

# Fast Video Fire Detection Using Luminous Smoke and Textured Flame Features

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## Abstract

In this article, a video based fire detection framework for CCTV surveillancesystems is presented. Two novel features and a novel image type with their corresponding algorithmsareproposed for this purpose. One is for the slow-smoke detection and another one is for fast-smoke/flame detection. The basic idea is slow-smoke has a highly varying chrominance/luminance texture in long periods and fast-smoke/flame has a highly varying texture waiting at the same location for long consecutive periods. Experiments with a large number of smoke/flame and non-smoke/flame video sequences outputs promising results in terms of algorithmic accuracy and speed.

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**Keywords:** Fast smoke and flame detection, patch-wise framework, periodical analysis of smoke and flame features, chrominance/luminance variation, fire surveillance systems.

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A preliminary version of this paper appeared in IEEE International Conference on Industrial Technology (ICIT2014), Feb. 26 – March 1, Busan, South Korea. This version includes a concrete analysis and supporting implementation results on video based smoke and flame detection for real-time surveillance systems. Fast smoke detection is also added to this version.

## 1. Introduction

Video based smoke and flame detection is an essential requirement of any video fire surveillance system since it can avoid huge catastrophic fires at an early stage [1]. Conventional fire sensors can detect fire in a narrow range; especially in closed environments; therefore, image processing based video fire detection can provide a wide range of detection is a good solution for any video surveillance alarm units [2].

In the last decade, there have been several significant improvements in video smoke detection [3-11] which mostly use special frequency range of smoke by extracting image features such as motion, edge blurring, flickering, and growing contours [5, 9 and 10]. Temporal and spatial wavelet transformation is a well-known method used in various scenarios to detect smoke [6, 11]. Several researchers used energy lowering of smoke in high frequency analysis [7, 8]. Noise factor in videos makes detection challenging especially when frequency information is used since frequency patterns similar to smoke are highly available in most videos [3, 5]. Tung et al. [12] proposed a four-stage smoke detection algorithm which uses approximate median motion segmentation to create motion vectors to be used in support vector machines (SVM) [13] pattern classification. They achieved high accuracy but their method was computationally expensive, in which almost 15 fps is attained as the average processing rate in tested videos [14]. Yuan et al. [10] presented a fast smoke detection method that uses integral image for speed enhancement. Their method accumulates the motion vectors with their corresponding orientation angles in time domain. As second step, irregularity in motion is analyzed in each candidate region for smoke detection. The method [10] performed fast (30 fps) in tested videos [14], but not robust enough since it is just evaluating the motion patterns which can also be created due to the noise in video sequences. Therefore, a fast and robust smoke detection method is required in video surveillance systems. Considering the standard requirements of surveillance applications, it is required to process maybe 16 channels at the same time. It means 16 different videos should be processed simultaneously in real-time surveillance application.

Similarly, several researchers contributed to video-based flame detection methods in the literature [1, 2, 15-22]. Most of them use high-frequency motion of flame in different methods [2]. Image features such as color [1, 20, and 23], motion [15], flickering edges [16], probabilistic turbulence models [21], trained dynamic textures [18, 19] and sharp corners [1] are put into spatio-temporal analysis to detect flame in video sequences for high-frequency pattern detection [17]. Jiang et al. [24] proposed a highly accurate flame detection method in which speeded up robust features (SURF) [25] were trained in SVM [13] to detect flame patterns in real-time videos. Even the results reach 92% precision and 82% recall rates in 64 video clips, computational cost is still high (25 fps) due to machine learning part. Habiboglu [26] presented a novel method in flame detection that extracts the covariance matrix of each block in the entire image and performed tests with SVM [13]. It also reduced the running speed of framework even though it is highly robust. Their method had 20 frames per second processing rate with almost the same hardware and image resolutions used in this study.

As the primary contribution, this paper aims to attain high accuracy rates with low computational cost in smoke and flame detection in real-time applications. In previous versions of this study [27, 28], methods were explained briefly without a conductive benchmarking study. In addition, smoke was evaluated in single type.

In this study, smoke is evaluated in two types: slow and fast referring to low-frequency and high-frequency smoke, respectively. Flame is also categorized in the same group with fast smoke since they both indicate high-frequency motion patterns in time domain.

In case of slow-smoke detection, a novel image type is presented for accurate luminous foreground and chromatic background segmentation. In the proposed model, slow-smoke is assumed as luminous and thereby black smoke is excluded. Linearly interpolated chrominance/luminance subtraction image is introduced for automated binary classification. Binary classification is performed with thresholding operation. Optimum threshold is calculated depending on the standard deviation and mean of the chrominance/luminance subtraction image that is presented in section 2.5 in detail. The advantage of using thresholded image leads an accurate calculation of correlation between blacks (luminous) and gray (chromatic) pixels while reducing the amount of possible noise conducted to local and global defections in the input image. For instance, standard definition (SD) and high definition (HD) images will output similar results by this way. Since binary classification is performed by the mean and standard deviation of the input image, same-frequency noise in the entire input image will lose its defect for pattern detection. After all, luminous pixels are signed with black pixels while the chromatic background keeps its original gray value. Next step is to calculate the change in luminous foreground over the chromatic background. Thresholded image is divided into the patches to perform periodical analysis in terms of the behavior of luminous pixels (black) over the chromatic pixels (gray) in each patch region. The advantage of this way is that it is much faster than pixel-wise computation. By considering the algorithmic cost and nature of smoke, periodical normalized cross-correlation analysis is performed in histogram bins instead of two-dimensional image context that makes algorithm faster and efficient for smoke detection. In this regard, two kinds of histogram are employed to observe change in luminance/chrominance texture and shape. Intensity histogram, which consists of 256 bins, and oriented gradients histogram with 8 bins are employed for this purpose. Slow-smoke creates transparent textures in which histogram bins create high variations. In order to minimize the noise factor, background/foreground classification is performed. Lab color space is used for luminance and chrominance channels separation. Smoke cannot be fully black, gray and white or smoke cannot be fully colorful. Therefore, highly luminous and less chromatic pixels are employed as a feature of smoke. Since blackish smoke has high chrominance value and low luminance value, only transparent regions on blackish smoke that have low chrominance and high luminance can be detected. Since the chrominance value of fully white, gray and black colors is 128 and their luminance values are 255, 137, and 0 in Lab color space, a subtraction image is obtained by subtracting the luminance value of each pixel from its chrominance value by re-scaling the range from  $[-255, 255]$  to  $[0, 255]$ . In order to distinguish the background and foreground, subtraction image is thresholded. Instead of using binary thresholding, a special thresholding method is used in which upper class keeps its gray value while sub-class remains black. Finally, correlation analyses of black pixels on four feature vectors: temporal intensity, temporal oriented gradients, background intensity and background oriented gradients is performed. Analysis is conducted on the histogram bins instead of spatial patch images. Smoke like regions create high variations of intensity and shape in long periods. No other objects like car, human, tree can make such a noticeable change like smoke.

For accurate fast-smoke and flame detection, RGB color space which is a non-linear color model is used for color modeling. Approximate median motion segmentation is employed to mask fast-smoke and flame colored pixels [29]. The ratio of motion masked colored pixels in

each patch is accumulated at the end of each period. Consecutive periodical re-occurrence analysis of motion in a given duration is used to initialize fast-smoke / flame alarm.

The remaining part of the paper is organized as follows. In Section 2, proposed framework is introduced by its seven sub-categories. Section 3 presents the experimental results and benchmarking study. Finally, Section 4 concludes the paper.

## 2. Proposed Framework

A patch-wise video processing framework is introduced to analyze each patch region of video frames in a given period. Proposed framework assumes that the camera is stationary. It mainly consists of seven parts; image resizing, gray-scale transformation, zoom/tilt/pan detection, motion segmentation, color modeling, periodical analysis and blob tracking. Fig. 1 shows the flow-chart diagram of proposed framework.

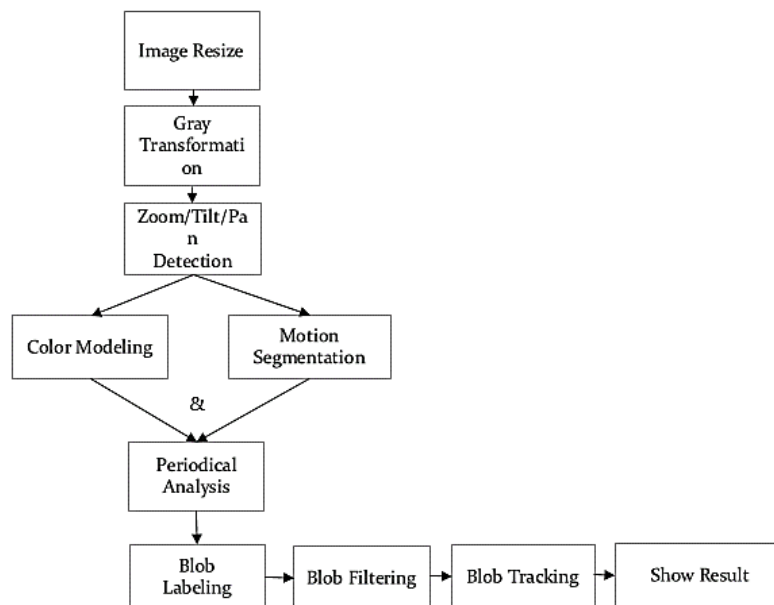


Fig. 1. Flow Chart of Proposed Framework for Smoke and Flame Detection

Since pixel-wise framework has high algorithmic cost, a patch-wise periodical analysis is performed for smoke and flame detection. Additionally, smoke detection is evaluated in terms of its low-frequency (slow-smoke) and high-frequency (fast-smoke) motion patterns whereas flame is detected only by its high-frequency motion patterns. Therefore, in this paper; fast-smoke and flame detection algorithms are using the same algorithm but with different parameter sets.

### 2.1 Video Input Resizing

In order to minimize the overall computational cost, input video size is reduced by using a particular image decimation technique for each frame. Instead of using super-resolution bi-cubic interpolation method [30] (CV\_INTER\_CUBIC [31]) which is highly used in two-dimensions, re-sampling using pixel-area relation method (CV\_INTER\_AREA [31]) is used to perform image decimation. This method is fast and accurate on reducing the size of video frames since it employs a simple averaging operator rather than a parametric form such

as a cubic function that leads having more free results. Since proposed algorithm uses area information rather than frequency, noises are minimized by this interpolation technique. The type of interpolation method is highly important in this regard.

## 2.2 Gray-Scale Transformation

Resized input video is converted to gray-scale from RGB space for each frame. Gray-scale input is used for zoom/tilt/pan detection and motion segmentation in further steps.

## 2.3 Zoom/Tilt/Pan Detection

Normalized cross-correlation between previous frame and current frame is performed and second-derivative test is applied to find local minima and maxima of change between frames. Normalized cross-correlation between two vectors  $CF = (cf_0, cf_1, \dots, cf_{N-1})$  and  $PF = (pf_0, pf_1, \dots, pf_{N-1})$ , where  $N$  is the number of pixels in each frame is given by,

$$NCC = \frac{1}{\sigma_{cf}\sigma_{pf}} (CF - \overline{CF}) \cdot (PF - \overline{PF}) \quad (1)$$

where  $CF$  and  $PF$  represents current and previous frames,  $\sigma_{cf}$  and  $\sigma_{pf}$  are the standard deviations over the vectors and  $\overline{CF}$  and  $\overline{PF}$  are the vectors containing the means as follows;

$$\sigma_{cf} = \sqrt{(CF - \overline{CF})(CF - \overline{CF})} \quad (2)$$

$$\overline{cf} = \frac{1}{N} \sum_{i=0}^{N-1} cf_i \quad (3)$$

$$\overline{CF} = (\overline{cf}, \overline{cf}, \dots, \overline{cf}) \quad (4)$$

A given threshold of change between consecutive frames is used to detect zoom/tilt/pan events including any other immediate changes. By this way, misdetections are avoided due to camera ego-motion. Detection criteria of zoom/tilt/pan is given in (5).

$$|NCC_i(f_i, f_{i+1}) - NCC_{i+1}(f_{i+1}, f_{i+2})| \geq T \quad (5)$$

where  $f$  and  $T$  are frame and threshold, respectively. Cross correlation coefficient is obtained in a range of  $[-1, 1]$  which indicates a total similarity in case of 1 and dissimilarity in case of -1. Therefore, the absolute difference of two cross-correlation coefficients is in the range of  $[0, 2]$ . In this study this range is mapped to  $[0, 1]$  by taking its half.

## 2.4 Motion Segmentation

Motion segmentation is required to determine the region of interest in pattern recognition applications. Since smoke and flame have a continuous motion, motion itself can be used as a clue to reduce the computational task while enhancing the performance of classifier. In this regard, background regions are not computed and the amount of possible noise is minimized. However, smoke and flame have different motion characteristics. Indeed, smoke includes two types of motion as low frequency and high frequency while flame includes high frequency motion only. Therefore, slow motion segmentation is required to detect the slow-smoke motion and fast motion segmentation is conducted for fast-smoke and flame motion detection.

In this study, approximate median motion segmentation is employed for motion detection

since it is computationally low-cost and yields good performance in noisy environments. Algorithm is slightly modified for better thresholding by parameterizing the difference threshold according to the standard deviation of the background frame. This provides a relative evaluation of the motion according to the n-sigma rule.

Additionally, two versions of approximate median segmentation are introduced; one for slow motion and another is for fast motion detection. For slow-smoke detection, approximate median slow motion segmentation is used to segment motion areas [29]. Since system skips  $n-1$  number of frames in a given skip period  $n$ , slow motion detection is achieved. Table 1 shows the algorithm of slow motion segmentation for slow-smoke detection:

**Table 1.** Approximate Median Slow Motion Detection

```

Let curr be the current frame
Let bg be the median background
Let fg be the median foreground
Let  $\Delta$  be the absolute difference between bg and fg
Let N be the sensitivity parameter in a range of [1,255]

for each pixel  $\tau$ 
   $\Delta = |bg - f|$ 
  IF  $\Delta > \frac{\sigma_{bg}}{N}$  THEN
    fg = curr
  IF  $curr_{\tau} > bg_{\tau}$  THEN
     $bg_{\tau} = bg_{\tau} + 1$ 
  ELSE IF  $curr_{\tau} < bg_{\tau}$  THEN
     $bg_{\tau} = bg_{\tau} - 1$ 

```

Similarly, approximate median fast motion segmentation is used to segment motion areas for fast-smoke and flame detection [29]. Fast motion detection is obtained by evaluating two consecutive frames without skipping any frames. Table 2 shows the algorithm of fast motion detection as follows:

**Table 2.** Approximate Median Fast Motion Detection

```

Let curr be the current frame
Let bg be the median background
Let fg be the median foreground
Let  $\Delta$  be the absolute difference between bg and fg
Let N be the sensitivity parameter in a range of [1,255]

for each pixel  $\tau$ 
   $\Delta = |bg - f|$ 
  IF  $\Delta > \frac{\sigma_{bg}}{N}$  THEN
    fg = curr
  IF  $curr_{\tau} > bg_{\tau}$  THEN
     $bg_{\tau} = bg_{\tau} + \Delta$ 
  ELSE IF  $curr_{\tau} < bg_{\tau}$  THEN
     $bg_{\tau} = bg_{\tau} - \Delta$ 

```

Motion detection is applied for four reasons: avoiding the misdetection, terminating the detection, periodically accumulating the patches with motion and resetting the accumulation to zero in case of no motion is detected.

## 2.5 Color Modeling

Resized input video is converted to Lab space from RGB space for luminance/chrominance separation to be used in slow-smoke detection algorithm. In this space,  $L$  denotes luminance while  $a$  denotes red-yellow and  $b$  represents blue-yellow chrominance channels. A split operation is performed to separate luminance and chrominance channels. In case of chrominance channel selection, blue-yellow chrominance channel  $b$  is chosen since it gives less noisy and more accurate results.

In order to model the slow-smoke color, luminance channel is subtracted from chrominance channel and linear interpolation is performed to fit the range of values to  $[0,255]$ . For each pixel  $i$ , (6) is satisfied.

$$\frac{1}{2}(C_i - L_i + 255) = S_i \quad (6)$$

where  $C$ ,  $L$  and  $S$  represents chrominance, luminance and subtraction image, respectively. **Table 3** shows the construction of chrominance/luminance subtraction image.

**Table 3.** Luminance/Chrominance Values in LAB Space

Intensity/Colors	White	Gray	Black
Red	255	128	0
Green	255	128	0
Blue	255	128	0
Luminance ( $L$ )	255	137	0
Chrominance ( $b$ )	128	128	128
$b - L$	-127	-9	128
Interpolated ( $b - L$ )	64	123	$191.5 \approx 192$

Afterwards, background-foreground classification is performed by a threshold and mean operation. In order to minimize the luminous noise in video, mean value is weighted by a factor of  $(1 - \lambda)$  in which  $\lambda$  is the relative probable error ratio defined in (7).

$$\lambda = 0.3255 \times \frac{\min(\sigma_{Chrominance}, \sigma_{Luminance})}{\max(\sigma_{Chrominance}, \sigma_{Luminance})} \quad (7)$$

where at least the second moment of mean should exist when standard deviations of chrominance and luminance channels are equal. Instead of using binary thresholding, a modified thresholding is used in which the upper class keeps its gray value while the sub-class remains black. **Table 4** shows the modified thresholding.



**Table 4.** Thresholding of Chrominance/Luminance Image

*Let  $S$  be the interpolated subtraction image*  
*Let  $T$  be the thresholded grayscale image*  
*Let  $\mu_S$  be the average brightness of  $S$*   
*Let  $\lambda$  be the relative probable error ratio*  
*Let  $\theta$  be the estimated threshold value*  
  
*for each pixel  $i$*   
 $\theta = \mu_S \times (1 - \lambda)$   
 IF  $S_i > \theta$  THEN  
 $T_i = S_i$   
 ELSE  
 $T_i = 0$

**Fig. 2** shows the chrominance/luminance subtraction image after thresholding.

**Fig. 2.** Thresholded Chrominance/Luminance Subtraction Image

Luminous smoke pixels fall into sub-class while chromatic smoke pixels stay at the upper class by thresholding the subtraction image. In each frame, intensity and Sobel gradient orientation values are used to create intensity and orientation histograms for each patch. Additionally, a color modeling in RGB space is performed for fast-smoke detection. Thus, fast motion pixels with smoke color model are masked and evaluated in periodical analysis to attain the true turbulence rate of fast-smoke. **Table 5** shows the color modeling conditions for fast smoke detection.



**Table 5.** Conditions for Fast Smoke Color Modeling

Let  $V_B$  be the brightness value of the image  
 Let  $V_C$  be the colorlessness value of the image  
 Let  $T_B$  be the given threshold value for  $V_B$   
 Let  $T_C$  be the given threshold value for  $V_C$   
 Let  $M$  be the color mask image  
 Let  $\mu_B$  be the average brightness of the image  
  
 for each pixel  $i$   
 $V_B = \max(R_i, G_i, B_i)$   
 $V_C = \frac{\min(R_i, G_i, B_i)}{V_B}$   
 IF  $V_B > \mu_B$  AND  $V_B \geq T_B$  AND  $V_C \geq T_C$  THEN  
 $M_i = 255$   
 ELSE  
 $M_i = 0$

Colorlessness or saturation information is used to model the fast-smoke. **Fig. 3** shows a sample video frame thresholded according to proposed fast-smoke color modeling conditions.

**Fig. 3.** Sample Video Frame after Fast Smoke Color Modeling

Different from the slow-smoke color modeling, this model includes also chromatic smoke pixels such as black and dark gray colors. However, slow-smoke color model extracts only the luminous pixels excluding the black and dark gray pixels.

Red channel of RGB input video is used as a key feature for flame color modeling. Three basic rules [23] are applied as shown in **Table 6**.

**Table 6.** Conditions for Flame Color Modeling

Condition 1.  $Red > \mu_{Red}$   
 Condition 2.  $Red \geq T_{Red}$   
 Condition 3.  $Red \geq Green > Blue$

where  $\mu$  denotes mean and  $T$  represents predetermined threshold for red channel. Fig. 4 shows the flame-color masked fast motion image.

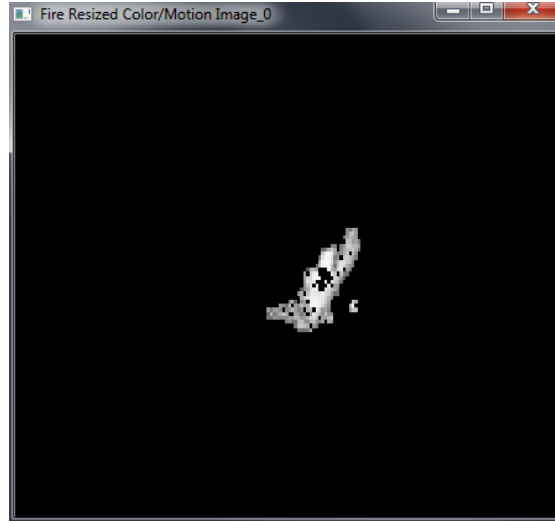


Fig. 4. Color masked fast motion flame pixels

By using this color model, binary masking is performed on fast motion pixels to be periodically analyzed in each patch for flame detection. Same operation is also performed for fast-smoke to mask its fast motion pixels with proposed fast-smoke color modeling conditions.

## 2.6 Periodical Analysis

Luminous pixels which are black after thresholding periodically analyzed in each patch by their correlation variation over chromatic background for slow-smoke detection. Normalized-cross correlation coefficients of histogram bins are calculated as given in (8).

$$NCC = \frac{1}{\sigma_{ch}\sigma_{ph}} (CH - \overline{CH}) \cdot (PH - \overline{PH}) \quad (8)$$

where  $CH$  and  $PH$  are current and previous histograms and  $\sigma_{ch}$  and  $\sigma_{ph}$  are standard deviations over histograms. Two kinds of evaluation: temporal and background analysis are performed. In temporal analysis, each frame is compared to previous frame by their inter-correlation coefficients in two types of histogram: intensity and oriented gradients. On the other hand; in background analysis, each frame is compared to background frame instead of previous frame. Fig. 5 shows the periodical analysis structure for slow-smoke detection.

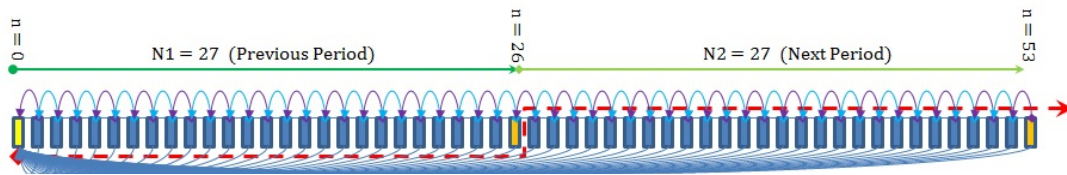


Fig. 5. Periodical Analysis Structure for Slow Smoke Detection

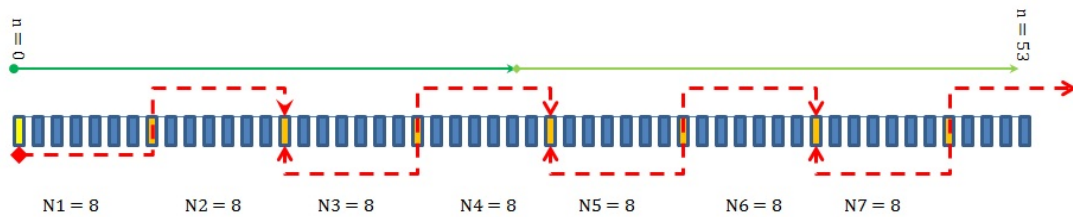
In each period, median value of correlation coefficients is used as the representative correlation value of belonging period. At the end of each period, median values of correlation coefficients of corresponding period are set as previous period's median values. **Table 7** shows the detection criteria for slow-smoke detection.

**Table 7.** Conditions for Slow Smoke Detection

Condition 1.	$M_{N2TempIntensity}$	—	$M_{N1TempIntensity}$	$\geq T_{intensity}$
Condition 2.	$M_{N2BGIntensity}$	—	$M_{N1BGIntensity}$	$\geq T_{intensity}$
Condition 3.	$M_{N2Temporientation}$	—	$M_{N1Temporientation}$	$\geq T_{orientation}$
Condition 4.	$M_{N2BGorientation}$	—	$M_{N1BGorientation}$	$\geq T_{orientation}$
where				
$M_{N2TempIntensity} = M_{N2Temporientation} = M_{N2BGIntensity} = M_{N2BGorientation} = 0$				

Additionally, background histograms are periodically updated when *Condition 2* and *Condition 4* are satisfied in case of no motion is detected for each patch. Finally, each period is compared with previous period by their absolute difference in belonging median values of correlation coefficients. The magnitude of this difference in a given period is used as a feature of slow-smoke.

Fast-smoke and flame have similar motion behavior in which motion contours create turbulence in short periods. The continuity of turbulence in a given duration is used as a feature of fast-smoke and flame. Skip period parameter is used in this module to enhance true turbulence detection in which  $n-1$  frames of a given skip period of  $n$  are not obtained from fast motion detection module. This provides a periodical spatio-temporal motion analysis that depends on patch motion ratio, skip period and motion analysis period. **Fig. 6** and **Table 8** show the periodical analysis structure and pseudo-code of algorithm, respectively.



**Fig. 6.** Periodical Analysis Structure of Fast Smoke and Flame Detection

Instead of analyzing the fast-smoke/flame motion frame by frame, motion ratio of each patch is evaluated at the end of each period to attain actual turbulence of fast-smoke and flame in terms of re-occurrence of fast-smoke/flame colored motion in a given duration. At the end of each period, accumulation is reset to zero in case of no motion is detected. In a given duration, patches which have continuous consecutive re-occurrence of motion greater than the accumulation threshold is detected as fast-smoke/flame.

**Table 8.** Pseudo-code of Fast Smoke and Flame Detection Algorithm

```

Let  $\theta$  be the motion ratio of any patch
Let  $\beta$  be the threshold for motion ratio of any patch
Let  $\alpha$  be the number of active periods of any patch
Let  $\partial$  be the threshold for accumulation of any patch

for each period  $N$ 
  for each patch  $p$ 
    IF  $\theta_p \geq \beta$  THEN
       $\alpha = \alpha + 1$ 
      IF  $\alpha \geq \partial$  THEN
        Detect fast smoke or flame
      ELSE
         $\alpha = 0$ 
        Terminate fast smoke or flame

```

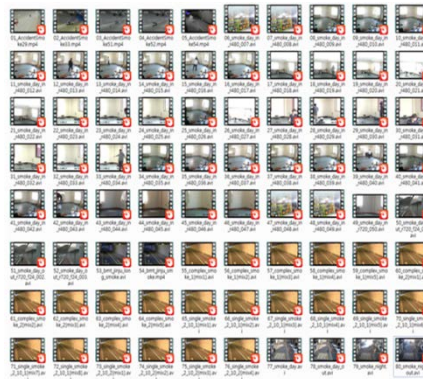
## 2.7 Blob Tracking

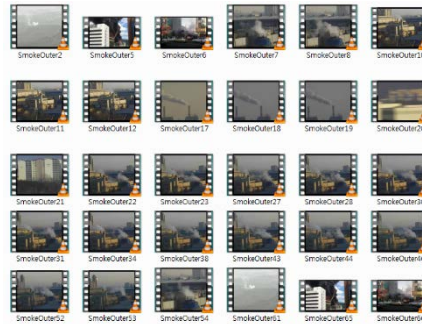
Binary label images are constructed from the detected patches by filling each patch with white while keeping the background as black for smoke and flame localization. Finally, label images are employed for blob tracking. An open source blob tracking library is used for this purpose [32].

## 3. Experimental Results and Analysis

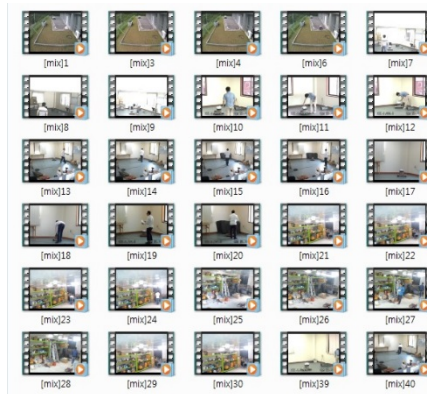
The proposed framework is initially tested with various indoor and outdoor video sequences including live and off-line videos which have been taken by surveillance cameras with different conditions. Secondly, a public dataset [14] is used for benchmarking study with existing methods. For experimental setup, videos recorded by stationary cameras are particularly selected since proposed zoom/tilt/pan detection module cannot detect small camera motions which are able to create similar motion frequency patterns with slow-smoke, fast-smoke and flame.

Thumbnail snapshots of publicly unavailable dataset are shown in Fig. 7, Fig. 8 and Fig. 9 for slow-smoke, fast-smoke and flame detection, respectively.

**Fig. 7.** Thumbnail snapshots of test videos for slow-smoke detection



**Fig. 8.** Thumbnail snapshots of test videos for fast-smoke detection



**Fig. 9.** Thumbnail snapshots of test videos for flame detection

First, a publicly unavailable video database which includes 80 number of videos for slow-smoke detection and 30 number of videos for both fast-smoke and flame detection are tested with optimum parameter sets. Optimum parameter lists and their corresponding true results with 4 numbers of snapshots for each of the slow-smoke, fast-smoke and flame detection algorithms are shown below, respectively.

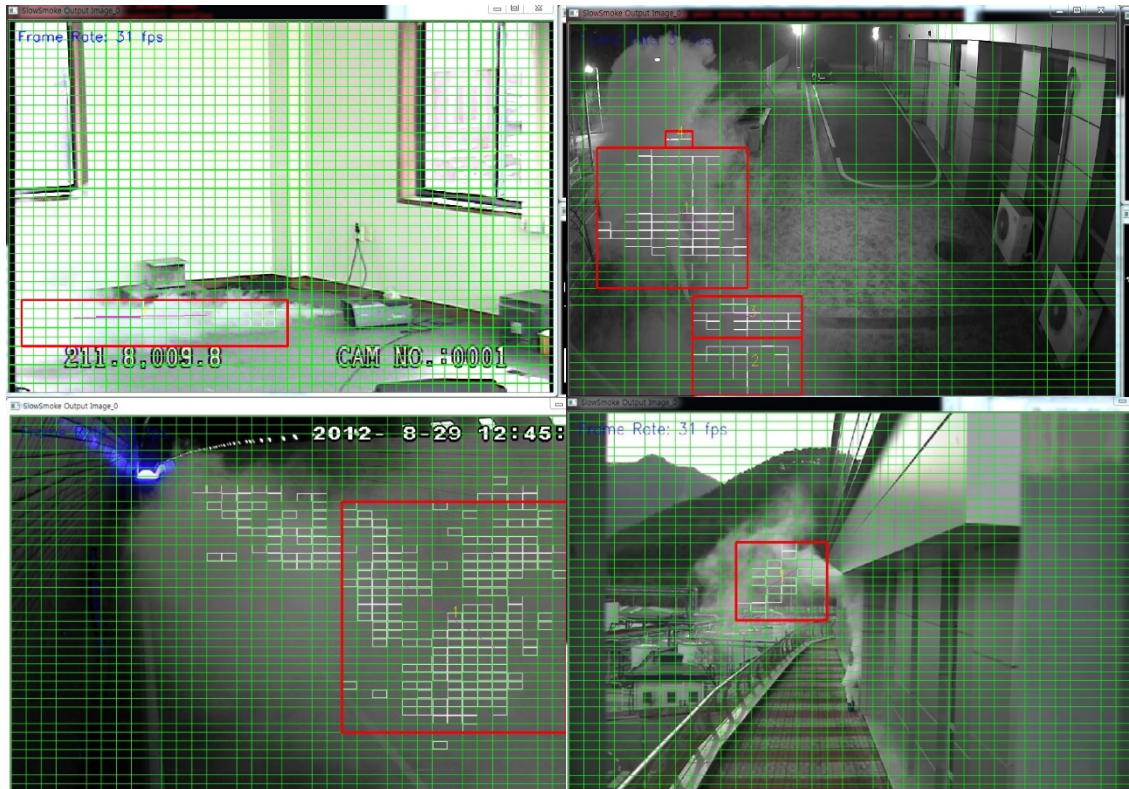
For slow-smoke detection, the best results (accuracy over 0.90) are taken with parameters shown in **Table 9** as follows:

**Table 9.** Optimum Parameter Settings for Proposed Slow Smoke Detection Algorithm

Parameters	Unit	Value	Range
Resize Ratio	-	0.50	[0,1]
Patch Size Ratio	-	0.02	[0,1]
Zoom/Tilt/Pan Threshold	-	0.25	[0,1]
Minimum Number of Slow Smoke Patches	-	3	[1,∞]
Minimum Active Time	seconds	1.00	[0,∞]
Motion Sensitivity	-	0.03	[0,1]
Patch Motion Ratio	-	0.50	[0,1]
Frames Skip Period	frame	5	[1,∞]
Patch Correlation Analysis Period	frame	20	[1,∞]
Patch Intensity Correlation Threshold	-	0.01	[0,1]
Patch Orientation Correlation Threshold	-	0.25	[0,1]



**Fig. 10** shows successful detection of slow-smoke in four different conditions.



**Fig. 10.** Sample snapshots of successful detection of slow-smoke

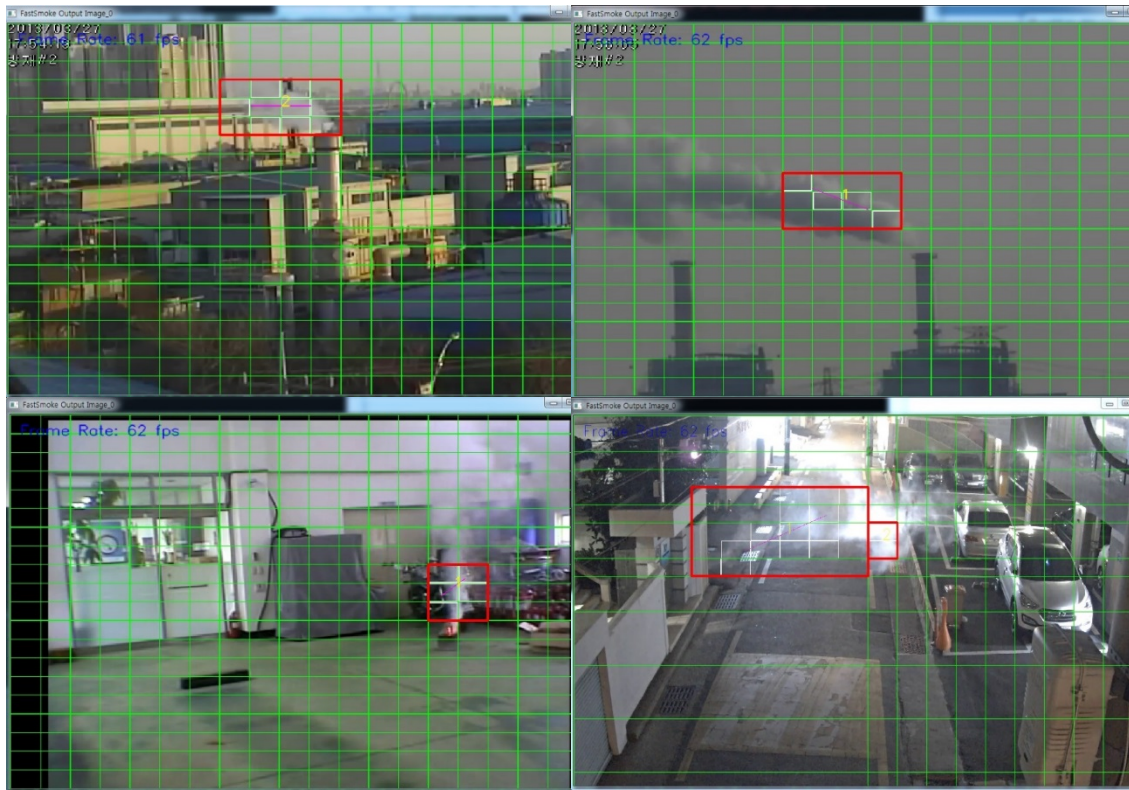
Except blackish smoke, any kind of slow-smoke is detected in a given period. In case of black smoke, only the regions neighbor to black smoke which create luminous behavior and make change in the intensity and orientation are detected. Skip period parameter is very useful since it is easy to remove high-frequency light changes by skipping  $n-1$  number of frames in a given skip period of  $n$ .

For fast-smoke detection, the best results (accuracy over 0.95) are taken with parameters shown in **Table 10** as follows:

**Table 10.** Optimum Parameter Settings for Proposed Fast Smoke Detection Algorithm

Parameters	Unit	Value	Range
Resize Ratio	-	0.25	[0,1]
Patch Size Ratio	-	0.05	[0,1]
Zoom/Tilt/Pan Threshold	-	0.25	[0,1]
Minimum Number of Fast Smoke Patches	-	1	[1,∞]
Minimum Active Time	seconds	0.25	[0,∞]
Fast Smoke Color Saturation Threshold	-	0.90	[0,1]
Motion Sensitivity	-	0.05	[0,1]
Patch Motion Ratio	-	0.07	[0,1]
Frames Skip Period	frame	2	[1,∞]
Motion Analysis Period	frame	5	[1,∞]
Number of Consecutive Motion Periods	period	3	[1,∞]

**Fig. 11** shows successful detection of fast-smoke in four different conditions as follows:



**Fig. 11.** Sample snapshots of successful detection of fast-smoke

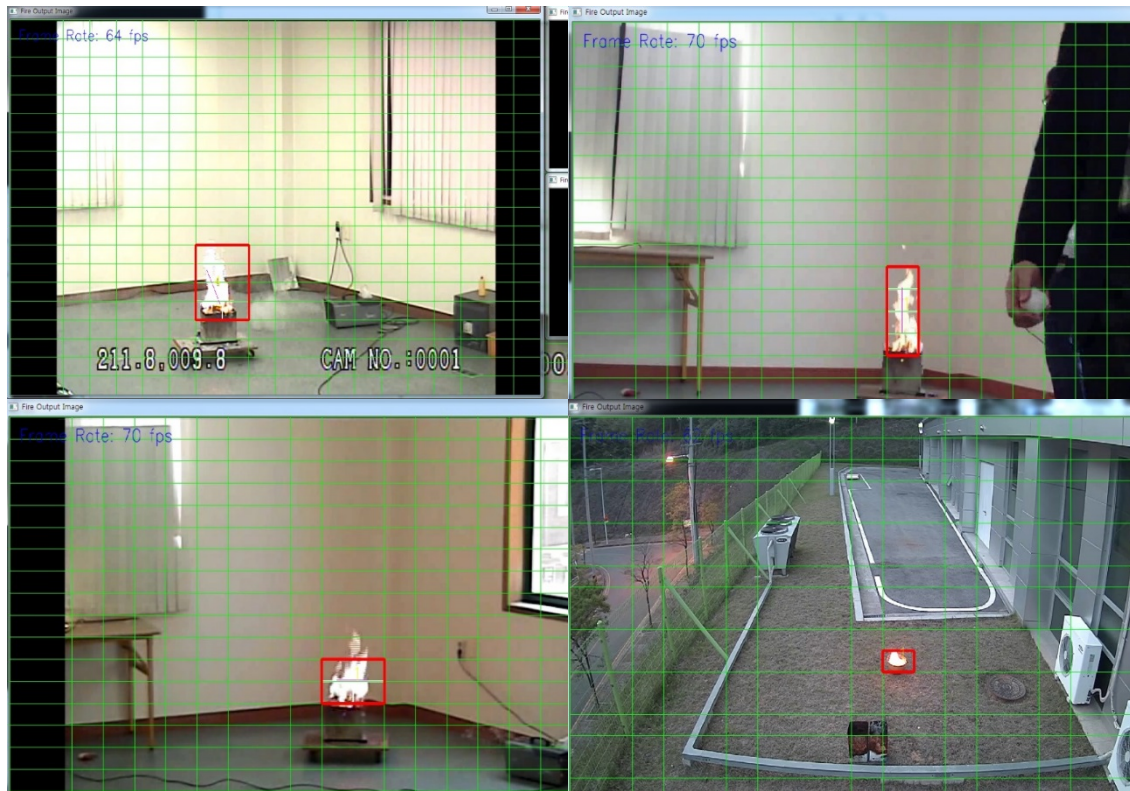
For flame detection, the best results (accuracy over 0.95) are taken with parameters shown in **Table 11** as follows:

**Table 11.** Optimum Parameter Settings for Proposed Flame Detection Algorithm

Parameters	Unit	Value	Range
Resize Ratio	-	0.25	[0,1]
Patch Size Ratio	-	0.05	[0,1]
Zoom/Tilt/Pan Threshold	-	0.25	[0,1]
Minimum Number of Flame Patches	-	1	[1,∞]
Minimum Active Time	seconds	0.25	[0,∞]
Flame Color Red Threshold	-	0.85	[0,1]
Motion Sensitivity	-	0.03	[0,1]
Patch Motion Ratio	-	0.01	[0,1]
Frames Skip Period	frame	3	[1,∞]
Motion Analysis Period	frame	9	[1,∞]
Number of Consecutive Motion Periods	period	10	[1,∞]

**Fig. 12** shows successful detection of flame in four different conditions as follows:





**Fig. 12.** Sample snapshots of successful detection of flame

Except texture-less fast-smoke/flame, any kind of fast-smoke/flame is detected in a given number of active periods. In case of texture-less fast-smoke/flame, only the regions that have high motion variations at fast-smoke/flame borders are detected.

As a measure of performance, precision and recall metrics are employed for a robust benchmarking with existing methods. Precision and recall are defined in (9) as follows:

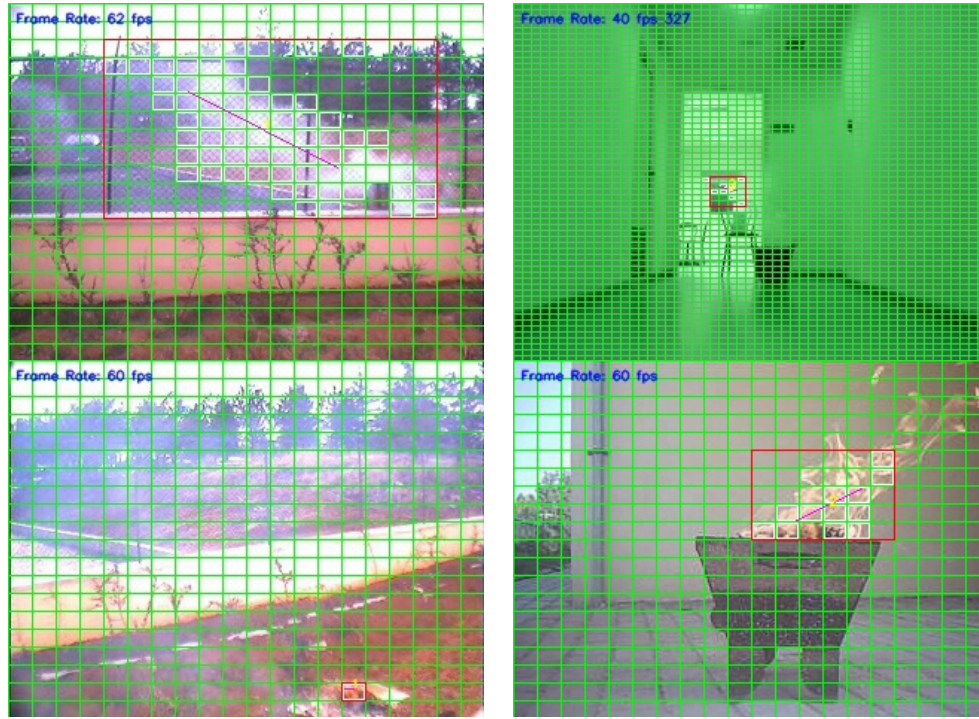
$$\text{Precision} = \frac{tp}{tp + fp} \quad \text{Recall} = \frac{tp}{tp + fn} \quad (9)$$

According to the selected performance metrics, results shown in **Table 12** are taken on the publicly unavailable dataset as follows:

**Table 12.** Performance Analysis on Experimental Results on Private Dataset

Performance Metrics	Slow Smoke	Fast Smoke	Flame
<b>Recall rate</b>	91.2 % 73/(73 + 7)	96.6 % 29/(29 + 1)	96.6 % 29/(29 + 1)
<b>False alarm rate</b>	6.2 % 5/80	6.6 % 2/30	3.3 % 1/30
<b>Precision</b>	93.5 % 73/(73 + 5)	93.5 % 29/(29+2)	96.6% 29/(29 + 1)

In second step, same parameter lists are used in Bilkent dataset [14] which is a public dataset of videos with 320 X 240 resolution previously used by various researchers [10, 12, 24, and 26] to test their methods for smoke and flame detection. Fig. 13 shows sample successful snapshots of smoke and flame detection by using proposed methods from Bilkent dataset [14].



**Fig. 13.** Sample snapshots of successful detection of smoke and flame (Public Dataset [14])

For benchmarking study, confusion matrices of tested videos are extracted and employed in comparative work with existing methods. Since existing methods [15, 12, 24, and 26] employ True-Positive Rate (TPR) as a benchmarking metric in their conductive papers, benchmarking study in this paper is performed in the same way shown in Table 13, Table 14 and Table 15.

**Table 13.** Performance Analysis on Experimental Results on Public dataset [14]

Video File Name	Number of Frames	TP	TN	FP	FN
sBtFence2.avi (320x240) (Top-Left)	698	670	15	3	10
ShorterIsyamNight.avi (320x240) (Top-Right)	830	756	28	12	34
sMoky.avi (320x240) (Bottom-Left)	448	437	6	2	3
barbeqraw.avi (320x240) (Bottom-Right)	218	208	5	1	4

**Table 14.** Benchmarking with Existing Methods on Public Dataset [14]

Video File Name	Method1(TPR%)	Method 2(TPR%)	Proposed Method (TPR%)
<b>sBtFence2.avi</b> (320x240) (Fast Smoke)	85.5 [10]	92.7 [12]	95.9
<b>ShorterIsyamNight.avi</b> (320x240) (Slow Smoke)	82.5 [10]	83.5 [12]	91.1
<b>sMoky.avi</b> (320x240) (Flame)	90.5 [26]	97.8 [24]	97.5
<b>barbeqraw.avi</b> (320x240) (Flame)	98.2 [26]	95.6 [24]	95.4

According to the benchmarking study shown in **Table 14**, proposed fast-smoke detection method leads amongst other two existing methods [10, 12] with almost 96% true-positive rate while slow-smoke detection method overwhelms the existing methods [10, 12] with almost 8 percent difference in selected performance metric. When it comes to flame detection, proposed method almost attain the same true-positive rate (over 95%) with other methods [24, 26] previously described in the literature.

Comparison of processing speed between the proposed method and existing methods is performed by benchmarking the methods that use the same video resolutions (320 x 240) in their experimental study. Benchmarking of speed with existing methods in the literature is given in **Table 15**. The unit of the values is in fps. According to the outcomes of the experiments, proposed method surpasses both of the existing methods.

**Table 15.** Benchmarking of Speed with Existing Methods in the Literature

SMOKE DETECTION		FLAME DETECTION	
Ref. [33]	10 fps	Ref. [37]	58 fps
Ref. [34]	35 fps	Ref. [26]	22 fps
Ref. [35]	35 fps	Ref. [38]	51 fps
Ref. [36]	25 fps	Ref. [34]	32 fps
Ref. [12]	15 fps	Ref. [24]	25 fps
<b>Proposed Method</b>	<b>50 fps</b>	<b>Proposed Method</b>	<b>60 fps</b>

Proposed method reaches up 40 fps in slow-smoke detection, 60 fps in fast-smoke and flame detection and attains 50 fps speed as the average of slow and fast smoke detection results. As a consequence, proposed methods for slow-smoke, fast-smoke and flame detection attain high percentages of True-Positive Rate with higher processing speed.

## 4. Conclusion

In this paper, a real-time video slow-smoke detection approach based on the periodical normalized cross-correlation of luminous pixels over chromatic pixels in a patch-wise paradigm is introduced. Instead of using spatial two-dimensional input, histogram bins are employed in correlation analysis. This method ideally suited for slow-smoke detection since slow-smoke creates transparency different from other object types. Depending on different parameter sets, different results are taken in different scenarios. Besides, same framework is applied on fast-smoke and flame detection based on the re-occurrence continuity of fast motion in a given duration. A periodical patch-wise paradigm is employed to analyze the fast-smoke and flame turbulence since fast-smoke/flame contours exceeds the borders of patch with high magnitudes of motion periodically. The method works well when the texture contours have some variations in itself which can create fast motion. Detection accuracy was enhanced by adding size and time filtering on active blob tracks. Instead of processing number of  $n$  frames coming from input video,  $n-1$  of them were skipped in a given period. This creates noticeable performance enhancement in speed. Frame rate of proposed method is measured around 40 fps for slow-smoke detection module and 60 fps for fast-smoke/flame detection module with optimum parameter settings on an Intel® Core (TM) i5-3570 CPU at 3.40 GHz and 8 GB of RAM. Additionally; a robust Pan/Tilt/Zoom detection module is employed to reset the system in immediate scene changes. The algorithm was tested with numerous videos (indoor/outdoor) and gives promising results with high percentages of accuracy and speed.

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## References

- [1] E. Çetin, K. Dimitropoulos, B. Gouverneur, N. Grammalidis, O. Günay, Y. H. Habiboglu, B. U. Töreyn, and S. Verstockt, "Video fire detection – Review," *Digit. Signal Process*, vol. 23, no. 6, pp.1827-1843, December, 2013. [Article \(CrossRef Link\)](#).
- [2] K. Dimitropoulos, O. Gunay, K. Kose, F. Erden, F. Chaabene, F. Tsalakanidou, N. Grammalidis, and E. Cetin, "Flame detection for video-based early fire warning for the protection of cultural heritage," in *Proc. of the 4th Int. Conf. on Progress in Cultural Heritage Preservation*, pp.378-387, October 29-November 3, 2012. [Article \(CrossRef Link\)](#).
- [3] B. Ko, J. Park, and J.Y. Nam, "Spatiotemporal bag-of-features for early wildfire smoke detection," *Image Vision Computing*, vol. 31, no.10, pp.786-795, October, 2013. [Article \(CrossRef Link\)](#).
- [4] H. Tian, W. Li, L. Wang, and P. Ogunbona, "A Novel Video-Based Smoke Detection Method Using Image Separation," in *Proc. of the IEEE Int. Conf. on Multimedia and Expo*, pp. 532-537, July 9-13, 2012. [Article \(CrossRef Link\)](#).
- [5] W. Yu, H. Ning, and L-Q. Juan, "A Smoke Detection Algorithm Based on Discrete Wavelet Transform and Correlation Analysis," in *Proc. of the 4th Int. Conf. on Multimedia Information Networking and Security*, pp.281-284, November 2-4, 2012. [Article \(CrossRef Link\)](#).
- [6] Feiniu Yuan, "A double mapping framework for extraction of shape-invariant features based on multi-scale partitions with AdaBoost for video smoke detection," *Pattern Recognition*, vol. 45, no. 12, pp.4326-4336, December, 2012. [Article \(CrossRef Link\)](#).



- [7] S. Calderara, P. Piccinini, and R. Cucchiara, "Vision based smoke detection system using image energy and color information," *Machine Vision Applications*, vol. 22, no. 4, pp.705-719, July, 2011. [Article \(CrossRef Link\)](#).
- [8] C. Long, J. Zhao, S. Han, L. Xiong, Z. Yuan, J. Huang, and W. Gao, "Transmission: a new feature for computer vision based smoke detection," in *Proc. of the Int.Conf.on Artificial Intelligence and Computational Intelligence*, pp.389-396, October 23-24, 2010. [Article \(CrossRef Link\)](#).
- [9] Dong-Keun Kim, "Smoke detection using boundary growing and moments," in *Proc. of the Int. Conf. on Hybrid Information Technology*, pp.430-433, August 27-29, 2009. [Article \(CrossRef Link\)](#).
- [10] Feiniu Yuan, "A fast accumulative motion orientation model based on integral image for video smoke detection," *Pattern Recognition Letters*, vol. 29, no.7, pp.925-932, May, 2008. [Article \(CrossRef Link\)](#).
- [11] S. Calderara, P. Piccinini, and R. Cucchiara, "Smoke detection in video surveillance: a MoG model in the wavelet domain," in *Proc. of the 6th Int. Conf. on Computer visionsystems*, pp. 119-128, May 12-15, 2008. [Article \(CrossRef Link\)](#).
- [12] Truong Xuan Tung and Jong-Myon Kim, "An effective four-stage smoke-detection algorithm using video images for early fire-alarm systems," *Fire Safety Journal*, vol.46, no.5, pp.276-282, July, 2011. [Article \(CrossRef Link\)](#).
- [13] Hearst, M. A., Dumais, S. T., Osman, E., Platt, J., and B. Scholkopf, "Support vector machines," *IEEE Intelligent Systems and their Applications*, vol. 13, no.4, pp. 18-28, August, 1998. [Article \(CrossRef Link\)](#).
- [14] Bilkent Video Dataset, Accessed June 6 2016. [Article \(CrossRef Link\)](#).
- [15] A. Vincitore, H. Wang, A. Finn, and O. Erdinc, "Spatial-temporal structural and dynamics features for Video Fire Detection," in *Proc. of the IEEE Workshop on Applications of Computer Vision*, pp.513-519, January 15-17, 2013. [Article \(CrossRef Link\)](#).
- [16] Truong Xuan Tung and Jong-Myon Kim, "Fire flame detection in video sequences using multi-stage pattern recognition techniques," *Engineering Applications of Artificial Intelligence*, vol. 25, no. 7, pp. 1365-1372, October, 2012. [Article \(CrossRef Link\)](#).
- [17] A. Ravichandran and S. Soatto, "Long-Range spatio-temporal modeling of video with application to fire detection," in *Proc. of the 12th European Conf. on Computer Vision*, pp. 329-342, October 7-13, 2012. [Article \(CrossRef Link\)](#).
- [18] Truong Xuan Tung and Jong-Myon Kim, "Fire detection with video using fuzzy c-means and back-propagation neural network," in *Proc. of the 8th Int.Conf.on Advances in Neural Networks*, pp.373-380, May 29-June 1, 2011. [Article \(CrossRef Link\)](#).
- [19] T.X. Truong, Y. Kim, J.M. Kim, "Fire Detection in Video Using Genetic-Based Neural Networks," in *Proc. of the Int. Conf. on Information Science and Applications*, pp. 1-5, April 26-29, 2011. [Article \(CrossRef Link\)](#).
- [20] Ishita Chakraborty and Tanoy Kr. Paul, "A Hybrid Clustering Algorithm for Fire Detection in Video and Analysis with Color Based Thresholding Method," in *Proc. of the Int. Conf. on Advances in Computer Engineering*, pp.277-280, June 20-21, 2010. [Article \(CrossRef Link\)](#).
- [21] P.V.K. Borges, E. Izquierdo, "A Probabilistic Approach for Vision-Based Fire Detection in Videos," *IEEE Transactions on Circuit and Systems for Video Technology*, vol. 20, no.5, pp. 721-731, May, 2010. [Article \(CrossRef Link\)](#).
- [22] Feiniu Yuan, "An integrated fire detection and suppression system based on widely available video surveillance," *Machine Vision Applications*, vol. 21, no.6, pp.941-948, October, 2010. [Article \(CrossRef Link\)](#).
- [23] T. Celik, H. Demirel, H. Ozkaramanli, and M. Uyguroglu, "Fire detection using statistical color model in video sequences," *Journal of Visual Communication and Image Representation*, vol. 18, no. 2, pp. 176-185, April, 2007. [Article \(CrossRef Link\)](#).

- [24] Jiang, B., Lu, Y., Li, X., and Lin, L., "Towards a solid solution of real-time fire and flame detection," *Multimedia Tools and Applications*, vol.74, no.3, pp. 689-705, February, 2015. [Article \(CrossRef Link\)](#).
- [25] H. Bay, A. Ess, T. Tuytelaars and L.V. Gool, "Speeded-up robust features (SURF)," *Computer Vision and Image Understanding*, vol. 110, no.3, pp. 346-359, June, 2008. [Article \(CrossRef Link\)](#).
- [26] Y. Habiboglu, H., Gunay, O., and A.E. Cetin, "Covariance matrix-based fire and flame detection method in video," *Machine Vision and Applications*, vol.23, no.6, pp.1103-1113, November, 2012. [Article \(CrossRef Link\)](#).
- [27] I.F. Ince, J.K. Do, G.Y. Kim and J.S. Park, "Patch-wise periodical re-occurrence analysis of motion for real-time video fire detection," in *Proc. of the IEEE Int. Conf. on Industrial Technology*, pp.651-654, February 26-March 1, 2014. [Article \(CrossRef Link\)](#).
- [28] Ince, I.F., Kim, G.Y., Lee, G.H., Park, J.S., "Patch-wise periodical correlation analysis of histograms for real-time video smoke detection," in *Proc. of the IEEE Int. Conf. on Industrial Technology*, pp.655-658, February 26-March 1, 2014. [Article \(CrossRef Link\)](#).
- [29] N. McFarlane, C. Schofield, "Segmentation and Tracking of Piglets in Images," *Machine Vision and Applications*, vol. 8, no.3, pp. 187-193, May, 1995. [Article \(CrossRef Link\)](#).
- [30] Robert G. Keys, "Cubic convolution interpolation for digital image processing," *IEEE Transactions on Acoustics, Speech and Signal Processing*, vol. 29, no.6, pp. 1153-1160, December, 1981. [Article \(CrossRef Link\)](#).
- [31] OpenCV: Geometric Image Transformations - OpenCV Documentation, Accessed June 6, 2016. [Article \(CrossRef Link\)](#).
- [32] cvBlob – Blob Library for OpenCV, Accessed June 6, 2016. [Article \(CrossRef Link\)](#).
- [33] Feiniu Yuan, "Video-based smoke detection with histogram sequence of LBP and LBPV pyramids," *Fire Safety Journal*, vol.46, no.3, pp.132-139, April, 2011. [Article \(CrossRef Link\)](#).
- [34] W.S. Qureshi, M. Ekpanyapong, M.N. Dailey, "QuickBlaze: Early Fire Detection Using a Combined Video Processing Approach," *Fire Technology*, vol.52, no.5, pp.1293-1317, September, 2016. [Article \(CrossRef Link\)](#).
- [35] Y. Wang, T. W. Chua, R. Chang and N. T. Pham, "Real-time smoke detection using texture and color features," in *Proc of the 21st Int. Conf. On Pattern Recognition*, pp. 1727-1730, November 11-15, 2012. [Article \(CrossRef Link\)](#).
- [36] S. Wang, Y. He, J.J. Zou, D. Zhou, J. Wang, "Earlysmokedetection in video usingswayinganddiffusionfeature," *Journal of IntelligentandFuzzySystems*, vol. 26, no.1, pp. 267-275, January, 2014. [Article \(CrossRef Link\)](#).
- [37] O. Günay, K. Taşdemir, B. U. Töreynand A. E. Çetin, "Video basedwildfiredetection at night," *Fire SafetyJournal*, vol.44, no.6, pp.860-868, August, 2009. [Article \(CrossRef Link\)](#).
- [38] Z. G. Liu, Y. Yang and X. H. Ji, "Flamedetectionalgorithm based on a saliency detection technique and the uniform local binary pattern in the YCbCr colorspace," *Signal, Image and Video Processing*, vol.10, no.2, pp. 277-284, February, 2016. [Article \(CrossRef Link\)](#).



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