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Video Based Ambient Smoke Detection By Detecting Directional Contrast Decrease

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***Abstract*—**Fire-related incidents account for extensive loss of life and material damage. Quick and reliable detection of occurring fires has high real world implications. Whereas a major research focus lies on the detection of outdoor fires, indoor camera-based fire detection is still an open issue. Cameras in combination with computer vision helps to detect flames and smoke more quickly than conventional fire detectors. In this work, we present a computer vision-based smoke detection algorithm based on contrast changes and a multi-step classification. This work accelerates computer vision-based fire detection considerably in comparison with classical indoor-fire detection.

***Keywords*—**Contrast analysis, early fire detection, video smoke detection, video surveillance.

I. Introduction

FIRE is a leading hazard affecting daily life around the world. In Europe alone, damages from fire cost nearly 1% of the Gross Domestic Product (GDP), affecting both industry as well as private households. Additionally and even more significantly, it is the associated human cost. It is estimated that fire related incidents result in 20,000 to 25,000 fatalities per year throughout Europe [1].

An approach for early and reliable detection may thus both impact society and economy by saving several lives and mitigating damages in households, plants and machines. A significant portion of fires occurs within building, e.g. inside households, factory halls or warehouses. Most existing indoor fire detection systems include sensors such as point type smoke or optical beam detectors. Such sensors requires direct contact between the sensor and smoke particles. Therefore, smoke first has to spread and reach the sensor. Then a certain density of smoke needs to build up before an alarm is triggered. Both these requirements can lead to a significant delay between the starting of a fire and the raising of an alarm. The first requirement is usually overcome by placing multiple sensors to ensure adequate smoke detection coverage. In an industrial scenario this can lead to a large cost and maintenance overhead. Decreasing of thresholds would be a solution for the second requirement however, this may lead to an increase in false alarms which also has negative cost repercussions.

Our smoke detection method provides an improvement over the aforementioned traditional detection techniques as it relies on a video recorded by a camera and computer vision-based analysis of the smoke produced by a fire. The presented fire detection method is capable of detecting smoke even when the smoke plume is occluded or the smoke density is low. Additionally, video based fire detection approaches also offer meta information, such as exact location, intensity and type of fire. This information can prove to be invaluable for fire fighting.

Existing approaches in this area rely on detecting the rising smoke plume with high smoke density. Our approach allows detecting a fire shortly after smoke is rising and gathering under the ceiling. In Video Fire Detection (VFD) smoke gathering under the ceiling is called *ambient smoke*. It leads to a reduction of observable structures in a recorded video frame. We detect this loss of structure and raise an alert. The proposed approach reliably detects smoke and reduces smoke detection time by up to 300% as compared to ceiling smoke detectors.

The contributions of this work are four-fold: (1) a novel computer-vision based smoke detection algorithm, which shows a superior detection time to existing methods, (2) fire detection even under partial occlusions by relying on smoke as feature, (3) tracking of contrast changes and (4) reliable detection of smoke even under changing lighting conditions and despite other degradations.

II. Related Work

Recently, smoke detection methods have been explored by computer scientists for detecting fires in initial stages. A method by Chen et al. [2] utilizes a strategy using a combination of chromatic and diffusion decision rules. Their system is limited to the detection of grayish smoke in the RGB color space. Smoke induced by fire can have a high variance of colors, limiting the application of this method. Long et al. [3] extended the method used for image dehazing to detect smoke. Utilizing the *airlight-albedo* ambiguity model, as specified by Fattal [4], Long et al. were able to detect smoke based on its light scattering effects. Their method, however is only valid for white smoke, which significantly limits its application. In the indoor detection scenario color is not such an effective feature due to the presence of objects with color similar to smoke. To address the color distribution of smoke, color models have been proposed by Celik et al. [5]. They construct models by

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analyzing samples extracted from different videos containing fire. They utilized the Luma, blue difference, red difference chroma components (YCbCr) color space due to its ability to distinguish luminance from chrominance information.

Calderara et al. [6] develop an RGB color space based method introducing a background model to segment moving objects from the scene. The moving smoke is detected by an analysis of energy variation within the scene. Motion as a feature is used by Kolesov et al. [7], too. They propose a method based on optical flow to detect occurring smoke. The problem of detecting smoke is modeled as a supervised Bayesian classification problem. The RGB color values and optical flow features are modeled as a fused feature. In the indoor detection scenario, objects with colors similar to smoke may be present which reduce the effectiveness of color as a smoke detection feature. This approach is particularly useful when the moving column of smoke is dense and visible. In case in which the smoke is sparsely distributed an optical flow cannot be calculated accurately, and therefore smoke detection is not possible. The approach of Rubaiyat [8] aims to perform smoke verification using the direction of smoke propagation as a feature. The approach relies on performing initial detection using color thresholds. After marking possible smoke candidate pixels statistical analysis by means of dynamic programming is carried out to determine the direction of propagation of smoke.

Toreyin et al. [9] utilize the decrease in background detail accompanied by smoke accumulation as a feature to detect smoke in an image by performing energy analysis. The edge energy decrease in the image is calculated using the Discrete Wavelet Transform (DWT). The decrease in energy is monitored over time in order to detect smoke.

Bogush et al. [10] developed a method for detection of smoke based on the decrease of contrast and motion analysis.

Our method is based on detecting the physical changes, perceivable to humans that accompany the accumulation of smoke. Our proposed method reliably and quickly detects smoke even when the smoke source or smoke column are not visible.

III. Contrast-Based Smoke Detection

This section discusses the presented method for ambient smoke detection. The algorithm leverages the fact that a smoke accumulation results in a decrease in background detail in a room. This loss of background detail can be measured using the contrast values in consecutive video frames. After such a decrease in contrast is detected, a motion analysis step tracks the decrease of contrast in order to detect smoke.

The algorithm consists of a four-step approach for smoke detection, including the detection of a change in contrast (see Section III-A), the removal of disturbances (see Section III-B), the smoke motion analysis (see Section III-C) and the alerting (see Section III-D).

A. Change in Contrast

The first step in determining the presence of smoke in a given scene is the calculation of the local image contrast. Contrast at each pixel position is calculated using the root mean square (RMS) contrast as defined by Eli Peli [11]. The RMS contrast is defined as the standard deviation of a given image pixel in a specified neighborhood (1).

$$C_{rms} = \sqrt{\frac{1}{n-1} \sum_{j=1, j\epsilon\mathcal{N}(i)}^{n} (x_j - \hat{x})^2} \tag{1}$$

$$\hat{x} = \frac{1}{n} \sum_{j=1, j\epsilon\mathcal{N}(i)}^{n} (x_j) \tag{2}$$

n is the total number of pixels in the neighborhood of a pixel i and $\mathcal{N}(i)$ is the neighborhood of pixel i. $\hat{x}$ is the mean of pixel values in the neighborhood $\mathcal{N}(i)$. Thus, pixels located in textured areas have high contrast values due to variations in gray scale intensity in the defined neighborhood and subsequently a high standard deviation. The central concept of this algorithm is the fact that with increasing ambient smoke in a room the contrast values between consecutive video frames decrease. The change in contrast between successive frames is calculated by differencing the contrast images in consecutive frames as shown in (3).

$$\Delta C(x, y, t) = C_{rms}(x, y, t) - C_{rms}(x, y, t-1) \tag{3}$$

ΔC represents the change in contrast, $C_{rms}(x, y, t)$ is the RMS contrast at pixel position (x, y) at time instant t and $C_{rms}(x, y, t-1)$ is the RMS contrast at pixel position (x, y) at time instant $t-1$. An exponentially weighted moving average time window is used to smoothen the contrast change values and detect a steady decrease in contrast (3). The smoothing constant α ensure that older values are assigned a higher weight than recently gathered ones α,

$$\alpha = exp^{\frac{1}{framerate\ *\tau}} \tag{4}$$

Weighing older values higher than recent values ensures stability of the system as our studies showed. τ is the time constant while frame rate refers to the frame rate used for processing the video.

$$C_{smoothed}(x, y, t) = \begin{array}{l} C_{smoothed}(x, y, t-1) * \alpha \\ +\Delta C(x, y, t) * (1-\alpha) \end{array} \tag{5}$$

B. Disturbance Removal

Disturbances can trigger a false alarm causing the system to behave incorrectly. In order to make the algorithm more robust these disturbances must be filtered out. Two main types of disturbances may occur: *brightness changes* and *contrast jumps*.

Brightness changes are caused by variations in ambient light introduced by a light source in the scene or due to moving shadows. In order to detect these changes, first a frame difference matrix is generated from two consecutive gray-scaled frames.

The obtained brightness difference matrix is divided into a 3x8 grid and brightness values are averaged both spatially and

(a) Instanteneous (b) DHI

Fig. 1 Smoke candidate pixels images, in which (a) is showing the detection data and (b) a DHI representation

temporally. A 3x8 grid size is utilized based on the used video resolution and typical distance we detect smoke. For each cell the average of the difference values is calculated, representing the spatial mean. Furthermore, the average of the spatial mean across ten brightness difference frame is calculated. Thus the brightness difference values are averaged both spatially and temporally.

Contrast jumps imply a high difference in contrast values of consecutive frames, generated e.g. by occurring shadows. Furthermore, contrast changes due to disturbances are abrupt and more intense than those occurring by smoke. Contrast differences exceeding a threshold $C_{Ju,T}$ can reliably be excluded as non-smoke moving objects. This threshold can be defined independent of the type of smoke and the source of the fire.

C. Motion Analysis

The motion analysis portion of the algorithm verifies whether the smoke candidate pixels are actually smoke or are due to some disturbance. The temporal evolution of the smoke cloud is very typical which the motion analysis algorithm seeks to identify. Smoke candidate pixels are passed onto the motion analysis algorithm. They are accumulated into a detection history image (DHI) as shown in Fig. 1. Fig. 1(a) shows the instant detection image while (b) shows the DHI. As can be seen the DHI encodes the time progression of the decrease of contrast. This allows us to track the spread of decrease of contrast and use it as an indicator for horizontal motion of smoke.

As a first step for motion analysis, the detection history image uses the 3x8 grid introduced in Section III-B. Each cell of this grid is processed independently of other cells.

Once 5% of the pixels in a cell are marked as smoke candidates, the cell is considered active and motion analysis is performed on it. The weighted center of mass (CoM) of the active cells is calculated according to the formula in (6).

$$Centroid\,Position_x(t) = \frac{\sum_{y=1}^{Y_{lim}} \sum_{x=1}^{X_{lim}} w_{x,y}(t) * x}{\sum_{y=1}^{Y_{lim}} \sum_{x=1}^{X_{lim}} w_{x,y}(t)} \quad (6)$$

Here $Centroid\,Position_x(t)$ is the current location of the centroid of a given cell at time instant t, Y_{lim} and X_{lim} are the maximum distances in the Y and X direction respectively, $w_{x,y}(t)$ is the pixel value at position (x, y) of the DHI. The division is done to normalize the results.

We concern ourselves with the horizontal spreading of the smoke and therefore, calculation is only performed in the horizontal dimension of a frame. Fig. 2 illustrates the spread of smoke. Initially the smoke begins to rise and starts collecting under the ceiling. It then starts to spread radially to the extent of the ceiling. Our developed algorithm focuses on detecting the horizontal spread of the smoke cloud and therefore only requires the 'x' component of the center of mass. The vertical axis of the center of mass is not calculated since it deals with the vertical spread of smoke, information that we do not need.

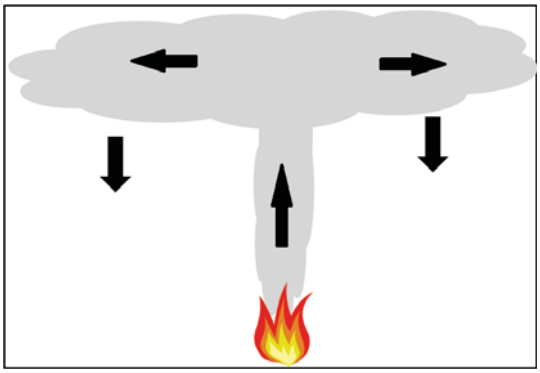


Fig. 2 Smoke moves up from the fire source. As smoke rises it starts collecting under the ceiling and spreading radially to the extent of the ceiling. The layer under the ceiling begins to descend downwards

Once a cell is active its weighted CoM is continuously calculated. The shift in the position of the CoM is indicative of the direction of spread of smoke. The evolution of the smoke cloud is expected to cause a gradual shift in the CoM of each cell. If there is movement in adjacent Sudden changes in the cell CoM are attributed to being caused by smoke aliases and are filtered out.

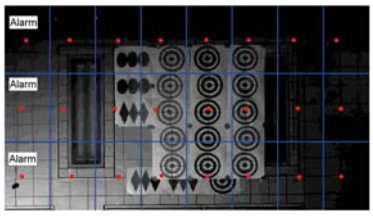
D. Alerting

Based on observations of horizontal spreading of smoke and the grid size for DHI division, a rule is derived to decide about the presence of smoke in a given scene. If at least three adjacent centroids move in the same direction, a pre-alarm is raised. However, if this movement occurs in the same time instant for all cells it is attributed to a disturbance since this is contrary to observed smoke behavior. When the pre-alarm persists for five seconds then an alarm is triggered. Those values are chosen empirically and can be adjusted according to the precision needs. Leveraging a two-step approach ensures that only stable and consistent results of motion analysis trigger an alert. Fig. 3 presents the visualization of the smoke decision results for smoke and disturbance class.

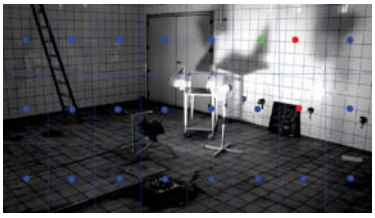
IV. Evaluation

A. Evaluation Setup

A parameter study was performed in order to optimize the design parameters of our algorithm and analyze the influence of particular parameters on the overall system performance. A training dataset of 40 videos has been established. The videos were selected so as to encompass different types of smoke, various disturbances and scenes containing different backgrounds. An additional evaluation dataset containing



(a) Smoke



(b) Disturbance

Fig. 3 Output of the detection algorithm: (a) Smoke class video, in which smoke entered the scene from the right; (b) Disturbance class video including moving shadows

TABLE I
PARAMETER VALUES USED FOR EVALUATION

Parameter:	C_T	$C_{Ju,T}$	$I_{Ju,T}$	Grid size (Rows x Col.)
Value:	-0.075	-3	3	4 x 11

65 videos has been created to evaluate the overall system performance. 15 of the videos were purely disturbance videos while the remaining 50 contained smoke. The videos used in the training and evaluation datasets were recorded in various locations including laboratory environments as well as industrial environments. The ceiling height of the rooms varied from 2.5 meters up to 6 meters while the distance of the camera from the smoke source goes up to 42 meters.

Parameters evaluated are contrast decrease threshold (C_T), contrast jump ($C_{Ju,T}$) and brightness jump ($I_{Ju,T}$) thresholds and the size of the grid used to divide the DHI. The optimized parameters (see Table I) were used to evaluate the performance of our algorithm on the evaluation video dataset. In order to test the robustness of the algorithm we use illumination changes and moving people in the field of view to simulate disturbances. Furthermore, smoke is generated using various types of fuels, such as wood, paper and plastic. The system performance is evaluated based on precision, recall and elapsed time till an alert is triggered.

B. Detection Rates

Within the smoke video class the algorithm had a detection rate of 100%. Even among the most difficult videos with multiple illumination changes or difficult conditions the algorithm is able to raise a consistent stable alert.

Among the fifteen disturbance class videos two were incorrectly labeled as smoke. One video was surveillance footage from an underground train station while the second included the opening of blinds in an office environment. The former error was due to the slow moving shadow of a person, which caused a localized illumination change. This illumination change was perceived as a contrast change leading to a false alert. The later video raised a false alarm due to the perceived contrast change resulting from camera adaptations as the blinds open. Both videos produced short-lived false alarms.

A per-frame analysis of all the videos was also done. The algorithm gives a recall of 70% and precision of 99%.

TABLE II
STATISTICAL OVERVIEW OF THE DETECTION SPEED EXPERIMENTS

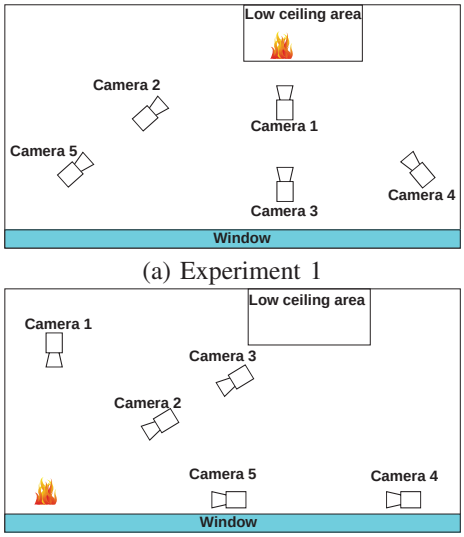
Detector Type	E1: Time till Alert [s]	E2: Time till Alert [s]
Smoke detector: G1	37	11
Smoke detector: G2	134	180
Developed Algorithm	45	15

C. Detection Speed

For the existing video database the smoke detection algorithm achieved valid detections in approx. 30 seconds (Std.Dev.: 15.15) for all videos. The detection time for conventional ceiling smoke detectors varies greatly based on their installation position. Under ideal installation conditions, i.e., with the detector right above the smoke source, the required time is similar to our proposed system. In case of non ideal conditions, such as when the smoke source is further away from the detector, they perform significantly worse. In order to further investigate this difference and also compare our developed algorithm with conventional ceiling smoke detectors two experiments were setup. In both experiments two groups of ceiling smoke detectors were placed in various positions in a room. One group of smoke detectors was placed right above the smoke source while a second group was positioned in the center of the room. The camera was mounted on an opposing wall such that it had a view of the whole room. The first experiment was performed in an open room while the second experiment was performed in a narrow corridor. The time required to trigger an alert by the two groups of smoke detectors and our ambient smoke detection algorithm is summarized in Table II. An ideally positioned ceiling detector has the fastest detection time. Our developed smoke detection algorithm is marginally slower. As compared to the more realistic placement of smoke sensors, in group 2, the developed ambient smoke detection algorithm performs exceptionally well.

D. Detection Distance

The ability of our developed algorithm to correctly and quickly detect smoke is also affected by the distance of the camera from the smoke source. In order to study how increasing distance affects the smoke detection, both in terms of time to alarm and correctness of alarm, two experiments were setup according to the plan show in Fig. 4. In experiment one the ceiling height is two and a half meters while for experiment two the ceiling height is siy meters. In addition, the view of the cameras was partially obstructed by over hanging pipes and cables. In these experiments a paper fire was lit to produce real smoke as opposed to the smoke cartridges used in the speed of detection experiments.



(a) Experiment 1

(b) Experiment 2

Fig. 4 Evaluation setup for studying effect of increasing distance on detection

TABLE III
STATISTICAL OVERVIEW OF THE DETECTION DISTANCE EXPERIMENTS

Camera Number	Experiment 1		Experiment 2	
	Distance [m]	Time till Alert [s]	Distance [m]	Time till Alert [s]
Camera 1	8	50	8	60
Camera 2	14	85	16	125
Camera 3	16	110	16	140
Camera 4	17	100	21	200
Camera 5	25	180	42	300

Initially a video resolution of 640 by 360 was used. With this resolution smoke was detected only in videos recorded using camera one, two and three. For all other cameras the required number of cells were not activated and therefore no alarm was raised. In order to counter act this problem high resolution video recordings, 1920 by 1080, were utilized. Further more the number of columns of the grid were increased to 22. The effect of detection speed on increasing distance between smoke source and camera is summarized in Table III. The results support the initial assertion that by increasing the video resolution and number of columns of the grid smoke can be detected at larger distances. With increasing distance between smoke source and camera a delay in triggering of alarm is also observed. Further away from the smoke source, the smoke cloud requires more time to spread before the required number of cells in the movement analysis algorithm are activated and an alarm is triggered.

It can also be observed in Table III that the detection time for comparable distances from the fire are different. For experiment one the alarm for similar distances was triggered earlier as compared to experiment two. This is due to the fact that ceiling height for experiment one was lower. This allows the smoke to rise quickly and spread out faster than it does for higher ceiling distance, such as in experiment two.

V. CONCLUSION

This work addresses fire detection in indoor scenarios which is of significant importance for societies as well as the economy. We have proposed and evaluated a novel video based method for early detection of fire. The algorithm leverages that even occluded fire sources can be detected using ambient smoke. A contrast-based method including a multiple step classification is used to detect the amount of ambient smoke and reliably detect fire. Our evaluation supports our initial aim to ensure a reliable low delay detection of smoke. In comparison to a common point type smoke detector setup the system can boost up detection rates by 12 times. Additionally, as the method relies on ambient smoke, the proposed method is robust against occlusions as well as against other disturbances including lighting changes. This is demonstrated by the low false alarm rate and a recall rate of 70% and higher. Even more important is that such a system is reliable in detecting fires and avoids false negatives. Our experimental evaluations have shown that firstly there are no missed detections and secondly the speed of detection is considerably faster than traditional ceiling smoke detectors. Furthermore it is experimentally shown that the developed algorithm detects smoke successfully at large distances making it possible to monitor large halls with few cameras. By comparisons we would need several ceiling smoke sensors to monitor the same area adequately. Due to its high reliability and low detection time it is a promising approach to both reduce economical effects of fires as well as save lives.

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