

CONTOUR BASED SMOKE DETECTION IN VIDEO USING WAVELETS

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ABSTRACT

This paper proposes a novel method to detect smoke in video. It is assumed the camera monitoring the scene is stationary. The smoke is semi-transparent at the early stages of a fire. Therefore edges present in image frames start losing their sharpness and this leads to a decrease in the high frequency content of the image. The background of the scene is estimated and decrease of high frequency energy of the scene is monitored using the spatial wavelet transforms of the current and the background images. Edges of the scene produce local extrema in the wavelet domain and a decrease in the energy content of these edges is an important indicator of smoke in the viewing range of the camera. Moreover, scene becomes grayish when there is smoke and this leads to a decrease in chrominance values of pixels. Periodic behavior in smoke boundaries is also analyzed using a Hidden Markov model (HMM) mimicking the temporal behavior of the smoke. In addition, boundary of smoke regions are represented in wavelet domain and high frequency nature of the boundaries of smoke regions is also used as a clue to model the smoke flicker. All these clues are combined to reach a final decision.

1. INTRODUCTION

In this paper, we present an automatic real-time smoke detection method in video. Conventional point smoke and fire detectors typically detect the presence of certain particles generated by smoke and fire by ionization or photometry. An important weakness of point detectors is that in large rooms, it may take a long time for smoke particles to reach a detector and they cannot be operated in open spaces.

The main importance of using ordinary video in fire detection is the ability to serve large and open spaces. Current fire detection algorithms are based on the use and analysis of color and motion information in video to detect the flames [1, 2, 3, 4, 5]. However, smoke detection is vital 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.

Smoke gradually smoothens the edges in an image. This characteristic property of smoke is a good indicator of its

presence in the viewing range of the camera. Edges in an image correspond to local extrema in wavelet domain. Degradation of sharpness in the edges result in a decrease in the values of these extrema. However, these extrema values corresponding to edges do not totally boil down to zero when there is smoke in the scene. In fact, they simply lose some of their energy but they still stay in their original locations, occluded partially by the semi-transparent smoke.

Independent of the fuel type, smoke naturally decrease the chrominance channels U and V values of pixels. Apart from this, it was reported that turbulent flames flicker with a frequency of around 10Hz [2]. In practice, flame flicker process is time-varying and it is far from periodic. Therefore, a Markov model based modeling of flame flicker process produces more robust performance compared to frequency domain based methods trying to detect peaks around 10 Hz in the Fourier domain [4]. As a result, smoke boundaries also oscillate with a lower frequency at the early stages of fire.

In this paper, boundaries of smoke regions are estimated in each video image frame. A one-dimensional curve (1-D) representing the distance to the boundary from the center of mass of the region is extracted for each smoke region. The wavelet transform of this 1-D curve is computed and the high frequency nature of the contour of the smoke region is determined using the energy of the wavelet signal. This spatial domain clue is also combined with temporal clues to reach a final decision.

2. SMOKE DETECTION ALGORITHM

The flames of a fire may not always fall into the visible range of the camera monitoring a scene covering large areas like plane hangars or open spaces. Fire detection systems should tackle with such situations by successful detection of smoke without flame. In this paper, temporal and spatial wavelet analysis as well as an analysis of contours of possible smoke regions are carried out for the detection of smoke.

Smoke detection algorithm consists of five steps: (i)moving pixels or regions in the current frame of a video are determined, (ii)the decrease in high frequency content corresponding to edges in these regions are checked using spatial wavelet transform. If the edges lose their sharpness without vanishing completely (iii)the decrease in U and V channels of them are checked, (iv)flicker analysis is carried out by HMMs which use temporal wavelet transform coefficients. Finally (v)wavelet domain analysis of object contours are carried out. Moving objects in video are detected using the background estimation method developed by Collins et al. [6].

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Fig. 1. Image frame with smoke and its single level wavelet subimages. Blurring in the edges is visible. The analysis is carried out in small blocks.

This method assumes that the camera is stationary. Moving pixels are determined by subtracting the current image from the background image and thresholding. A recursive threshold estimation is described in [6]. Other methods can be also used for moving object estimation.

It is necessary to analyze these moving regions further to determine if the motion is due to smoke or an ordinary moving object. Smoke obstructs the texture and edges in the background of an image. Since the edges and texture contribute to the high frequency information of the image, energies of wavelet subimages drop due to smoke in an image sequence. Based on this fact we monitor wavelet coefficients as in Fig.1 and we detect decreases in local wavelet energy, and detect individual wavelet coefficients corresponding to edges of objects in background whose values decrease over time in video. It is also possible to determine the location of smoke using the wavelet subimages as shown in Fig.1.

Let $w_n(x,y) = |LH_n(x,y)|^2 + |HL_n(x,y)|^2 + |HH_n(x,y)|^2$ represent a composite image containing high-frequency information at a given scale. This subband image is divided into small blocks of size $(K1,K2)$ and the energy $e(l1, l2)$ of each block is computed as $e_{(l1,l2)} = \sum_{(x,y) \in R_i} w_n(x+l1K1, y+l2K2)$ where R_i represents a block of size $(K1,K2)$ in the wavelet subimage. If the wavelet subimages are computed from the luminance (Y) image then there is no need to include the chrominance wavelet images. If wavelet transforms of R, G, and B color images are computed then the energy $e(l1, l2)$ is computed using all of wavelet subimages of the R, G, and B color images. In our implementation, subimages are computed from the luminance image and the block size is taken as 8 by 8 pixels.

The above local energy values computed for the wavelet transform of the current image are compared to corresponding local high-frequency energies computed from the wavelet transform of the background which contains information about the past state of the scene under observation. If there is a decrease in value of a certain $e(l1, l2)$ then this means that the texture or edges of the scene monitored by the camera no longer appear as sharp as they used to be in the current image of the video. Therefore, there may be smoke in the image region corresponding to $(l1, l2)^{th}$ block. One can set up thresholds for comparison. If a certain $e(l1, l2)$ value drops below the pre-set threshold a warning is issued. It is also well-known that wavelet subimages contain the edge information of the original image. Edges produce local extrema in wavelet subimages [7]. Wavelet subimages LH , HL and HH

contains horizontal, vertical and diagonal edges of the original image, respectively. If smoke covers one of the edges of the original image then the edge initially becomes less visible and after some time it may disappear from the scene as the smoke gets thick. Let the wavelet coefficient $HL_n(x,y)$ be one of the wavelet coefficients corresponding to the edge covered by the smoke. Initially, its value decreases due to the reduced visibility, and in subsequent image frames it becomes either zero or close to zero whenever there is very little visibility due to thick smoke. Therefore locations of the edges of the original image is determined from the significant extrema of the wavelet transform of the background image in our system. Slow fading of a wavelet extrema is an important clue for smoke detection. If the values of a group of wavelet coefficients along a curve corresponding to an edge decrease in value in consecutive frames then this means that there is less visibility in the scene. In turn, this may be due to the existence of smoke. An instantaneous disappearance or appearance of a wavelet extremum in the current frame cannot be due to smoke. Such a change corresponds to an ordinary moving object covering an edge in the background or the boundary of a moving object and such changes are ignored. In order to determine the decrease in visibility of the edges, we set two thresholds $1 > T1 > T2 > 0$. For a decrease in visibility to occur, at a given scale, the composite image value $w_n(x,y)$ corresponding to an edge in the current image at location (x,y) and the composite image value $wb_n(x,y)$ similarly calculated for the background image at the same location, must satisfy $T1wb_n(x,y) > w_n(x,y) > T2wb_n(x,y)$. Since $T2 > 0$, we guarantee to have edges that are not totally invisible due to semi-transparent nature of initial smoke.

Color information is also used for identifying smoke in video as the third step. Initially, when the smoke starts to expand, it is semi-transparent thus it preserves the direction of the RGB vector of the background image. This is another clue for differentiating between smoke and an ordinary moving object. By itself, this information is not sufficient because shadows of moving objects also have the same property. As the smoke gets thicker, however, the resemblance of the current frame and the background decreases and the chrominance values U and V of the candidate region in the current frame become smaller than corresponding values in the background image. Only those pixels with lower chrominance values are considered to be smoke.

The flicker in smoke is also used as an additional information. The candidate regions are checked whether they continuously appear and disappear over time. It was reported in mechanical engineering literature that turbulent flames due to an uncontrolled fire flicker with a frequency of 10 Hz [2]. This, in turn induces a less frequent flicker in the smoke boundaries. In [8], the shape of fire regions are represented in Fourier domain. 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. Furthermore, one may not observe a peak at 10 Hz but a plateau around it, which may be hard to distinguish from the Fourier domain background.

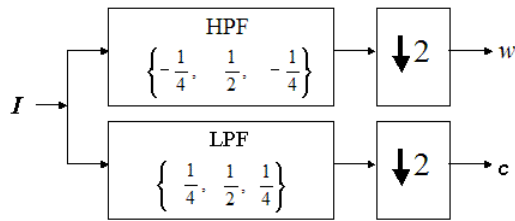


Fig. 2. Single-stage wavelet filter bank.

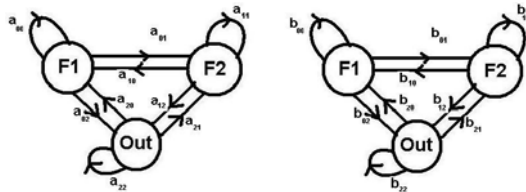


Fig. 3. Three-state Markov models for smoke(left) and non-smoke moving pixels.

Another problem is that, one may not detect periodicity in fast growing fires because the boundary of smoke region simply grows in video. Actually, the smoke and fire behaviors are wide-band random activities around 10 Hz and a random process based modelling approach is naturally suited to characterize the rapid time-varying characteristic of smoke and flame boundaries. In general, a pixel especially at the edge of a smoke becomes part of the smoke and disappears in the background several times in one second of a video at random. This characteristic behavior is very well suited to be modeled as a random Markov model which are extensively used in speech recognition systems and recently they have been used in computer vision applications [9].

In this paper, three-state Markov models are temporally trained for both smoke and non-smoke pixels (cf.Fig.3). These models are trained using a feature signal which is defined as follows: Let $I(n)$ be the intensity value of a pixel at frame n . The wavelet coefficients of I is obtained by the filter bank structure shown in Fig.2. Non-negative thresholds $T1 < T2$ introduced in wavelet domain, define the three states of the hidden Markov models for smoke and non-smoke moving objects. At time n , if $|w(n)| < T1$, the state is in $F1$; if $T1 < |w(n)| < T2$, the state is $F2$; else if $|w(n)| > T2$, the state Out is attained. The transition probabilities between states for a pixel are estimated during a pre-determined period of time around smoke boundaries. In this way, the model not only learns the way smoke boundaries flicker during a period of time, but also it tailors its parameters to mimic the spatial characteristics of smoke regions.

3. WAVELET DOMAIN ANALYSIS OF OBJECT CONTOURS

In addition to temporal and color analysis, contours of possible smoke regions are further analyzed. For this purpose, the centers of masses of the moving objects are determined. A one dimensional (1-D) signal is obtained by computing the



Fig. 4. Two moving objects in video: smoke image (top), and a vehicle (bottom). The object boundaries are determined by the background subtraction algorithm.

distance from the center of mass of the object to the object boundary for $0 \leq \theta < 2\pi$. In Fig.4, two image frames are shown. Example feature functions for moving vehicle and the fire region in Fig.4 are shown in Fig.5 for 64 equally spaced angles. The high-frequency variations of the feature signal of the smoke region is clearly distinct from that of the car and lights.

To determine the high-frequency content of a curve, we use a single scale wavelet transform shown in Fig.2. The absolute wavelet (w) and low-band (c) coefficients of the smoke region and the moving car are shown in Fig.6 and Fig.7, respectively. The ratio of the wavelet domain energy to the energy of the low-band signal is a good indicator of a smoke region. This ratio is defined as $\rho = \frac{\sum_n |w[n]|}{\sum_n |c[n]|}$. The likelihood of the moving region to be a smoke region is highly correlated with the parameter ρ .

4. EXPERIMENTAL RESULTS

The proposed method (Method1) is implemented in a PC with an AMD AthlonXP 2000+ 1.66GHz processor and tested for a large variety of conditions including real-time and off-line videos containing only smoke, both flame and smoke, and videos with no smoke or flame.

The computational cost of the wavelet transform is low. The filterbank in Fig.2 have integer coefficient low and high-pass Lagrange filters. The same filters are used for a single level wavelet decomposition of image frames in the spatial

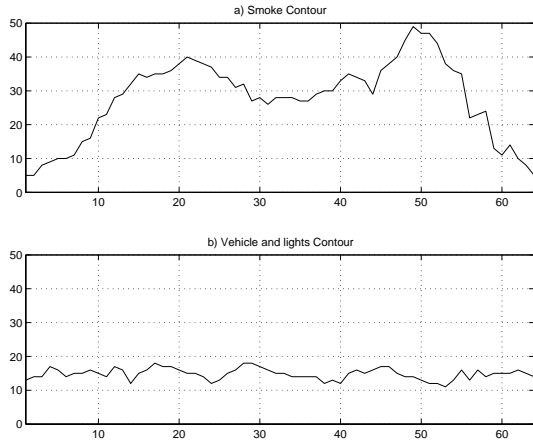


Fig. 5. Equally spaced 64 contour points of the smoke (top) and the vehicle regions (bottom) shown in Fig.4.

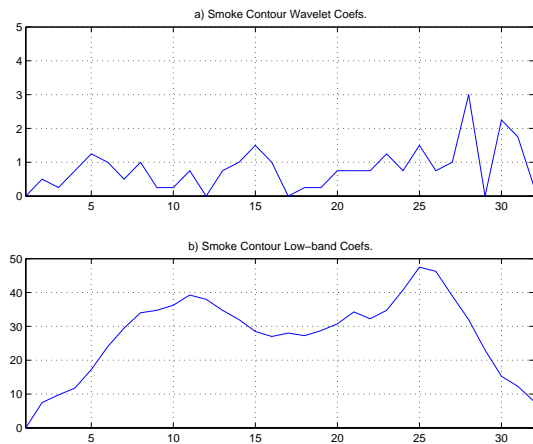


Fig. 6. The absolute a)wavelet and b)low-band coefficients for the smoke region.

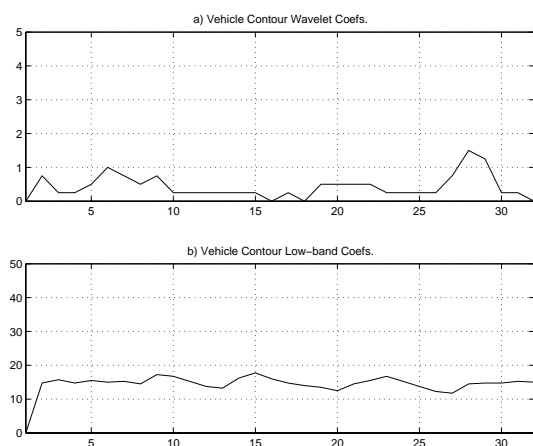


Fig. 7. The absolute a)wavelet and b)low-band coefficients for the vehicle.

Table 1. Detection results of Method1 and Method2 for some live and off-line videos.

Video Sequences	# of Shots with Smoke	# of Shots detected as Smoke		Description
		Method1	Method2	
Movie 1	0	0	0	A smoke-colored parking car
Movie 2	5	5	5	Fire in a garden
Movie 3	5	5	5	Fire in a garden in snow
Movie 4	7	7	7	A burning box
Movie 5	6	6	6	A burning pile of woods
Movie 6	3	3	3	Fire in a waste basket in the garden monitored from an indoor camera
Movie 7	0	0	0	Three men walking in a room
Movie 8	8	8	8	Fire in a fireplace
Movie 9	0	0	1	A parking car in the night

wavelet analysis step and also for contour analysis. Smoke detection is achieved in realtime. The processing time per frame is about 5 msec for frames with sizes of 160 by 120 pixels.

Detection results for some of the test sequences are presented in Table 1. Smoke is successfully detected in all of the shots containing smoke. No false alarms are issued in live tests and off-line videos recorded in the day time. False alarms are eliminated also for the videos recorded in the night with the help of the contour analysis. A false alarm is issued with the method in [10], Method2, in Movie 9 which is recorded at night. A parking car is captured from its front in this video. The driver intentionally varies the intensity of the front lights of the car. The light beams directed towards the camera at night defines artificial edges around them. These edges appear and disappear continuously as the intensity of the lights change. The U,V channel values of the pixels decrease as the light intensities are lowered, since everywhere in the scene is dark other than the car lights. In this way, car lights at night mimic the smoke characteristics in the day time and a false alarm is issued using Method2. However, using the method proposed in this paper (Method1), this false alarm is eliminated, because the contour of the moving region defined by the car lights does not possess high frequency characteristics as in a smoke region.

Proposed smoke detection method, Method1, is also compared with the fire detection method presented in [5], Method3, in videos containing both smoke and flame. The comparison results in some of the test sequences are presented in Table 2. At the early stages of fire, smoke is released before flames become visible. Method1 successfully detects smoke in such situations earlier than Method3. Hence, early detection of fire is possible with the proposed smoke detection method. In Movies 11 and 12, flames are not in the viewing range of the camera. A fire detection system without smoke detection capability fails in detecting the fire before it spread around.

5. CONCLUSION

A novel method for detecting smoke in video is developed. The algorithm is mainly based on determining the edge regions whose wavelet subband energies decrease with time

Table 2. Smoke and flame detection time comparison of Method1 and Method3, respectively. Smoke is an early indicator of fire. In Movie 11 and 12, flames are not in the viewing range of the camera.

Video Sequences	Method	Detection at frame#	Description
Movie 10	Method1	25	Fire in a garden
	Method3	87	
Movie 11	Method1	14	Fire in a trash bin
	Method3	-	
Movie 12	Method1	97	Fire at a distance of 25m.
	Method3	-	

and wavelet based contour analysis of possible smoke regions. These regions are then analyzed along with their corresponding background regions with respect to their RGB and chrominance values. The flicker process of the smoke is also modeled and set as a clue for the final decision.

The method can be used for detection of smoke in movies and video databases as well as real-time detection of smoke. It can be incorporated with a surveillance system monitoring an indoor or an outdoor area of interest for early detection of fire. It can also be integrated with the flame detection method in [5] in order to have a more robust video based fire detection system.

6. REFERENCES

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