An Effective Algorithm to Detect Both Smoke and Flame Using Color and Wavelet Analysis[1]

Shiping Ye[a], Zhican Bai[a], Huafeng Chen[a]*, R. Bohush[b], and S. Ablameyko[c]*****

[a] *Zhejiang Shuren University, Hangzhou, People's Republic of China*

[b] *Polotsk State University, Novopolotsk, Republic of Belarus*

[c] *Belarusian State University, Minsk, Republic of Belarus*

*e-mail: *eric.hf.chen@outlook.com, **bogushr@mail.ru, ***ablameyko@bsu.by*

Abstract— Fire detection is an important task in many applications. Smoke and flame are two essential symbols of fire in images. In this paper, we propose an algorithm to detect smoke and flame simultaneously for color dynamic video sequences obtained from a stationary camera in open space. Motion is a common feature of smoke and flame and usually has been used at the beginning for extraction from a current frame of candidate areas. The adaptive background subtraction has been utilized at a stage of moving detection. In addition, the optical flow-based movement estimation has been applied to identify a chaotic motion. With the spatial and temporal wavelet analysis, Weber contrast analysis and color segmentation, we achieved moving blobs classification. Real video surveillance sequences from publicly available datasets have been used for smoke detection with the utilization of our algorithm. We also have conducted a set of experiments. Experiments results have shown that our algorithm can achieve higher detection rate of 87% for smoke and 92% for flame.

Keywords: color image segmentation, video sequence, moving object, object recognition

DOI: 10.1134/S1054661817010138

1. INTRODUCTION

A fast response to fire occurrence is essential to reduce or prevent damage. The smoke and flame are primary signs of fires. Traditional fire detection methods which have been widely applied in the buildings are generally based on infrared sensors, optical sensors, or ion sensors that depend on certain characteristics of fires, such as smoke, heat, or radiation. These detection approaches require sensors located in very close proximity to fire or smoke and often send out false alarms. So they may be not reliable and cannot be applied into open spaces and larger areas because of the close distance between detectors and targets. Due to the rapid developments of digital camera technologies and video processing techniques, intelligent video surveillance systems have been equipped in various public places currently for monitoring. Therefore, it is a noticeable trend to employ such systems for early fire detection with special software.

Generally, video processing-based fire detection algorithms have been carried out using two principal characteristics of fire, flame and smoke [1, 2]. The joint detection of smoke and flame with the utilization of video processing technologies is still a problem, mainly due to following reasons: different characteristics of smoke and flame, diversity of background, lighting and none of the primitive image features such as intensity, motion, edge and texture characterizes smoke and flame as well.

Motion information has played a key role as the pre-condition to clarify the possible regions of smoke and flame. Traditionally, previous background subtraction algorithms have been applied to movement definition in video sequence [2–5]. Some common techniques prefer using the adaptive Gaussian Mixture Model to approximate the background modeling process [2, 3]. In [6], optical flow calculation has been applied to the movement detection of smoke. The approach has some drawbacks, including high sensitivity to noise and high computational cost. There are as well many studies with algorithms based on color and dynamic characteristics of smokes, to classify the pre-defined moving blocks. In [7], authors have proposed an algorithm to conduct comparative evaluation of the histogram-based pixel level classification. The training set of video sequences with smoke has been applied into the analysis. The area of decreased high frequency energy component has been identified as smoke using wavelet transforms [2, 3]. However, the changing of scene illumination can be the potential cause of contours degradation. Therefore, additional estimations are required in these approaches men-

[1] The article is published in the original.

Received September 30, 2016

tioned above. Color information also should be employed to identify smoke and flame in videos. Smoke color at different stages of ignition and with different burning material would vary from almost transparent white to saturated gray and black. In [2], authors have estimated the decreased value of chromatic components U and V of color space YUV.

Phillips et al. [8] have adopted a Gaussian distribution-based color model to color histogram for flame detection. This algorithm has employed information gained through both color and temporal variation to detect the fire. In [9] flame has been detected through analyzing the video in the wavelet domain in addition to ordinary motion and color clues. The algorithm checks flicker in flames using 1D temporal wavelet transform and color variation in fire-colored moving regions using 2D spatial wavelet transform. Töreyin et al. [10] have employed Hidden Markov Models and the wavelet transform for flickering pixels detection to indicate the presence of flames. Hidden Markov models usually have been used temporally and spatially to determine whether flame colored pixels flicker or not. In [11], authors have proposed a video fire detection algorithm based on the covariance texture representation method, which does not use a background subtraction method and therefore can be used with moving cameras. However, this algorithm can work well with clearly visible fire and in close range such that the flicker and irregular nature of flames are observable. There are also few studies on video fire detection that can detect both flame and smoke, but they are not effective and need to be improved [12, 13].

In this paper, we have proposed an algorithm to detect both smoke and flame in color video sequences obtained from a stationary camera. The algorithm allows effective and stable detection of smoke and flame, consisting of following steps: frame preprocessing, three frame differentiation, background update, foreground construction, morphological processing, contour analysis, chaotic motion estimation, and moving blob classification. The moving blob classification is based on spatial and temporal wavelet analysis, Weber contrast analysis and color segmentation in YCbCr color space.

2. ALGORITHM DESCRIPTION

In this section, we propose an algorithm using motion, color and contrast as key features for smoke and flame detection. On an input of the preprocessing block enter four consecutive frames I_{t-2}, I_{t-1}, I_t and I_{t+1}, and obtained from the stationary video surveillance camera. This block has carried out some transformations which can improve contrast qualities of input frames and reduce calculations. Then adaptive background subtraction has been applied to the extraction from a frame of slowly moving areas and pixels of the so-called foreground. For clearing of foreground noise and merge of the slowly moving areas and pixels into blobs the connected components analysis has been used. The received connected blobs would be transferred in the classification block for Weber contrast analysis. Simultaneously connected blobs enter on an input of the block for optical flow calculation. Finally, the classification block would process the information to achieve final result of smoke detection. The algorithm consisting of a group of following modules has been shown in Fig. 1.

2.1. Frame Preprocessing

The preprocessing block has applied some image processing methods which would be able to increase the performance of the proposed detection algorithm and reduce false alarms. Frame preprocessing block has comprised three steps, grayscale transformation, histogram equalization and the discrete wavelet of the current input frame. Cameras and image sensors must usually not only deal with the contrast on a scene but also deal with the image sensors exposure to the resulting light on that scene. Histogram equalization has been mostly used for the 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 has been applied. Wavelet transform to Haar basis is the simplest and the fastest algorithm that is important for systems of video processing.

2.2. Slowly Moving Areas and Pixels Segmentation

For motion segmentation background subtraction method has been used. In the course of the distribution smoke and flame gradually blended to a background. The adaptive algorithm of background subtraction offered by us considers this characteristic of smoke and is based on the ideas stated in works [3, 14]. 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 [14]:

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

where (x, y) represents 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, the pixels belonging to the smoke did not fix in a background quickly, value α should be close to 1.

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 [14]:

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

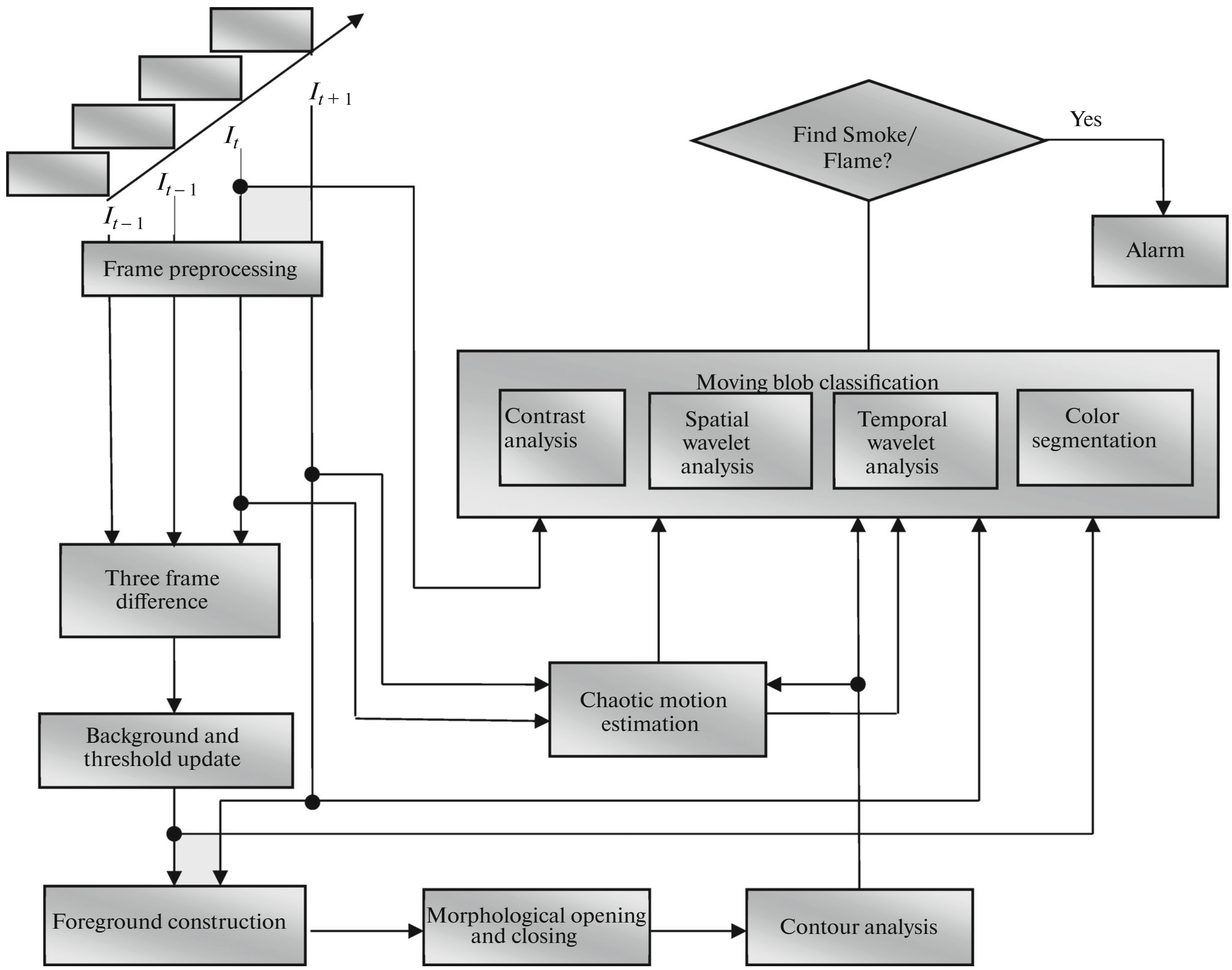

Fig. 1. The flow chart of the algorithm.

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:

$$T_t(x,y) = \begin{cases} \alpha T_{t-1}(x,y) + (1-\alpha)(5\times|I_{t-1}(x,y) - B_{t-1}(x,y)I_{t-1}(x,y) - B_{t-1}(x,y)|), \text{if } (x,y) \text{ is moving} \\ T_{t-1}(x,y),\ if\ (x,y) \text{ is stationary} \end{cases}. \quad (3)$$

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 [15] 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 parameterβ:

$$I_{t+1}(x, y) = \beta F_{t+1}(x, y) + (1 - \beta)B_t(x, y). \quad (4)$$

for opaque objects value of β is equal to 1, for transparent objects value of β is equal to 0 and for the semi-transparent objects, such as smoke, value of β lies 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, current frame I_{t+1} and set β 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}. At the current step of algo-

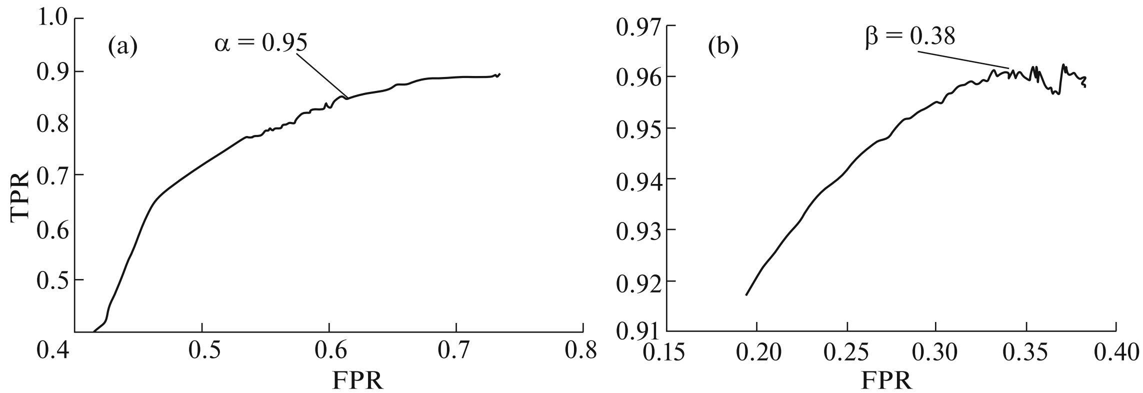

Fig. 2. ROC curve for variable α (a) and β (b).

rithm 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 we calculated True Positive Rate (TPR) and False Positive Rate (FPR) as follows:

$$TPR = \frac{TP}{P}; \quad FPR = \frac{FP}{N}, \tag{5}$$

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 (Fig. 2a).

Using the ROC curve, an optimum value for αcan 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 ofα that slowly moving objects will not join a background too quickly, i.e. that a smoke will not 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 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 (Fig. 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

On the next step of algorithm to clear of noise and to connect of moving blobs the connected components analysis has been used. This form of analysis has taken in a noisy input foreground. Morphological operations have been applied to reduce the noise:

• morphological opening to shrink areas of small noise:

$S \circ M = (S(-)M) \oplus M$, where S – image, M – structuring element 3×3;

• morphological closing to rebuild the area of surviving components that was lost in opening:

$S \bullet M = (S \oplus M)(-)M$, 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. Chaotic Motion Estimation

For smoke and flame generally characterized by disordered, random movement of the particles. Therefore, we have chosen optical flow to make statistics of smoke and flame moving characters. Optical flow calculation has been done only for the blocks belonging to the foreground. This procedure can decrease false detection rate effectively. Here we use the Farneback optical flow method [16]. Coefficient of co-directional motion of the particles is determined as:

$$C = V_c / V_t, \tag{6}$$

where V_c – number of motion vectors collinear, V_t – the total number of motion vectors for regions of interest.

2.5. Moving Blob Classification

2.5.1. Color segmentation and contrast analysis. The color properties of the fire signs are different, so we use the color segmentation of the flame and the contrast analysis to smoke. Segmentation for flame is performed in YCbCr color space according to the method proposed in [17], taking into account the global frame analysis and the analysis of the local area candidate. The region is considered to be owned by the flame, if:

$$Y_i > Y_m, \quad Cb_i < Cb_m, \quad Cr_i < Cr_m$$

where Y_i, Cb_i, Cr_i are the mean values of luminance, chrominance blue, and chrominance red channels of pixels in region of interest; Y_m, Cb_m, Cr_m are the mean values of luminance, chrominance blue, and chrominance red channels of pixels in frame;

Smoke can change its brightness-color performance in a very wide range of values, from transparent gray to black, so we applied analysis of areas of contrast. For the analysis of areas suspected to contain the smoke, we use Weber contrast:

$$C_w = \frac{1}{n}\sum_{i=1}^{n}\frac{F_{t+1}(x,y) - B_t(x,y)}{B_t(x.y)}, \tag{7}$$

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

2.5.2. Spatial and temporal wavelet analysis. For moving blob classification, we used energy and temporal statistics for each region of interest in the scene. Smoke is semi-transparent, so the edges of image frames can lose their sharpness and this leads to a decrease in the high frequency content of an image [18]. There are several techniques to estimate block energy, such as the Fourier Transform, Wavelet Transform, Laplace Transform. Wavelet tools usually are good at expressing image texture and edge characters, so smoke area usually is reflected by high wavelet energy. Decrease in high-frequency energy was monitored using a spatial wavelet transform of the current and background image. The energy is then given by:

$$E(B_k, I_t) = \sum_{m,n\in B_k}[LH(m,n)^2 + HL(m,n)^2 + HH(m,n)^2], \tag{8}$$

where B_k is the kth block of the region of interest; It is the input image; *LH, HL, HH* are wavelet transform coefficients which contain horizontal, vertical, and diagonal high frequency information from the original image, respectively.

A background image of the scene usually is smooth and lack of object and these areas usually own lower wavelet energy. Therefore, the background of the scene is estimated and decrease of high frequency energy of the scene is monitored using the wavelet transforms of the current and the background images based on [19]:

$$\lambda(B_k, I_t, BG_t) = \frac{E(B_k, I_t)}{E(B_k, BG_t)}, \text{ where } BG_t \text{ is background.} \tag{9}$$

The threshold value for λ is determined on the basis of experimental data obtained by the ROC-analysis. We have established an λ value equals to 0.75.

A one-dimensional temporal wavelet analysis of the spatial energy ratio λ is proposed as an indicator of flame flickering. Using temporal analysis we calculated wavelet extremes amount for each image region:

$$\varphi(B_k) = \sum_n |L[n]|/N, \tag{10}$$

where $L[n]$ is the high-frequency information of the energy ratio λ and N is a number representing the amount of time with a nonzero value for the details.

3. RESULTS AND DISCUSSION

The developed algorithm has been tested on the real cases. Test has been run on a laptop (Intel Core i5, 2,4 GHz, RAM 4GB). 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 and obtained by the authors using a video camera Panasonic SDR-S50. Test video sequences contain a smoke, flame, flame and smoke, moving people, moving transport, a dynamic background, and also a number of video sequences without any smoke and flame. Figure 3 shows some examples of smoke and flame detection. The video sequences have a complex background, video objects for which the color and brightness properties are very similar to smoke or flame (Fig. 3). In addition we studied the video sequence (a,g), which were attended by the smoke and flames with a fairly abrupt change of direction and structure, which was due to the strong gusts of wind.

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. Average processing time per frame is about 56 ms for frames with sizes of 320 by 240 pixels, about 147 ms for frames with sizes of 480 by 320 pixels, about 316 ms for frames with sizes of 640 by 480 pixels.

Detection results for some of the test sequences are presented in table 1. From table, we can see that the algorithm has a low false alarm level, but false alarms on objects with properties similar to a smoke and

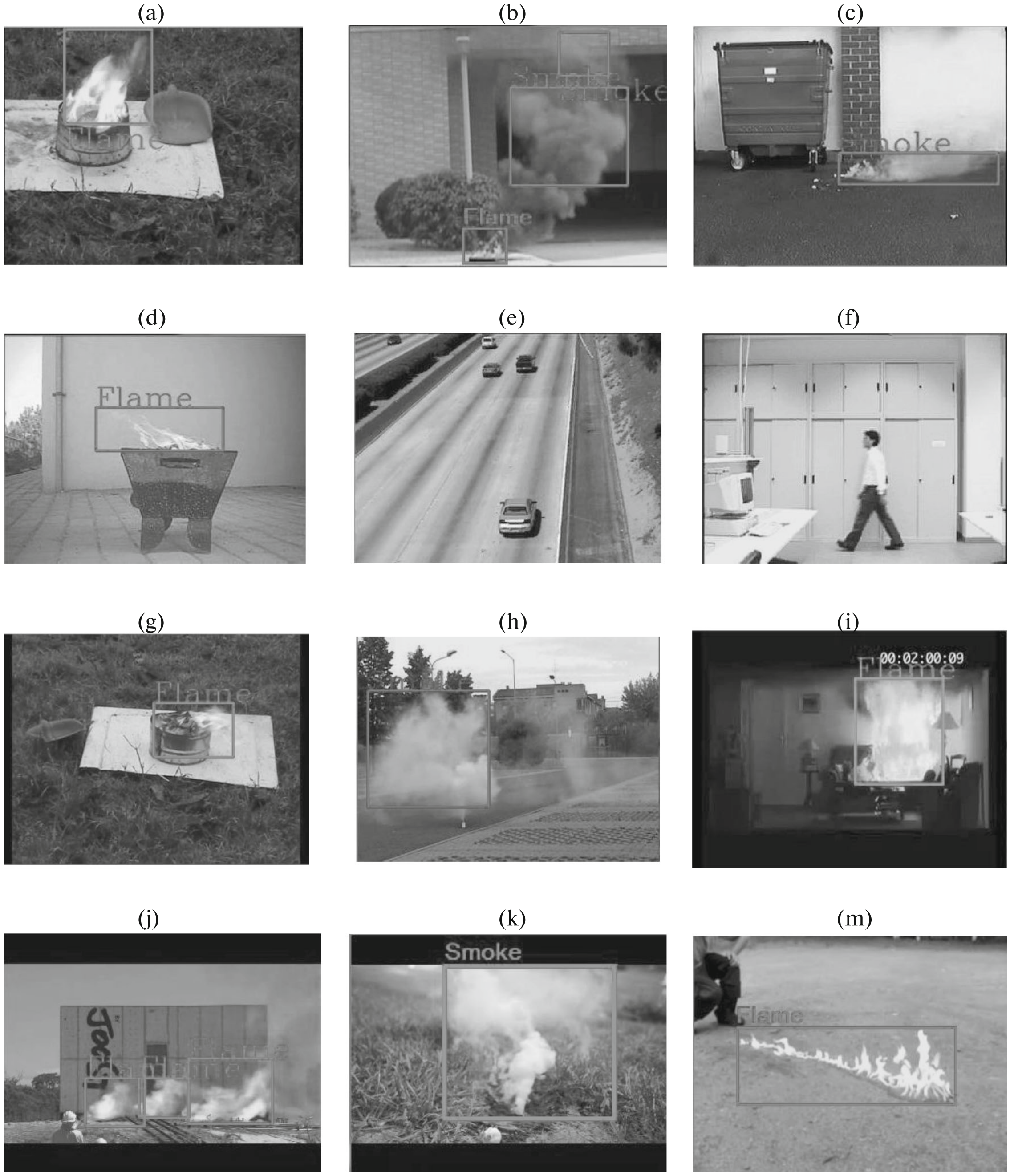

Fig. 3. Smoke and flame detection in real video sequences.

flame are sometimes possible. We defined an average true detection rate of 87% for smoke and 92% for flame. An average smoke true detection rate is 84.08% for algorithm in [18], 83.05% for algorithm in [19] and 91.6% for algorithm in [20]. Our algorithm can detect both of the main fire signs, smoke and flame, so we used a video data base, distinct from [18–20].

The presented algorithm can be effectively used in video surveillance systems for early detection of fire on open space.

4. CONCLUSION

We have presented an algorithm for smoke and flame detection in video sequences in this paper. 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, chaotic motion estimation, and moving blob classification. We use adaptive background subtraction at a stage of moving detection. Moving blobs

Table 1. Algorithm experimental results

Video sequences (Figure 3)	Flame found/ present (total of frames)	The flame was presented with/ is found with (number of frame)	Smoke found/ present (total of frames)	The smoke was presented with/ is found with (number of frame)	Smoke and flame found/ present (total of frames)	The count of frames on which was false alarm/ total of frames
a)	528/589	88/109	201/238	-/-	348/423	3/1375
b)	–/–	1/32	–/–	1/33	469/517	2/517
c)	–/–	–/–	858/866	9/10	–/–	0/900
d)	368/413	1/24	–/–	–/–	–/–	4/439
e)	–/–	–/–	–/–	–/–	–/–	6/500
f)	–/–	–/–	–/–	–/–	–/–	0/887
g)	1089/1216	460/483	–/–	–/–	–/–	8/1443
h)	–/–	–/–	1412/1497	421/452	–/–	4/1879
i)	867/908	1/33	15/26	428/431	–/–	3/934
j)	2019/2325	1/24	168/189	1026/1027	–/–	0/2325
k)	–/–	–/–	664/689	39/51	–/–	1/790
m)	947/967	168/191	–/–	–/–	–/–	9/1289

classification is based on spatial and temporal wavelet analysis, Weber contrast analysis and color segmentation in YCbCr color space. The efficiency of our approach has been illustrated and confirmed by our experimental videos.

ACKNOWLEDGMENT

This work is supported by Zhejiang Provincial Natural Science Foundation of China (LQ12D01004), the National High-end Foreign Experts Program (GDW20163300034) and Public Welfare Technology Applied Research Program of Zhejiang Province (2015C33074, 2015C33083).

REFERENCES

1. S. G. Kong, D. Jin, S. Li, and H. Kim, "Fast fire flame detection in surveillance video using logistic regression and temporal smoothing," Fire Safety J. **79**, 37–43 (2016).
2. P. Piccinini, S. Calderara, and R. Cucchiara, "Reliable smoke detection system in the domains of image energy and color," in *Proc. 15th IEEE Conf. on Image Processing ICIP* (San Diego, 2008), pp. 1376–1379.
3. B. U. Toreyin, et al., "Wavelet based real-time smoke detection in video," Signal Processing: Image Communication, EURASIP No. **20**, 255–256 (2005).
4. D. Kim and Y. Wang, "Smoke detection in video," in *Proc. WCCSIE* (Los Angeles, 2009), pp. 759–763.
5. B. U. Toreyin, Y. Dedeoglu, and A. Cetin, "Contour based smoke detection in video using wavelets," in *Proc. ESPC* (Saguenay, 2006), pp. 123–128.
6. F. Comez-Rodriuez, et al., "Smoke monitoring and measurement using image processing. Application to forest fires," in *Proc. SPIE Conf. on Automatic Target Recognition* (2003), pp. 404–411.
7. D. Kristinić, T. Jakovčević, and D. Stipaničev, "Histogram-based smoke segmentation in forest fire detection system," Inf. Technol. Control. **38** (3), 237–244 (2009).
8. W. Phillips, M. Shan, and V. Lobo, "Flame recognition in video," Pattern Recogn. Lett. **23** (1-3), 319–327 (2002).
9. B. U. Toreyin, Y. Dedeoglu, U. Gudukbay, and A. E. Cetin, "Computer vision based method for real-time fire and flame detection," Pattern Recogn. Lett. **27** (1), 49–58 (2006).
10. B. U. Toreyin, Y. Dedeoglu, and Y. Enis-Cetin, "Flame detection in video using hidden Markov models," in *Proc. IEEE Int. Conf. on Image Processing ICIP* (Genova, 2005), Vol. 2, pp. 1230–1233.
11. Y. Habiboglu, O. Gunay, and A. E. Cetin, "Flame detection method in video using covariance descriptors," in *Proc. ICASSP* (Prague, 2011), pp. 1817–1820.
12. C. Yu, Z. Mei, and X. Zhang, "A real-time video fire flame and smoke detection algorithm," in *Proc. 9th Asia-Oceania Symp. on Fire Science and Technology* (Hefei, 2013), Vol. 62, pp. 891–898.
13. A. Filonenko, D. C. Hernandez, A. Shahbaz, and K.-H. Jo, "Unified smoke and flame detection for intelligent surveillance system," in *Proc. ISIE 2016* (Santa Clara, 2016).
14. R. T. Collins, "A system for video surveillance and monitoring," in *Proc. American Nuclear Society 8th Int. Topical Meeting on Robotics and Remote Systems* (Pittsburgh, 1999), pp. 68–73.
15. T. Porter and T. Duff, "Compositing digital images," Comput. Graph. **18** (3), 253–259 (1984).

16. G. Farneback, “Two-frame motion estimation based on polynomial expansion,” in *Proc. 13th Scandinavian Conf. on Image Analysis* (Gothenburg, 2003), pp. 363–370.
17. T. Celik and H. Demirel, “Fire detection in video sequences using a generic color model,” Fire Safety J. **44** (2), 147–158 (2009).
18. K. Avgerinakis, A. Briassouli, and I. Kompatsiaris, “Smoke detection using temporal HOGHOF descriptors and energy colour statistics from video,” in *Proc. Int. Workshop on Multi-Sensor Systems and Networks for Fire Detection and Management Fire Sense* (Antalya, 2012), pp. 3–8.
19. L. Chen-Yu Lee, Chin-Teng Lin, Chao-Ting Hong, and Miin-Tsair Su, “Smoke detection using spatial and temporal analyses,” Int. J. Innovative Comput., Inf. Control **8** (8), 1–11 (2012).
20. W. H. Li, B. Fu, L. Xiao, Y. Wang, and P. X. Liu, “A video smoke detection algorithm based on wavelet energy and optical flow Eigen-values,” J. Software **8** (1), 63–69 (2013).

Shiping Ye. Born in 1967. Professor and Vice President of Zhejiang Shuren University. Graduated from Zhejiang University in 1988. In 2009 he got his master’s degree in Computer Science and Technology from Zhejiang University. His scientific interests include application of computer graphics and image, GIS. He has published more than 40 academic articles. Four research projects he has taken part in have been awarded second prize of Zhejiang Provincial Scientific and Technological Achievement. Two teaching research programs he has presided over have been awarded first prize and second prize of Zhejiang Provincial Teaching Achievement respectively.

Zhican Bai. Born in 1962. Assistant Professor of Zhejiang Shuren University. Graduated from Hangzhou Normal University in 1984. His scientific interests include digital image processing and computer network technology. He has published 10 academic articles and 4 books.

Huafeng Chen. Born in 1982. Lecturer of Zhejiang Shuren University. Graduated from Zhejiang University in 2003. In 2009 he got his PhD in the field of Earth Exploration and Information Technology at the Institute of Space Information & Technique, Zhejiang University. His scientific interests include remote sensing image processing, GIS application, image and video processing, multi-agent system. He has published 5 academic articles.

Rykhard Bohush. Graduated from Polotsk State University in 1997. In 2002 he got his PhD in the field of Information Processing at the Institute of Engineering Cybernetics, the National Academy of Sciences of Belarus. Head of Computer Systems and Networks Department of Polotsk State University. He is a member of the National Qualifications Framework of Higher Education of Belarus in IT and Electronics Science. His scientific interests include image and video processing, object representation and recognition, intelligent systems, digital steganography. Author of approximately 120 works, including one book on image processing.

Sergey Ablameyko. Born in 1956, DipMath in 1978, PhD in 1984, DSc in 1990, Prof in 1992. Rector (President) of Belarusian State University from 2008. His scientific interests are: image analysis, pattern recognition, digital geometry, knowledge based systems, geographical information systems, medical imaging. He has more than 400 publications. He is in Editorial Board of Pattern Recognition Letters, Pattern Recognition and Image Analysis and many other international and national journals. He is Editor-in-Chief of two national journals. He is a senior member of IEEE, Fellow of IAPR, Fellow of Belarusian Engineering Academy, Academician of National Academy of Sciences of Belarus, Academician of the European Academy, and others. He was a First Vice-President of International Association for Pattern Recognition IAPR (2006-2008), President of Belarusian Association for Image Analysis and Recognition. He is a Deputy Chairman of Belarusian Space Committee, Chairman of BSU Academic Council of awarding of PhD and DSc degrees. For his activity he was awarded by State Prize of Belarus (highest national scientific award) in 2002, Belarusian Medal of F. Skoryna, Russian Award of Friendship and many other awards.