Real-time smoke and flame detection in video

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REAL-TIME FIRE AND FLAME DETECTION IN VIDEO

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ABSTRACT

This paper proposes a novel method to detect fire and/or flame by processing the video data generated by an ordinary camera monitoring a scene. In addition to ordinary motion and color clues, flame and fire flicker is detected by analyzing the video in wavelet domain. Periodic behavior in flame boundaries is detected by performing temporal wavelet transform. Color variations in fire is detected by computing the spatial wavelet transform of moving fire-colored regions. Other clues used in the fire detection algorithm include irregularity of the boundary of the fire colored region and the growth of such regions in time. All of the above clues are combined to reach a final decision.

1. INTRODUCTION

Conventional point smoke and fire detectors typically detect the presence of certain particles generated by smoke and fire by ionisation or photometry. An important weakness of point detectors is that they are distance limited and fail in open or large spaces. The strength of using video in fire detection is the ability to monitor large and open spaces. Current fire and flame detection algorithms are based on the use of color and motion information in video [1]. In this paper, we not only detect fire and flame colored moving regions but also analyze the motion. It is well-known that turbulent flames flicker. Therefore, fire detection scheme can be made more robust by detecting periodic high-frequency behavior in flame colored moving pixels compared to existing fire detection systems described in [1].

If the contours of an object exhibit oscillatory behavior with frequency greater than 0.5 Hz then this is an important sign of presence of flames in the scene. High-frequency analysis of moving pixels is carried out in wavelet domain in this paper. Wavelet transform is a time-frequency analysis tool and one can examine an entire frequency band in wavelet domain [2]. Hence, it is ideally suited to determine an increase in high-frequency activity in some fire and flame colored objects. In addition, turbulant high-frequency behavior exist not only on the boundary but also inside a fire region. Spatial wavelet analysis makes it possible to detect high-frequency behavior inside a fire region.

2. FIRE AND FLAME DETECTION USING THE WAVELET ANALYSIS OF VISIBLE-RANGE VIDEO

Methods of identifying flame in video include [1], [3]. The method in [3] only makes use of the color information. On the other hand, the scheme in [1] is based on detecting the fire colored regions in the current video first. If these fire colored regions move then they are marked as possible regions of fire in the scene monitored by a camera.

By incorporating periodicity analysis around object boundaries, one can reduce the false alarms which may be due to flame colored ordinary moving objects. Turbulent flames flicker which significantly increase the Fourier frequency content between 0.5 Hz and 20 Hz [4]. In other words, a pixel especially at the edge of a flame could appear and disappear several times in one second of a video. The appearance of an object where the contours, chrominance or luminosity oscillate at a frequency greater than 0.5 Hz is a sign of the possible presence of flames. In [4], Fast Fourier Transforms (FFT) of temporal object boundary pixels are computed to detect peaks in Fourier domain. In [5], the shape of fire regions are represented in Fourier domain, as well. Since, Fourier Transform does not carry any time information, FFTs have to be computed in windows of data and temporal window size is very important for detection. If it is too long then one may not get enough peaks in the FFT data. If it is too short than one may completely miss cycles and therefore no peaks can be observed in the Fourier domain. Another problem is that, one may not detect periodicity in fast growing fires because the boundary of fire region simply grows in video. In [4], FFT analysis inside flame regions was not carried out.

In this paper, temporal and spatial wavelet analysis are carried out not only on flame boundaries but also inside the fire region. An increase in energy of wavelet coefficients indicate an increase in high frequency activity. For example, a fire colored moving object will not exhibit any increase in values of wavelet coefficients because there will not be any variation in fire colored pixel values.

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3. DETECTION ALGORITHM

Fire detection algorithm consists of four steps: i)moving pixels or regions in the current frame of a video are determined, ii)the colors of moving pixels are checked. If colors of pixels match to the fire colors then wavelet analysis in iii)time and iv)space are carried out to determine high-frequency content within the region of moving pixels. As an additional step, the irregularity of the boundaries and the growth of these regions are examined.

Moving pixels and regions in the video are determined by using a background estimation method developed in [6]. In this method, a background image B_{n+1} at time instant $n+1$ is recursively estimated from the image frame I_n and the background image B_n of the video as follows:

$$B_{n+1}(k,l) = \begin{cases} aB_n(k,l) + (1-a)I_n(k,l) & (k,l) \text{ stationary} \\ B_n(k,l) & (k,l) \text{ moving} \end{cases} \tag{1}$$

where $I_n(k,l)$ represent a pixel in the n^{th} video frame I_n, and a is a parameter between 0 and 1. Moving pixels are determined by subtracting the current image from the background image and thresholding. A recursive threshold estimation is described in [6]. Moving regions are determined by connected component analysis. Other methods like [7] and [8] can also be used for moving pixel estimation.

The color of moving pixels is compared with fire colors using a pre-estimated color histogram. Fire color information is obtained off-line by constructing a histogram describing possible flame colors. It is constructed from various videos containing fire and flame examples. This histogram can be in any one of the color spaces including Red, Green, and Blue (RGB), luminance, and chrominance signal representation (YUV), and Hue, Saturation (HSV) representation. The histogram can be normalized and smoothed to obtain an estimate of probability density distribution. The amount of match can be determined using probabilistic concepts because the histogram containing the fire information is determined off-line from many examples. If the value of current pixel falls into a high-probability region then there is a high chance of this pixel being a part of a flame or a fire region in the current image frame. For each pixel at time instant n, we associate a probability value $p_n[k,l]$ whose value is determined according to the estimated fire color histogram. If $p_n[k,l]$ exceeds a threshold then high-frequency analysis is carried out for such pixels. This is computationally more advantageous than applying temporal periodicity analysis to all the pixels of the image.

A third step can be added to the fire detection scheme of [1] by keeping track of frequency history of pixels in the fire colored region. In order to detect flicker in pixels due to fire in a reliable manner the video capture rate should be high enough to capture high-frequency flicker in flames. FFT is used to estimate the unusual activity in [4]. In this paper we describe a wavelet domain approach which is used to determine the temporal high-frequency activity in a pixel. A two-stage wavelet filterbank is used for a pixel whose fire-color probability exceeds a threshold at some time instant n as shown in Fig. 1. Input $x_n[k,l]$ to the filterbank is a one-dimensional signal representing the temporal variations at location $[k,l]$. The signal $x_n[k,l]$ can be the luminance (Y component) of the image or the red component in RGB color representation. We examine the wavelet subsignals $d_n[k,l]$ and $e_n[k,l]$ at 5 Hz image capture rate. In a stationary pixel, values of these two subsignals should be equal to or very close to zero because of high-pass filters used in subband analysis. If there is an ordinary fire-colored moving object going through pixel $[k,l]$ then there will be a single spike in one of these wavelet subsignals because of the transition from the background pixel to the object pixel as shown in Fig. 2. If the pixel is part of a flame boundary then there will be several spikes in one second due to transitions from background to flame and flame to background as shown in Fig. 3. Corresponding wavelet signals are also shown in these figures. Therefore, if $|e_n[k,l]|$ and/or $|d_n[k,l]|$ exceed a threshold value several times in a few seconds then an alarm is issued for this pixel.

The number of wavelet stages that should be used in flame flicker analysis is determined by the video capture rate. In the first stage of dyadic wavelet decomposition we obtain the low-band subsignal and the high-band wavelet subsignal $d_n[k,l]$ of the signal $x_n[k,l]$. The subsignal $d_n[k,l]$ contains [1.25 Hz, 2.5 Hz] frequency band information of

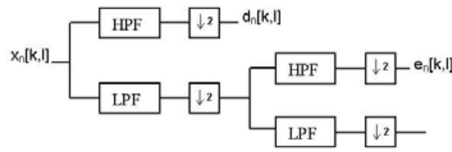

Fig. 1. A two stage filter bank.

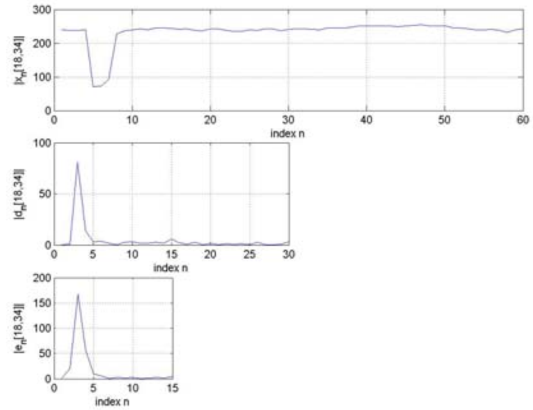

Fig. 2. Temporal history of the pixel [18,34] in time (top). Wavelet domain subsignals d_n and e_n exhibit a stationary behaviour for $n > 8$.

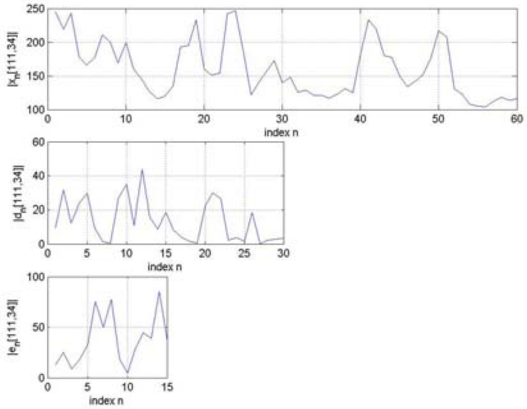

Fig. 3. Temporal variation of image pixels located at [111,34] in time (top). Corresponding subsignals d_n and e_n reveal the fluctuations.

the original signal $x_n[k,l]$ in 5 Hz video frame rate. In the second stage the lowband subsignal is processed once again using a dyadic filterbank and the subsignal $e_n[k,l]$ is obtained containing [0.625 Hz, 1.25 Hz] frequency band information of the original signal. This means that by monitoring the wavelet subsignals $e_n[k,l]$ and $d_n[k,l]$ one can detect 0.625 to 2.5 Hz fluctuations in the pixel $[k,l]$ whose fire-color probability exceeds a threshold in an image frame.

A forth step that we introduce in fire analysis is the spatial wavelet analysis of a moving region obtained by background subtraction. We first check if there are fire-colored pixels in the moving region. In order to capture flicker in pixel values we perform a spatial wavelet analysis of a rectangular frame containing the pixels forming the moving region. In an ordinary fire-colored object there will be little spatial variations in the moving region whereas there will be more spatial variations in a genuine fire region. A decision parameter v_4 where the subscript indicates the fourth stage of the algorithm can be defined according to the energy of the wavelet subimages:

$$v_4 = \frac{1}{MxN}\sum_{k,l}|x_{lh}[k,l]|^2 + |x_{hl}[k,l]|^2 + |x_{hh}[k,l]|^2 \quad (2)$$

where $x_{lh}[k,l]$, $x_{hl}[k,l]$ and $x_{hh}[k,l]$ are the low-high, high-low and high-high subimages of the wavelet transform, and MxN is the number of pixels in the fire-colored moving region. If the decision parameter v_4 exceeds a threshold then it is likely that this moving and fire-colored region under investigation may be a fire region.

The third and fourth steps are very important in fire and flame detection because they distinguish ordinary motion in the video from the motion due to turbulent flames and fire.

In addition to the wavelet domain analysis, the boundary and area of the fire-colored region are also determined. The boundary of a fire region should be irregular and the area of an uncontrolled fire should grow in image plane.

The fractal dimension [9] and the irregularity measure defined in [10] are computed to determine the irregularity of the flame-colored region. These values increase when the shape of the object becomes irregular or the boundaries become jerky, as in fire regions. It is experimentally observed that it may not be necessary to compute these measures. Because, irregular contours may occur in many moving objects like walking people. In our system, we only check the convexity of the fire region. In an uncontrolled fire, we expect the fire colored region should have a non-convex boundary. This eliminates the false alarms due to match lights, etc.

To determine the growth of the area of a fire-colored region, temporal analysis of the video is carried out. In order to obtain a robust measure, it is first determined, if fire-colored regions in two consecutive frames overlap. Then the areas and percentage growth of these regions are computed. If the amount of overlap is less than 50% of the area in the previous frame, this indicates an ordinary moving object. In addition, if the area of a fire colored region does not grow in-time, this indicates there is either a controlled fire or an ordinary fire-colored object.

We used a variant of m-out-of-n voting for decision fusion, the so-called T-out-of-v voting in which the output is accepted if $H = \sum_i w_i v_i > T$ where w_i's are the user-defined weights, v_i's are the decisions of the four stages of the algorithm, and T is a user-defined threshold. Decision parameters v_i can take binary values, 0 and 1 corresponding to normal case and the existence of fire, respectively. The decision parameter v_1 is 1, if the pixel is moving, and 0, if it is stationary. Decision parameters v_i can also take real values between 0 and 1. For example, the parameter v_2 can be equal to the color probability or v_2 can be equal to 1, if the color probability of the pixel exceeds a threshold, and 0 otherwise. The parameter v_3 is 1, if $|e_n[k,l]|$ and/or $|d_n[k,l]|$ exceed a threshold value several times in a few seconds, and 0 otherwise. The parameter v_4 is defined in Equation (2).

4. EXPERIMENTAL RESULTS

The proposed method (Method1) is implemented in real-time in a lap-top with a Mobile AMD AthlonXP 2000+ 1.66GHz processor and tested for a large variety of conditions in comparison with the method utilizing only the color and temporal variation information (Method2). The computational cost of the wavelet transform is low. The filterbank in Fig. 1 have integer coefficient low and high pass Lagrange filters. Both of the methods have similar timing performances. Method1 processes an image of size 360 by 288 at 15 msec. The comparison results for the test sequences is presented in Table 1. Method2 is successful in determining the fire and does not recognize stationary fire-colored objects as fire, like the sun for example. However it gives false alarms when the fire-colored ordinary objects start to move.

(a) (b)

Fig. 4. (a) False alarms on the fire colored line on the moving truck and the ground with the method using color and temporal variation based method in Movie 1 in Table 1, (b) our method does not produce any false alarms.

(a) (b)

Fig. 5. Sample images (a) and (b) are from Movies 2 and 4, respectively. Flames are successfully detected in (a), although they are partially occluded with the fence. Fire pixels are painted in bright green.

An example of this is shown in Fig. 4. The fire-colored strip on the cargo track triggers an alarm in Method2 when the truck starts to move. Similarly, false alarms are issued with Method2 in Movie 7 and 9 although there are no fires taking place in these videos. Similar to the situation presented in Fig. 3, these moving fire-colored objects does not cause an alarm to be raised if Method1 is used. Because, in Method1 the cyclic movement of flames are taken into account as well as the spatial variation in the color/brightness values of the moving fire-colored regions. Method1 detects fire successfully in videos covering various scenarios including partial occlusion of the flame. Sample images showing the detected regions are presented in Fig. 5.

5. CONCLUSION

A robust method for detecting fire and/or flame in color video is developed. The algorithm not only uses color and temporal variation information, but also it determines flicker using temporal wavelet transform and color variation in moving regions using the spatial wavelet transform. Methods based on only color information and ordinary movement detection may produce false alarms. The experimental results indicate that false alarms can be drastically reduced by

Table 1. Comparison of the proposed method (Method1) and the method based on color and temporal variation clues

Video Sequences	# of Shots with Fire	Method	# of Shots detected as Fire	# of False+ Frames	Description
Movie 1	0	Method1	0	0	A fire-colored moving truck
		Method2	5	46	
Movie 2	5	Method1	5	0	Fire in a garden
		Method2	5	0	
Movie 3	0	Method1	0	0	A car leaving a fire-colored parking lot
		Method2	1	1	
Movie 4	3	Method1	3	0	A burning box
		Method2	3	7	
Movie 5	8	Method1	8	0	A burning pile of woods
		Method2	10	24	
Movie 6	4	Method1	4	0	Fire behind a man with a fire colored shirt
		Method2	5	15	
Movie 7	0	Method1	0	0	Three men walking in a room
		Method2	2	4	
Movie 8	2	Method1	2	0	Fire in a fireplace
		Method2	2	0	
Movie 9	0	Method1	0	0	A crowded parking lot
		Method2	1	5	
Movie 10	0	Method1	0	0	Traffic on a highway
		Method2	0	0	

wavelet and object boundary analysis.

The method can be used for fire detection in movies and video databases as well as real-time detection of fire. It can be incorporated with a surveillance system monitoring an indoor or an outdoor area of interest for early fire detection.

6. REFERENCES

[1] W. Phillips III, M. Shah, and N. V. Lobo, "Flame recognition in video," *Pattern Recognition Letters*, vol. 23(1-3), pp. 319–327, 2002.

[2] A. E. Cetin and R. Ansari, "Signal recovery from wavelet transform maxima," *IEEE Trans. on Signal Processing*, vol. 42, pp. 194–196, 1994.

[3] G. Healey, D. Slater, T. Lin, B. Drda, and A. D. Goedeke, "A system for real-time fire detection," in *CVPR '93*, 1993, pp. 15–17.

[4] Fastcom Technology SA, *Method and Device for Detecting Fires Based on Image Analysis*, PCT Pubn.No: WO02/069292, Boulevard de Grancy 19A, CH-1006 Lausanne, Switzerland, 2002.

[5] C. B. Liu and N. Ahuja, "Vision based fire detection," in *ICPR '04*, 2004, vol. 4.

[6] R. T. Collins, A. J. Lipton, and T. Kanade, "A system for video surveillance and monitoring," in 8^{th} *Int. Topical Meeting on Robotics and Remote Systems*. 1999, American Nuclear Society.

[7] M. Bagci, Y. Yardimci, and A. E. Cetin, "Moving object detection using adaptive subband decomposition and fractional lower order statistics in video sequences," *Elsevier, Signal Processing*, pp. 1941–1947, 2002.

[8] C. Stauffer and W. E. L. Grimson, "Adaptive background mixture models for real-time tracking," in *CVPR '99*, 1999, vol. 2.

[9] M. F. Barnsley, *Fractals Everywhere*, Academic Press, San Diego, 1988.

[10] A. Amer, "Voting-based simultaneous tracking of multiple video objects," in *SPIE-VCIP*, 2003, vol. 5022, pp. 500–511.