Nighttime Fire Smoke Detection System Based on Machine Vision

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KEYWORDS: Surveillance system, Machine vision, Fire smoke detection, Nighttime fire detection, Fuzzy reasoning system, Active laser imagery

A real-time machine vision–based nighttime fire smoke detection method that can be incorporated into a surveillance system for early fire alert is proposed in this paper. Nowadays, video surveillance–based early fire smoke detection is crucial to the prevention of large fires and the protection of life and goods. However, many of the known video smoke detection methods require that minimum illumination be provided for the cameras to recognize the existence of fire smoke in a scene. To overcome the nighttime limitations of video smoke detection methods, a laser light is projected into the monitored field of view, and the returning projected light section image is analyzed in order to fire smoke. If the fire smoke appears within the monitoring zone created from the diffusing or scattering projected light path, the camera sensor receives a corresponding signal. The successive processing steps of proposed real-time algorithm are using the spectral, diffusing, and scattering characteristics of the fire smoke regions in the image sequences to register the possible smoke position in a video. Characterization of smoke is carried out by calculating arithmetic mean and deviation from the extracted feature vectors, and a classification method using a fuzzy reasoning system is applied to assign a score to the potential fire smoke candidate. Experimental results in a variety of nighttime conditions demonstrate that the proposed fire smoke detection method can successfully and reliably detect fire smoke.

Manuscript received: January XX, 2011 / Accepted: January XX, 2011

NOMENCLATURE

I = light intensity
I_0 = initial light intensity
l = light path length
α = light absorption coefficient
O_S = diffused laser light coefficient
P_S = particle sensing coefficient of the scattered laser
u = fire smoke index
G_O = scaling constant of O_S
G_P = scaling constant of P_S
G_u = scaling constant of u

1. Introduction

Damage caused by fire has always been a major area of concern for museums, warehouses, and residential buildings. The evolution of a fire can be divided into five phases: ignition phase, growth phase, flashover phase, fully developed fire phase, and decay phase [1]. In the ignition phase, small and invisible particles of smoke and gases are forced upward by the thermal energy released during combustion. During fire combustion in the growth stage, small and invisible particles of fire smoke are forced upward by the thermal energy release. Smoke is a compound of hydrogen, carbon, and oxygen. The constituents and quantity of the smoke depend on the chemical components of the combustible material, the burning temperature, the supply of oxygen, and so on. The visual pattern of smoke is difficult to model, and the smoke density varies with the surroundings. However, smoke from an uncontrolled fire can be easily observed, even if the flames are not visible, and the fire can be detected before it spreads. For this reason, smoke detecting sensors play a leading role in fire detection. Traditional fire smoke protection methods use mechanical devices or humans to monitor the surroundings. The most frequently used fire smoke detection techniques are based on particle sampling, temperature sampling, and air transparency testing. An alarm is not raised unless the particles reach the sensors and activate them. Further, traditional detectors seldom provide additional descriptive information, such as the smoke location or extent.

Video surveillance can be used to monitor fires and fire-related disasters. However, surveillance systems require numerous people to watch the monitor screens all day long, leading to the possibility of human error; other disadvantages include the large amount of data that needs to be stored and the high cost. In recent times, more attention has been given to the detection of fire smoke using surveillance cameras with machine vision. Video fire smoke detection methods based on signal processing and the related research work can be found in References [2,3,4,5,6,7,8,9]. The image processing approach involves the extraction of the smoke plume from the background using frame difference technologies. Image features such as motion, flickering, edge-blurring of moving segments, and edge-blurring of regions were extracted from the video to detect smoke. The methods used to extract these features were background subtraction, temporal wavelet transformation, and spatial wavelet transformation. Smoke pixels were judged with a chromaticity-based static decision rule and a diffusion-based dynamic characteristic decision rule. A video smoke detection technique comprises background subtraction, flickering extraction, contour initialization, and contour classification using both heuristic and empirical knowledge about smoke [6]. To avoid false flame detection due to interference from background illumination, neon colors, or traffic lights, the time-varying property of flame geometry is taken into account. In the case of the segmentation of smoke features, color processing has advantages over grayscale processing. Color processing can avoid the generation of false alarms due to variations in lighting conditions—e.g., natural background illumination—better than grayscale processing can. Further, a video camera is a volume sensor, and it potentially monitors a larger area. However, many of the known video-based fire surveillance systems have a major weakness regarding detecting smoke at night. Video-based camera systems can only sense the variations when sufficient lighting in the monitored region is provided. The illumination at night is usually insufficient, and consequently smoke from a smoldering fire cannot be detected in time.

To overcome the limitations related to illumination and the shortcomings of conventional smoke sensors, multi-sensor systems [10] and infrared cameras [8,11,12] have been used instead of regular visible-range cameras. Ruser and Magori [10] presented a fire detection method that utilized a combination of ultrasonic and microwave sensors to avoid false alarms. YunChang et al. [8] presented a smoke recognition method based on active infrared CCD video imagery. However, smoke detection using an active infrared camera to capture video in the night is still difficult on account of the high background noise. A false alarm for a fire may be caused by a variety of sources, such as a heater, the sun, or a spotlight. Yuan et al. [11] presented a fire detection method based on a plurality of infrared radiation arrays mounted in an area to detect smoke. In [12], light section image detection is proposed to overcome the shortcomings of conventional beam-type smoke sensors and to achieve early detection of fire smoke. However, the drawback of these methods is that the detection system requires a setup involving many elements, such as infrared radiation arrays, infrared cameras, and signal processing units. Moreover, such systems are limited to monitoring only the fire smoke flow.

To address these problems, a smoke recognition method based on a color camera with an active laser imagery that is able to sense smoke in a nighttime indoor environment under zero lux illumination is proposed. This paper is organized as follows: The overall nighttime fire smoke detection algorithm structure is introduced and analyzed in Section 2. Then, some experimental results are given in Section 3. Finally, conclusions are given in Section 4.

2. Nighttime fire smoke detection

To realize a nighttime fire smoke detection system, the proposed system is composed of a line-strip laser and a color CCD camera. The line-stripe laser emits light in the monitoring region of the camera. A general digital color video camera is used to capture several laser-projected smoke sample image sequences with a pixel resolution of 1280 × 720. The fire smoke detecting process consists of four steps. In the first step, the input color image is transformed into the YCbCr color space. Then, the diffusing light intensity of the projected line-stripe laser is obtained by the camera. Next, the scattering light signal from the small and invisible particles of fire smoke is obtained using a color CCD camera. In the final step, statistical distribution of the diffusing and scattering probability density is weighted with the fuzzy reasoning system to determine the potential fire smoke candidate score.

2.1 Color models for the laser

To determine the fire smoke probability, the first step is to transform the color space into YCbCr color space; analysis can then be performed. YCbCr is a color format commonly used in digital video surveillance systems for data compression; Y is the luminance, and Cb and Cr contain blue and red chrominance components. The YCbCr color space is applied instead of other color spaces because it can separate luminance from chrominance information. It is also apparent from experimentation that the Cr component outperforms the Cb component as the diffusing and scattering laser signal received by the camera.

Image capturing and processing are the two major challenges involved in the construction of a laser light intensity measuring system. In the proposed fire smoke system, the video signal capturing process is conducted using a low-cost CCD camera with a resolution of 1280 × 720 pixels. The captured synchronizing concurrent video frames are then transmitted via USB to a PC. The image processor, which is buffered by the PC's system memory and which eventually displays the capture windows, uses windows driver model (WDM) functions of the PC. WDM functions can achieve high video frame rates—up to 30 images per second. Multimedia timer functions and PC-based real-time control are used along with specific software modules written in C++. Highly flexible multiple threads for the detection and tracking process are assigned by the multimedia timer scheduling thread software. The system is based on the open source computer vision library (OpenCV) [13], which provides the programming framework. Hence, real-time detection can be achieved.

2.2 Detection of obscured light signal

Most fires in buildings start with a strong emission of fire smoke. The produced particles and air turbulence yield partial obstructions in the projecting laser section image, so the fire smoke is sensed. Using the light absorption coefficient, the attenuation of light radiation can be obtained from Bouguer's law as $I / I_0 = \exp(-\alpha l)$. Bouguer's law can be applied for optical measurements of smoke [14,15]. It relates the intensity of incident light I_0 with the transmitted light intensity I after a travel path length l. Smoke visibility refers to the attenuation of light or opacity along the line of sight, and the saturation will decrease when opacity increases. By relating the reduction in laser light intensity, I / I_0, directly to smoke obscuration, the obscuring coefficient of the diffused laser light is defined as O_S and is normalized into the range [0, 1]. A decrease in the light intensity of the sensed line-strip laser indicates that there is smoke in the region that is obscuring light from the line-strip laser, and the resulting light gradually becomes invisible to the camera. Smoke between the laser light source and the projected wall surface will decrease the quantity of incident light on the sensor. Light signal obscuration detection will cause an alarm if smoke particles block part of a laser light beam transmitted to a camera such that laser light intensity decreases to a specified threshold.

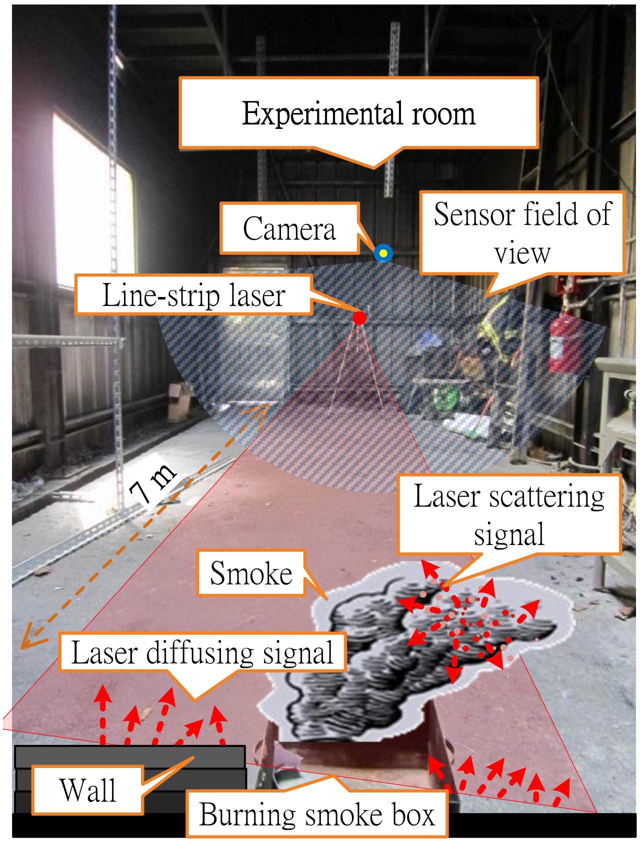

Fig. 1 Perspective view of proposed nighttime fire smoke detection system.

2.3 Detection of scattered light signal

When particles of fire smoke interact with the laser beam, the light is scattered to the camera, whose light intensity response is a direct count of the number of particles [16]. The laser light scattered from the particles can be imaged to allow for detection. The amount of smoke can be characterized by the scattered signal intensity received by the camera. Detection of scattered light signals will cause an alarm if the amount of smoke increases such that incident light scattering increases to a predetermined threshold.

The operating principle of the proposed scattering light signal detection is to transform the camera surveillance area into a light scattering detection zone by directing a line-strip laser beam across it, as shown in Fig. 1. Hence, the light scattered by particles of fire smoke in the beam can be used to calculate the smoke density detected by the camera. The particle sensing coefficient of the scattered laser light is defined as P_S and is normalized into the range $0 \le P_S \le 255$.

2.4 Fuzzy reasoning system

For improved resistance to nuisance alarms, fire smoke recognition requires evaluation of the characteristic features of both obscured light and scattered light. In this work, fuzzy logic is applied to improve the performance and to address the problem of false alarms. A fuzzy logic–enhanced approach is used to decide if fire smoke is being detected and if the fire could spread. A single output decision quantity is used to give a better fire smoke likelihood score.

In this work, the two main input variables for the fuzzy logic are the obscuring coefficient O_S and the particle sensing coefficient P_S, as shown in Fig. 2.

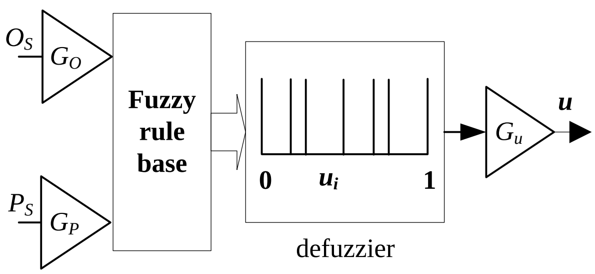

Fig. 2 The fuzzy logic decision engine.

Table 1 Fuzzy associative matrix.

Fire Smoke Index u		O_S ZE	O_S PS	O_S PM	O_S PL
P_S	ZE	u_4	u_3	u_2	u_1
	PS	u_4	u_3	u_2	u_1
	PM	u_4	u_4	u_3	u_2
	PL	u_4	u_4	u_4	u_3

Scaling constants G_O and G_P are used to rescale the values of $G_O O_S$ and $G_P P_S$ into the range [0, 1]. Then, values of $G_O O_S$ and $G_P P_S$ are fed into a fuzzy system to produce fire smoke likelihood—i.e., fire smoke index u—information from the output. Both $G_O O$ and $G_P P_S$ values comprise four fuzzy regions: ZE (zero), PS (positive small), PM (positive middle), and PL (positive large). For simplicity, four standard triangular membership functions for the fuzzy region variables {ZE, PS, PM, PL} are used here. Then, the maximum operation is introduced into the fuzzy inference engine to evaluate the decision rules stored in the fuzzy rule base. The fuzzy rules are as given in Table 1, which represents the fuzzy associative matrix. The columns and rows correspond to obscuring coefficient and particle sensing coefficient (inputs to the fuzzy reasoning system); the values of the matrix correspond to a measure index that indicates how likely it is that a region located at a sensed spatial location belongs to the fire smoke (output of the fuzzy reasoning system). The fuzzy output consists of four singletons $\{u_1, u_2, u_3, u_4\}$. Weighted average defuzzification is applied on the union of all rule outputs in order to find a fire smoke index u. In weighted average defuzzification, the output value u is the geometrical center based on the above fuzzy rules. With the values of the four singletons in hand, the fuzzy aggregated output—the centroid u—can then be calculated with a defuzzifier formula.

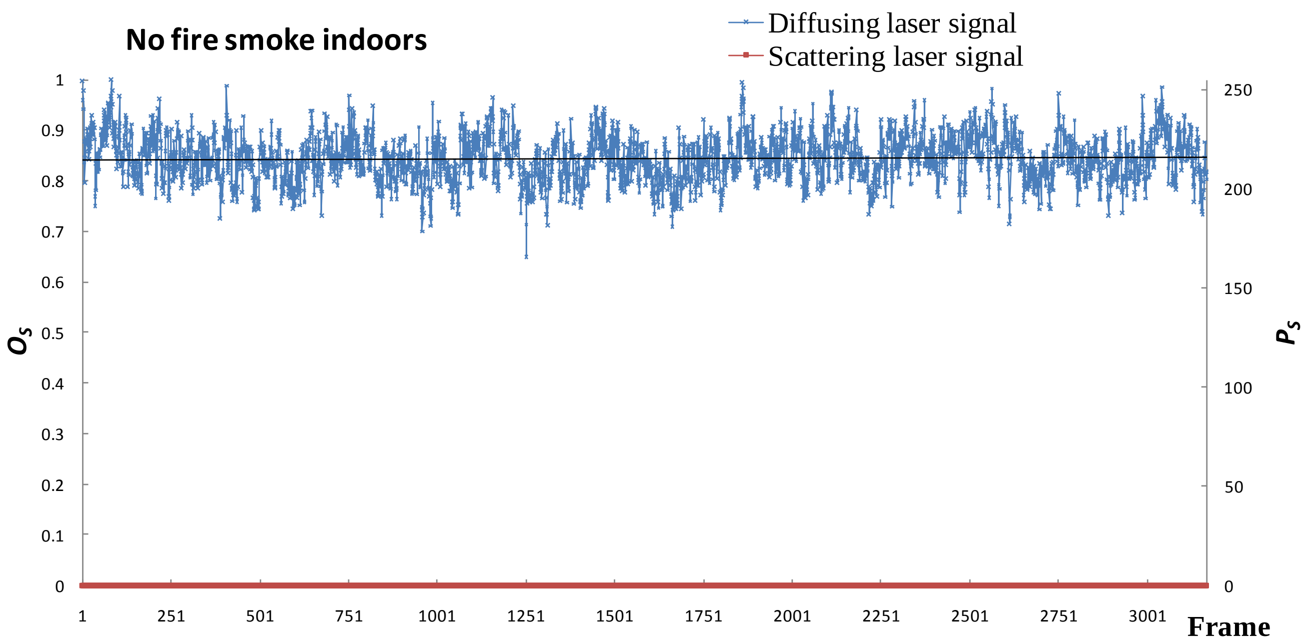

Fig. 3 The first experiment: evaluate the results of the light obscuration and scattering characteristic features for the tested images with no fire smoke inside the experimental room.

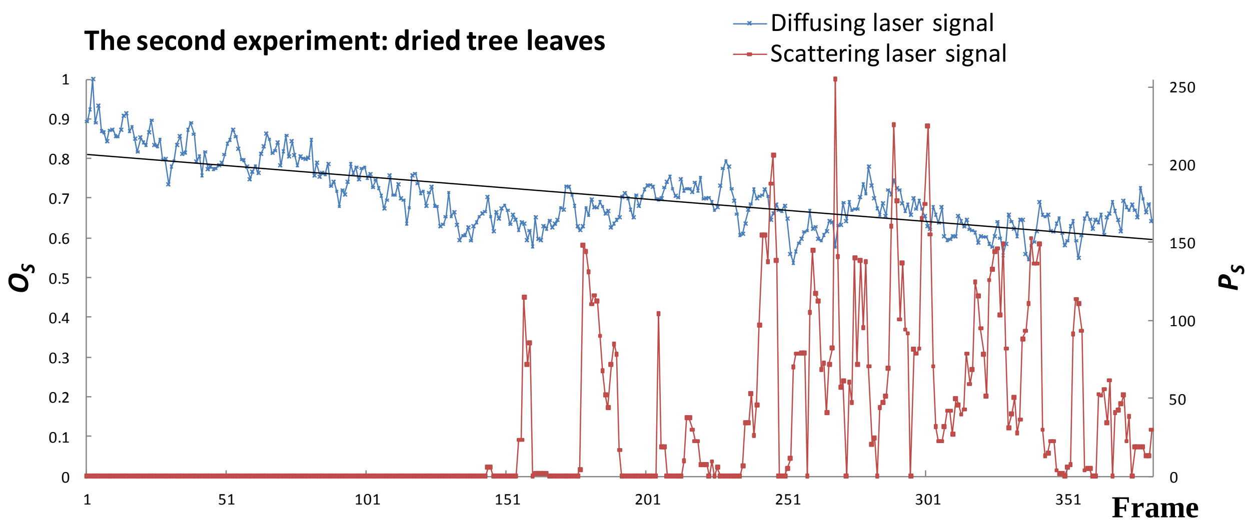

Fig. 4 The second experiment: dried tree leaves are selected as the burning material.

3. Realization and measurements

This section presents the analysis of experiments implementing the proposed process derived in previous sections. To realize the proposed nighttime fire smoke detection system, a general digital color video camera (Microsoft LifeCam HD-5000) is used to capture several fire smoke sample image sequences, along with a harmless low-power laser light emitter (LT-B65100-GLD, 45 mW). The computer used in our system is a 2.5 GHz Pentium E5200 PC with 2 GB of RAM running Windows 7. The laser source emits a spatially modulated line-strip laser, and the laser beam is projected on a displaced wall surface. The camera receives radiant energy from the diffusing and scattering line-strip laser beam and processes it to determine the existence of a fire smoke condition. The additional 15 score level crossing detection prior to the decision is also required to separate smoke and smoke-like alias. The proposed system can readily be made to work in complete darkness. The laser and camera are mounted on a tripod at a distance of 7 m from the burning smoke box. The feasibility of the proposed approach was investigated with four test fire series.

Fig. 3 evaluates the results of the light obscuring and scattering characteristic features for the tested images with no fire smoke inside the experimental room. Since the line-strip laser is not obscured, the value of diffused laser light coefficient O_S is close to one. The employed off-the-shelf commercial laser diodes operate at a single wavelength. However, the wavelength is unstable on account of the fluctuations of the supplied power and the temperature [17]. Peak intensity varies as the wavelength varies, and consequently the consecutive O_S value fluctuates, as shown in Fig. 3. Also, no scattered laser is sensed, and hence the value of particle sensing coefficient P_S is zero.

In the second experiment, dried tree leaves are selected as the burning material. As shown in Fig. 4, the line-strip laser is obscured by smoke, and hence the value of diffused laser light coefficient O_S is

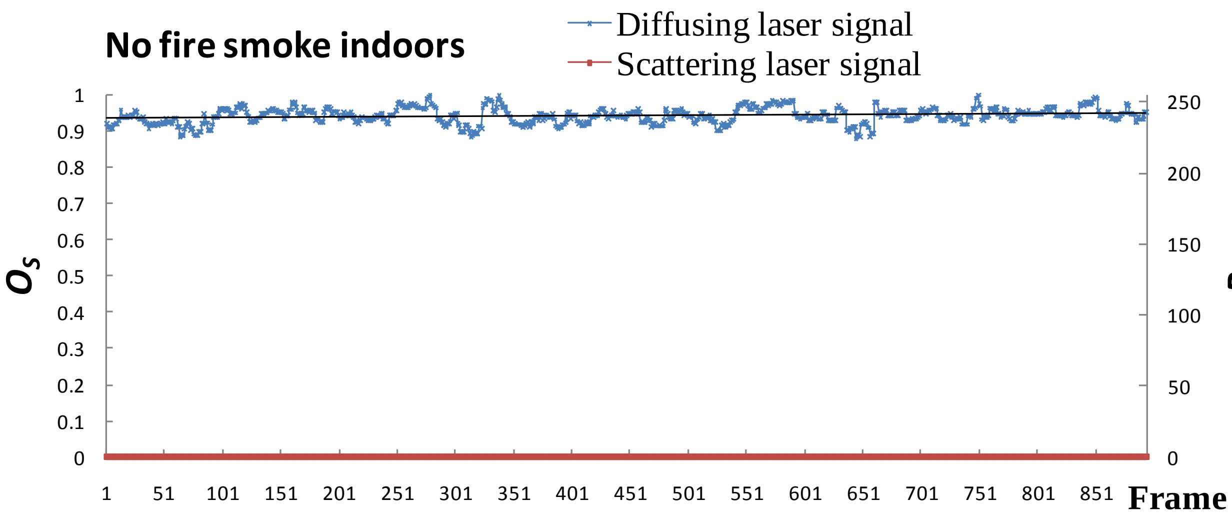

Fig. 5 The third experiment: evaluate the results of the light obscuration and scattering characteristic features for the tested images with no fire smoke inside the experimental room.

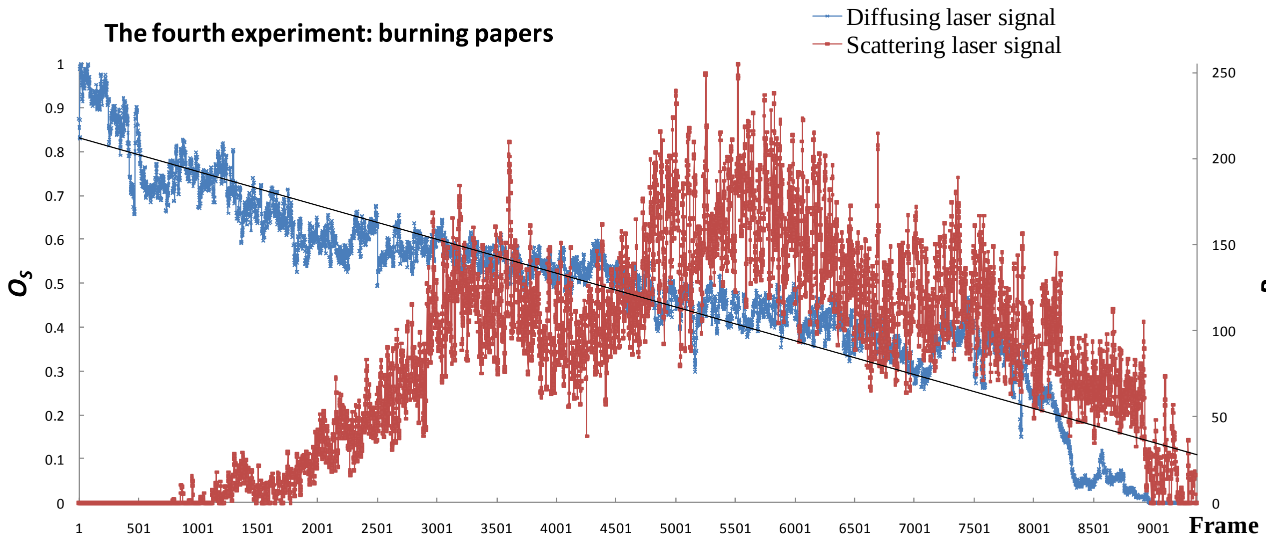

Fig. 6 The fourth experiment: papers are selected as the burning material.

decreased. Also, particles of smoke in the view region are scattering light from the laser beam, appearing as a visible blob to the camera; hence, the value of particle sensing coefficient P_S is increased. Since fire smoke is turbulent and will fluctuate with periodic oscillations, the particle sensing coefficient P_S also fluctuates periodically. Demo video clips of the experiment are available on the Web site (http://www.youtube.com/watch?v=n5H0VvkEaZs). As shown in video clips, the fire smoke candidate is detected at the 269th frame with the summed-score level crossing the threshold, and the smoke became thicker at the 353th frame.

In the last experiment, papers are selected as the burning material. Before the last experiment, no fire smoke is produced in the burning smoke box. The line-strip laser is not obscured, and hence the value of diffused laser light coefficient O_S is close to one. Also, no scattered laser light is sensed, and hence the value of particle sensing coefficient P_S is zero, as shown in Fig. 5. Then, the smoke is generated and the line-strip laser is obscured by smoke; as a result, the value of diffused laser light coefficient O_S decreases, as shown in Fig. 6. Also, particles of smoke in the view region are scattering light from the laser beam, appearing as a visible blob to the camera; hence, the value of particle sensing coefficient P_S is increased. Since fire smoke is turbulent and will fluctuate with periodic oscillations, the particle sensing coefficient P_S also fluctuates periodically. The value of particle sensing coefficient P_S decreases from frame number 6000, whereas the diffused laser light coefficient O_S decreases continuously. This occurs because the amount of smoke increases to the point at which the laser light beam is blocked completely. Since the strength of the received scattering light beam is also diminished, the value of particle sensing coefficient P_S decreases to zero. Demo video clips of the experiment are available on the Web site (http://www.youtube.com/watch?v=QuGrGuAtlHU). As shown in video clips, the image at the 869th frame is detected as fire smoke with the summed-score level crossing the threshold, and the smoke became thicker at the 1357th frame.

As shown in Fig. 7(a), no fire smoke is observed at the 325th frame, at which point the diffused laser light coefficient O_S is 0.9 and the particle sensing coefficient P_S is 0. As shown in Fig. 7(b), fire smoke is observed progressively at the 1350th frame, at which point the diffused laser light coefficient O_S is 0.7 and the particle sensing coefficient P_S is 14. As shown in Fig. 7(c), fire smoke gradually increases at the 4135th frame, at which point the diffused laser light coefficient O_S is 0.5 and the particle sensing coefficient P_S is 81. As

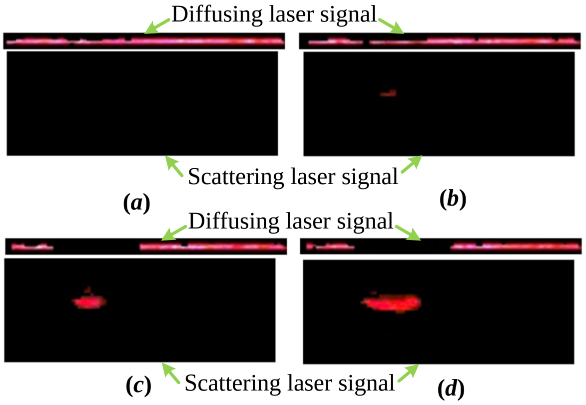

Fig. 7 The fourth experiment: the value of diffused laser light coefficient O_S is decreased, and the value of particle sensing coefficient P_S is increased. (*a*) No fire smoke is observed at the 325th frame. (*b*) Fire smoke is observed progressively at the 1350th frame. (*c*) Fire smoke gradually increases at the 4135th frame. (*d*) Fire smoke dramatically increases at the 5725th frame.

shown in Fig. 7(*d*), fire smoke dramatically increases at the 5725th frame, at which point the diffused laser light coefficient O_S is 0.4 and the particle sensing coefficient P_S is 147.

4. Conclusions

In this paper, a fast and reliable approach to detecting nighttime fire smoke in the earliest stages of a fire with a real-time alarm system is presented. Through the combination of a line-strip laser and a surveillance camera, reliable and sensitive fire smoke detection is achieved. Analysis of diffused, obscured, and scattered laser light signals with fuzzy logic is employed to provide validation of the fire smoke. The experimental results show that fire smoke can be successfully detected in complete darkness under various indoor environmental conditions. The proposed algorithm can be integrated into existing surveillance systems to achieve detection of fire smoke in video databases and in real-time applications.

In future work, a neural network will be applied to train the predetermined thresholds, thus increasing reliability in complex environments.

ACKNOWLEDGMENTS

This research was partially supported by the National Science Council in Taiwan under Grant NSC 98-2218-E-224-003 and by the Industrial Technology Research Institute. Special thanks are given to anonymous reviewers for their helpful suggestions.

REFERENCES

1. B. Karlsson and J. G. Quintiere, Enclosure fire dynamics: CRC Press, 2000.
2. B. U. Toreyin, et al., "Wavelet based real-time smoke detection in video," In Proceedings of the 13th European Signal Processing Conference, EUSIPCO, pp. 4–8, 2005.
3. B. U. Toreyin, et al., "Contour-based Smoke Detection in Video using Wavelets," in Proceedings of 14th European Signal Processing Conference, 2006.
4. C. L. Lai, et al., "A Real Time Video Processing Based Surveillance System for Early Fire and Flood Detection," in Proceedings of Instrumentation and Measurement Technology Conference, pp. 1-6, 2007.
5. Z. Xiong, et al., "Video-based Smoke Detection: Possibilities, Techniques, and Challenges," In Proceedings of Suppression and Detection Research and Applications, vol. 112, 2007.
6. C.-C. Ho, "Machine vision-based real-time early flame and smoke detection," Measurement Science and Technology, vol. 20, p. 045502(13pp), 2009.
7. C.-C. Ho and T.-H. Kuo, "Real-Time Video-Based Fire Smoke Detection System," in Advanced Intelligent Mechatronics. IEEE/ASME International Conference on Singapore 2009, pp. 1845 - 1850.
8. L. YunChang, et al., "Nighttime video Smoke detection based on active infrared video image," in International Conference on Electrical and Control Engineering, Wuhan, China, 2010, pp. 1359-1362.
9. C.-C. Ho, et al., "Machine vision-based intelligent fire fighting robot," Key Engineering Materials, vol. 450, pp. 312-315, 2011.
10. H. Ruser and V. Magori, "Fire detection with a combined ultrasonic-microwave Doppler sensor," in Proceedings of IEEE Ultrasonics Symposium, Sendai , Japan 2002, pp. 489-492.
11. H. Yuan, et al., "Method for detecting fire with light section image to sense smoke," United States Patent 6611207, Aug 26, 2003.
12. J. Fang, et al., "Early fire smoke movements and detection in high large volume spaces," Building and Environment, vol. 41, pp. 1482-1493, 2006.
13. G. Bradski and A. Kaehler, Learning OpenCV: Computer vision with the OpenCV library: O'Reilly Media, Inc., 2008.
14. G. W. Mulholland, "Smoke production and properties," in The SFPE Handbook of fire protection engineering. vol. 3, ed: National Fire Protection Association, 2002, pp. 2-258.
15. K. Kang, "A smoke model and its application for smoke management in an underground mass transit station," Fire Safety Journal, vol. 42, pp. 218-231, 2007.
16. D. W. Weinert, et al., "Light scattering characteristics and size distribution of smoke and nuisance aerosols," in Proceedings of the seventh international symposium, Worcester, MA, 2003, pp. 209-220.
17. S. Donati, et al., "A PC-interfaced, compact laser-diode feedback interferometer for displacement measurements," Instrumentation and Measurement, IEEE Transactions on, vol. 45, pp. 942-947, 2002.