

Smoke Detection in Video

DongKeun Kim¹ and Yuan-Fang Wang²

¹*Division of Computer Science and Engineering, Kongju National University, 330-717, Korea*
dgkim@kongju.ac.kr

²*Department of Computer Science, University of California at Santa Barbara, CA, 93106, USA*
yfwang@cs.ucsb.edu

Abstract

In this paper, we propose a method for smoke detection in outdoor video sequences. We assume that the camera is mounted on a pan/tilt device.

The proposed method is composed of three steps. The first step is to decide whether the camera is moving or not. While the camera is moving, we skip the ensuing steps. Otherwise, the second step is to detect the areas of change in the current input frame against the background image and to locate regions of interest (ROIs) by connected component analysis. The block-based approach is applied in both the first and second steps. In the final step, we decide whether the detected ROI is smoke by using the k -temporal information of its color and shape extracted from the ROI. We show the experimental results using in the forest surveillance videos.

1. Introduction

In recent years, video surveillance has become a widely used tool for monitoring. It is useful in many fields such as law enforcement, security, and protection of the environment, etc. Conventional smoke sensors have difficulty detecting in outdoor open spaces.

We are interested in monitoring forest fires automatically via video processing. Conventional smoke sensors are not suitable for fire detection in outdoor open spaces. Early detection of forest fires is very important to reducing fire damage. Flames and/or smoke are usually the first warning signs that a forest fire is incipient. Flames may not be visible to the monitoring camera if the flames occur a long distance or are obscured by obstacles like mountains or buildings. Smoke is a good indicator of a forest fire, but it can be difficult to identify smoke in images because it does not have a specific shape or color patterns.

Generally, methods for detecting fires using cameras can be categorized as smoke detection methods [1, 2, 3, 4, 5] and flame detection methods [5, 6, 7, 8, 9, 10]. Smoke detection methods often use color and motion information to detect smoke from digital images. [5, 6, 7] detect flames from video images and [8, 9, 10] detect flames using IR images. In [1], Toreyin et al. proposed a smoke detection method based on background subtraction, and temporal and spatial wavelet transformation. The area of decreased high frequency energy component is identified as smoke using wavelet transforms. In [2], fractal encoding is used to segment smoke regions from an image, and smoke regions are then classified using self-similarity of smoke boundary shapes. In [4], optical flow is calculated to extract the moving areas, and smoke is detected using features like speed, column growing, volume, and height.

In this paper, we propose a smoke detection method which is based on block difference against the background in video captured from a CCD camera. It is assumed that the camera is moving on a pan/tilt device. Our proposed method comprises three steps. The first step is to decide whether the camera is moving or not. While the camera is moving, we do not perform the ensuing steps. The second step is to segment the areas of change, or regions of interest, between background image and current input frame; that is, to extract changed regions against the background. The changed regions are represented as blobs by connected components. The blobs in close proximity are merged with one another. The block-based approach which is used in both the first and second step has advantages such as speed and robustness. The final step is to determine, using temporal information of color and shape in the detected blobs, whether each blob of the current input frame is smoke.

The remainder of the paper is organized as follows. Section 2 presents our smoke detection approach. Section 3 presents experimental results, and section 4 contains the concluding remarks and future work.

2. Proposed Smoke Detection Approach

A flow chart of the proposed smoke detection method is shown in Fig. 1. To ensure efficiency and robustness, our proposed method is applied in the block-based manner.

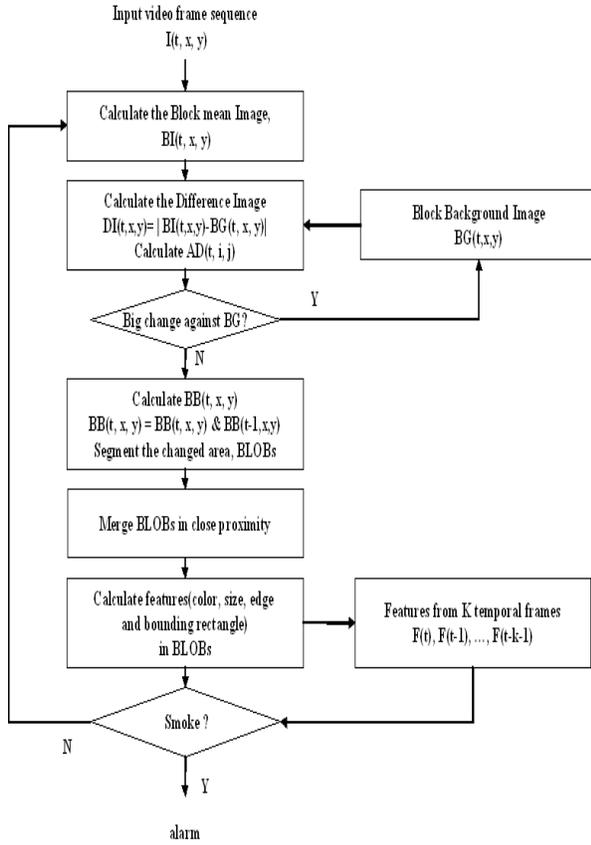


Fig. 1 Flow chart of our proposed method

2.1 Color Model and Absolute Block Mean Difference

In this paper, we use the luminance(Y) value in the YUV color model to determine whether the camera is moving and to extract ROIs, or blobs, which are connected components of areas of change. After a current input image $I(t, x, y)$ is grabbed from a camera, we calculate a block mean image $BI(t, x, y)$ using 2×2 window from the Y-component of $I(t, x, y)$. Initially, $BI(0, x, y)$ is set as a background block

image $BG(0, x, y)$. The absolute block mean difference is calculated as follows:

$$BD(t, x, y) = |BG(t, x, y) - BI(t, x, y)| \quad (1)$$

2.2 Camera Motion Detection and Background Update

In order to provide large spatial coverage, a surveillance camera is often mounted on a pan/tilt device, with the movement controlled remotely. A surveillance camera with a pan/tilt device moves in both the horizontal(pan) or vertical (tilt) directions. If the aim of camera is being manipulated by the pan/tilt device, the images show a big difference in $BD(t, x, y)$ of equation (1). We calculate a sub-block average of the difference by the equation (2).

$$AD(t, i, j) = \frac{1}{WX \times WY} \left(\sum_{y=i \times WY}^{(i+1) \times WY - 1} \sum_{x=j \times WX}^{(j+1) \times WX - 1} BD(t, x, y) \right) \quad (2)$$

Where i and j are sub-block indexes, $WX \times WY$ is sub block image size, and $M \times N$ is image size of $BD(t, x, y)$.

If the number of sub-blocks with $AD(t, i, j) > Th$ is greater than half of all sub-blocks, we conclude that the current input frame has a big change against the background due to pan/tilt movement. If so, we update $BG(t, x, y)$ as $BI(t, x, y)$. Otherwise we segment blobs using absolute block mean difference.

2.3 Change Detection: BLOBs segmentation

If the camera is stationary, then we extract the changed areas, $BLOBs(t, i)$ by using $BD(t, x, y)$. The binary image which records significant change is obtained by equation (3). And to eliminate temporally isolated areas, we use bitwise AND operation with $BB(t-1, x, y)$ by equation (4).

$$BB(t, x, y) = \begin{cases} 1 & \text{if } BD(t, x, y) \geq Th \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$BB(t, x, y) = BB(t, x, y) \& BB(t-1, x, y) \quad (4)$$

Applying the connected component algorithm, we can find $BLOBs(t, i), i = 0, \dots, N(t) - 1$. Where $N(t)$ is number of blobs at time t . Morphological operations like erode and dilate can be applied to remove small sized blobs.

2.4 BLOBs Merging

If a distance between $BLOBs(t, i)$ and $BLOBs(t, j)$ is small, they are merged into larger blobs by using an equivalence relation. The distance of blobs is calculated using two points which have a minimum distance between the two blobs. The merged blobs are represented using a bounding polygon from a convex-hull algorithm. It merges a lot of small blobs into one big one.

2.5 Classification of Smoke

From each $BLOB(t, i), i = 0, \dots, N(t) - 1$, we calculate features including area, bounding rectangle, the average and standard deviation of Y-value, and the average and standard deviation of UV-value. The statistics of UV-value can be calculated from the current input image $I(t, x, y)$. We keep the features, $F(t), F(t-1), F(t-2), \dots, F(t-k-1)$ which are calculated from k previous temporal frames where k is a queue size for tracking blobs. Where $F(t)$ is the features which are calculated from segmented blobs at time t . For each $BLOB(t, i), i = 0, \dots, N(t) - 1$ of time t , we determine whether it is smoke or not. We classify as smoke if it changes its shape and area continuously and has similar statistics in the Y-value in all k frames.

3. Experimental Results

In our experiments, we consider smoke detection in two videos recorded from a surveillance camera for forest fire prevention. Our program is implemented using Visual C++ and OpenCV on PC. The smoke in videos is generated on purpose for experiments. We used $Th = 4$, $k = 15$ and the distance for merging blobs is used 20 pixels. In Fig2 and Fig3, the top image is the block mean image and the bottom image is the background image at t . Fig. 2 shows experiments in video1 that has no pan/tilt motion and no smoke in initial background. The first blob is detected at $t = 571$, but the first smoke is detected at $t = 636$. We declare smoke when our tracking blobs satisfy smoke features in all $k = 15$ frames. We can detect smokes in all the frames after $t = 657$.

Table 1. Smoke detection results

Video sequence	Pan/tilt motion	# of background change	# of detected smoke frames	Total # of frames
Video1	No	1	1393	2044
Video2	Yes	169	5124	7418



(a) $t = 636$



(b) $t = 1100$

Fig. 2 Smoke detections in video1



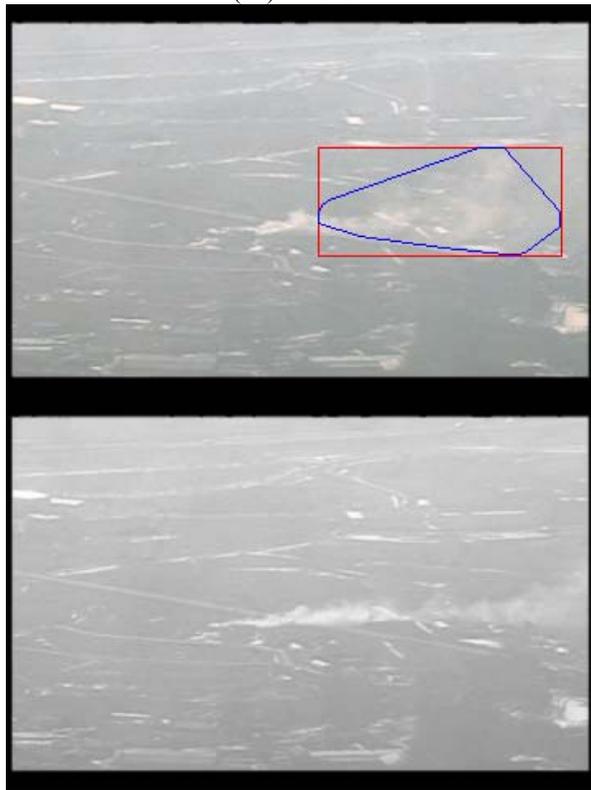
(a) $t = 373$



(c) $t = 2627$



(b) $t = 511$



(d) $t = 6500$

Fig. 3 Smoke detections in video2

Fig. 3 shows experiments in video2 that has pan/tilt motion and smoke in background. The number of changing background image is 169 and detected smoke in 5124 frames. We can effectively change the background image while the camera is moving by the pan/tilt device. If pan/tilt is stopped and has smoke in frames, although smoke is included background image, smoke is successfully detected in a few frames thereafter. While zooming, some blobs are detected in the sky and the mountain. If pan/tilt stops in that condition, false detection occurs. Because background has smoke already, we can not detect smoke immediately if smoke moves slowly.

4. Conclusion and Feature work

In this paper, we propose a method for smoke detection in outdoor video sequences. It works well in videos captured by surveillance cameras monitoring forest fires. Our proposed method is composed of three steps. The first step is to detect whether the camera is moving or not. While the camera is moving, we do not skip the ensuing steps. The second step is to detect the changing areas between the background image and the current input frame and to find blobs by connected components. The block subtraction approach is applied in both the first and second steps. The final step is to determine whether the detected blob indicates smoke. We use temporal change information of color and shape in the detected blobs. In the feature work, the algorithm needs some improvements in tracking of blobs and the classification of smoke.

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