QBS
Vol. 37, No. 2, pp. 81-89 (2018)
https://doi.org/10.22283/qbs.2018.37.2.81
pISSN 2288-1344 eISSN 2508-7185 **Original Article**

**Quantitative Bio-Science**
Official Journal of the Institute of Natural Science at Keimyung University
Available Online at https://qbs.kmu.ac.kr:442/

# Computer Vision-based Method to Detect Fire Using Color Variation in Temporal Domain

Ung Hwang[1], Jechang Jeong[1], Jiyeon Kim[2], JunSang Cho[3], SungHwan Kim[4,*]

[1]Department of Electronics and Computer Engineering, Hanyang University, Seoul 04763, Korea
[2]Department of Statistics, Keimyung University, Daegu 42601, Korea
[3]Industry-University Cooperation Foundation, Konkuk University, Seoul 05029, Korea
[4]Department of Applied Statistics, Konkuk University, Seoul 05029, Korea
(Received September 28, 2018; Revised November 7, 2018; Accepted November 12, 2018)

## ABSTRACT

It is commonplace that high false detection rates interfere with immediate vision-based fire monitoring system. To circumvent this challenge, we propose a fire detection algorithm that can accommodate color variations of RGB in temporal domain, aiming at reducing false detection rates. Despite interrupting images (e.g., background noise and sudden intervention), the proposed method is proved robust in capturing distinguishable features of fire in temporal domain. In numerical studies, we carried out extensive real data experiments related to fire detection using 24 video sequences, implicating that the propose algorithm is found outstanding as an effective decision rule for fire detection (e.g., false detection rate $<10\%$).

**Key words :** Fire detection, Computer vision, Temporal domain

## 1. Introduction

Devastating damages caused by forest fire become increasingly critical as reported in TV news or magazine. Needless to say, it is imperative to detect fire at an early stage to minimize damages prior to dispersion of fire and smoke. And yet, recent study in 2006 for fire accidents in Korea reports that the electrical cause of fire accounts for nearly 30% out of the total number of fire accidents. This study also shows that detection rates of fire accidents remain 30% below, and thus an automatic fire alarming system is urgently required to prevent fire damages. The direction of fire detection is largely two-fold: (1) the sensor based and (2) vision-based approaches. Related to vision-based models, any form of signal processing whose inputs are video frames [1-5] is also commonly video processing. Sensor-based detection has an advantage of low cost and simple configurations, whereas vision-based detection can monitor wide areas as use of CCTVs is prevalent at present (See Fig. 1) [6]. Thus far, a range of vision-based fire detection algorithms have been developed on the basis of color, motion, flicker, spatial difference, disorder, and image training. The color-based fire detection algorithm is one of the most efficient methods to detect fire.

For instance, Fillips et al. [7] proposed a fire detection algorithm using a pixel intensity difference in temporal domain and fire color characteristics with well-designed detection steps. This method, however, does not take into account sequences including flickering lights (e.g., electronic display

* Correspondence should be addressed to SungHwan Kim, Assistant Professor, Department of Applied Statistics, Konkuk University, Seoul 05029, Korea. Tel: +82-2-450-3658, E-mail: shkim1213@konkuk.ac.kr
Ung Hwang is a PhD student, Department of Electronics and Computer Engineering, Hanyang University, Seoul 04763, Korea. Jechang Jeong is a professor, Department of Electronics and Computer Engineering, Hanyang University, Seoul 04763, Korea. Jiyeon Kim is a graduate student, Department of Statistics, Keimyung University, Daegu 42601, Korea. JungSang Cho is a research fellow, Industry-University Cooperation Foundation, Konkuk University, Seoul 05029, Korea.

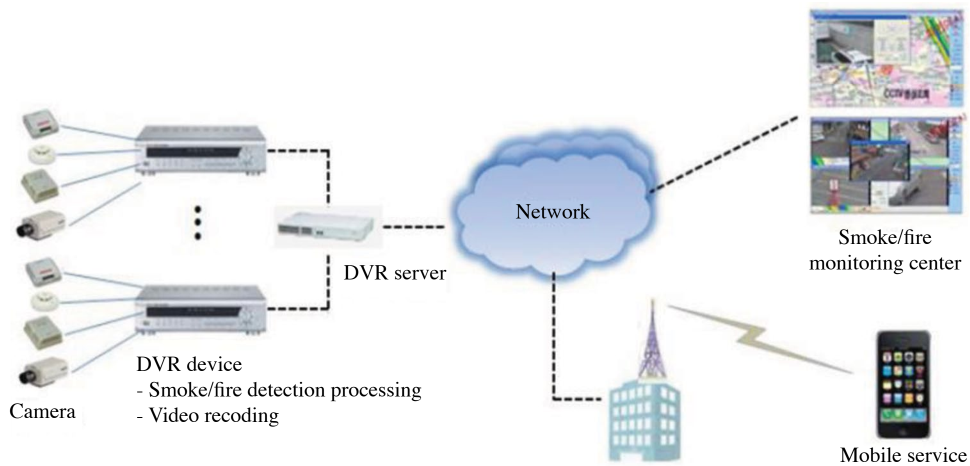



**Fig. 1.** General vision based monitoring system.

or sirens) and thus is not always suited to all circumstances despite its methodological novelty. Chen et al. [8] developed an equation on the basis of fire colors in RGB (Red, Green and Blue) space to detect characteristics of fire motion, and proposed a method that counts fire pixels by fire color. Intensive R values and the pattern order (i.e., R > G > B) are found common in fire. Relative to fire accidents, Chen et al. [9] also proposed the color based smoke detection method. Importantly, smoke detection can be supportive, at least in part, to fire detection as smoke often accompanies fire. Yuan [10] proposed an algorithm that detects smoke by using the upward motion of smoke that occurs in the hot air flow. Toreyin et al. [11] used wavelet subimage calculated by Discrete Wavelet Transform (DWT) to detect fire. Dedeoglu et al. [12] proposed an algorithm that uses flicker that using DWT torrential temporal value. Interestingly, Chiu et al. [13] proposed an algorithm to detect fire in a tunnel environment. To this end, Chiu et al. [13] lights fires via diverse types of fuel in a tunnel to validate the utility of the detection algorithm (e.g., wind-driven conditions).

Verstockt et al. [14] proposed a fire detection algorithm adapted for car parks in collaboration with special equipment called a TOF (Time Of Flight) camera to measure depth and intensity of an image. When utilizing CCTVs, it is common that fire alarms are manually operated (i.e., eye-ball detection). Generally, many existing fire detection algorithms suffer from false detection if feather appearance of fire like flicker lighting happens to appear on the screen; hence it is worthwhile that a fire detection algorithm builds on many video sequences. As related to all concerns above, we develop an

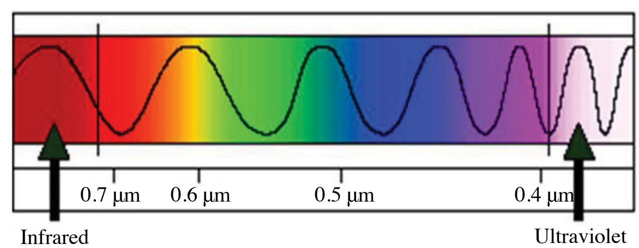



**Fig. 2.** Visible light region of the electromagnetic spectrum.

algorithm that makes use of color variations in temporal domain. We tested if the proposed algorithm efficiently performs in the real video sequences captured in various scenarios (e.g., flickering electronic signs, dancing in red color top, running people and CCTVs).

The paper is outlined as follows. In section 2, we discuss the definition and color characteristics of fire for detection in video, and a novel decision benchmark for fire detection that leverages the temporal domain. In an effort to verifying performance, we implement many experimental studies. Finally, we make concluding remarks in section 5.

## 2. Method

### 2.1 Colorific features of fire

Generic colors of fire are red and yellow when the temperature lies below 1,000°C. Fire in low temperatures emits low frequency light that determines color of fire. Due to this color mixture, fire color is made of red and yellow colors for the

**Fig. 3.** Two different types of fire (i.e., natural and artificial fire).

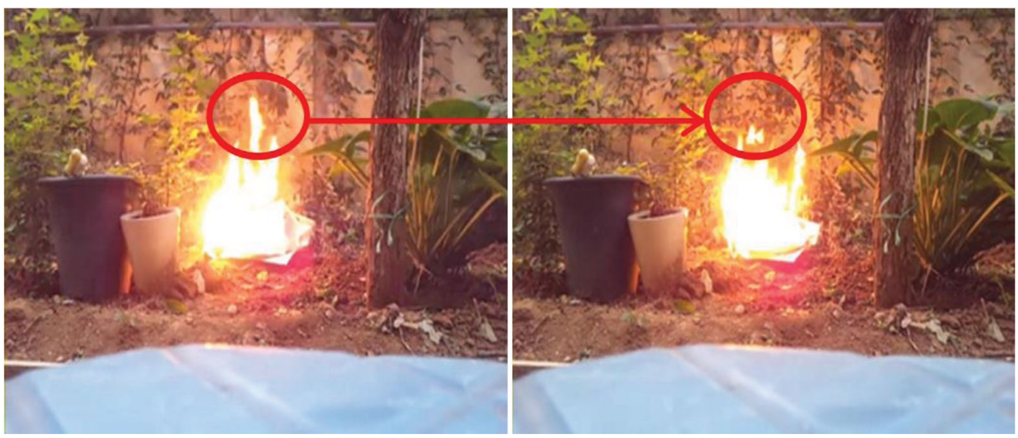


**Fig. 4.** A part of fire (blaze) that appear for a short term.

**Fig. 5.** A part of fire (light) that appears for a long term.

most part. For instance, we can clearly observe in Figs. 2 and 3 the distinctive color alternations depending on temperatures. In this regard, we can selectively focus on colors between red and yellow associated with high R and low B values in the RGB domain. Since the G is featured with red and yellow colors, the variation in G, at least in part, provides distinguishable signals to capture fire in video. On top of that, it is clear in Fig. 9 that variation of G overtime appears to be obvious,

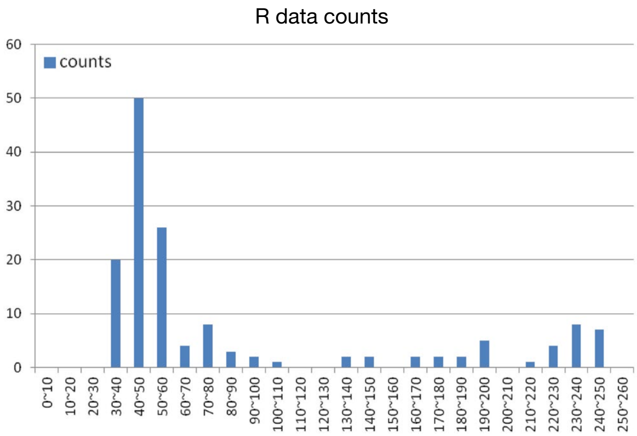



**Fig. 6.** R data counts on pixels of short-term fire. Some intense R values are observed. X-axis : value range, Y-axis : number of counts.

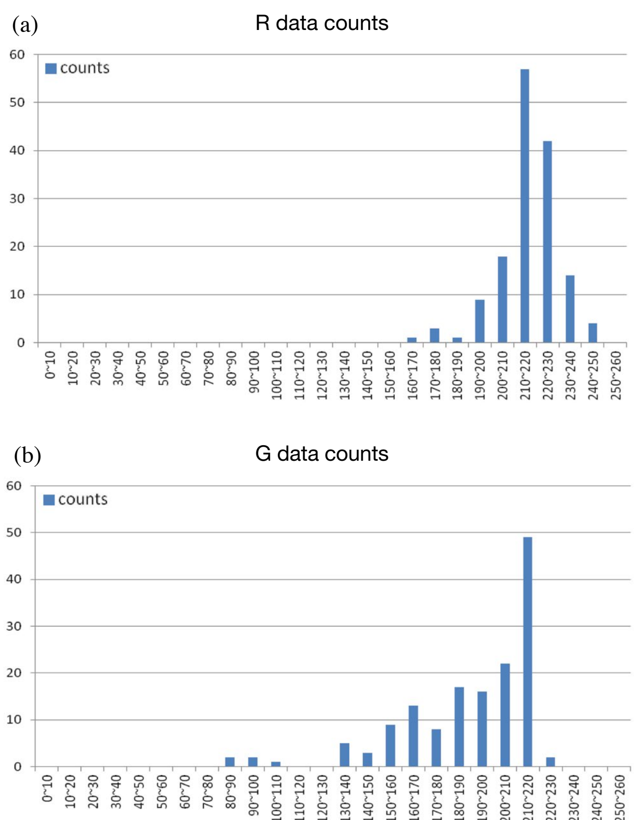



**Fig. 7.** R and G data counts graph on pixels of long-term fire. Very high R and G values are observed.

and thus G counts come into play as essentials for classifier. Importantly note that fire lights in various forms. Precisely, flickering flames in Fig. 3 (i.e., blaze) continue for a short time, while those of Fig. 4 last long as dominating the central body in fire. The central body and peripheral blaze determines the shape and types of fire on the whole. Putting together, we propose a fire detection algorithm exploiting two major components: (1) colors and (2) forms in fire.

## 3. Proposed Algorithm

In this chapter, we introduce a novel method to detect fire on the basis of temporal data in RGB domain. In what follows, we categorize characteristics of fire into short-term fire (SF), long-term fire (LF) and flickered fire (FF).

### 3.1 Short-term fire (SF)

$R$, $G$ and $B$ counts are benchmarked by:

$$R_{x,y(k-j)} = \sum_{x,y,n=0}^{N-1} if\left(k \le R_{x,y,n} < j\right) \text{ then } 1 \text{ else } 0,$$

$$G_{x,y(k-j)} = \sum_{x,y,n=0}^{N-1} if\left(k \le G_{x,y,n} < j\right) \text{ then } 1 \text{ else } 0,$$

$$B_{x,y(k-j)} = \sum_{x,y,n=0}^{N-1} if\left(k \le B_{x,y,n} < j\right) \text{ then } 1 \text{ else } 0$$

respectively, where $n$ is the number of frame and $x$, $y$ indicate the indices of $n^{th}$ frame. $N$ represents the total number of frame, being 150 as default unless otherwise noted. Short-term fire (SF) is defined as

$$\text{if } \left(G_{x,y(30-100)} > TH_1,\ B_{x,y(30-100)} > TH_1 \text{ and } R_{x,y(190-255)} > TH_2\right), \quad SF_{x,y} = 1 \quad \text{else } SF_{x,y} = 0, \tag{1}$$

where $TH_1$ and $TH_2$ denote the pre-defined constants, where $TH_1 = 0$ and $TH_2 = 3$. This numerical benchmark in (1) is designed to characterize the upper end of fire in Fig. 4, whose temperature is lower than inner parts of that. The proposed algorithm binds 150 frames as a basis for analysis, equivalently total frames over five seconds (30 frames/seconds).

### 3.2 Long-term fire (LF)

Generally fire at center is seen constantly glowing over the period of combustion, and thus long-term fire (LF) is subject to temporal information such as persistence of fire light. Below we construct the second benchmark purposely targeting at deep red color: high R, low G and low B values: long-term fire (LF) is defined as follows:

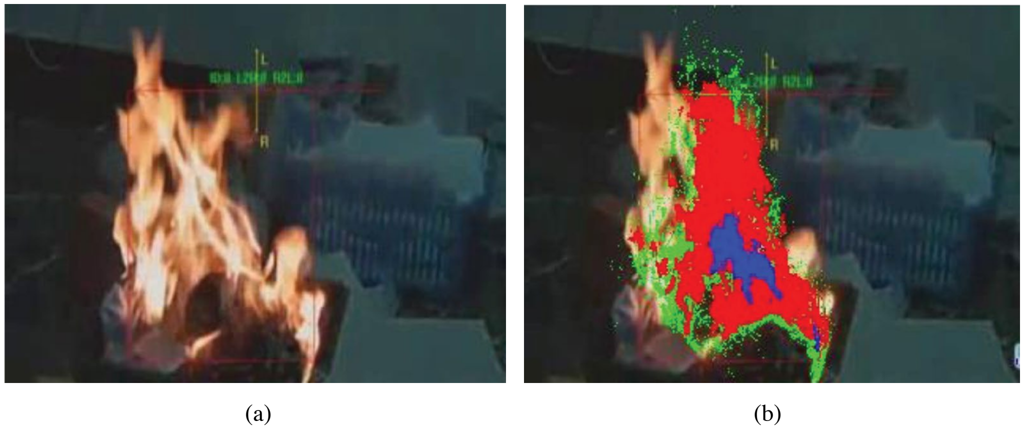



**Fig. 8.** (a) Original image of fire, (b) Fire image delineated by using three conditions (short-term fire (SF) - green, long-term fire (LF) - blue, flickering fire (FF) - red).

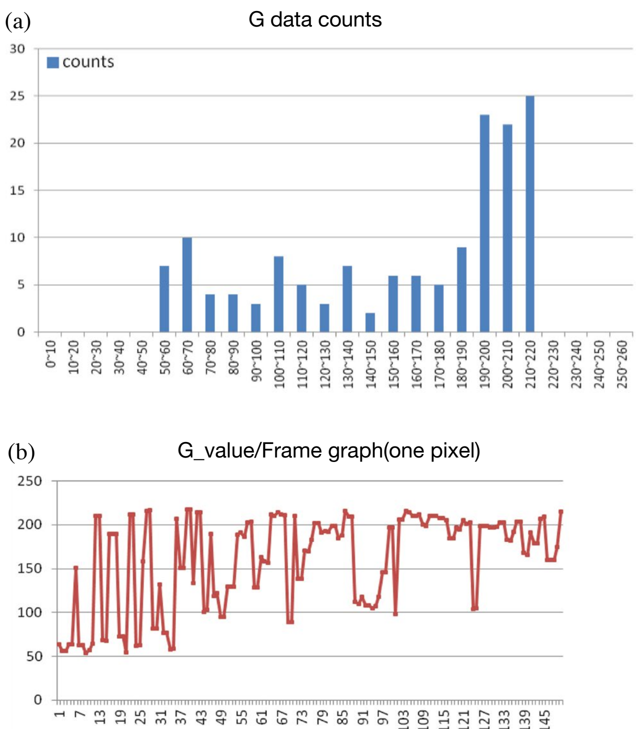



**Fig. 9.** (a) G data counts graph of flickering fire, (b) G value variation graph for 150 frames; (b) shows that G values are frequently changed in flickering part of fire. X-axis of (b): frame number, Y-axis of (b): value of G.

$$\text{if}\left(\begin{array}{c} R_{x,y(190-255)} > TH_3\ G_{x,y(190-255)} > TH_4 \\ or\ \ R_{x,y(190-255)} > TH_3\ B_{x,y(190-200)} > TH_5 \\ G_{x,y(190-200)} > TH_5 \end{array}\right), \quad (2)$$
$$LF_{x,y} = 1$$
$$\text{else } LF_{x,y} = 0,$$

where $TH_3 = 120$, $TH_4 = 50$ and $TH_5 = 0$, respectively. The histogram in Fig. 7 displays R counts observed at a pixel of long-term fire over the whole frames. It is interesting to note that high R and G values account for most frequencies. Inspired by this graphical phenomenon, we implement (2) to put weight on high R and G.

### 3.3 Flickering fire (FF)

Flickering fire (FF) is commonly observed in the midst of LF and SF. To gauge G values in FF, the sum of differences in G values (GDIF) is denoted by

$$\text{if}\left(\begin{array}{l} R_{(x,y,n-1)} > 190,\ B_{(x,y,n-1)} < 190 \\ \text{ or } R_{(x,y,n)} > 190,\ G_{(x,y,n)} < 190 \end{array}\right) \quad (3)$$

$$GDIF_{(x,y)} = \sum_{n=1}^{N} abs\left(G_{(x,y,n-1)} - G_{(x,y,n)}\right).$$

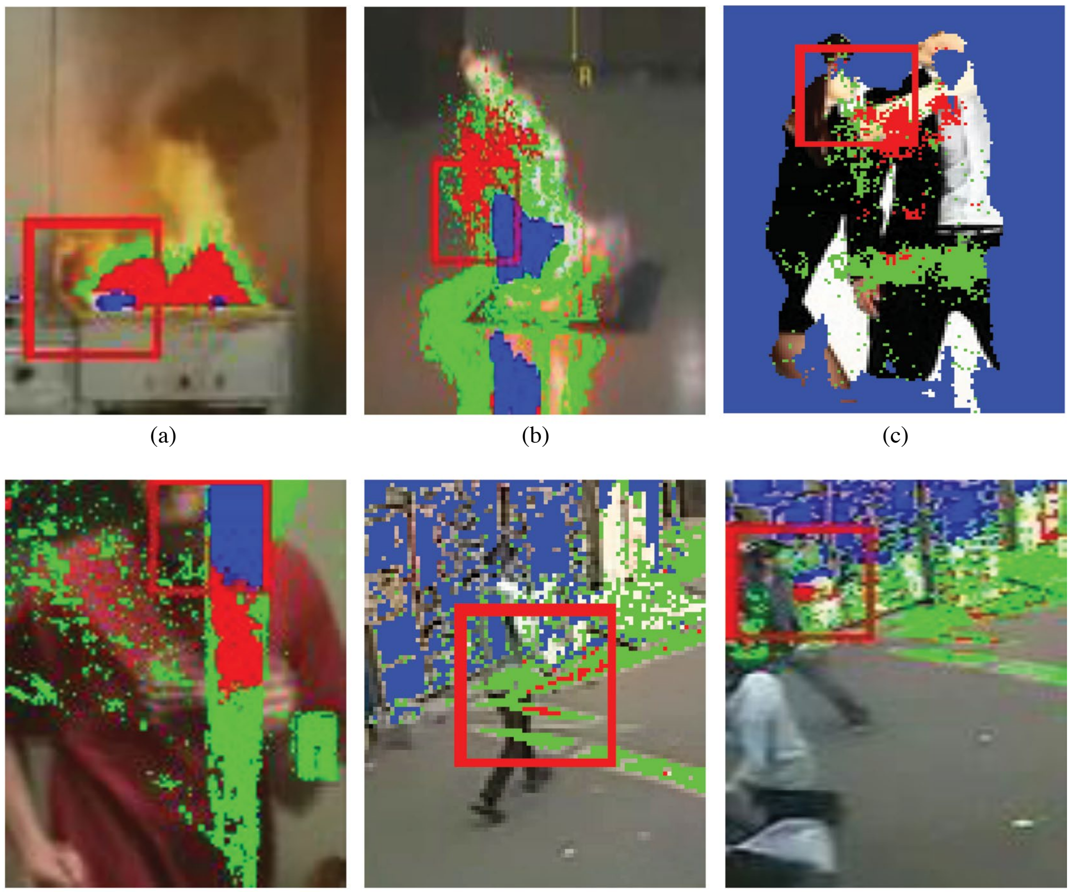
We initialize $GDIF_{(x,y)} = 0$. Simply put, flickering fire (FF) is defined as

$$LF_{x,y} = 1\ if\left(GDIF_{(x,y)} > TH_6\right) \quad (4)$$
$$\text{else } LF_{x,y} = 0,$$

subject to $TH_6 = 1600$. Fig. 8(b), it is clear to say that FF is present in the middle of SF and LF.

### 3.4 Final decision

In this section, we define a decision rule that accommodates topological attributes of image pixels. (1) The initial task examines if a $16 \times 16$ pixel block satisfies simultaneous presence of LF, SF and FF. Fig. 10 enumerates failures of fire detection when feathers-like images interrupt fire detection.



(a) (b) (c)

(d) (e) (f)

**Fig. 10.** (a)-(b): fire images, (c)-(f): images of moving people. In the (a)-(b), *LF* (blue) is consistently placed at the bottom. To the contrary, no regular order of SF, LF and FF appears in (c)-(f).

To tackle this challenge, we figure out distinctions in motion between genuine fire and confounding images. (2) The second condition is that LF is to appear in bottom areas. Surprisingly most of fire in Fig. 10 is formed with LF at the bottom regions, whereas other non-fire images show that LF scatters in no order. (3) The following is the third condition: if a current pixel whose neighboring pixels nearby placed in diagonal positions (i.e., four pixels: left, right above and below) are not at least two identical ones of SF, LF and FF, the target pixel is excluded for decision as likely be non-fire pixels. Chances are that separated individual pixels constitute non-fire images as in Fig. 10. Taken together, the final decision rule effectively rules out dancing people and running people in the streets as non-fire sequences.

## 4. Experimental Studies

In the experiments, we assess whether the proposed algorithm effectively reduces low false detection rates using $320 \times 240$ or $352 \times 240$ video sequences. In Table 1, true positive (TP) indicates that the algorithm correctly detects fire, and false positive (FP) means the algorithm falsely declares fire. Table 1 includes the class labels of fire (i.e., true or false), video sequence descriptions and causes of false detection. It is evident to say that the proposed algorithm outstandingly distinguishes fire events with almost no false detection. Diverse experiments remain a hint of false detection or late detection. This is due to white color and light because oversaturation of bright light in a camera, resulting in false detection. On the contrary, too little light hampers correct detection. Besides white color in non-fire images is colorific equivalent to light in temporal domain. A majority of non-professional cameras cannot distinguish light and white color. And yet there is room for improvement if applying infrared cameras [15]. Out of 24 videos, our algorithm precisely detects 23 video sequences. However, the falsely detected one implicates

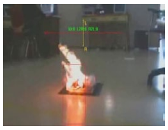
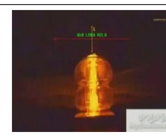
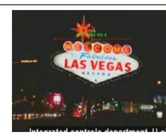
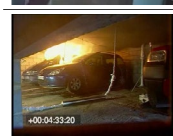
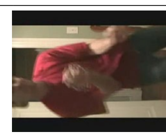
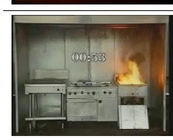
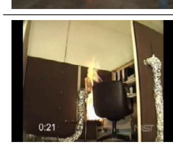
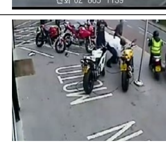
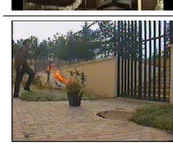
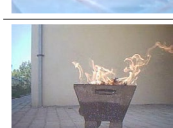
**Fig. 11.** Images detected by proposed algorithm that appear in Table 1.

that our algorithm less effective to capture fire extinguished too soon to discern.

## 5. Conclusion

Of late, a variety of fire detection methods have been practically applied but yet none of vision-based algorithms (e.g., CCTV) is shown effective to false detection rates. It is essential to improve false detection rates as a central challenge to embed into an alarm monitoring system. To this end, we propose the fire detection method that builds on fire forms together with RGB values. Our algorithm is found to efficiently detect fire and reduce the false alarm possibly attributed to fire flickers. From the experimental studies using 24 video sequences, the proposed algorithm obtains accuracy higher than 90%. Putting together, this surpassing perfor-

**Table 1.** The number of frame that the first alarm has occurred.

| Snapshot image | Info | | | Snapshot image | Info | | |
|---|---|---|---|---|---|---|---|
| | Number of frame(f) | Detection | Description | | Number of frame(f) | Detection | Description |
|  | 300 | T | Fire indoors |  | – | T | Car lights in the dark |
|  | 150 | T | Fire indoors |  | – | T | Electronic lights in the dark |
|  | 150 | T | Fire indoors |  | – | T | Flickering lights in the dark |
|  | 150 | T | Fire indoors |  | – | T | Electronic signs in the dark |
|  | 450 | T | Oversaturated fire behind the car |  | – | T | Dancing in red top |
|  | 150 | T | Fire indoors |  | – | T | Surveillance camera of library |
|  | 150 | T | Industrial fire |  | – | T | Tollgate |
|  | 150 | T | Fire indoors |  | – | T | CCTV |
|  | 150 | T | Fire indoors |  | – | T | CCTV |
|  | – | F | Due to dark tones |  | – | T | Running people in CCTV |
|  | 150 | T | Fire in the garden |  | – | T | CCTV |
|  | 150 | T | Fire in the barbeque grill |  | – | T | Moving camera |

mance suggests that our algorithm can potentially facilitate fire monitoring. Nevertheless, the proposed algorithm has a tendency to fall in false negative in case of low light intensity. To overcome this, permutation tests to get P-value [16] designed to capture blurred signals or $l_1$-Penalty estimation model [17] can be solutions to algorithm improvement We leave this topic to improve further for future study.

## Acknowledgements

This research is supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (NRF-2016R1A6A3A11932875 and NRF-2017R1C1B5017528).

## References

1. Jeon G, Anisetti M, Bellandi V, Jeong J. Fuzzy rule-based edge-restoration algorithm in HDTV interlaced sequences. IEEE T Consum Electr 2007;53:725-731.
2. Jeon G, Anisetti M, Bellandi V, Damiani E, Jeong J, Rough sets-assisted subfield optimization for alternating current plasma display panel. IEEE T Consum Electr 2007;53:825-832.
3. Jeon G, Anisetti M, Bellandi V, Damiani E, Jeong J, Fuzzy weighted approach to improve visual quality of edge-based filtering. IEEE T Consum Electr 2007;53:1661-1667.
4. Jeon G, Anisetti M, Lee J, Bellandi V, Damiani E, Jeong J. Concept of linguistic variable-based fuzzy ensemble approach: application to interlaced HDTV sequences. IEEE T Fuzzy Syst 2009;17:1245-1258.
5. Jeon G, Jung MY, Anisetti M, Bellandi V, Damiani E, Jeong J. Specification of the geometric regularity model for fuzzy if-then rulebased deinterlacing. J Disp Technol 2010;6:235-243.
6. Ha C, Hwang U, Jeon G, Cho J, Jeong J. Vision-based fire detection algorithm using optical flow. IEEE Int'l Conf. on Complex, Intelligent and Software Intensive System: 526-530. Palermo; July. 2012.
7. Phillips III W, Shah M, Lobo NV. Flame recognition in video. Pattern Recognition Lett 2002;23:319-327.
8. Chen TH, Wu PH, Chiou YC. An early fire-detection method based on image processing. IEEE Image Proc 2004;3:1707-1710.
9. Chen TH, Yin YH, Huang SF, Ye YT. The smoke detection for early fire-alarming system base on video processing. in: Proceedings of the IEEE Int'l Conf. on Intelligent Information Hiding and Multimedia Signal Processing: 427-430. Pasadena; Dec. 2006.
10. Yuan F. A fast accumulative motion orientation model based on integral image for video smoke detection. Pattern Recognition Lett 2008;29:925-932.
11. Toreyin BU, Dedeoglu Y, Cetin AE. Contour based smoke detection in video using wavelets. Eur Sig Pr Conf: 123-128. Florence; Sept. 2006.
12. Dedeoglu Y, Toreyin BU, Gudukbay U, Cetin AE. Real-time fire and flame detection in video. Int'l Conf. Acoust Spee: 669-672. Philadelphia; May. 2005.
13. Chiu CW, Lu T, Chao HT, Shu CM. Performance assessment of video-based fire detection system in tunnel environment. Tumm Undergr Sp Tech 2014;40:16-21.
14. Verstockt S, Van Hoecke S, Beji T, Merci B, Gouverneur B, Cetin AE, et al. A multi-modal video analysis approach for car park fire detection. Fire Safety J 2013;57:44-57.
15. Arrue BC, Olero A, Martinez de Dios JR. An intelligent system for false alarm reduction in infrared forest-fire detection. IEEE Intell Syst App 2000;15:64-73.
16. Kim TY, Choi M, Lee HS. P-value and reduction to absurdity. QBS 2017;36:1-6.
17. Jhong JH, Lee JJ, Kim SH, Koo JY. Joint modeling for mean vector and covariance estimation with $l_1$-Penalty. QBS 2017;36:33-38.