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Smoke detection algorithm for intelligent video surveillance system

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Abstract

An efficient smoke detection algorithm on color video sequences obtained from a stationary camera is proposed. Our algorithm considers dynamic and static features of smoke and is composed of basic steps: preprocessing; slowly moving areas and pixels segmentation in a current input frame based on adaptive background subtraction; merge slowly moving areas with pixels into blobs; classification of the blobs obtained before. We use adaptive background subtraction at a stage of moving detection. Moving blobs classification is based on optical flow calculation, Weber contrast analysis and takes into account primary direction of smoke propagation. Real video surveillance sequences were used for smoke detection with utilization our algorithm. A set of experimental results is presented in the paper.

Keywords: smoke detection, video sequences, background subtraction, Weber contrast analysis

1 Introduction

Reliable and early fire detection on open spaces, in buildings, in territories of the industrial enterprises is important making any system of fire safety. Traditional fire detectors which have been widely applied in the buildings are based on infrared sensors, optical sensors, or ion sensors that depend on certain characteristics of fire, such as smoke, heat, or radiation. Such detection approaches require a position of sensor in very close proximity to fire or smoke and often give out false alarms. So they may be not reliable and cannot be applied into open spaces and larger areas. Due to the rapid developments in digital camera technology and video processing techniques currently intelligent video surveillance systems are installed in various public places for monitoring, therefore there is a noticeable trend to use such systems for early fire detection with special software applied. Smoke detection is rather for fire alarm systems when large and open areas are monitored, because the source of the fire and flames cannot always fall into the field of view. However, smoke of an uncontrolled fire can be easily observed by a camera even if the flames are not visible. This results in early detection of fire before it spreads around.

Motion and color are two usually used important features for detecting smoke on the video sequences. Motion information provides a key as the precondition to locate the possible smoke regions. The algorithm of background subtraction is traditionally applied to movement definition in video sequence [1-4]. Common technique uses adaptive Gaussian Mixture Model to approximate the background modeling process [1, 2].

In [5], optical flow calculation is applied to smoke movement detection. Lacks of the given approach are high sensitivity to noise and high computational cost. Algorithms based on color and dynamic characteristics of a smoke are applied for classification of the given moving blobs. In [6] the algorithm comparative evaluation of the histogram-based pixel level classification is considered. In this algorithm the training set of video sequences on which there is a smoke is applied to the analysis. Methods based on preliminary training are dependent on classification quality on a training set. It demands many qualitative characteristics of processed video images. The area of decreased high frequency energy component is identified as smoke using wavelet transforms [1, 2]. However change of scene illumination can be contours degradation reason. Therefore such approach requires additional estimations.

Color information is also used for identifying smoke in video. Smoke color at different stages of ignition and depending on a burning material is distributed in a range from almost transparent white to saturated gray and black. In [1] decrease in value of chromatic components U and V of color space YUV is estimated.

In this paper we propose an algorithm for smoke detection on color video sequences obtained from a stationary camera. Our algorithm consists of the following steps: preprocessing; slowly moving areas and pixels segmentation in a current input frame based on adaptive background subtraction; merge slowly moving areas with pixels into blobs; classification of the blobs obtained before. We use adaptive background subtraction at a stage of moving detection. Moving blobs classification is based on optical flow calculation, Weber contrast analysis and takes into account primary direction of smoke propagation.

2 Algorithm description

The proposed algorithm uses motion and contrast as the two key features for smoke detection. Motion is a primary sign and is used at the beginning for extraction from a current frame of candidate areas. In addition to consider a direction of smoke distribution the movement estimation based on the optical flow is applied. The relation of smoke intensity to background intensity above than at objects with similar behavior, such as a fog, shadows from slowly moving objects and patches of light. Therefore contrast calculated with Weber formula is a good distinctive sign for a smoke. The algorithm is a group of the following modules as it is shown in Figure 1. A consecutive frames I_{t-2},I_{t-1}, I_t and obtained from the stationary video surveillance camera are entered to an input of the preprocessing block. This block carries out some transformations which improve contrast qualities of the input frames and reduce calculations. Then adaptive background subtraction is applied to extract from the frame I_{t+1} of slowly moving areas and pixels of the so-called foreground. The background subtraction adaptive algorithm considers that a smoke gradually is mixed to a background. Then the connected components analysis is used in order to clear the foreground noise and to merge the slowly moving areas with pixels into blobs. The received connected blobs are transferred into the classification block for Weber contrast analysis. At the same time the connected blobs are entered to an input of the block for optical flow calculation.

Finally the classification block processes the information to obtain the final result of smoke detection.

2.1 Frame preprocessing

The preprocessing block applies some methods of image processing which increase the performance of the proposed detection algorithm and reduce false alarms. Frame preprocessing block comprises three steps: grayscale transformation, histogram equalization and the discrete wavelet of the current input frame. Cameras and image sensors must usually deal not only with the contrast on a scene but also with the image sensors exposure to the resulting light on that scene. Histogram equalization is a most commonly used method for improvement of contrast image characteristics. To resize the image and to remove high frequencies on horizontal, vertical and diagonal details the discrete wavelet transform to Haar basis is applied. Wavelet transform to Haar basis is the simplest and the fastest [7] algorithm that is important for systems of video processing.

2.2 Slowly moving areas and pixels segmentation

In the course of the distribution a smoke is being gradually blended to the background. Our adaptive algorithm of background subtraction considers this characteristic of a smoke and is based on the ideas stated in works [2,8]. A background image B_t at time instant t is recursively estimated from the image frame I_{t-1} and the background image B_{t-1} of the video as follows [9]:

$$B_t(x,y) = \begin{cases} \alpha B_{t-1}(x,y) + (1-\alpha) I_{t-1}(x,y),\ if\ (x,y)\ is\ moving, \\ B_{t-1}(x,y),\ if\ (x,y)\ is\ stationary, \end{cases}$$

where (x,y) represent a pixel video frame and α is an adaptation parameter between 0 and 1. As the area of a smoke frame by frame grows slowly, so that the pixels belonging to a smoke quickly are not fixed in a background, value α should be close to 1.

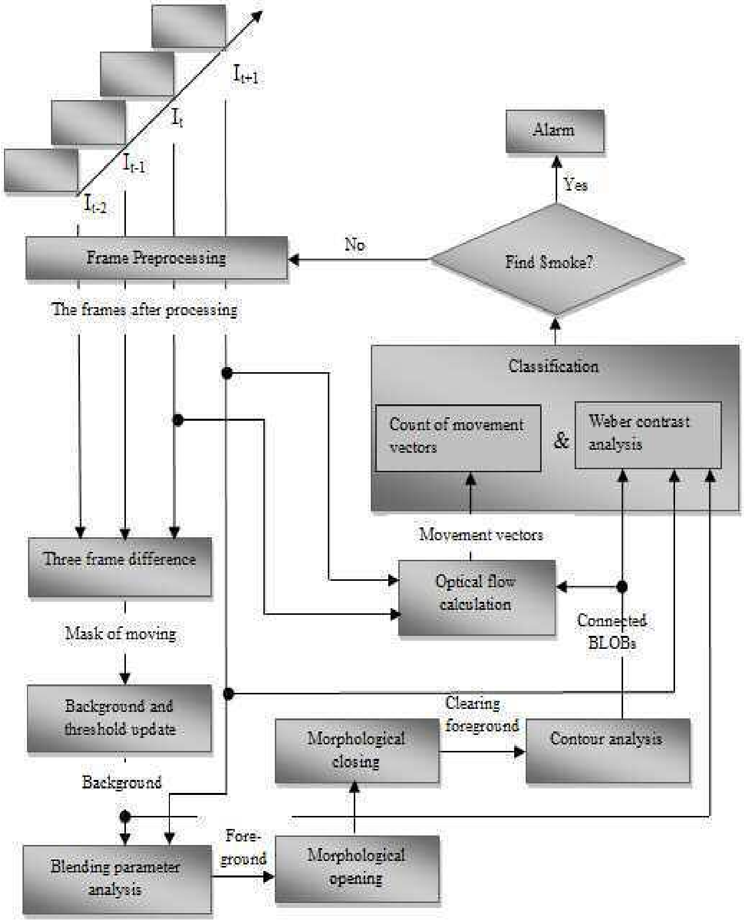


Figure 1. Flow chart of our proposed algorithm

At the initial moment of time $B_0(x,y) = I_0(x,y)$. Pixel (x,y) belongs to moving object if the following condition is satisfied [8]:

$$(|I_t(x,y) - I_{t-1}(x,y)| > T_t(x,y))\&(|I_t(x,y) - I_{t-2}(x,y)| > T_t(x,y)),$$

where $I_{t-2}(x,y)$, $I_{t-1}(x,y)$, $I_t(x,y)$ values of intensity of pixel (x,y) at time instant $t-2$, $t-1$ and t respectively; $T_t(x,y)$ is adaptive threshold for pixel (x,y) at time instant t calculated as follows:

$$T_t(x,y) = \begin{cases} \alpha T_{t-1}(x,y) + (1-\alpha)(5 \times |I_{t-1}(x,y) - B_{t-1}(x,y)|), \\ \quad if\ (x,y)\ is\ moving, \\ T_{t-1}(x,y),\ if\ (x,y)\ is\ stationary. \end{cases}$$

At the initial moment of time $T_0(x,y) = const > 0$.

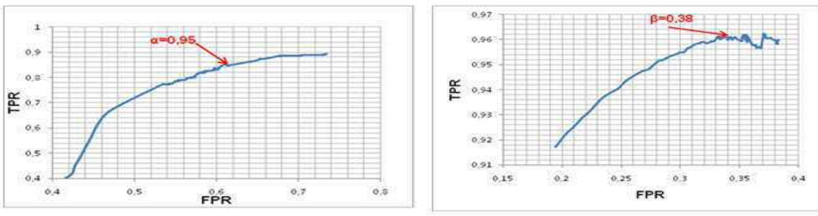
Accurate separating of a foreground object from the background is the main task of digital matting. Porter and Duff [9] introduced the blending parameter (so-called alpha channel) as a solution of this problem and a mean to control the linear combination of foreground and background components. Mathematically the current frame I_{t+1} is modeled as a combination of foreground F_{t+1} and background B_t components using the blending parameter β:

$$I_{t+1}(x,y) = \beta F_{t+1}(x,y) + (1-\beta)B_t(x,y).$$

For opaque objects the value of β is equal to 1, for transparent objects the value of β is equal to 0 and for the semitransparent objects, such as smoke, the value of β lays in a range from 0 to 1. As it is shown further in this section, we have experimentally established the optimum value for β to be equal to 0.38.

So, as soon as we have obtained B_t component on background update step, the current frame I_{t+1} and β set to 0.38, we can estimate the foreground component F_{t+1}. Then we apply the threshold processing to receive the binary foreground F_{bin}:

$$F_{bin} = \begin{cases} 1,\ if\ F_{t+1} > 245, \\ 0,\ otherwise. \end{cases}$$



(a) (b)

Figure 2. ROC curve for variable α (a) and β (b)

At the current step of algorithm we have 2 parameters α and β which are necessary to be estimated. Optimum values of α and β can be estimated using receiver operating characteristic (ROC) analysis. For estimation implementation the training set from 5 video sequences of the 200 frames length which contain and do not contain smoke were used. Using the ground truth regions which have been online marked as a smoke in the training frames, rates of true and false detection were calculated for the whole frame set. We received a background for each value of α within a range of (0, 1). After that we applied a background subtraction and thresholding to each frame from a training set. And then True Positive Rate (TPR) and False Positive Rate (FPR) were calculated as follows:

$$TPR = \frac{TP}{P}; FPR = \frac{FP}{N},$$

where TP – number of correctly classified pixels, P – number of all positive classified pixels; FP – number of incorrectly classified pixels, N – number of all negative classified pixels. For each value of α, the average TPR and FPR is evaluated on a training frame set and used in the ROC curve (Figure 2a).

Using the ROC curve, an optimum value for α can be easily selected for the smoke detection algorithm based on a pre-defined correct detection versus false detection rates. It is necessary to choose such value of α that slowly moving objects will not join a background too quickly, i.e. that a smoke will not be fixed in a background too fast. At the given stage of algorithm high TPR is important and high enough FPR is acceptable as it is necessary to receive as much as possible pixels for the analysis, and incorrectly classified pixels should be excluded at the following stages. Therefore we have established that an α value equals to 0.95. Similarly using the training frame set, receiving a foreground component F_{t+1} and after that the foreground F_{bin} and counting FPR and TPR for all values β from a range (0,1) with the step 0.001 we build a ROC curve for β (Figure 2b). Value of β has been chosen to be equal to 0.38, because such value of β provides high TPR and low FPR.

2.3 Connected component analysis

At the next step of algorithm to clear of noise and to connect moving blobs the connected components analysis is used. This form of analysis takes in a noisy input foreground. Morphological operations are applied to reduce the noise:

$$S \circ M = (S(-)M) \oplus M,$$

where S is image, M – structuring element 3×3; morphological closing to rebuild the area of surviving components that was lost in opening is the following:

$$S \bullet M = (S \oplus M)(-)M,$$

where M – structuring element 3×3.

Then search of all contours is carried out. Then it tosses the contours that are too small and approximate the rest with polygons.

2.4 Moving blobs classification

Blocks matching approach for optical flow calculation assumes that the frame is divided into small regions called blocks. It considers a primary direction of smoke propagation. In [10] it is shown, that global direction of smoke is 0-45°. This statement allows to simplify procedure of blocks matching detection and, hence, considerably to reduce number of calculations. Blocks are typically squares and contain some number of pixels. These blocks do not overlap. In our implementation frames of the size 320×240 pixels are divided into blocks of 2×2 pixels. Block matching algorithm attempts to divide both the previous and current frames into such blocks and then computes the motion of these blocks. Each block of size 2×2 can move in eight possible directions. Our implementation searches in three directions of the original block $q^{prev}_{x,y}$ (in the previous frame) and compares the candidate new blocks $q^{curr}_{x-1,y-1}$, $q^{curr}_{x,y-1}$ and $q^{curr}_{x+1,y-1}$ (in the current frame) with the original. This comparison is calculated as follows:

$$F(q^{prev}_{x,y}, q^{curr}_{x+k,y-1})^{k\in\{-1;0;1\}}_{x,y\in[2;N]} = \left(\frac{min(I^{prev}_{i,j}, I^{curr}_{i,j})}{max(I^{prev}_{i,j}, I^{curr}_{i,j})}\right),$$

where $I^{prev}_{i,j}$ is the intensity value of pixel on the previous frame, belonging to the block $q^{prev}_{x,y}$; $I^{curr}_{i,j}$ is the intensity value of pixel on the current frame, belonging to the block $q^{curr}_{x,y}$; N is the number of blocks into which the previous and current frame are divided.

The block $q^{prev}_{x,y}$ in the previous frame will correspond to the block in the current frame if function F has the maximum value. Optical flow calculation (function F) is done only for the blocks belonging to the foreground (Figure 3b). The result of this step is the set of vectors c_s having a direction corresponding to primary propagation of smoke (Figure 3c).

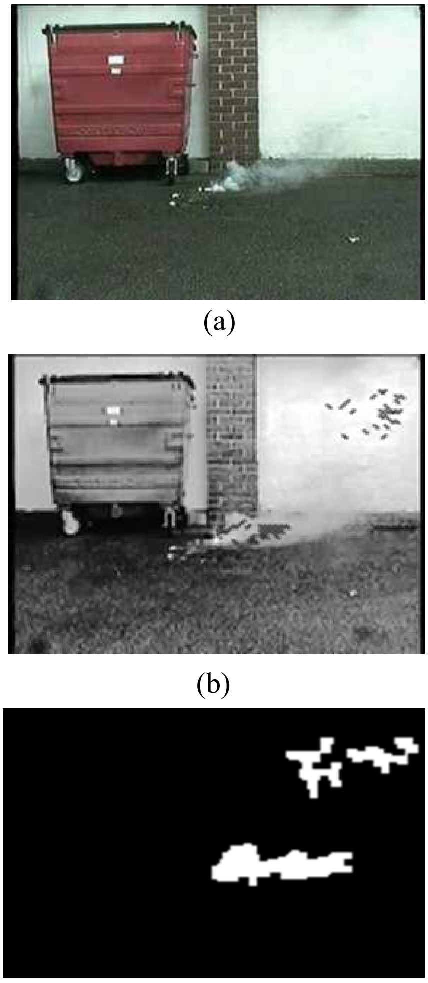
From each blob from the previous steps we calculate percentage ρ of blocks which have moved in primary direction of smoke:

$$\rho = \frac{c_s}{c}100\%,$$

where c – the total number of blocks on a current frame, and Weber contrast C_w:

$$C_w = \frac{1}{n}\sum_{i=1}^{n}\frac{I_{t+1}(x,y) - B_t(x,y)}{B_t(x,y)},$$

where $F_{t+1}(x,y)$ – value of pixel intensity (x,y) at time instant t, belonging to a blob, $B_t(x,y)$ – value of background pixel intensity (x,y)



(c)

Figure 3. The current frame (a), the clean up foreground (b) by the connected components analysis and the results of optical flow calculation (c)

at time instant t under blob, n – number of the pixels belonging to a blob.

If the blob has been successfully checked out, then we classify it as a smoke. Experimentally established values $C_w > 0,5$ and $\rho > 20\%$ allow efficient distinguishing of a smoke from objects with similar behavior: a fog, shadows from slowly moving objects and patches of light.

3 Results and discussion

The developed algorithm was tested on the real cases. Tests were run on a PC (Pentium(R) DualCore CPU T4300, 2,1 GHz, RAM 1,96GB). Our program was implemented using Visual C++ and an open source computer vision library OpenCV. The proposed algorithm has been evaluated using data set publicly available at the web address http://signal.ee.bilkent.edu.tr/VisiFire/Demo/SampleClips.html and http://www.openvisor.org. Test video sequences contain a smoke, moving people, moving transport, a complex dynamic background, and also a number of video sequences without any smoke. Figure 4 shows some examples of smoke detection.

Detection results for some of the test sequences are presented in Table 1. Processing time of a current frame depends on the blob sizes and frequency of changes occurring in a background. If the background is stable and few blobs are detected, then processing time decreases. Table 1 (the second column) contains average processing time on all frames for each test video sequence. The smoke has been found successfully out on all test video sequences with a smoke.

If at first a strongly rarefied smoke moves slowly, then it is gradually included into the background. Therefore in this case, we cannot directly find out a smoke, and the detection time increases. The performed experiments have shown that the algorithm quickly finds out a smoke on a complex dynamic scene. Smoke detection is achieved practically in real time. The processing time per frame is about 15 ms. for frames with sizes of 320 by 240 pixels. The algorithm considers both dynamic and static features of a smoke. The algorithm has a low false alarm level. False alarms on objects with properties similar to a smoke are

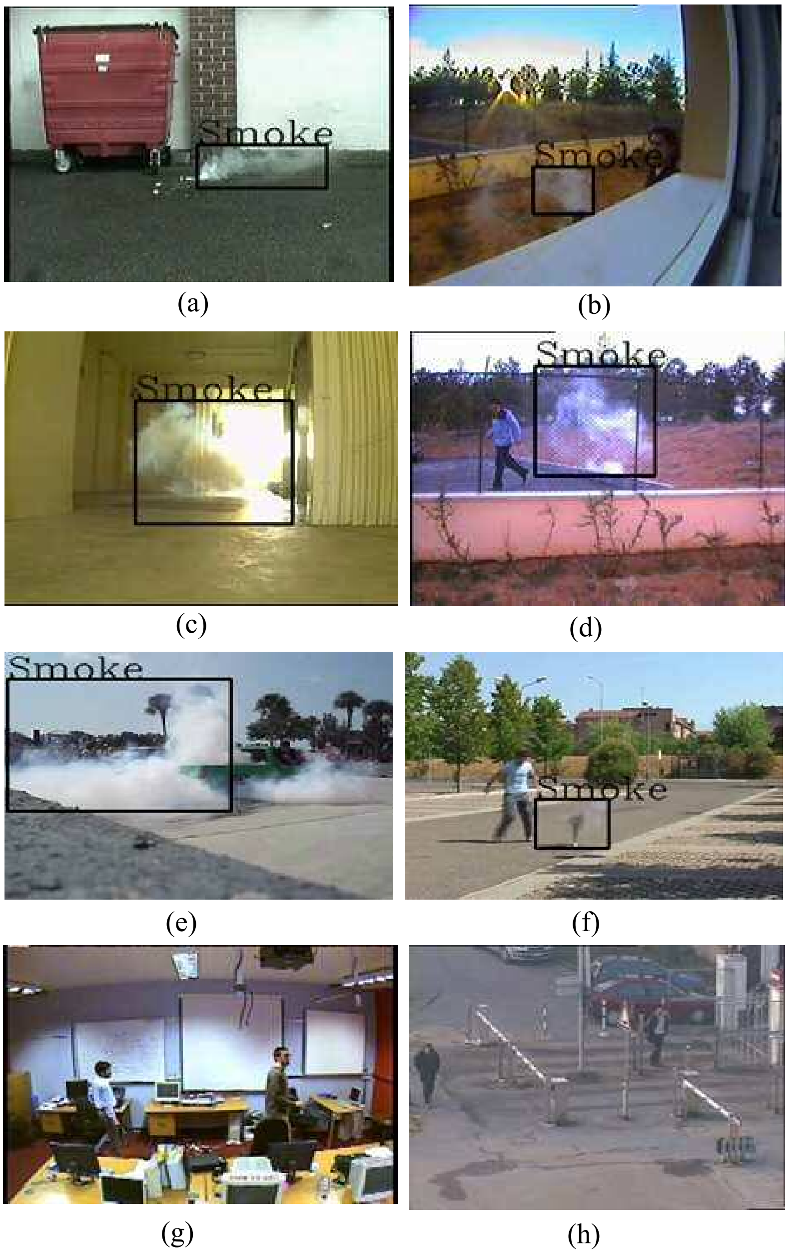


Figure 4. Smoke detection in real video sequences

sometimes possible. Tracing of smoky properties during some frames can solve this problem.

The smoke and flame are primary signs of a fire. Often there is a visible smoke development prior to flame. It can be important for early fire prevention. Therefore our algorithm can be effectively used in video surveillance systems for early detection of fire on open spaces.

Table 1. Detection results of our algorithm for some of the test sequences

Video sequences (Figure4)	The processing time per frame (ms)	The smoke was presented with / is found with (number of frame)	The number of frames on which there was false alarm / total of frames
a	12,665	10 / 12	0 / 900
b	14,786	20 / 112	0 / 244
c	14,969	80 / 87	0 / 483
d	15,003	30 / 117	0 / 630
e	15,491	360 / 388	0 / 2200
f	14,039	463 / 469	0 / 1835
g	16,346	-	0 / 1073
h	14,567	-	0 / 1179

4 Conclusion

We have presented in this paper an algorithm for smoke detection in video sequences. Our algorithm consists of the following steps: preprocessing; slowly moving areas and pixels segmentation in a current input frame based on adaptive background subtraction; merge slowly moving areas with pixels into blobs; classification of the blobs obtained before. We use adaptive background subtraction at a stage of moving detection. Moving blobs classification is based on optical flow calculation, Weber contrast analysis and takes into account primary direction of smoke propagation. The efficiency of our approach is illustrated and confirmed by our experimental videos.

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