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DOI 10.1007/s11760-017-1102-y

ORIGINAL PAPER

Video fire detection based on Gaussian Mixture Model and multi-color features

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Received: 25 October 2016 / Revised: 16 April 2017 / Accepted: 22 April 2017

Abstract This paper proposes a new approach to detect fire from a video stream. It takes full advantage of the motion feature and color information of fire. Firstly, motion detection using Gaussian Mixture Model-based background subtraction is applied to extract moving objects from a video stream. Then, multi-color-based detection combining the RGB, HSI and YUV color space is employed to obtain possible fire regions. Finally, the results of the above two steps are combined to identify the accurate fire areas. The experimental results obtained by applying this method on different fire videos show that the proposed method can achieve better effectiveness, adaptability and robustness.

Keywords Video fire detection · Gaussian Mixture Model · RGB · HSI · YUV

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1 Introduction

Early fire detection plays an important role in the prevention of life and property safety [1]. However, conventional fire detection technologies [2] use built-in smoke and temperature sensors. It takes a long time to activate sensors, which may have already caused injuries and damages. The detection radius of sensors is limited [3] and cannot be applied to an open or large space, such as forest [4]. Moreover, these detectors cannot give valuable information about fire such as location, scale [4,5] and burning degree [6]. In addition, the conventional sensors may produce errors (false alarm) [7].

Currently, with the wide use of digital cameras and advancement of video processing techniques, video fire detection [8,9] shows better flexibility, effectiveness and reliability and presents solutions to the above-mentioned problems caused by traditional sensors. Furthermore, video fire detection can make full use of existing video equipment. Therefore, video fire detection is attracting more and more attention among researchers.

Several outstanding achievements have been made in video fire detection. Cetin et al. [10] provided a comprehensive review of the state-of-the-art video fire detection methods in recent years, where color being as one of the important features used in many approaches to determine the fire-like candidate regions. Commonly used color spaces [11,12] in this review are RGB [5,9,13–17], YUV [8,18], YCbCr [19–22], HIS [6], HSV [23,24]and the combination of these different color spaces [2], YUV/RGB [25], YCbCr/RGB [26], RGB/HSI [2,27,28], RGB/HSV [29]. Shidik et al. [30] presented a fire detection method using a multi-color features in the RGB, HSV and YCbCr spaces.

By studying these methods, we propose a new approach, which uses Gaussian Mixture Model as a background subtraction method and employs a multi-color features using the

RGB, HSI and YUV spaces to detect fire. This method makes use of the motion character and the advantages of three color spaces. The organization of the remainder of this paper is as follows: Sect. 2 illustrates a detail description of the method we proposed. The result and discussion of the experiment appear in Sect. 3. Finally, there is a conclusion in Sect. 4.

2 Fire detection

The approach proposed in this paper is mainly composed of two critical steps: (1) motion detection using Gaussian Mixture Model-based background subtraction; (2) a multi-color model is used over moving objects to filter out non-fire objects. The detail description of each step will be presented in the following subsections.

2.1 Motion detection

Identifying moving objects from a video is a fundamental and critical task in many computer-vision applications [31]. Because fire can be naturally viewed as a moving object in the video, the motion character can be utilized to determine the fire-like region.

Background subtraction [2,9,15,28,32], being as one of outstanding moving object detection algorithms, has been applied extensively in the video fire detection.

In order to filter out the file-like background object in video streams, Gaussian Mixture Model [33]-based background subtraction is used as the first step of the proposed method to remove the disturbance of background and detect moving objects in the foreground. The GMM models the values of each pixel as a mixture of K Gaussian distributions. The GMM algorithm outperforms other background modeling algorithms in terms of effectiveness, robustness and adaptability. The formula is defined as follows.

$$R_{motion}(i, j, n) = gmm(I(i, j, n)) \tag{1}$$

where I denotes the nth image frame in a video stream. R is the result of the GMM algorithm, namely foreground moving region. Function gmm() indicates the operation of the Gaussian Mixture Model algorithm. Figure 1 shows the results of motion detection using the GMM over three different fire video streams.

2.2 Multi-color detection

It is well known that color is the most notable feature of fire, which has been widely used for distinguishing the fire from other objects. Therefore, the second step of the proposed approach is color detection, which combines the RGB, HSI and YUV color spaces to obtain the possible fire areas.

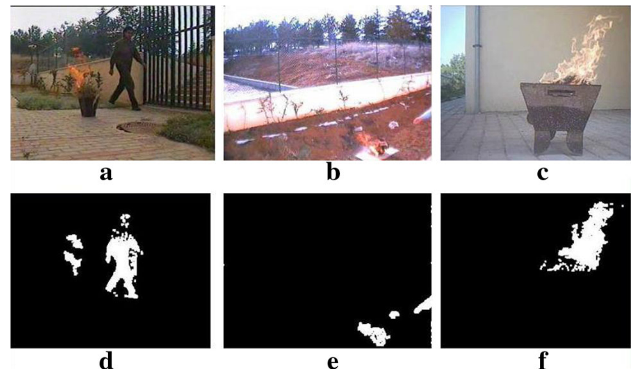

Fig. 1 Result of motion detection using Gaussian Mixture Model. **a**–**c** Original images from three different videos streams. **d**–**f** Moving objects detected in foreground corresponding to **a**–**c**, respectively

2.2.1 RGB

The reason for using RGB is that almost all visible range cameras capture video in RGB format [10] and the spectral content obviously associates with RGB space. According to previous approaches on fire detection and analysis of fire images, there are various colors of fire. And red-to-yellow color range is the initial stage of the fire exhibition. The corresponding RGB value is defined as $R \geq G > B$. In addition, because of the domination of R channel in the fire image, R should be given a larger value. And this adds another condition for R, that R has to be over a threshold R_T. However, the background light condition may have an adverse effect on the saturation of fire, resulting in false fire detection (non-fire pixels are regarded as fire). The saturation values of pixels, therefore, should also be set to a higher value than a threshold to avoid the influence mentioned above. Based on these facts, the rules summarized in [27,28,34,35] are employed in our research to extract fire candidates from an image and presented in following description:

$$Rule1: R \geq G > B \tag{2}$$

$$Rule2: R > R_T \tag{3}$$

$$Rule3: S > (255 - R) * S_T / R_T \tag{4}$$

where R, G, B are the red, green and blue components of a pixel. R_T denotes the threshold value of R component, ranging from 55 to 65, while S_T denotes the threshold of saturation and $115 \leq S_T \leq 135$ [27,35]. A pixel can be viewed as a possible fire candidate pixel if it meets all rules (2), (3) and (4). Meanwhile, $R_{RGB}(i, j, n)$ is used to represent the possible fire region, which is determined by the above RGB color model.

2.2.2 HSI

HSI describes the color space using hue, saturation and intensity from the view of the human visual system. Compared with RGB, HSI is more suitable for simulating the color sensing properties of the human visual system [6], because the hue and saturation components are intimately related to the way in which human beings perceive color [35].

According to the analysis of fire features, the values of hue for fire from 0 to 60 correspond to the red-to-yellow range. As mentioned in Sect. 2.2.1, the background illumination has impact on the saturation of fire. The saturation got from the brighter environments is larger than that from the darker scenes. This is because that the fire will become the major and only illumination if there is no other background illumination [27]. In this case, there is more white in hue for fire. In order to guarantee enough brightness in video processing, the intensity should be given a value over certain threshold. Hence, the HSI-based rules [6,36,37] are used as the second part of multi-color detection to obtain the fire candidates denoted as $R_{\mathrm{HIS}}\,(i,\ j,n)$, which can be described as follows:

$$\text{Rule1: } 0 \leq H \leq 60 \tag{5}$$

$$\text{Rule2: } 20 \leq S \leq 100 \tag{6}$$

$$\text{Rule3: } 100 \leq I \leq 255 \tag{7}$$

where H, S and I are the hue, saturation and intensity components of an image, respectively. The HSI can be translated from RGB using formulas (8), (9) and (10) [38]. Similarly, only the pixel that simultaneously meets all three rules can be regarded as a candidate.

$$i = \frac{1}{3}(r + g + b) \tag{8}$$

$$s = 1 - \frac{3}{(r + g + b)}[\min(r, g, b)] \tag{9}$$

$$h = \begin{cases} \theta & \text{if } (b \leq g) \\ 360 - \theta & \text{if } (b > g) \end{cases} \tag{10}$$

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}[(r-g)+(r-b)]}{[(r-g)^2+(r-b)(g-b)]^{\frac{1}{2}}} \right\} \tag{11}$$

where r, g and b of RGB are normalized in range [0, 1].

2.2.3 YUV

YUV color space is used in multi-color model because of its importance that the separation between luminance and chrominance is more discriminate [22,31]. Moreover, YUV color space is insensitive to light condition and can reduce the effect of illumination changes. From the analysis of fire images, it obviously noticed that luminance value should be high, while the chrominance values should be low. The YUV-based rules [10] are introduced to extract possible fire areas marked as $R_{\mathrm{YUV}}\,(i,\ j,n)$:

$$\text{Rule1: } Y \geq Y_T \tag{12}$$

$$\text{Rule2: } |U - 128| \leq U_T \tag{13}$$

$$\text{Rule3: } |V - 128| \leq V_T \tag{14}$$

where Y is the luminance value while U and V are the chrominance values of a pixel. Values Y_T, U_T, and V_T are thresholds of Y, U and V, respectively, which are experimentally determined [39]. Finally, the union operation is utilized to combine the rules of RGB, HSI and YUV color spaces together to form the multi-color model, which is applied on an image to identify the fire candidate regions, defined as $R_{\mathrm{color}}\,(i,\ j,n)$.

$$R_{\mathrm{color}} = R_{\mathrm{RGB}} \cup R_{\mathrm{HSI}} \cup R_{\mathrm{YUV}} \tag{15}$$

The results of multi-color detection are illustrated in Fig. 2.

2.3 Combining motion and multi-color

From the detail analysis of the motion and color features of fire described above, we can conclude that using motion or multi-color detection alone to identify fire will lead to high false-alarms, because of appearance of other moving objects or fire-color objects. Consequently, we need to do further operation that combines the result of Gaussian Mixture Model and that of multi-color detection to make full use of motion and color feature to obtain the accurate fire region $R_{\mathrm{fire}}\,(i,\ j,n)$.

$$R_{\mathrm{fire}}(i,\ j,n) = R_{\mathrm{motion}}(i,\ j,n) \cap R_{\mathrm{color}}(i,\ j,n) \tag{16}$$

Figure 3 shows the result of combination.

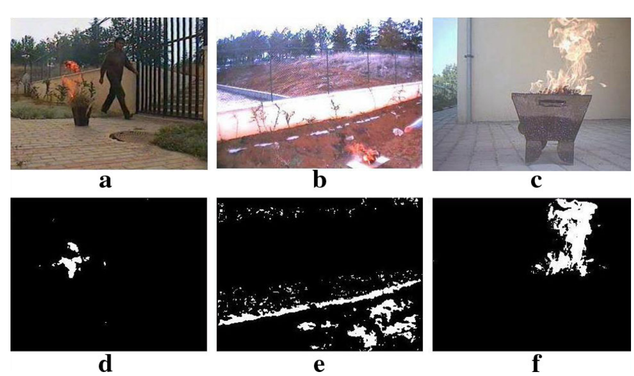

Fig. 2 Result of multi-color detection. **a–c** Frames from different videos streams. **d–f** Corresponding results

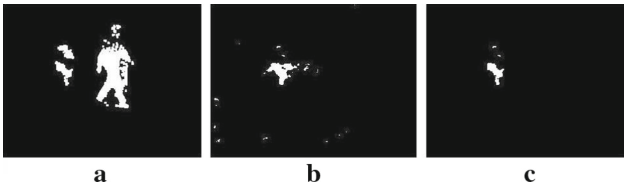

Fig. 3 Results of combination. **a** Result of motion detection. **b** Result of multi-color detection. **c** Result of combination (**a**) and (**b**)

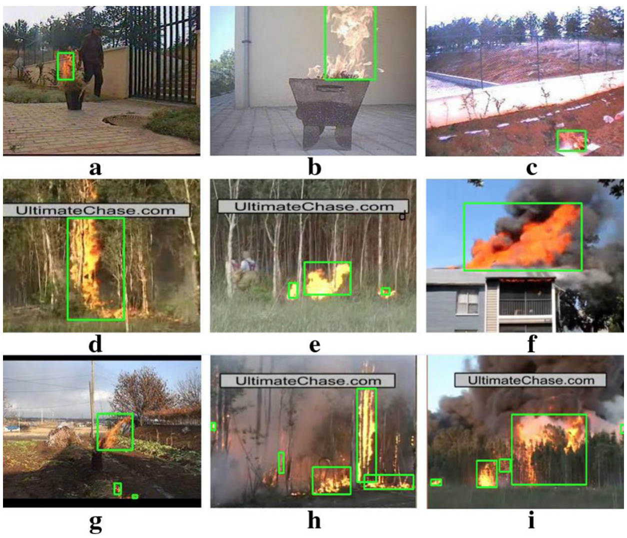

Fig. 4 Result of fire detection using the method proposed in this paper

Table 1 Empirical results of proposed method

Video	N_n	N_d	R_d
Barbeq	439	428	0.975
Controlled1	260	259	0.996
Controlled2	246	246	1.000
Controlled3	208	207	0.995
Fbackyard	1201	1198	0.996
Fire1	708	545	0.770
Forest1	200	200	1.000
Forest2	245	245	1.000
Forest3	255	254	0.996
Forest4	219	218	0.995
Forest5	216	216	1.000
Forestfire1	218	218	1.000
Total	4415	4234	0.959

Table 2 Empirical results of Shidik's method

Video	N_n	N_d	R_d
Barbeq	439	439	1.000
Controlled1	260	105	0.404
Controlled2	246	246	1.000
Controlled3	208	208	1.000
Fbackyard	1201	567	0.472
Fire1	708	520	0.734
Forest1	200	200	1.000
Forest2	245	245	1.000
Forest3	255	254	0.996
Forest4	219	218	0.995
Forest5	216	216	1.000
Forestfire1	218	218	1.000
Total	4415	3436	0.778

3 Experimental results

The proposed method is implemented by using Visual Studio 2013 and OpenCV3.0. The running environment is Windows 8.1, Inter(R) Core(TM) i7 3.60GHz and RMA 16GB. The test video database is from http://signal.ee.bilkent.edu.tr/VisiFire/Demo/FireClips/ [30,34] with a large variety of scenes including different environment background and conditions. The resolution is 320 × 240.

Figure 4 demonstrates testing results over nine different scenes. From the illustration, it can be seen that the proposed method is able to eliminate the disturbance of non-fire moving objects, such as Fig. 4a, c and e, and fire-color background areas, like Fig. 4c and g, which may cause false detection. In addition, the fires in the videos streams were successfully determined.

The experimental results are presented in Table 1, where N_n is the number of frames and also is the number of frames containing fire in a video. N_d indicates the number of frames that correctly detected using the proposed method. And R_d is the fire detection rate of a video

$$R_d = N_d / N_n \tag{17}$$

The average detection rate can reach 95.9% on the videos shown in Table 1. The encouraging experimental results exhibit the effectiveness, adaptability and robustness of the raised fire detection method under different scenes.

We compare the proposed approach with other fire detection methods based on different motion and color features. Shidiks method [30] discriminated fire and non-fire objects by combining RGB, HSV and YCbCr as Multi-Color features with frame difference-based background subtraction, while Chen et al. [2], Celik and Demirel [9] and Marbach et al. [8] used RGB/HSI, RGB and YUV as color features of their methods, respectively. The experimental results over the same fire database are illustrated in Tables 2, 3, 4 and 5.

Moreover, we also carry out some experiments which adopt the same motion detection GMM and different color space (namely RGB and RGB/HSV/YCbCr) to test our

Table 3 Empirical results of Chen's method

Video	N_n	N_d	R_d
Barbeq	439	421	0.959
Controlled1	260	259	0.996
Controlled2	246	246	1.000
Controlled3	208	207	0.995
Fbackyard	1201	761	0.634
Fire1	708	540	0.763
Forest1	200	200	1.000
Forest2	245	245	1.000
Forest3	255	254	0.996
Forest4	219	218	0.995
Forest5	216	216	1.000
Forestfire1	218	218	1.000
Total	4415	3785	0.857

Table 4 Empirical results of Celik's method

Video	N_n	N_d	R_d
Barbeq	439	415	0.945
Controlled1	260	259	0.996
Controlled2	246	246	1.000
Controlled3	208	207	0.995
Fbackyard	1201	1003	0.835
Fire1	708	700	0.989
Forest1	200	200	1.000
Forest2	245	245	1.000
Forest3	255	254	0.996
Forest4	219	218	0.995
Forest5	216	216	1.000
Forestfire1	218	218	1.000
Total	4415	4181	0.947

Table 5 Empirical results of Marbach's method

Video	N_n	N_d	R_d
Barbeq	439	400	0.911
Controlled1	260	259	0.996
Controlled2	246	246	1.000
Controlled3	208	207	0.995
Fbackyard	1201	983	0.818
Fire1	708	680	0.960
Forest1	200	200	1.000
Forest2	245	245	1.000
Forest3	255	254	0.996
Forest4	219	218	0.995
Forest5	216	216	1.000
Forestfire1	218	218	1.000
Total	4415	4126	0.935

Table 6 Empirical results of GMM/RGB

Video	N_n	N_d	R_d
Barbeq	439	380	0.866
Controlled1	260	256	0.985
Controlled2	246	244	0.992
Controlled3	208	207	0.995
Fbackyard	1201	1000	0.833
Fire1	708	532	0.751
Forest1	200	192	0.960
Forest2	245	241	0.984
Forest3	255	252	0.988
Forest4	219	217	0.991
Forest5	216	216	1.000
Forestfire1	218	208	0.954
Total	4415	3945	0.894

Table 7 Empirical results of GMM/RGB–HSV–YCbCr

Video	N_n	N_d	R_d
Barbeq	439	436	0.993
Controlled1	260	232	0.892
Controlled2	246	245	0.996
Controlled3	208	206	0.990
Fbackyard	1201	1100	0.916
Fire1	708	600	0.847
Forest1	200	200	1.000
Forest2	245	243	0.992
Forest3	255	251	0.984
Forest4	219	219	1.000
Forest5	216	216	1.000
Forestfire1	218	218	1.000
Total	4415	4166	0.944

approach. From the results illustrated in Tables 6 and 7, it can be clearly demonstrated that our multi-color strategy outperforms the other two color models.

From these above tables (from Tables 1, 2, 3), it can be found that our proposed approach provides higher detection rates than other methods on the whole. But for video barbeq.avi, Shidiks method obtains a better result than ours as the background of this video is simple and stable. And, as for videos, like controlled2, forest 1 to 5 and forestfire1, whose scene is simpler without the disturbance of fire-like moving objects and the features of fire are considerably distinguishing. Consequently, almost all of these methods give the same detection rates tested on each of these videos; however, the methods for comparison produce many false detection areas (see Fig. 5) which seriously affect the detection performance. Our method can effectively deal with these areas to

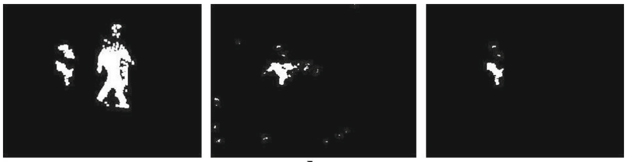

Fig. 5 **a**–**c** Results of fire detection on Controlled2.avi using our method, Chens method and Marbachs method, respectively

Table 8 Number of false positive frames

Video	N_f	Chen's	Celik's	Marbach's	Shidik's	Ours
Movie1	0	10	23	21	13	9
Movie2	0	8	10	12	6	2
Movie3	0	0	0	0	0	0
Movie4	0	26	34	39	30	29
Average	0	11	16.75	18	12.25	10

reduce false alarm. Finally, our approach exhibits prominent advantages and fire detection ability tested on videos with a complex environment and changing background, such as controlled1.avi and fbackyard.avi.

Table 8 gives the number of false positive frames using different methods, where N_f is the number of frames with fire in movies. And the movie 1, movie 2, movie 3 and movie 4 (used in [39]) are a fire-colored moving truck, three men walking in the room, traffic on a highway and dancing man with fire-colored shirt, respectively. From Table 8, it can be clearly seen that our method outperformed other approaches with a lower average false positive rate. In addition, the algorithm we proposed demonstrated a better result on every movie except for movie 4. Therefore, other features should be added to our future research to lower the false positive rate.

Overall, it is evident from the above discussion that our approach overall outperforms the other methods in terms of detection robustness and effectiveness.

4 Conclusion

In this paper, a new method for detecting the fire over the video stream is proposed. It is based on combining motion feature and color information of fire. This method includes two key stages: moving object detection using Gaussian Mixture Model-based background subtraction; multi-color-based detection utilizing the RGB, HSI and YUV color space models to obtain possible fire regions. Combination of the results of two steps is needed to determine the final fire areas. This method is tested over different video streams.

According to the experimental results, the method can achieve an average detection rate of approximately 96%, which well manifests the effectiveness, adaptability and robustness.

For further development, other characteristics of fire, such as flicker, geometric feature, could be considered to improve the detection performance and accuracy while reducing the rate of false alarm.

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