Motion Blobs as a Feature for Detection on Smoke

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***Abstract*— Disturbance that is caused due to visual perception with the atmosphere is coined as smoke, but the major problem is to quantify the detected smoke that is made up of small particles of carbonaceous matter in the air, resulting mainly from the burning of organic material. The present work focuses on the detection of smoke immaterial it being accidental, arson or created one and raise an alarm through an electrical device that senses the presence of visible or invisible particles or in simple terms a smoke detector issuing a signal to fire alarm system / issue a local audible alarm from detector itself.**

Keywords- Motion blobs; Blob Extraction; Feature Extraction.

I. Introduction

Smoke**:** Any disturbance that is caused due to visual perception with the atmosphere can be termed as smoke. But on a contrary it can also be defined in many ways such as, the vaporous system made up of small particles of carbonaceous matter in the air, resulting mainly from the burning of organic material, such as wood or coal OR a suspension of fine solid or liquid particles in a gaseous medium OR a cloud of fine particles OR something insubstantial, unreal, or transitory OR a substance used in warfare to produce a smoke screen OR something used to conceal or obscure OR a pale to grayish blue to bluish or dark gray OR smoke is the collection of airborne solid and liquid particulates, gases emitted when a material undergoes combustion or pyrolysis[17,21]. Research in detecting smoke using surveillance cameras has become very active recently. It is now possible to address the problems in traditional smoke detectors based on particle sampling with the aid of video smoke detection namely:

1) Traditional smoke detectors require a close proximity to the smoke.

2) They usually do not provide information about fire location, size etc.

The most interesting concept of this paper is to differentiate the type of smoke based on the texture or colour such as:

Type 1: White smoke: This occurs due to anti-freeze burning of the piston cylinder. The possible ways of causes are a cracked head, blown head gasket, (warped head), or cracked cylinder block (normally uncommon).

Type 2: Black smoke: Black smoke is oftentimes a result of too much fuel and not enough air in the combustion chamber. In rare cases, it can be caused by weak fuel pressure causing fuel to 'drip' from injectors rather than 'spray'. It can also be caused by weak fire in the combustion chamber.

Type 3: Gray smoke: Gray smoke is caused by brake fluid. It generally means that the brake master cylinder is bad and is getting sucked through the vacuum brake hose. *Type 4:* B*lue smoke:* Blue smoke is generally caused by the burning of oil in the combustion chamber. Normal causes of oil getting into the combustion chamber are weak piston rings, bad valve guides, bad valve seals or plugged up engines where oil is sucked back through PCV system [8, 15, 17, 21].

II. Literature Survey

A. Video Based method for Smoke Detection

In video-based smoke detectors, CCTV (Closed-circuit television) cameras can monitor and recognize smoke and flames overlooking large spaces at great distances, while providing video surveillance capabilities as a bonus [23,25]. This shall detect fire in seconds, supply vital situational awareness in the form of live video to remotely located guards, trigger fire alarms and provide vast amounts of pre-recorded

Video forensic evidence for future fire investigations. The video based detectors can sense:

- Presence of flames within the field of view of the camera.
- Reflected fire light when flames are obstructed.
- Presence of pluming smoke clouds.
- Presence of ambient smoke.
- Unauthorized Intrusion.

Ugur Toreyin et. al., presented a method for smoke detection in video. It is assumed that camera monitoring the scene is stationary. Since the smoke is semi-transparent, edges of image frames start losing their sharpness and this leads to a decrease in the high frequency content of the image. To determine the smoke in the field of view of the camera, the background of the scene is estimated and decrease of high frequency energy of the scene is monitored using the spatial wavelet transformations of the current and the background images[7]. Edges of the scene are especially important because they produce local extrema in the wavelet domain.

A decrease in the values of local extrema is also an indicator of smoke. In addition, scene becomes grayish when there is smoke and hence this leads to a decrease in chrominance values of pixels. Periodic behavior in smoke boundaries and convexity of smoke regions are also analyzed. All of these clues are combined to reach a final decision. Fire detection algorithms are based on the use of color and motion information in video to detect the flames [12]. 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.

Edges in an image correspond to local extrema in wavelet domain. A Gradual decrease in their sharpness results in the decrease of the values of these extrema. However, these extrema values corresponding to edges do not boil down to zero when there is smoke [11,13]. In fact, they simply loose 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 decreases the chrominance channels U and V values of pixels. Apart from this, it is well-known that the flicker frequencies of flames are around 10 Hz, this flicker frequency is not greatly affected by either the fuel type or the burner size [5, 12]. As a result, smoke boundaries also oscillate with a lower frequency at the early stages of fire. Another important feature of the smoke that is exploited in this method is that smoke regions have convex shapes [11].

An algorithm for detecting smoke in video was developed which is based on determining the edge regions whose wavelet sub-band energies decrease with time. These regions are then analyzed along with their corresponding background regions with respect to their RGB and chrominance values. The flicker of the smoke and convexity of smoke regions are also set as clues for the final decision. This method can also be used for the detection of smoke in movies and video databases. In addition to this can also be incorporated with a surveillance system monitoring an indoor or an outdoor area of interest for early detection of fire [1,2,4].

R.J. Ferraria et.al, proposed a real-time image processing technique for the detection of steam in video images. The problem of detecting steam is treated as a supervised pattern recognition problem. A statistical Hidden Markov Tree (HMT) model derived from the coefficients of the Dual-Tree Complex Wavelet Transform (DT-CWT) in small (48×48) local regions of the image frames is used to characterize the steam texture pattern. The parameters of the HMT model are used as an input feature vector to a Support Vector Machine (SVM) technique, specially tailored for this purpose [6,18]. By detecting and determining the total area covered by steam in a video frame, a computerized image processing system can automatically decide whether if the frame can be used for further analysis. The proposed method was quantitatively evaluated by using a labeled image data set with video frames sampled from a real oil sand video stream. The classifications of results were 90% correct when compared to human labeled image frames. This technique is useful as a pre-processing step in automated image processing systems [10, 16, 23].

Real-time automated image processing systems, used in size analysis, depend on good quality high contrast images in order to correctly segment and measure oil sand fragment size including oversize lumps [6]. According to Ziyou Xiong et.al. When a fire occurs, minimum detection latency is crucial to minimize damage and save 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 wherein a point sensor looks at a point in space, which may not be affected by smoke or fire. But 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.

B. *Background Subtraction*

We follow the approach of Stauffer and Grimson [27] 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. Gaussians are grouped using connected component analysis as moving blobs.

C. *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 have used the Mean Crossing Rate (MCR) method [3].

D. *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 have used are based on the work by Catrakis et al. in characterizing turbulent phenomena. Smoke [13] and (non-laminar flow) flames [19] are both based on turbulent phenomena. The shape complexity of turbulent phenomena may be characterized by a dimensionless edge/area or surface/volume measure [13,26]. One way, of detecting smoke is to determine the edge length and area, or the surface area and volume of smoke in images or video[15,26].

E. *Flame Recognition in Video*

Walter Phillips III, Mubarak Shah and Niels da Vitoria Lobo, presented a paper based on an automatic system for fire detection in video sequences. Particle sampling, temperature sampling and air transparency testing are simple methods that are used most frequently today for fire detection. Unfortunately, these methods require a close proximity to the fire. In addition, these methods are not always reliable, as they do not always detect the combustion itself, most of them detect smoke, which could be produced in other ways.

Existing methods of visual fire detection rely almost exclusively upon spectral analysis using rare and costly spectroscopy equipment. This limits fire detection to those individuals who can afford the high prices of the expensive sensors that are necessary to implement these methods. In addition, these approaches are still vulnerable to false alarms caused by objects that are of the same colour as fire, especially the sun. Healey, 1993 and Foo, 1995 have presented two previous vision-based methods that seem quite promising.

III. Data Collection

An Olympus digital camera with the specification (AF 3x optical zoom 6.5-19.5mm, 7.1 megapixel) is used for collecting the different data sets and we have assumed the camera to be stationary.

The fragrance sticks were used as the source of smoke. While recording the video, initially the still black background is captured for approximately one second and later the smoke is introduced, which was recorded for one more second.

Several such videos were collected and used to find the mean, standard deviation and variance of all the three components or channels of an RGB image (colored image).

The proposed architecture for the Video Based Smoke Detector is as shown below in fig 1 and comprises of the following five stages namely.

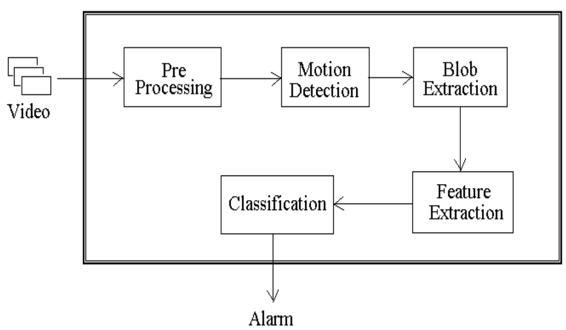


Fig 1: Proposed architecture of Video Based Smoke detector

Stage 1: The preprocessing stage:

In this stage of processing the image is filtered and noise is eliminated. Later the images are segmented for further processing

Stage 2: The Motion detection Stage:

This stage accepts the filtered image as input that involves the detection of moving objects entering the field of view.

Stage 3: The Blob Extraction Stage:

In this stage we make use of a unimodel and multimodel thresholding method for monochrome and color images respectively.

Stage 4: The Feature Extraction Stage:

This stage extracts the features of the input data to a reduced representation set of features, i.e. if the data is suspected to be notoriously redundant with not much of information.

Stage 5: The classification Stage:

This stage involves the classification of the extracted blobs depending on the presence of smoke or not and to raise an alarm subsequently.

IV. Implementation

The proposed architecture for the Video Based Smoke Detector comprises of different stages. The first stage is the *preprocessing* stage where the image will be filtered and noise will be eliminated. The filtered image is then given as input to the *motion detection* stage which involves the detection of moving objects entering the field of view. In *Blob Extraction*, we make use of unimodel thresholding and multimodel thresholding for monochrome and colour images respectively which provides presence of moving objects. The next stage is *Feature Extraction* where the output contains only required information obtained out of the large input data set (which is suspected to be notoriously redundant), this output data will be transformed into a reduced representation to obtain set of features.

The last and the final is the *Classification* stage where the extracted blobs are classified to check the presence of smoke or not.

Stage 1: The Preprocessing Stage

This stage is used to remove the noise present in the video as shown in fig 2 below. First the image is converted from RGB to gray scale. Once the image is converted to. grayscale, the Discrete Fourier Transform is used to transform the image from spatial domain to frequency domain.

For a square image of size (N×N), the two-dimensional DFT (Discrete Fourier Transform) is given by:

$$F(k,l) = \frac{1}{N^2} \sum_{a=0}^{N-1} \sum_{b=0}^{N-1} f(a,b)\, e^{-\iota 2\pi (\frac{ka}{N} + \frac{lb}{N})}$$

where $f(a, b)$ is the image in the spatial domain and the exponential term is the basis function corresponding to each point $F(k, l)$ in the Fourier space.

Stage 2: The Motion detection Stage

As shown in the fig 3 above, after changing the data set, the portion of the frame affected by smoke is white in colour and the background is black.

Stage 3: The Blob Extraction Stage:

Blob extraction is an image segmentation technique that categorizes the pixels in an image as a part belonging to one of many discrete regions.

Fig 2: The Preprocessing Stage

Input frame	Output frame
	

The Motion Detection stage involves detection of moving objects entering the field of view. There are many approaches for motion detection in a continuous video stream. All of them are based on comparing the current video frame with the one from the previous frames or with something that is known as background. One of the most common approaches is to compare the current frame with the previous one. Also another approach is to compare the current frame not with the previous one but with the first frame in the video sequence. So if there were no objects in the initial frame, comparison of the current frame with the first one will give us the whole moving object good results in the cases where there is no guarantee that the first frame will contain only static background.

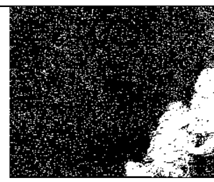
Input frame (Filtered image)	Output frame (With threshold =0.025)
	

Fig 3: The Motion Detection

Fig 4: The output of blob extraction

The outcome after the blob extraction and cropping of blobs are as shown above in fig 4.

Blob extraction is generally performed on the resulting binary image from a thresholding step. Blobs may be counted, filtered and tracked. Inconsistent terminology for this procedure exists, including *region labelling*, *connected-component labelling and blob discovery* or *region extraction*.

Stage4: The Feature extraction Stage:

Feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant that is much data, but not much information, then the input data will be transformed into a reduced representation set of features called as features vector. Transforming the input data into the set of features is called features extraction. If the features extracted are carefully chosen then it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm that over fits the training sample and generalizes poorly to new samples.

Feature extraction is a general term for methods of constructing combinations of the variables.

V. Conclusion

A video smoke detection system is termed as a volume sensor than an point delay sensor. 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, for example, in tunnels, mines, and other areas with forced ventilation and in areas with air stratification, for example, 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.

In the present work, Video Based Smoke Detection, we process a given video to detect the presence of smoke and store it as sequence of images to a location on the disk. Since working on the video directly is not supported by Mat lab, we first convert the given video into *.avi* format (Audio/Video Interleaved) file format and later these frames were fetched sequentially for the filtering process and written back to the disk.

Work is not done in the field of developing an interface for a device to record the videos and to the hardware that connects to the fire alarm.

The goal of feature extraction is to characterize an object to be recognized by measurements whose values are very similar for objects in the same category and very different for objects in different categories. This leads to the idea of seeking distinguishing features that are invariant to irrelevant transformations of the input. In general, features that describe properties such as shape, color and many kinds of textures are invariant to translation, rotation and scaling.

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