, while the other additional feature: *level alarm trigger is* to increase the sensitivity of the system. These experiments' results have shown improved performance of the new enhanced fire detection algorithm.

5 References

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6 Biographical Information

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