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Real-Time Video-Based Fire Smoke Detection System

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***Abstract*—A real-time video-based fire smoke detection method that can be incorporated with a automatic monitoring system for early alerts is proposed by this paper. The successive processing steps of our real-time algorithm are using the motion history segmentation algorithm to register the possible fire smoke position in a video and then analyze the spectral, spatial and temporal characteristics of the fire smoke regions in the image sequences. The spectral probability density is represented by comparing the fire smoke color histogram model, where HSI color spaces are used. The spatial probability density is represented by computing the fire smoke turbulent phenomena with the relation of perimeter and area. Statistical distribution of the spectral and spatial probability density is weighted with the fuzzy reasoning system to give the potential fire smoke candidate region. The temporal probability density is represented by extracting the flickering area with level crossing and separating the alias objects from the fire smoke region. Then, the continuously adaptive mean shift (CAMSHIFT) vision tracking algorithm is employed to provide feedback of the fire smoke real-time position at a high frame rate. Experimental results in a variety of conditions show the proposed method is capable of detecting fire smoke reliably.**

I. INTRODUCTION

VIDEO surveillance can be used to monitor fires and burn disasters. Traditional fire protection methods use mechanical devices or humans to monitor the surroundings. The most frequently used fire smoke detection techniques are usually 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 about the flame location, size, burning degree, and so on. Surveillance systems require a large number of people to watch the monitor screens all day long, and hence the disadvantages are the increased possibility of human errors, the amount of data required to be stored, and the high cost [1]. In [2], light section image detection is proposed to overcome the shortcomings of conventional beam-type smoke sensors and detect the early fire. However, the drawback of this method is that the detection system requires many elements such as infrared radiation arrays, infrared cameras, and a signal-processing unit to be set up. Moreover, such systems are limited to monitoring only the fire smoke flow.

In recent times, research on detection of fire smoke using surveillance cameras with machine vision has gained momentum. The image processing approach involves the extraction of the smoke-plume from the background by using frame difference technologies. In the case of the segmentation of fire features, color processing scores over gray-scale processing. Color processing can avoid the generation of false alarms due to the variations in lighting conditions, e.g., natural background illumination, better than gray-scale processing can. Further, video camera is a volume sensor, and potentially monitors a larger area. The traditional point sensor looks at a point in space. Since the point sensor may not be affected by smoke, fire would be undetected. However, vision-based smoke detection still has great technical challenges, since fire smoke are non-rigid objects, none of the primitive image features and variability in density, lighting, etc.

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 early on before it spreads around.

Fire smoke detection methods via video processing and the related research work can be found in [3]–[7]. In [3,4], image features such as motion, flickering, edge-blurring to segment moving and edge-blurring regions were extracted from video to detect smoke. The methods used to extract these features were background subtraction, temporal wavelet transformation, and spatial wavelet transformation. In [5], smoke-pixel was judged with a chromaticity-based static decision rule and a diffusion-based dynamic characteristic decision rule. In [6], proposed a video smoke detection technique comprising background subtraction, flickering extraction, contour initialization, and contour classification using both heuristic and empirical knowledge about smoke. In [7], to avoid the false flame detection due to the interference of background illumination and color such as neon or traffic light, the time-varying property of flame geometry is taken into account.

To achieve fully automatic surveillance of fire smoke detection, a novel visual real-time fire smoke detection method is proposed on the basis of color video processing to meet the above requirements.

The proposed real-time fire smoke detection technique

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employs spectral features (i.e., saturation and chromatic features), spatial features (i.e., disordered features), and temporal features (i.e., flicking feature) for extracting fire smoke pixels.

Fire detection is first derived by the chromatic feature of smoke. With regard to the general color of fire smoke, the proposed system acknowledges that the fire smoke chromatic feature can dominate the decision function of fire smoke pixels. With regard to the spatial features of fire smoke, the fire smoke will flicker suddenly, which implies that the fire smoke shape is dynamically changeable in visual images. Thus, the extracted fire smoke pixels will be further verified through a check of the disordered characteristics of the burning fire. Statistical distribution of the chromatic and disordered measurement value is weighted with the fuzzy reasoning system to give the potential fire smoke candidate region. The temporal probability density is applied by extracting the flickering area with level crossing to separate the alias objects with the fire smoke region. Then, the continuously adaptive mean shift (CAMSHIFT) vision-tracking algorithm is employed to provide feedback of the fire smoke real-time position.

The main differences and advantages of the proposed approach are as follows:

It combines the spectral, spatial, and temporal fire smoke characteristics to perform the machine vision-based fire early detection and tracks the fire smoke region based on the CAMSHIFT algorithm.

The image sequences are processed and the fire smokes are recognized at 20[ms] or lower video rates by applying the detection and tracking algorithm. After fire smoke is detected, only limited regions surrounding the current tracking window need to be processed, and hence there tends to be a substantial reduction in computational costs.

The proposed fire smoke detection algorithm not only has a high correct decision rate and has better capability to avoid false alarms caused by environmental illumination, but it can also track the fire smoke regions from the image much more precisely than the other systems.

This paper is organized as follows. The overall fire smoke detecting algorithm structure is introduced and analyzed in Section II. Then some experimental results are given in Section III. Finally, the conclusions are given in Section IV.

II. Fire Smoke Detection Method

A. Moving Motion Segmentation with Motion History Image (MHI)

The proposed fire smoke detection algorithm consists of four steps: (1) moving pixels or regions in the current frame of a video are determined with the motion history image (MHI); (2) the HSI colors of moving pixels are checked; (3) if the histogram of moving pixels is correlated with the fire smoke color histogram, then the disordered measurement and temporal analysis are performed to determine if fire smoke colored pixels flicker or not; and (4) CAMSHIFT is applied to track the fire smoke region.

The region of interested moving pixels represents motion in successively layered image differences that create residual silhouettes of moving objects by using the MHI [8,9,10] where successive layering of image silhouettes is used to represent the patterns of motions. The MHI is a scalar-valued image where intensity is a function of recency of motion. This moving history representation can be used to determine the current movement of the object and to segment and measure the motions induced by the object (e.g., fire smoke) in a video scene. MHI representations have the following advantages: a range of times from frame to frame to several seconds may be encoded in a single image, direct recognition of the motion itself is possible, motion recognition is not computationally taxing and real-time implementation is possible, and the motion within the detecting scene can be monitored.

An MHI is used to represent how the motion of fire smoke is moving, since the outward boundaries of fire smoke are less prone to mis-detection than the source regions of fire smoke. In an MHI, pixel intensity is a function of the motion history at that location, where brighter values correspond to more recent motion. It should be noted that the final motion locations appear brighter in the MHIs. The MHI τ, where pixel intensity is a function of the temporal history of motion at that point, and representation is represented as follows [9]:

$$MHI_{\tau}(x,y,t)=\begin{cases}\tau & \text{if } \mathrm{D}(x,y,t)=1 \\ \max(0, MHI_{\tau}(x,y,t-1)-1) & \text{otherwise}\end{cases}, \quad (1)$$

where τ is the current time stamp, and *D(x,y,t)* is a binary image sequence indicating regions of motion. The result is a scalar-valued image where more recently moving pixels are brighter and implicitly represent the direction of movement. Hence, the motion gradient and segmentation are also acquired by the MHI algorithm and the orientation and direction of the object can be computed.

B. Spectral Chacteristics Correlation

To detect possible fire smoke pixel candidates, the first step is to transform the color space into HSI color space and spectral analysis can be performed. Hue is the dominant color (red, green, and blue) of an area, and saturation is the colorfulness of an area in proportion to its brightness. Intensity is related to the color luminance, e.g., human skin occupies a small portion of the H and S spaces. The advantages of the HSI space are intuitiveness of the components and explicit discrimination between luminance and chrominance. The hue, saturation, and intensity components of the HSI model are normalized into the following ranges: $0° \le \text{hue} \le 360°$, $0 \le \text{saturation} \le 255$, and $0 \le \text{intensity} \le 255$.

These important facts make the HSI color model useful to simulate the color sensing properties of the human visual system. This is because the hue and saturation components are intimately related to the way in which human beings perceive color [11]. The HSI color system that corresponds to projecting the standard red-green-blue (RGB color model) color space along its principle diagonal from white to black is applied to avoid the influence of lighting changes [12]. HSI Color histogram of moving regions are used to compute the correlation with a predetermined fire smoke histogram distribution, which represents the possible fire smoke-pixel spectrum in the video in HSI color space. To detect possible smoke-pixel candidates, the smoke histogram template is obtained from sample images containing smoke regions. The detection of smoke pixels is carried out using the saturation channel histogram correlation analysis with the smoke template, which maps the saturation value of general smoke to be distributed from 0 to 40.

The computed fire smoke spectral histogram correlation coefficient, S_{corr}, is used and measured by

$$S_{corr}(A,B) = \frac{\sum_i (A_i - \bar{A})(B_i - \bar{B})}{\sqrt{\sum_i (A_i - \bar{A})^2 \sum_i (B_i - \bar{B})^2}}, \tag{2}$$

where A and B represent the fire smoke analyzed region histogram and fire smoke histogram template respectively, while A_i and $\bar{A}$ are histogram bin value and its average. According to [13], smoke visibility refers to the attenuation of light or opacity along the line of sight, and the saturation will decrease when opacity increases. No matter what the smoke color is, the gray level histogram becomes concentrated if the smoke appears [7].

C. *Chaotic Spatial Structure Analysis*

Some smoke-like regions in an image may have the same colors as fire smoke, and these smoke-similar areas are usually extracted as the real fire smoke from an image. To validate a real burning fire, in addition to using chromatics, spatial features are usually adopted to distinguish other fire smoke aliases. Such fire smoke dynamics include sudden movements of flames, changeable shapes, growing rate, and oscillation (or vibrations) in the infrared response. Smoke is turbulent phenomena. In the case of turbulent flow the chaotic nature of the flow is an important feature. If the contours of an object exhibit rapid time-varying behavior then this is an important sign of presence of fire smokes in the scene. The shape complexity of turbulent phenomena may be characterized by a dimensionless edge/area or surface/volume measure.

The moving object regions with the disordered ratio of perimeter to area for the extracted fire smoke region Ω are defined as,

$$\Omega = \frac{P_r}{A_r}, \tag{3}$$

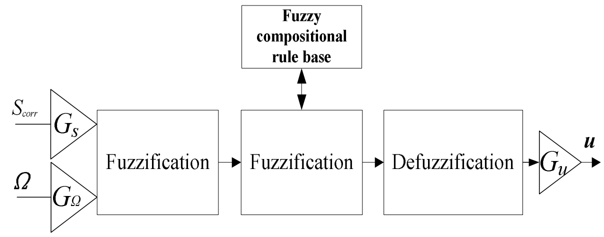


Fig. 1. The fuzzy logic used to discriminate between smoke and smoke-like colored objects.

where P_r represents the perimeter of the region and A_r represents the area of the region.

As the complexity of a shape increases (i.e., the perimeter increases with respect to the area), the value associated with disordered ratio Ω increases. The chaotic and turbulent nature of a region can be detected by relating the extracted spatial features to the fire smoke likelihood region [14]. The likelihood that a smoke-like region is a smoke region is highly correlated with the parameter Ω.

D. *Temporal Analysis*

To detect fire smoke correctly based on the color information is not always enough. There are lots of objects, which expose the similar color property with the fire smoke spectrum. The key to distinguishing between fire smoke and the fire smoke-colored objects is the nature of their motion. The flames in fire dance around, so any particular pixel will only see fire for a fraction of the time. This kind of temporal periodicity is commonly known as flickering. The flicker in smoke is also used as additional information. The candidate regions are checked whether they continuously appear and disappear over time.

To distinguish fire smoke like aliases, the temporal variation of fire smoke color regions is applied. Temporal variation in conjunction with fire smoke spectral histogram S_{corr}, and disordered ratio Ω is employed to detect fire smoke regions. A fuzzy-logic-enhanced approach is used to decide if the fire smoke are being detected and could spread to cause an accident. The single output decision quantity is used to give a better likelihood that a pixel is a fire smoke pixel.

In this work, the two main input variables for the fuzzy logic are the chromatic histogram correlation S_{corr}, and disordered ratio Ω shown in Fig. 1. There are scaling constants G_s and G_Ω using which the values of G_sS_{corr} and $G_\Omega\Omega$ are rescaled to fit the range [0, 1]. Then, values of G_sS_{corr}, and $G_\Omega\Omega$ are fed into a fuzzy system to give fire-smoke-likelihood, i.e., fire smoke index u information from the output. Both G_sS_{corr} and $G_\Omega\Omega$ 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 minimum implication operation is introduced into the fuzzy inference engine to evaluate the decision rules stored in the fuzzy rule base. The

TABLE I
FUZZY ASSOCIATIVE MATRIX

Fire smoke index u		S_{corr}			
		ZE	PS	PM	PL
Ω	ZE	u_1	u_1	u_2	u_2
	PS	u_1	u_1	u_2	u_3
	PM	u_1	u_2	u_3	u_4
	PL	u_1	u_3	u_4	u_4

fuzzy rules are as given in Table I, which represents the fuzzy associative matrix. The columns and lines correspond to chromatic histogram correlation and disordered ratio score, (inputs of the fuzzy reasoning system); the values of the matrix correspond to a measure index that shows how likely it is a region located at a spatial location belongs to the fire smoke pixel (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.

The fire smoke index u information with the history of 20 frames are used to search for the region having the highest probability of generating the output sequence. The region producing the highest probability is determined. If the region representing the fire smoke pixel has a higher probability than the other region, then temporal analysis is performed. To distinguish from fire smoke aliases, level crossing rate is utilized for validating these extracted fire smoke regions. Temporal variation for each pixel is computed by finding the level crossing rate of the most likely fire smoke candidate region above the k_1 threshold value among consecutive frames. The level crossing rate LCR is defined as,

$$LCR(x,y) = \frac{1}{T}\sum_{t=0}^{T-1} II\{u_t > k_1\}, \tag{4}$$

where u_t is a probability of length T and the indicator function $\mathrm{II}\{\varphi\}$ is one if its argument φ is true and zero otherwise. In this study, the interval length T for the level crossing detection was 40 frames.

The fire smoke spatial position can be determined as follows,

$$FireSmoke(x,y) = \begin{cases} TRUE, if \;\; LCR \geq k_2 \\ FALSE, if \;\; LCR < k_2 \end{cases}, \tag{5}$$

where k_2 is an experimentally determined threshold and (x, y) refers to the pixel's spatial location. The k_2 threshold is determined based on the fire smoke models in 6 video sequences. The k_2 is set at 0.05 for smoke determination.

E. CAMSHIFT Tracking Algorithm

The CAMSHIFT algorithm [15] is a non-parametric technique that can track a specified target's 2D position efficiently across a series of images. The CAMSHIFT tracking engine is based on the histogram projection algorithm that is a useful technique for color object recognition, especially for object identification in complex background surroundings. Histogram back-projection is a primitive operation that finds and identifies the association between pixel values in a grabbed image and the values in a particular histogram bin. Histogram and back-projection performed on any consecutive frame would generate a probability image on which the value of each pixel represents the probability of the exact same pixel from the input belonging to the target histogram that was used. Given that m histogram bins are used, we can define n image pixel locations. Thus, histograms $\{\hat{y}_u\}, u=1,\ldots,m$ and pixel locations $\{x_i\}, i=1,\ldots n$ can be calculated. Let us also define a function $c:R^2\rightarrow\{1,\ldots,m\}$ that associates a pixel at location x_i^* with a histogram bin index $c(x_i^*)$. Then, the histograms can be computed in the equation

$$\hat{y}_u = \sum_{i=1}^{n} \delta\left[c\left(x_i^*\right) - u\right], \tag{6}$$

Where δ is the Kronecker delta function. In all cases, values in the histogram bin are rescaled to fit within the discrete pixel range of the possible output 2D probability distribution image with the function

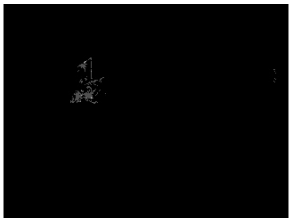
$$\left\{ \hat{p}_u = \min\left(\frac{UPPER}{\max\left(\hat{y}\right)} \hat{y}_u, UPPER \right) \right\}_{u=1\ldots m}. \tag{7}$$

That is, values in the histogram bin, originally in the range $[m, max(\hat{y}_u)]$, now lie in the new range $[0, UPPER]$. In the end, the input pixels with the highest probability of being in the sample histogram will be mapped onto a 2D histogram back-projection image with the highest visible intensities.

The CAMSHIFT algorithm is a non-parametric technique that can track a specified target's 2D position efficiently across a series of images. When tracking the 2D position of a colored object, in our case a fire smoke colored region, the CAMSHIFT operates on a color probability distribution image derived from color histograms. The center and size of the targeted object region is computed and used as settings for the search window on the following frame of the video sequence. Fig. 2 shows the images of the tracked object in the digital pictures that have been recognized and processed, and the yellow bounding ellipse presents the smoke region tracked by the CAMSHIFT algorithm.

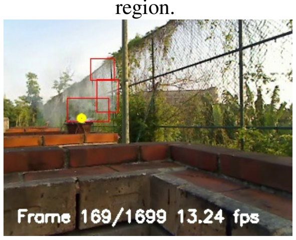
F. Real-Time Detection

The tracking routines can be done within 20[ms] video rates by applying the CAMSHIFT algorithm. The calculation of the



(a) *LCR(x,y)* probability distribution image, where brighter values indicate the most likely smoke candidate region.

(b) The moving smoke pixels are separated as shown, which smoke position was determined by *LCR*.



(c) The smoke at the 169th frame is detected.

(d) CAMSHIFT tracking algorithm is employed to track the smoke region.

Fig. 2. The image at the 169th frame is detected as smoke by searching the candidate regions, which are over the *LCR* threshold, and the CAMSHIFT tracking algorithm is employed at the 170th frame to track the movement of smoke pixels. The yellow bounding ellipse presents the smoke region tracked by the CAMSHIFT algorithm.

color probability distribution is not performed on the entire image, only on limited regions surrounding the current CAMSHIFT window, which includes images of the specified object that are transformed into a discrete probability image. This tends to result in a large reduction in the computational costs.

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, optimized for fire smoke detection.

III. Analysis and Comparison

The analysis of experiments implementing the proposed process derived in previous sections is presented in this section. To realize the proposed fire smoke detection system, a general digital color video camera is used to capture several fire smoke sample image sequences with the format of pixel resolutions of 320 × 240. The process rate of the system performs at the rate of 11–60 frames per second on an Intel Pentium computer running at 2.0 GHz. For the detailed evaluation, fuels were burned in different situations and use the decision rules on spectral, spatial and temporal features described previously.

Results of implementing the proposed fire smoke detection system in various situations of illumination (Movie 1-6) are shown in Fig. 3 and Table II. In Table III, we have tabulated smoke detection results, where the field n_t is the number of frames of a video clip. The field f_- is the number of false negative fire smoke, which means that the system does not detect fire smokes in an image frame while there is indeed fire smoke frames in it. Similarly, the field f_+ is the number of false positive fire smoke, which means that the system recognizes fire smoke in an image frame while there is no fire smoke at all.

Fig. 3. Example frames of experimental test data.

TABLE II
PROPERTIES OF THE TEST VIDEOS

Video Sequences	*Video description*
Movie 1	Burning the paper.
Movie 2	Smoking in front of a grayish concrete wall.
Movie 3	Fire in a garden and lighting a lamp to confuse.
Movie 4	A moving hand and walking in a room to confuse.
Movie 5	Burning paper at a barbecue site.
Movie 6	Smoking at a barbecue site.

The detection rate, r_d, of a video is defined as the ratio

$$r_d = \frac{n_d}{n_t}, \tag{8}$$

where n_d is the number of true positives and means the rate of correctly detecting a real fire smoke as a fire smoke in a video clip. It can be clearly observed that the fire smoke can be correctly extracted and an appropriate alarm given. Fig. 4 shows fire smoke detection results when using the proposed method in various test videos. In Table III, the average true positive detection rate of the proposed fire smoke detection is

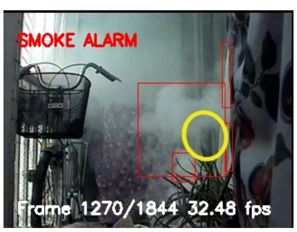
TABLE III
RESULTS OF PROPOSED FIRE SMOKE DETECTING ALGORITHM

Video Sequences	n_t	f_+	f_-	r_d (%)
Movie 1	1844	85	460	70.4
Movie 2	1295	0	929	28.3
Movie 3	688	4	83	87.4
Movie 4	2956	0	0	100
Movie 5	484	0	39	91.9
Movie 6	1699	0	446	73.7
Total	8966	89	1957	77.2

77.2%. The fire smoke detection rate falls short in the case of movie 2 due to the fact that airflow caused by wind causes the fire smoke to move randomly.

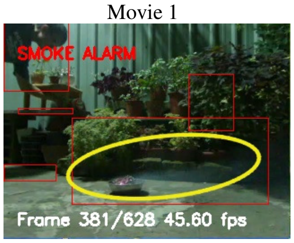
IV. CONCLUSIONS

In this paper, an approach to detect the fire smoke of real-time alarm systems is presented. Spectral, spatial, and temporal features and fuzzy logic are employed to extract real fire smoke and are adopted for helping the validation of that fire smoke. The experimental results show that fire smoke can be successfully detected under various environmental conditions, i.e., indoor, outdoor, day, simple, or complex background image, etc. The proposed algorithm can be integrated into the existing surveillance systems to achieve detection of fire smoke in video databases, as well as real-time detection of fire.

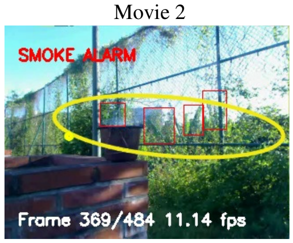


Movie 1

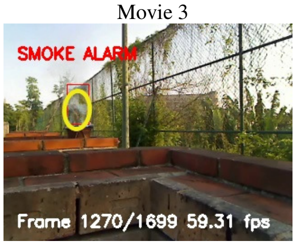
Movie 2



Movie 3



Movie 5



Movie 6

Fig. 4. Test videos which contain real fire smoke detection results using the proposed method.

REFERENCES

[1] D. Schroeder, "Evaluation of three wildfire smoke detection systems," *Advantage-Forest Engineering Research Institute of Canada (FERIC)*, vol. 5, pp. 1–8, 2004.

[2] J. Fang, J. Jie, Y. Hong-Yong, and Z. Yong-Ming, "Early fire smoke movements and detection in high large volume spaces," *Building and Environment*, vol. 41, pp. 1482–1493, 2006.

[3] B. U. Toreyin, Y. Dedeoglu, and A. E. Cetin, "Wavelet based real-time smoke detection in video," *In. Proc. European Signal Processing Conferenc*e, Antalya, 2005, pp. 4–8.

[4] B. U. Toreyin, Y. Dedeoglu, and A. E. Cetin, " Contour Based Smoke Detection in Video Using Wavelets," *in Proc. of 14th European Signal Processing Conference (EUSIPCO'06)*, Florence, 2006.

[5] T. H. Chen, Y. H. Yin, S. F. Huang, and Y. T. Ye, "The Smoke Detection for Early Fire-Alarming System Base on Video Processing," *In. Proc. Intelligent Information Hiding and Multimedia Signal Processing*, Pasadena, 2006, pp. 427–430.

[6] Z. Xiong, R. Caballero, H. Wang, A. M. Finn, M. A. Lelic, and P. Y. Peng, "Video-based Smoke Detection: Possibilities, Techniques, and Challenges," *In. Proc. of Suppression and Detection Research and Applications*, Orlando, 2007, pp. 112.

[7] C. L. Lai, J. C. Yang, and Y. H. Chen, "A Real Time Video Processing Based Surveillance System for Early Fire and Flood Detection," *In. Proc. of Instrumentation and Measurement Technology*, Warsaw, 2007, pp. 1–6.

[8] J. Davis, "Recognizing movement using motion histograms," Technical Report 487, MIT Media Lab, 1999.

[9] J. W. Davis and A. Bobick, "The Representation and Recognition of Action Using Temporal Templates," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 23, No. 3, pp.257–267, 2001.

[10] G. R. Bradski and J. W. Davis, "Motion segmentation and pose recognition with motion history gradients," *Machine Vision and Applications*, vol. 13, pp. 174-184, 2002.

[11] W. B. Horng, J. W. Peng, and C. Y. Chen, "A new image-based real-time flame detection method using color analysis," *In. Proc. Networking, Sensing and Control*, Tucson, 2005, pp. 100–105.

[12] K. R. Castleman, Digital image processing: Prentice Hall Press Upper Saddle River, NJ, USA, 1996.

[13] 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.

[14] T. Chen, P. Wu and Y. Chiou, "An Early Fire-Detection Method Based on Image Processing," *in Proc. of IEEE ICIP '04*, Singapore, 2004, pp. 1707–1710.

[15] G. R. Bradski, "Computer vision face tracking for use in a perceptual user interface," *Intel Technology Journal*, vol. 2, pp. 12-21, 1998.