

Video-based Smoke Detection: Possibilities, Techniques, and Challenges

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Introduction

When a fire occurs, minimum detection latency is crucial to minimizing damage and saving lives. Current smoke sensors inherently suffer from the transport delay of the smoke from the fire to the sensor. A video smoke detection system would not have this delay. Further, video is a volume sensor, not a point sensor. A point sensor 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.

Video smoke detection is a good option when smoke does not propagate in a “normal” manner, e.g., in tunnels, mines, and other areas with forced ventilation, and in areas with air stratification, e.g, hangars, warehouses, etc. Video is also a good option for large, open areas where there may be no heat or smoke propagation to a fixed point, e.g., saw mills, petrochemical refineries, forest fires, etc.

Research in detecting smoke using surveillance cameras has become very active recently. Just as the old saying “where there is smoke there is fire” puts, early smoke detection concerns people’s life and property safety. With video smoke detection, it is possible to address two problems in traditional smoke detectors that are mostly based on particle sampling:

1. Traditional smoke detectors require a close proximity to the smoke.
2. They usually do not provide information about fire location, size, burning degree etc.

However, video smoke detection still has great technical challenges since its current performance is inferior to those of traditional particle-sampling based detectors in terms of detection rate and false alarm rate. This is mainly due to the following reasons with video smoke signal:

- 1) Variability in smoke density, lighting, diverse background, interfering non-rigid objects etc.
- 2) None of the primitive image features such as intensity, motion, edge, and obscuration characterizes smoke well.
- 3) Visual pattern of smoke is difficult to model.

Existing Techniques

Recently several smoke detection methods from video captured in visible-spectrum have been proposed. These methods make use of such visual signatures as motion, edge, obscuration, and geometry of smoke regions. They then use Bayesian analysis, or rule-based analysis to decide whether smoke is detected. The key representative methods are summarized in the following:

1. Fujiwara and Terada [1] proposed to use fractal encoding concepts to extract smoke regions from an image. They used the property of self-similarity of smoke shapes to look for features of smoke regions in the code produced by fractal encoding of an image.
2. Kopilovic et al. [2] took advantage of irregularities in motion due to non-rigidity of smoke. They computed optical flow field using two adjacent images, and then used the entropy of the distribution of the motion directions as a key feature to differentiate smoke motion from non-smoke motion.
3. Töreyn et al. [3] extracted image features such as motion, flickering, edge-blurring to segment moving, flickering, and edge-blurring regions out from video. The methods to extract these features were background subtraction, temporal wavelet transformation, and spatial wavelet transformation.
4. Vicente and Guillemant [4] extracted local motions from cluster analysis of points in a multidimensional temporal embedding space in order to track local dynamic envelopes of pixels, and then used features of the velocity distribution histogram to discriminate between smoke and various natural phenomena such as clouds and wind-tossed trees that may cause such envelopes.
5. Grech-Cini [5] used more than 20 image features, such as the percentage of image change, correlation, variance etc., extracted from both reference images and current images, and then used a rule-based or a rule-first-Bayesian-next analysis method to differentiate smoke motion from non-smoke motion.

Our Approach

At the United Technologies Research Center (UTRC), we have recently started a research project to develop novel techniques for video smoke detection. The key components developed in this project are background subtraction, flickering extraction, contour initialization, and contour classification using both heuristic and empirical knowledge about smoke. In the following we will present more detail on our approach.

Background Subtraction

We follow the approach of Stauffer and Grimson [6], i.e., using adaptive Gaussian Mixture Model (GMM) to approximate the background modeling process. This is because in practice multiple surfaces often appear in a particular pixel and the lighting conditions change. In this process, each time the parameters are updated, the Gaussians are evaluated to hypothesize which are most likely to be part of the background process.

Pixel values that do not match one of the pixel's background Gaussians are grouped using connected component analysis as moving blobs.

Flickering extraction

A pixel at the edge of a turbulent flame could appear and disappear several times in one second of a video sequence. This kind of temporal periodicity is commonly known as flickering. Flickering frequency of turbulent flame has shown experimentally to be around 10Hz. Flickering frequency of smoke however, could be as low as 2 ~ 3 Hz for slowly-moving smoke. The temporal periodicity can be calculated using Fast Fourier Transform (FFT), Wavelet Transform, or Mean Crossing Rate (MCR). In our system, we use Mean Crossing Rate (MCR).

Contour initialization

Based on our observations from experiments that smoke flickering mask is sparse, we pick those moving blobs from the background subtraction module and check whether there is a sufficient number of flickering pixels within the blobs. Boundaries of the blobs that pass this test and a minimum size test are extracted as blob contours.

Smoke classification

Blobs with contours are candidates of smoke regions. Features are extracted from them and passed to a smoke classification module for further check. The features that we use are based on the work by Catrakis et al. in characterizing turbulent phenomena.

Smoke [9] and (non-laminar flow) flames [10] are both turbulent phenomena. The shape complexity of turbulent phenomena may be characterized by a dimensionless edge/area or surface/volume measure [7,8]. One way, then, of detecting smoke is to determine the edge length and area, or the surface area and volume, of smoke in images or video.

For a single image, turbulence is determined by relating the perimeter of the candidate region to the square root of the area as

$$\Omega_2 = \frac{P}{2\pi^{1/2} * A^{1/2}}$$

Where P represents the perimeter of the region and A represents the area of the region. Ω_2 is normalized such that a circle would result in Ω_2 would have a value of unity. As the complexity of a shape increases (i.e., the perimeter increase with respect to the area) the value associated with Ω_2 increases.

In three spatial dimensions, the shape complexity is determined by relating the surface area of the identified region to the volume of the identified region as

$$\Omega_3 = \frac{S}{6^{2/3} \pi^{1/3} * V^{2/3}}$$

Where S is the surface area and V is the volume. Once again, the ratio is normalized such that a sphere would result in Ω_3 having a value of unity. As the complexity of the shape increases the value associated with Ω_3 also increases.

For video sequences from a single camera, both the time sequence of estimates Ω_2 and an approximation to Ω_3 may be used for detection. The shape complexity defined with respect to Ω_2 and Ω_3 provides insight into the nature of a candidate region. The turbulent nature of a region can be detected (regardless of size) by relating the extracted spatial features to one another using a power law relationship. For instance, a power law relationship relating the perimeter to the area (or the equivalent for square root surface area to the cube root of volume) is defined as

$$P = c(A^{1/2})^q$$

The existence of turbulent phenomena is detected by the relation of perimeter P to area A by variable q , wherein c is a constant. Based on the study of natural rain clouds, a region may be defined as turbulent when q is approximately equal to a value of 1.35.

Based on the above empirical knowledge of turbulent phenomena, we use a line-fitting technique to estimate the value q from the contours of the blobs in a pre-defined time interval. One example of the scatter-plot of a sequence of smoke blobs is in Fig. 1. A value close to the empirical value of 1.35 from line-fitting in the log domain suggests the existence of turbulence within the time interval.

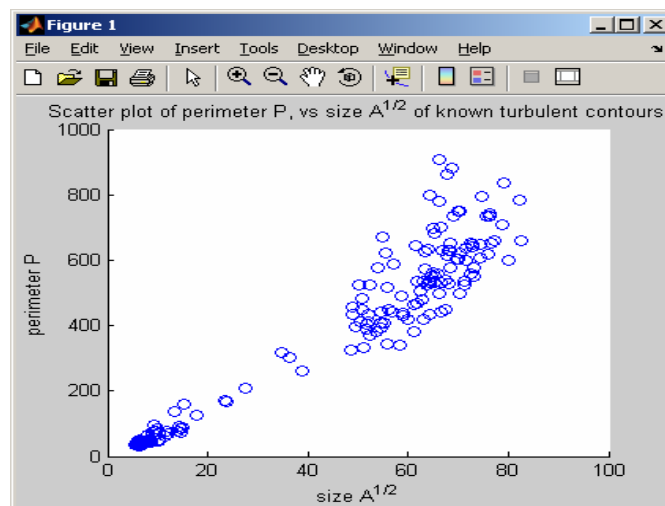


Figure 1. Scatter plot of Perimeter vs. Area of an exemplar smoke sequence

Experimental results

We use the dataset that is publicly available at <http://signal.ee.bilkent.edu.tr/VisiFire/Demo/SmokeClips/> for experiments. This dataset has been used in [3]. It can potentially be used to compare different algorithms.

Sample images showing the detected smoke regions are presented in Fig. 2. We have made the following observations:

1. An entire smoke region might be split into multiple smaller smoke regions due to different degree of flickering associated with different spreading speed of smoke particles.
2. Outward boundaries of smoke are less prone to miss-detection than the source regions of smoke. This is because the peripherals display more flickering than the core regions.



Figure 2. Sample images showing the detected smoke regions

Although no false alarms are issued in videos that do not have smoke, shown in Fig. 3, there are false alarms in some of the smoke video clips.



Figure 3. Snapshots of the video clips without smoke

Challenges

Although tremendous efforts by researchers have been made to improve the performance of video smoke detection systems, the following technical challenges remain:

1. Smoke pattern matching is an ill-defined problem because the smoke pattern varies. For example, smoke in open space without wind has a quite different visual pattern from smoke in open space with noticeable wind; upward smoke puffs also have a quite different pattern from horizontally spreading smoke or downward moving smoke.
2. Image features for smoke are seldom adaptive to lighting conditions, smoke density, or background scene, thus making threshold(s)-based systems fragile and subject to false alarms.
3. Lack of a standard test dataset to evaluate and compare performance. Unlike speech recognition or face recognition that has standard dataset such as TIMIT or FERET database for different researchers to share, video smoke detection has been tested on each group of researchers' own collection of data.

Besides technical challenges, the following industrial challenges also exist:

1. Lowering the cost of multi-spectrum based system. A combination of visible-spectrum smoke detection and infra-red spectrum flame detection can improve system performance, but the combined cost is too high for general fire surveillance applications.
2. Acceptance of a multi-modal system that uses video smoke detection as a warning module and use particle-sampling based detector as a confirming module.
3. Difficulty for human operators to use video smoke detection systems as assistants when they produce many false alarms in contrast to easy-to-use traditional smoke detectors without human-computer intelligent interaction.

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