Accurate Fire Detection System for Various Environments using Gaussian Mixture Model and HSV Space

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Received: 23/Sep/2012 Accepted: 21/Oct/2012

Abstract
Smart and timely detection of fire can be very useful in coping with this phenomenon and its inhibition. Enhancing some image analysis methods such as converting RGB image to HSV image, smart selecting the threshold in fire separation, Gaussian mixture model, forming polygon the enclosed area resulted from edge detection and its combination with original image, this papers addresses fire detection. Accuracy and precision in performance and rapid detection of fire are among the features that distinguish this proposed system from similar fire detection systems such as Markov model, GM, DBFIR and other algorithms introduced in valid articles. The average accuracy (95%) resulted from testing 35000 frames in different fire environments and the high sensitivity (96%) was quite significant. This system be regarded as a reliable suitable alternative for the sensory set used in residential areas, but also the high speed image processing and accurate detection of fire in wide areas makes it low cost, reliable and appropriate.
Keywords: Fire Detection, Gaussian Mixture Model, Image Processing, HSV Space, Edge Detection.

1. Introduction

Fire Detection is an important issue in today's world because it directly threatens the life of living organisms, especially human life. Researches dealing with fire detection have always been important since the spread and the impact of fire detection in residential areas, business centers, industrial areas and open areas is critical. However, the field of smart fire detection is not confined to these areas. Fire detection without human intervention seems necessary in jungles, parks and farms too. The conventional sensors of fire detection such as environmental heat detector or smoke detector has a significant role in fire and smoke detection. Nevertheless, recent studies have shown that in large places and buildings, smoke detectors and heat sensors are not desirables due to point detection [1]. On the other hand, the employment of these systems in such open areas as jungles and spacious storages is expensive, having reduced capability and accuracy and unable to entirely cover these areas. In jungles, we need monitoring, employing human resources and large quantity of sensory network. Fire detection through image processing system is a new method based on one or some main color indexes, composition or formal structure and brightness. In some methods, colored mass of fire used for fire detection. Turgay et al [2] attempted to detect fire using fuzzy logic and

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colored mass of fire. Of course they first attempt to trace the smoke in video sequences, but they detect fire flames by using combine methods in next steps. Wirth and Zaremba [3] developed an efficient system by analyzing Back projection histogram image and properties of fire pixels in the image. Flame region is target for them in video sequences with high rate detection to prevention from sudden firing in apartments. Cho and Bae [4] proposed a system which drew upon statistical models of flame color combination and image processing techniques. Xu and He [5], using neural-fuzzy grids in residential buildings, developed a fire detection system. This system is designed as alarm system in high-rise building. The main application in high-rise building was reason to detect the fire events. Chen and Chiou [6] also used image processing method for fire detection. But the main advantage of this system is prediction of fire events. Firstly the proposed system by tracking smokes in ambient, predicts the probability of fire event and so is called early fire-detection system. Phillips et al. [7] suggested an algorithm based on color and data obtained from flame movement in video images. Video sequences are analyzed by using image and video processing techniques in their work. Haralick et al. [8] detected fire flames using gray-level matrix (GLCM) and wavelet analysis as well as extraction of contextual features of image. Another method suggested by Healey et al. [9] drew on colored data of image for fire detection. But their work was real-time system that uses image processing techniques and features extracted from fire flames in images. Liu and Ahuja [10], used formal combination of fire for the sake of fire detection in Fourier transform space. They attempt to develop the accuracy and process speed for early fire detection.

In some of these systems, fire detection takes more than tens of seconds. Obviously, this problem would be very serious because the fire detection in early stages is very important in extinguishing fire. Low accuracy in detecting fires is another problem observed in some other methods. For example, the location of growing areas of fire is not addressed in some methods. Thus, there seems to be a need for a smart efficient system which is capable detecting fire accurately and rapidly. Using enhanced image processing techniques, this paper introduces an accurate reliable system.

2. The Proposed System

The method proposed for detection of the fire flames in this paper draw mainly on video processing techniques to detect the target area.

2-1Threshold

The brightness intensity of a gray-scale image can only vary between [0-255]. This is a very useful feature. Partial separation of an image through selecting appropriate threshold is based on dividing the image into background and foreground classes [11]. One of the effective methods in image processing, which is often used to separate the background from image, is threshold method which is based on selecting an appropriate threshold from image histogram. The more careful is this selection, the more accurate will be the accuracy of separating image background from its main framework. In image processing, mainly symmetrical threshold method is used. Image histogram will be split in half at t_0. Then, as to brightness intensity of $t < t_0$, $t > t_0$ average value will be calculated and we will be able to witness the greater average (either on left or right side). Thus, by changing the value of t_0 within certain brightness intensity, the means become equal, or at least, the difference between these two means becomes smaller than a minimal number. However, if partial separation of image is conducted according to brightness intensity, the threshold value or boundary is considered as the basic brightness intensity in division. That is, brightness intensities greater than threshold value will be equal to 1 and brightness intensities less than that will be equal to 0. Thus, we will have a binary image consisting of zero and one elements. Hence, the threshold of the image f (x, y) means to convert it into a binary image according to Eq. (1):

$$g(x,y)=\begin{cases}1 & f(x,y)\geq T\\ 0 & f(x,y)\leq T\end{cases} \tag{1}$$

where T is the selected threshold in separating background and foreground of the image. Figure 1 displays the stages of separation process based on overall separation for selecting appropriate threshold.

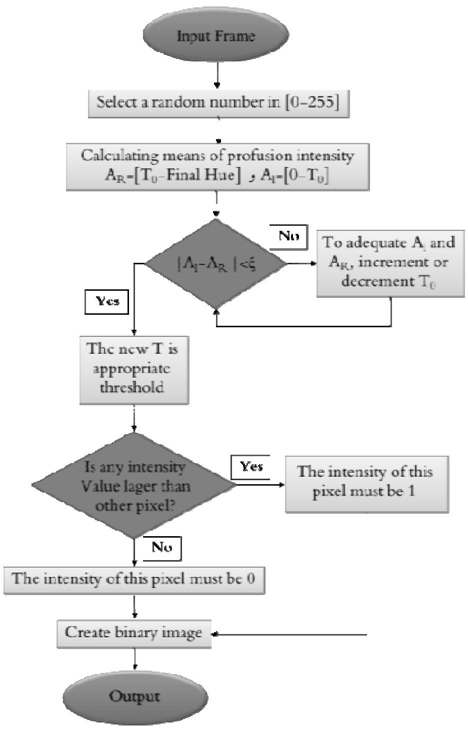


Figure 1. separation based on overall threshold selection

Drawing on this procedure, which is commonly called overall thresholding, the ideal condition takes place when there are sufficient changes between different parts of image. To select proper threshold for separating fire from other parts of image, in some methods, the formal and colored combination property will be used [12]. In Figure 2, the histogram of three constituting spectrum of RGB image for a random frame has been displayed. The main advantage of the histogram is capability detection the adequate threshold in image.

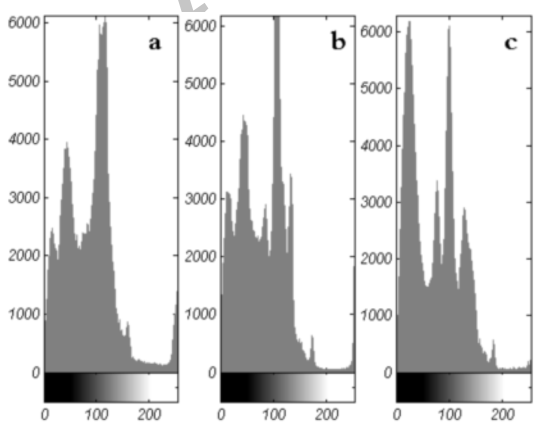


Figure 2. (a) Histogram of Red (b) Green and (c) Blue components in original frame

2-2 Gaussian Mixture Model

The subtraction of the backgrounds of a video sequence from each other is a method by which the target foreground section in each frame is separated. Among the conventional methods of thresholding, Gaussian mixture model is one of the techniques used for separation and display of different background images [13]. According to Eq. (2), Gaussian model for each pixel is the Gaussian density, i.e.:

$$p(x)=\frac{1}{\sqrt{2\pi\sigma}}\exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right] \qquad (2)$$

Where μ is the mean intensity of pixels brightness and σ is the variance. By constructing probability density function (PDF) with μ and σ variables, each pixel in each frame is distributed by K mixture in Gaussian model and the probability of the pixel having the value of X_n at the time of N is calculated according to Eq. (3):

$$P(x_N)=\sum_{j=1}^{K} w_j \eta\left(x_N,\theta_j\right) \qquad (3)$$

In which w_K is the weight parameter of K Gaussian factor and $\eta(x,\theta_K)$ is the normal distribution of K factor, which is calculated according to Eq. (4).

$$\eta(x,\theta_k)=\eta(x,\mu_k,\Sigma_k)\frac{1}{(2\pi)^{D/2}|\Sigma_k|^{1/2}}\exp(Z) \qquad (4)$$

μ_k and Σ_k are respectively mean and covariance of K factor and $Z=\left[-\frac{1}{2}(x-\mu_k)^T\Sigma_k^{-1}(x-\mu_k)\right]$. The number of distribution K is estimated according to the w_K divided σ_k sufficiency function and the first distribution of (B) is used as a foreground model. B function is calculated according to Eq. (5)

$$B=\arg\min_b\left(\sum_{j=1}^{b} w_j > T\right) \qquad (5)$$

where T threshold is the lowest decimal value in the foreground model.

2-3 HSV Space

The space which is useful for segmentation of the fire is the conversion of HSV space. Using the features of color space change in HSV, the fire position can be detected by calculating the final area relative to the area of the original image. Using features of color space change in HSV space, the complexity between the level of image and undesired light intensity, which can produces error, is largely reduced. Section H is formed after converting RGB input image into HSV space according to M=max (R, G, B), m=min (R, G, B) and d=M-m. Finally RGB image in form of Figure 1 is converted into HSV space. The values of r, g and b is calculated as a set of $b = (M - B)/d$, $g = (M - G)/d$ and $r = (M - R)/d$. All three H, S and V components change in [1-0] interval.

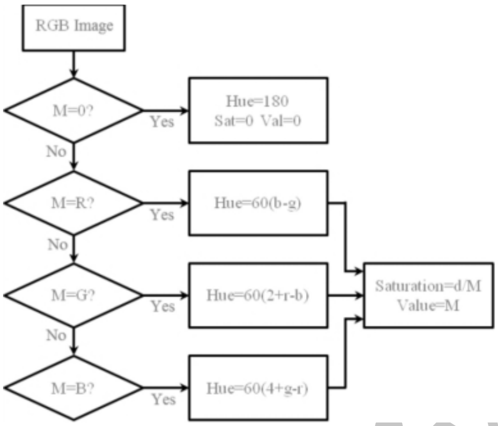


Figure 3. The final diagram of converting RGB space into HSV space for input frames contain fire flames

After converting image from RGB to HSV space, considering the difference between fire color and changes in the image histogram, we will separate the fire. During the conversion, the foreground and background are separated. Figure 4 shows a set of frames taken from a video sequence with threshold implementation as well as application of conversion to HSV space and Gaussian mixture model.

Figure 4. Images from top left to the right show 89 to 94 frames of a sample video sequence from the a fire event, in amidst column frames is converted to the HSV space and in the bottom column, the images produced after using Gaussian mixture model and thresholding has been presented in RGB format.

2-4 Edge Detection and Image Combining

Edge detection is one of the most widely used techniques in image processing in which basic components of the image like the framework of original image are extracted. Edge detection is the use of gradient matrix to detect those image pixels whose brightness intensities have sudden changes in contrast to their adjacent pixels [14]. This technique usually draws on first order and second order derivatives for each pixel. The operator of the first order derivative displays pixels in which the range of brightness intensity is greater than defined threshold value in the same part of image, and second order derivative seeks to find intersecting points of zero-crossing. If we display original image with f (x, y) the first order derivative will be $\frac{\partial f}{\partial x}$ and $\frac{\partial f}{\partial y}$. Pixel gradient of (x, y) is $\nabla\vec{f}$ which has been shown in Eq. (6):

$$\nabla\vec{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \qquad (6)$$

Where G_x and G_y respectively are the gradient along the x and y-axis, and the value of gradient operator has been introduced in Eq. (7):

$$\nabla f = \left[G_x^2 + G_y^2\right]^{1/2} \qquad (7)$$

In discrete space, variables x and y are replaced by quantized values of discrete m and n that represent the position of pixels in the image. Thus, the gradient is calculated in form of equation (8):

$$\nabla f = \sqrt{f_x^2(m,n) + f_y^2(m,n)} \qquad (8)$$

Where f_x and f_y are resulted gradients along X and Y axis respectively. To remove the extra elements that are associated with the threshold process, we use a range between [1-0] in edge detection. That is, if after processing of an edge pixel, the number of its adjacent pixels is less than a basic value, the brightness intensity of the target pixel becomes zero; otherwise, it will retain its previous brightness intensity. These two operators are applied to the images obtained from threshold stage.

For graphical display of fire and precise detection of its location, the brightness intensity of new edge color spectrum is turned into a red spectrum. If the original image is F and restructured colored edge matrix is t, then according to equation (9) we will have:

$$F(t) = 0 \qquad (9)$$

Thus, all elements of F matrix which are similar to zero elements of t remain and other elements become zero. Filling polygons of empty and enclosed areas is an algorithm which is carried out according to data structures, morphological properties and partial image processing. Filling the internal area of an enclosed region takes place within two classes of polygon filling and pixel filling [15]. Drawing on morphological reconstruction algorithm [16][17] of image which is based on technique of edge formal repairing, and using constructive lines of polygon, we will retrieve the data lost during threshold stage. It, thus, increase the accuracy of this stage. In Figure 5, the Filling polygons edge detection and combining images to trace the fire flames is shown.

Figure 5. Images from top left to the right show new edge image after filling polygon and and in the bottom column the final composition of the fire location and original image is shown.

3. Performance Analysis

The system was implemented on 57425 video frames taken from AMC channel [18] and video sequences containing the occurrence of the fires. There were 7 fire event cases in video sequences. All sequences were randomly converted into 4 categories of Movie with these details: AVI format, 120 × 160 pixels resolution and 15 fps. In Table 1, mean accuracy (MAC) and detection rate (DR) and false alarm rate (FAR) have been calculated according to Eq. (10) to Eq. (12) which are used for measuring the accuracy of detection in video sequences.

$$AAC = \left(\frac{N_{TP} + N_{TN}}{N_{TP} + N_{TN} + N_{FP} + N_{FN}}\right) \times 100 \quad (10)$$

$$DR = \frac{Number\ of\ True\ Positive}{Number\ of\ Fire\ Video\ Frames} \quad (11)$$

$$FAR = \frac{\sum Detected\ ROI}{Number\ of\ Video\ Frames} \quad (12)$$

In these equations,

$\mathbf{N_{TP}}$ is the number of frames in which fire flames has been detected by the algorithm.

$\mathbf{N_{FN}}$ is the number of frames in which the algorithm has failed to detect fire flames.

$\mathbf{N_{TN}}$ is the number of frames in which there is no sign of fire flames and the algorithm has not detected any by mistake.

$\mathbf{N_{FP}}$ is the number of frames in which there is no sign of fire but the algorithm has detected some by mistake.

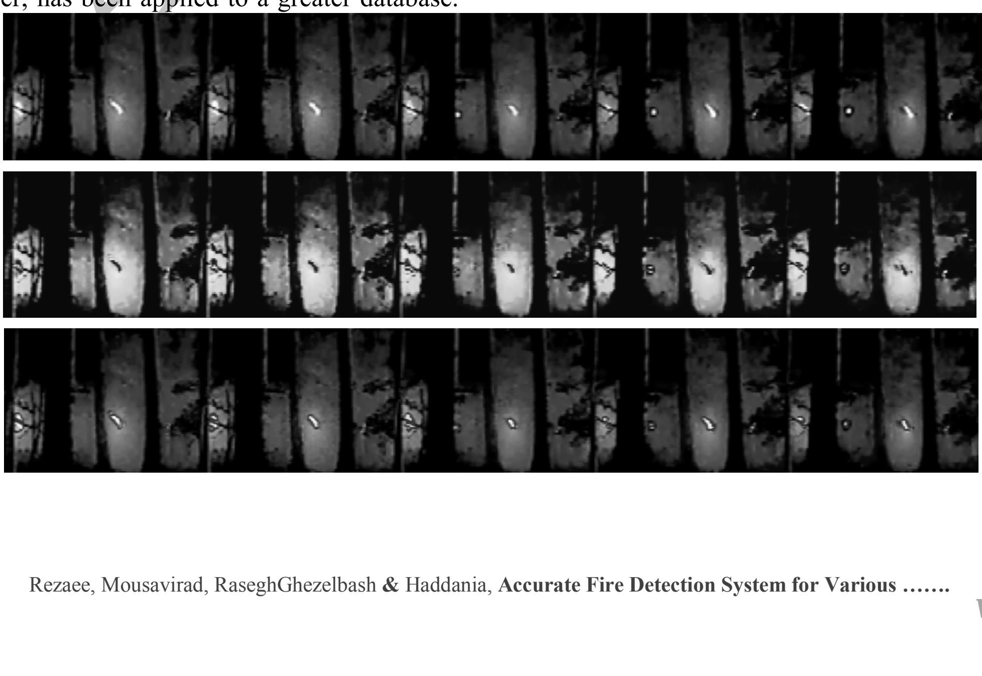
And ROI is also the objective area in the image which includes all three signs of fire in the ambient.

Table 1: How average accuracy, detection rate and false alarm rate are calculated.

Video Clips	***No. Frames***	The number frames with fire flames		The number frames without any fire events		Average Accuracy (AAC)	Detection Rate (DR)	False Alarm Rate (FAR)
		N_{TP}	N_{FN}	N_{TN}	N_{FP}			
Movie 1	10755	128	7	283	14	95.13%	94.81%	4.71%
Movie 2	5690	45	0	134	8	95.72%	100%	5.63%
Movie 3	9661	96	3	168	16	93.28%	96.96%	8.69%
Movie 4	8917	89	2	197	9	96.29%	97.80%	4.36%
Total	**35023**	**358**	**12**	**782**	**47**	**95.105%**	**97.39%**	**5.84%**

$SP = \left(\frac{N_{TN}}{N_{TN} + N_{FP}}\right) \times 100$ and $SE = \left(\frac{N_{TP}}{N_{TP} + N_{FN}}\right) \times 100$ are specificity and sensitivity which were respectively equal to 94.33% and 96.75%. It should be noted that this method is a new technique and a comparison has been drawn between the performance of this system and other methods used for detection of the fire events. Different methods use various databases. The proposed method in this paper, however, has been applied to a greater database.

At first, it should be noted that the use of a single camera would decrease the sensitivity and specificity of the third technique in contrast to other two techniques. Figure 6 displays the implementation of this method as well as detection of the location and condition of fire spread in different spaces. The experiments show that the algorithm is reliable and accurate. Also the fire experiments show that the shape and color of flame change randomly in fire image sequences.



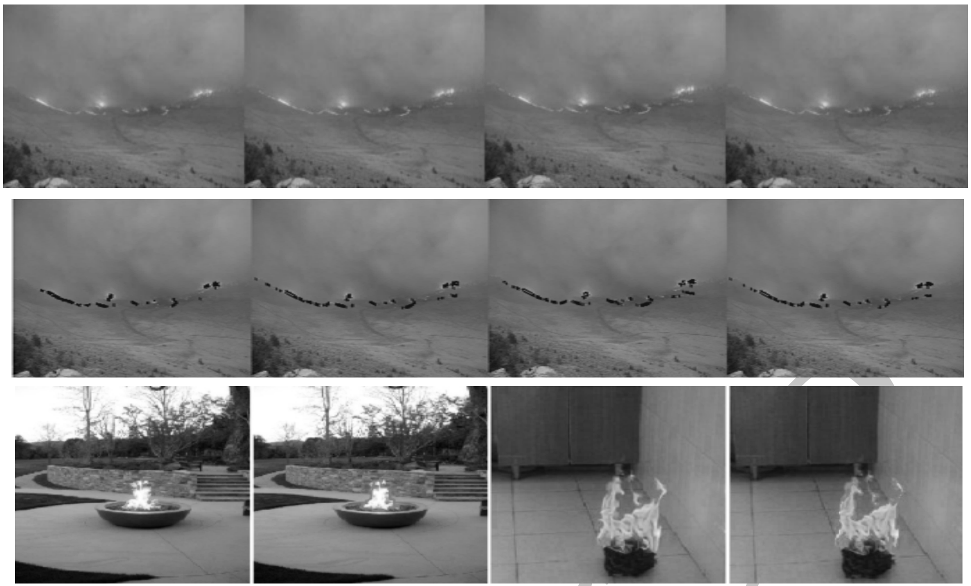


Figure 6. Implementation the proposed algorithm on 2 clips which contain fire events. The algorithm is implemented on two images in bottom coloumn

3-1 Discussion

The occurrence of error is only natural. Using multiple cameras, which simultaneously identify fire events, increases the accuracy, sensitivity and specificity of this system more than the other two techniques. Table 2 shows the greater ability of the system in detecting the occurrence of a fire. Inconsistency is another problem that may occur when decreasing the frames and the resulted time delay might result in lower sensitivity. In Figure 7 the proposed algorithm has been compared in 15 images using DFBIR and GM [19][20] methods. Randomly selecting 15 images out of 83 tested images, the average accuracy of 95% was compared in Table 2 with valid techniques. The highest accuracy belonged to the jungle image with 515×972 resolution and 99.58% accuracy. The least accuracy in detection of fire belonged to the image of house flames with 689×1034 resolution and 94.07% accuracy.

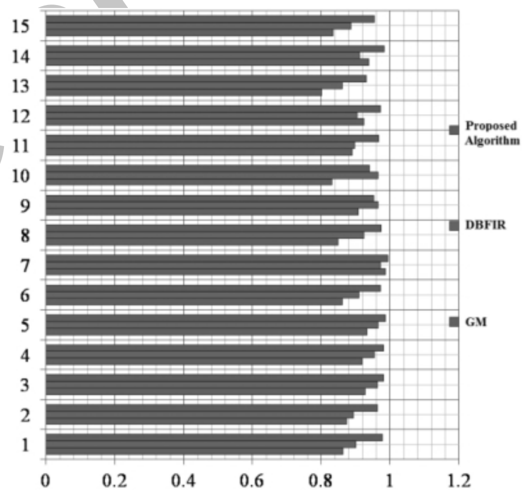


Figure 7. Comparison of the proposed algorithm with DFBIR and GM

Table 2. Comparison of detection rates and false alarm rates in different techniques with proposed algorithm

Technique	Detection Rate	False Alarm Rate
Chen et al [6]	93.90%	66.42%
Celik et al [21]	78.50%	28.21%
Celik et al [22]	97.00%	78.39%
YCbCr [2]	99.00%	31.00%
Lee [23]	85.2%	1.7%
Proposed Algorithm	97.39%	5.84%

4. Conclusions

This paper proposed a system with high accuracy and efficiency which was able to detect fire and its expansion pattern in a short time. In contrast to other fire detection, the performance of the proposed algorithm was at an acceptable level with an average error of 5% and sensitivity of 96%. The implementation of this system in residential and industrial areas as well as open areas such as jungles and farms obviates the need for employment of expensive sensory networks since such factors as low design cost, fast processing and response as well as high accuracy distinguishes this system from similar ones.

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