Early Recognition of Smoke in Digital Video

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Abstract: This paper presents a method for direct smoke detection from video without enhancement pre-processing steps. Smoke is characterized by transparency, gray color and irregularities in motion, which are hard to describe with the basic image features. A method for robust smoke description using a color balancing algorithm and turbulence calculation is presented in this work. Background extraction is used as a first step in processing. All moving objects are candidates for smoke. We make use of Gray World algorithm and compare the results with the original video sequence in order to extract image features within some particular gray scale interval. As a last step we calculate shape complexity of turbulent phenomena and apply it to the incoming video stream. As a result we extract only smoke from the video. Features such shadows, illumination changes and people will not be mistaken for smoke by the algorithm. This method gives an early indication of smoke in the observed scene.

Key–Words: Video, smoke detection, descriptors, color

1 Introduction

In many situations when fire ignition occurs there is visible smoke development prior to flames. This fact can be of great importance for efficient fire control. Installing video systems that are extremely sensitive to smoke in the scene can prevent unnecessary life threatening situations. Time is a crucial factor for minimizing damages caused by smoke and fire in public places. Most of the traditional chemical smoke sensors require short distances to the location of fire ignition in order to be efficient. Considerable delay of smoke to a sensor is a drawback of such smoke detectors. In many cases when a chemical alarm is going off the fire is already in place and the situation is out of control. Video smoke detection is an option that becomes increasingly important due to its low price, high efficiency and low maintenance. When there is a slightest chance that fire could start at a considerable distance from the sensor, video surveillance would be superior to a traditional smoke detector. Video is also a good option for large, open areas e.g., saw mills, petrochemical refineries, forest fires, etc. Further, video is a volume sensor as opposed to a point sensor, which looks at a point in space. That point may not be affected by smoke or fire, so the smoke would not be detected. A volume sensor potentially monitors a larger area and has much higher probability of successful early detection of smoke or flame. However, some drawbacks for video smoke detections should be mentioned. One of them is a high rate of false alarm mainly due to rapid change of lighting and smoke density in the scene. Another one is the difficulty to define smoke in terms of primitive image features such as intensity, motion, edge, and obscuration. Out of the many approaches that address these issues some classification could be in place:

- Fractal encoding concepts [6], where self-similarity of smoke shapes is used in the algorithm for fractal encoding of the image. This technique is primary used in forest fire detection since it is only smoke that exhibit self-similarity is such scenes. In our application this approach is not sufficient since there is possibility for other features, such as illumination changes, to be included in fractal encoding.
- Computation of optical flow field [9], [5], where two adjacent frames are used to calculate entropy of the distribution of the motion directions. After this process smoke and non-smoke regions can be separated from each other. This techniques together with chrominance detection can correctly detect the existence of smoke in many smoke scenes, however it is not very successful in scenes with objects similar to smoke, such as fog, illumination changes and shadows.
- Wavelet-based methods [11], [8], where local

extrema is found in Wavelets and then some frequency intervals are determined to represent smoke edges. This technique can produce much false alarm in case of nose present in the imagery.

- Image feature extraction [12], [4], where image primitives, such as edges, intensity values, color information and motion are used to estimate smoke regions. This approach is usually hard to implement so that generality is achieved.

In the work we first extract the background and then use a color balancing algorithm called Gray World [1]. The gray world algorithm averages the RGB of the whole image and uses it as balancing constant. The algorithm is based on the fact that the human vision lightness adaptation makes us perceive objects as medium gray, which reflect the average luminance of a scene. In terms of histogram properties of a digital image, this corresponds to a level distribution which has its center mass around the middle value. This is used to find all the gray features in the image. We subject each pixel to the Gray World algorithm and separate all the pixels that did not have the global chromatic dominance. This will be shown more specifically in Chapter 2.

Using the morphology of the scene we calculate the area and perimeter (or edge) of the smoke regions in each frame. This process will be further described in Chapter 2. In the calculation of edge/area relationship we are using modified function of shape complexity [2], where turbulence is calculated and thresholds are found. We evaluate the suggested method using 32 video streams with different smoke volume and different smoke propagation speed. We delimit ourself to such imagery where smoke is not present initially. We aim to present a method that detects smoke in an early stage from video. The robustness is evaluated using both smoke video and non-smoke video such as filmed shadows and illumination changes.

1.1 Smoke Characteristics

Smoke is usually semi-transparent at the early stages of a fire. When the temperature of the smoke is low, it is expected that the smoke will show color from the range of white-bluish to white [3]. When the smoke's temperature increases it shifts color from the range of white-grayish to black. Smoke does not exhibit much chrominance components thus the extraction can be based on the intensity and saturation values rather than the hue. Based on these characteristics there is reason to investigate how smoke color feature could be extracted in HSV domain, however, this approach does not fit into our implementation. We are working in the RGB domain since the automatic smoke color feature extraction that is suggested in this work works faster in RGB imagery than in HSV domain. One of the ways to describe color feature of the smoke regions of an RGB image is in [3]:

$$\begin{aligned} R - G &< T \\ G - B &< T \\ R - B &< T \end{aligned} \tag{1}$$

where R and G and B are intensity values from each pixel in each channel in the image. T is a threshold calculated globally for the smoke region. We should notice that the discrimination of smoke based only on Equation (1) is insufficient because of the nature of smoke. Other features should be added so that a robust segmentation is enabled. We are taking into consideration such features as gray descriptors and turbulence calculation. A threshold is based on values calculated from the difference between the original and the Gray Wold processed images.

Another smoke characteristic is smoothed edges of the background when the smoke has just started. Edges in an image correspond to local extrema [7]. The loss of sharpness in the edges results in a decrease in the values of this extrema. This leads to a loss of sharpness and decrease in the high frequency content of the image [10] and can be monitored in the Fourier domain or using Wavelets. 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. However, this method is quite heavy in computation and suggests the use of video streams where the smoke is visually dominant in the scene. In our application we are applying the method on video where in many cases the smoke is hardly visible to the human eye.

Generally, smoke is hard to describe using low level features, such as edges, color, movement pattern, intensity variation. In cases where other objects similar to smoke are present e.g. shadows, fog etc. the detection based on image primitives only, will be impossible.

2 Detection of smoke from video

We convert video stream into intensity level in order to achieve a desirable speed when calculating the background. We need to extract all the moving objects and then apply the smoke detection algorithm.

First, we have to deal with the fact that all smoke is gray with quite big variation of the intensity levels. This variation means that finding a combination of R,G and B values that build gray scale will require an effort, which is not justified by the goal of

this work. However, if we apply the Gray World algorithm, we will strive to achieve gray scale looking image from the incoming RGB image. After comparison with the original we leave only those pixels that were gray originally. After all, we can not change into gray anything that is already gray. After this step we have a video with moving gray objects.

Now we will deal with the fact that there could be other gray objects in the imagery than smoke. Features such as shadows, walking people and changes in illumination are subjected to the algorithm presented here. As a result we would expect only smoke to be detected. Shadows and illumination changes could easily be mistaken for smoke if we would not proceed any further with the algorithm. Given this consideration we apply turbulence calculation. For a single image, turbulence is determined by relating the perimeter of the candidate region to the square root of the area as follows:

1. Read an Mpeg4 coded video stream into Matlab. Mpeg4 produces smaller size of the imagery than Mpeg2, so the choice is obvious.

2. Calculate intensity image from the stream.

3. Compute the background based on the first and second frames of the video sequence.

4. Calculate Gray World algorithm of the incoming imagery.

5. Compute the difference between the original and the Gray World imagery.

6. We use logical AND with the motion tracking result from the previous step.

7. Now we estimate the rate of change for turbulence in the image. The basic formula for image turbulence is in (2). As we are dealing with smoke, its natural phenomena is that it strives to move up. This quality can be detected by monitoring positive local extrema of the turbulence. Rate of change of turbulence in the image is calculated using (3).

$$\Omega(t) = \frac{P(t)}{2\sqrt{\pi A(t)}} \tag{2}$$

$$\frac{d\Omega}{dt} = \frac{2P'(t)A(t) - P(t)A'(t)}{4\sqrt{\pi}A(t)^{3/2}} \tag{3}$$

where P represents the perimeter/edges of the remaining moving gray features and A represents the area of the region. As the complexity of a shape increases (i.e., the perimeter increase with respect to the area) the value associated with $\frac{d\Omega}{dt}$ increases.

8. As a last step we investigate the cumulative sum of each frame and the obtained $\frac{d\Omega}{dt}$ in this frame and create a set of value intervals, which are valid for smoke.

9. If smoke is detected the simulation produces a warning message.

Figure 1: One frame of the original video with people.

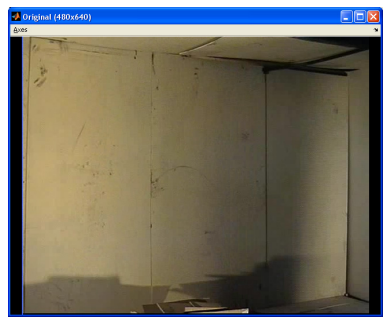

Figure 2: One frame of the original video with shadows.

We process the imagery with various content such as smoke like features, see Figures 1, 2, 3.

After the step described in 3) we have an video with moving objects. In Figure 4 and 5 we can see one frame with the results from this step.

In step 5) we calculate the difference between Gray World processed image and the original. After that we remain with the image that contains only shapes with gray intensities. However, in some cases it is enough to have edges that corresponds to gray intensity. The results are shown in Figures 6 and 7

By calculating turbulence in the final step we get values of turbulence rate of change for each blob (or region of interest). When the cumulative sum of turbulent blobs corresponds to approximately 30% of

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Figure 3: One frame of the original video with smoke.

Figure 4: People extracted from background.

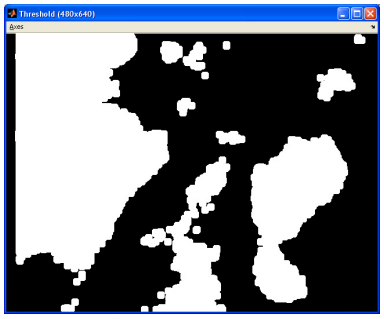

Figure 5: Smoke extracted from background.

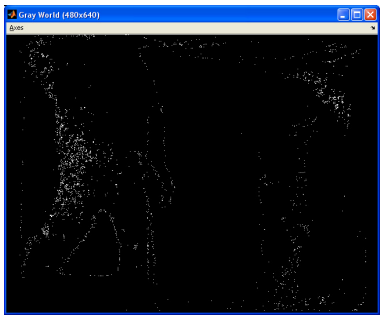

Figure 6: People after Gray World algorithm.

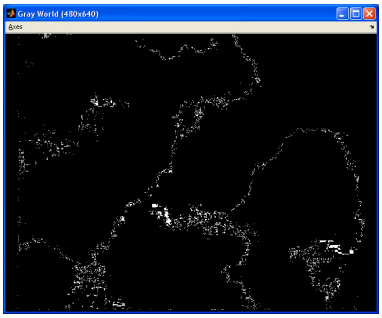

Figure 7: Smoke extracted from background.

Scene Content	Amount	Sucessful	Unsuccessful
Smoke Indoor	10	9	1
Smoke Outdoor	4	2	2
People without smoke	6	5	1
Shadows without smoke	6	4	2
Illumination changes	6	4	2

Table 1: Results from video smoke detection algorithm

maximum value smoke is detected. We could establish that the cumulative sum of turbulence derivatives of features such as shadows lies in the first 10% of the interval. Walking people in video results in cumulative sum of upper 10% of the interval. Illumination changes are in both lower and upper bounds.

Experimental results are based on 32 video sequences, where each lasts for 10 seconds. Both indoor and outdoor smoke scenes are tested. The background is the same for each indoor smoke scene. All of the indoor scenes are divided into eight settings, where ignition, shadows, walking people and the illuminance changes are filmed. Only one video in each setting has smoke. The other films content features similar to smoke against the same background.

In Figures 8 and 9 we see the results of successful smoke detection on two video sequences containing smoke. In the scene shown in Figure 8 detection took place after 1.2 seconds. In the video in Figure 9 the detection took 1.3 seconds. The time domain for the successful smoke detection lies in the interval of 1.1-4.6 seconds.

In our application we do not show the smoke blobs in the detected frame, we just indicate whether smoke is found or not. Automatic smoke detection is robust and produce the results shown in Table 1:

In two out of six tested films with illumination variance there are conditions that satisfy smoke descriptors. Our algorithm is least successful in such imagery. However, there is only one smoke containing video sequence where our algorithm was unsuccessful. Smoke in this particular scene is impossible to detect visually, so the smoke is present in such small

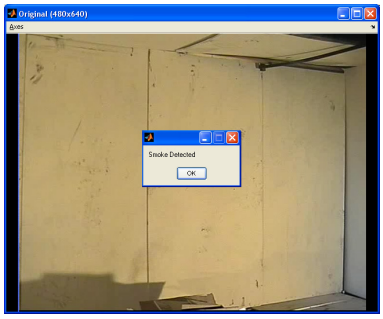

Figure 8: Smoke detected in the indoor scene.

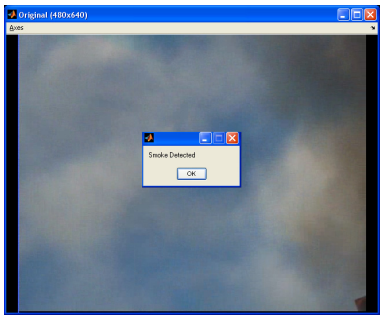

Figure 9: Smoke detected outside with the blue sky as background.

amount that the algorithm cannot extract it. By the tests performed in this work it was possible to estimate the lower time limit of 0.4 seconds for smoke to be present in the image that is necessary for the algorithm to detect it. If smoke will be visible at least that amount of time our algorithm will detect it. We can state that the overall performance is robust and the algorithm is quite simple to implement.

3 Conclusion and Discussion

In this paper we have shown a method for early smoke detection in indoor and outdoor scenes. The main difference between smoke detection algorithms presented earlier is that in this work we study smoke detection algorithms in video with features similar to smoke. The results explained above show that robust smoke detection can be achieved using color processing together with turbulence calculation. Simple implementation is a clear benefit of this approach. In this work we were concentrated with such video where smoke is not present in the first frame. This is for the sake of robust background extraction. In cases where smoke was already in place from the start, the algorithm worked unsatisfactory. This is due to a fact that much of the background is not possible to extract from such video stream and thus the algorithms is not valid. As an argument we can use the obvious usage of the algorithm where indoor or outdoor environment is monitored to detect smoke in early stages. In the tested videos the smoke did not reach the ceiling when the alarm went off. This makes our technique superior to the common chemical smoke detectors that are usually placed on ceilings.

Turbulence in images is given by a well known formula, which we have modified and thus not only detected smoke like features but also smoke the moves up. Generally, the turbulence calculation does not indicate any particular moving direction. In our case there is reason to state that we have eliminated possibility to mistake other turbulent features for smoke.

A crucial condition for the algorithm to successfully detect smoke is that the smoke should move upwards. In videos taken outdoors there were occasionally hard winds causing the smoke moved sidewards. In this particular case the algorithm would not signal for smoke. At present it is hard to establish detection of smoke in scenes with big and rapid variations of illuminance, since it is characterized by gray profile and turbulence that is occasionally the same as for the smoke.

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