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SMOKE DETECTION USING SPATIAL AND TEMPORAL ANALYSES

Chen-Yu Lee, Chin-Teng Lin, Chao-Ting Hong and Miin-Tsair Su

Department of Electrical Engineering
National Chiao Tung University
No. 1001, University Rd., Hsinchu 300, Taiwan
{ tbrsun; hong.chaotien }@gmail.com; ctlin@mail.nctu.edu.tw; bruce.ece93g@nctu.edu.tw

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Abstract. *Video-based fire detection is currently a fairly common application with the growth in the number of installed surveillance video systems. Moreover, the related processing units are becoming more powerful. Smoke is an early sign of most fires; therefore, selecting an appropriate smoke-detection method is essential. However, detecting smoke without creating a false alarm remains a challenging problem for open or large spaces with the disturbances of common moving objects, such as pedestrians and vehicles. This study proposes a novel video-based smoke-detection method that can be incorporated into a surveillance system to provide early alerts. In this study, the process of extracting smoke features from candidate regions was accomplished by analyzing the spatial and temporal characteristics of video sequences for three important features: edge blurring, gradual energy changes, and gradual chromatic configuration changes. The proposed spatial-temporal analysis technique improves the feature extraction of gradual energy changes. In order to make the video smoke-detection results more reliable, these three features were combined using a support vector machine (SVM) technique and a temporal-based alarm decision unit (ADU) was also introduced. The effectiveness of the proposed algorithm was evaluated on a PC with an Intel® Core^{TM}2 Duo CPU (2.2 GHz) and 2 GB RAM. The average processing time was 32.27 ms per frame; i.e., the proposed algorithm can process 30.98 frames per second. Experimental results showed that the proposed system can detect smoke effectively with a low false-alarm rate and a short reaction time in many real-world scenarios.*
Keywords: Alarm decision unit (ADU), Support vector machine (SVM), Surveillance system, Video smoke detection (VSD), Wavelet transform

1. **Introduction.** Numerous fires threaten human lives and property throughout the world every day; thus, there is a need for a reliable fire-detection technique. An enclosed fire may include some or all of the following phases of development: (1) incipient phase, (2) growth phase (pre-flashover), (3) flashover, (4) fully developed phase (post-flashover), (5) decay phase, and (6) extinction. Ignition is the start of fire development. The duration of the "incipient" period, shown in Figure 1, is dependent on a variety of factors including the fuel type, physical situation, and quantity of available oxygen. Heat generation increases during this period, producing light to moderate volumes of smoke. The characteristic smell of smoke is usually the first indication that an incipient fire is underway. Early detection at this stage, either human or automatic, can control the fire before significant losses occur if it is followed by a timely response from qualified fire-fighting professionals [1].

Conventional point-based sensors typically detect the presence of smoke particles by ionization or photometry [16], whereas video-based smoke-detection (VSD) systems use a newly developed technique based on machine vision, image processing, and pattern-recognition techniques. VSD provides advantages over traditional methods, such as fast response, non-contact, and the absence of spatial limits [25].

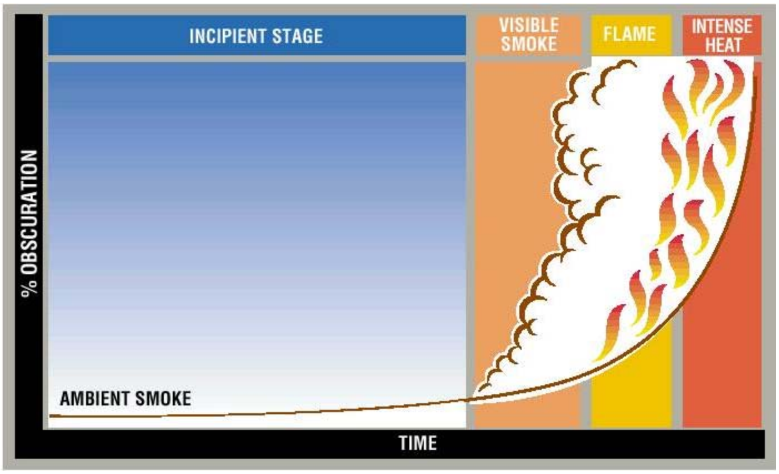


FIGURE 1. Duration of the incipient period of a fire (Source: http://www.det-fire.com.sg/info.htm

TABLE 1. State-of-the-art VFSD techniques

	Color Detection	Moving Object Detection	Flicker / Energy Analysis Temporal Difference Analysis	Spatial Difference Analysis	Disorder Analysis	Subblocking	Training	Cleanup Post-Processing	Localization/Propagation	Flame Detection	Smoke Detection	Published Year
W. Phillips III *et al.* [3]	RGB		X	X			X	X		X		2002
F. Gomez-Rodriguez *et al.* [4]		X	X		X						X	2002
F. Gomez-Rodriguez *et al.* [5]		X	X		X						X	2003
T.-H. Chen *et al.* [6]	RGB/HSI	X			X					X	X	2004
C.-B. Liu and N. Ahuja [7]	HSV		X		X					X		2004
B.U. Toreyin *et al.* [8]	YUV	X	X	X							X	2005
B.U. Toreyin *et al.* [9]	YUV	X	X		X						X	2006
B.U. Toreyin *et al.* [10]	RGB	X	X	X						X		2006
G. Marbach *et al.* [11]	YUV		X		X					X		2006
Z. Xu and J. Xu [12]		X	X		X					X	X	2007
T. Celik *et al.* [13]	RGB	X			X		X	X		X		2007
T. Celik *et al.* [14]	YCbCr/RGB/HSV									X	X	2007
B. Lee and D. Han [15]	RGB	X					X	X		X	X	2007
Z. Xiong *et al.* [16]		X	X		X						X	2007
P. Piccinini *et al.* [17]	RGB	X	X				X				X	2008
P.V.K. Borges *et al.* [18]	RGB				X					X		2008
S. Calderara *et al.* [19]	RGB	X	X			X	X				X	2008
F. Yuan [20]	RGB	X	X			X					X	2008
F.-X. Yu *et al.* [21]	RGB	X								X		2008
X. Qi and J. Ebert [22]	RGB/HSV		X	X				X		X		2009
R. Yasmin [23]	RGB/HSI	X			X	X			X		X	2009
J. Gubbi *et al.* [24]		X	X			X	X		X		X	2009
C. Yu *et al.* [25]		X	X				X				X	2010
S. Calderara *et al.* [26]	RGB	X	X			X			X		X	2010
Proposed Method	**RGB**	X	X	X		X	X	X	X		X	

Video fire and smoke detection (VFSD) has appeared with the development of computer technology and digital image-processing technology. Video-processing techniques for automatic fire and smoke detection have been a hot topic in computer vision over the last decade. Several vision-based detection algorithms have been proposed in literature, which has led to a large number of techniques for detecting the presence of fires at an early stage. Table 1 provides an overview of the state-of-the-art VFSD techniques, i.e., the most frequently referenced papers [2].

Color detection was one of the first VFSD detection techniques and it remains by far the most popular method. The majority of color-based VFSD approaches make use of *RGB* color space, sometimes in combination with HSI/HSV saturation [6,22]. The main rule-based techniques used to detect appropriate "fire"-colored pixels are Gaussian-smoothed color histograms [3], statistically generated color models [14], and blending functions [19]. The test results with color-based fire detection in the referenced studies were initially promising, but variations in color, density, lighting, and background question its applicability in real-world detection systems. A far more promising color-based smoke-detection method is the detection of a decrease in the chrominance [9], which exploits the semi-transparent characteristics of smoke in the incipient phase.

Moving-object detection is another technique that is frequently used as a first step in VFSD to eliminate stationary non-smoke objects. To detect possible motions caused by fire, any moving area in a video frame is detected using a motion-segmentation algorithm. Further analysis of moving regions is required to determine whether the motion is due to smoke or an ordinary moving object. The most effective algorithms for performing moving-object detection are background subtraction [9,10,12,13,16,17,19], temporal differencing [15], and optical flow [4,5].

Other frequently used fire-detection techniques include flicker detection [8-11,16,22] and energy analysis [9,17,19]. Both focus on the temporal behavior of flames and smoke. However, the flicker frequency of smoke varies with time. Thus, smoke-flicker detection does not appear to be a very reliable technique. A more interesting method for detecting the temporal behavior of smoke is energy analysis [17], which is described further in Subsection 2.3.2.

Another interesting approach for smoke detection is the disorder analysis of smoke regions over time. Frequently used metrics include the randomness of area size [18,27], boundary roughness [9], and turbulence variance [16]. These metrics differ in definition, but the outcome obtained by using each is almost identical.

Sub-blocking is commonly used in VFSD systems to simplify and improve the detection process, although it is not directly related to fire characteristics. Sub-blocking [19,23] reduces measurement disturbances; i.e., it filters out errors and measurement inaccuracies. Input images are subdivided into blocks of size $n \times n$, typically containing 16×16 pixels, and a block value is computed as the average of all the pixel values in the block. Further analysis is then performed at the block level, rather than at the pixel level.

The visual features used for VFSD in previous studies can be divided into four categories: (1) motion, (2) appearance, (3) color, and (4) energy (texture). However, none of these features is perfect, because each feature can cause false alarms in certain situations. Therefore, none of the existing algorithms is sufficiently robust and flexible enough to overcome all known problems typically encountered during automatic video fire and smoke detection, such as lighting conditions, scene complexity, and shadows. Recent research has combined various features to reduce the false-alarm rate [24,27,28].

This study proposes a novel smoke-detection approach using spatial and temporal analyses, which is based on the block-processing technique. This method analyzes energy-based and color-based features within the spatial, temporal, and spatial-temporal domains, before all the proposed features are combined using an SVM classifier. To decrease the false-alarm rate and maintain a high detection rate with a short reaction time, a temporal-based alarm decision unit (ADU) is proposed. Experimental results show that the proposed algorithm can detect smoke with a low false-alarm rate and a short reaction time in many real-world scenarios.

2. Video Smoke-Detection System.

2.1. System architecture. Smoke detection is a crucial task in many video surveillance applications and it could have a great impact in raising the level of safety in urban areas. However, video analysis tasks for smoke detection are not trivial because of the variability of shape, motion, and texture patterns of the smoke, where the appearance is also dependent on different luminance conditions, backgrounds, and scene colorations [19]. Thus, the majority of previous studies focused on a simple and specified environment, such as indoors [23], outdoors [12], and tunnels [15].

We propose a novel smoke-detection algorithm to provide greater flexibility to VSD and make it more suitable for a variety of conditions. Figure 2 shows the proposed VSD system architecture, which includes candidate-region extraction, a feature-extraction unit, a classification unit, and a verification unit.

- **Candidate-region extraction:**
  This requires the identification of candidate regions by change detection [29], using a combination of temporal difference and background subtraction techniques. Sub-blocking is also applied to achieve high computational performance.
- **Feature extraction:**
  This is directed at the ultimate goal of a high detection rate with a low false-alarm rate for a VSD system. This method exploits energy-based and color-based features of the candidate regions within spatial, temporal, and spatial-temporal domains.
- **Classification:**
  All the analyzed local features are combined using a support vector machine (SVM) algorithm. The SVM is trained and online testing is very rapid using a C++ program, which makes it suitable for real-time applications.
- **Verification:**
  A temporal-based ADU is introduced as the verification mechanism to reduce the false alarms and make the smoke-detection results more robust and flexible enough to overcome common problems encountered by automatic VSD systems, such as scene complexity and light reflexes.

2.2. Candidate-region extraction. The identification of moving objects in video sequences is a fundamental and critical task for many computer vision applications. To detect possible motions caused by smoke, the moving part in a current video frame is detected using a motion-segmentation algorithm. Further analysis of moving regions is necessary to determine whether the motion is due to smoke or an ordinary moving object. The most effective algorithms for moving-object detection are background subtraction [9,10,12,13,16,17,19], temporal differencing [15], and optical flow [4,5]. Temporal difference techniques are based on the subtraction of two consecutive frames followed by threshold detection [30]. Temporal difference techniques can effectively adapt to a changing environment, but they are usually incapable of extracting the complete contours of moving objects [31]. Background subtraction techniques detect moving objects by calculating the differences between the current frame and background images for each pixel and applying threshold detection [32]. Background subtraction techniques are capable of

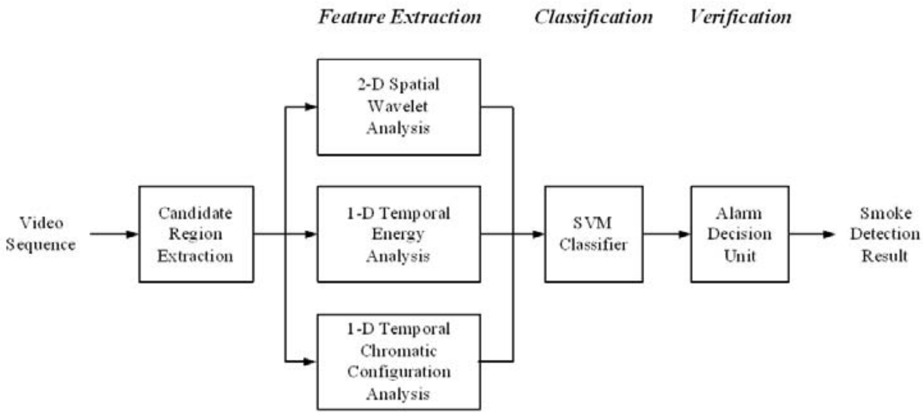


Figure 2. System architecture of the proposed VSD technique

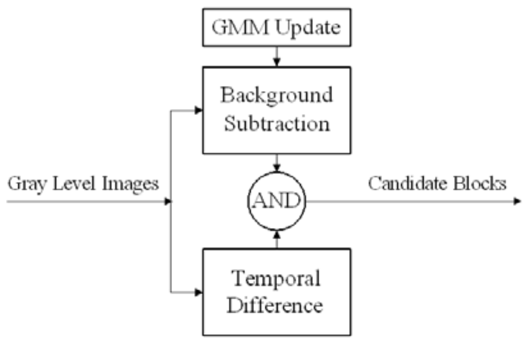


Figure 3. Framework for the candidate-region-extraction process

identifying most pixels involved in the motion and they are highly sensitive to dynamic changes in the environment, such as lighting or extraneous events [31]. Optical flow techniques detect moving objects by estimating the motion field before merging motion vectors that share similarities. However, most optical flow techniques are computationally complex and sensitive to noise, which leads to inadequate real-time processing of full-frame video streams [33].

In this study, a hybrid algorithm was developed, which was similar to change detection [29], for detecting moving objects using a combination of background subtraction and temporal difference techniques with a logical "AND" operator, as illustrated in Figure 3.

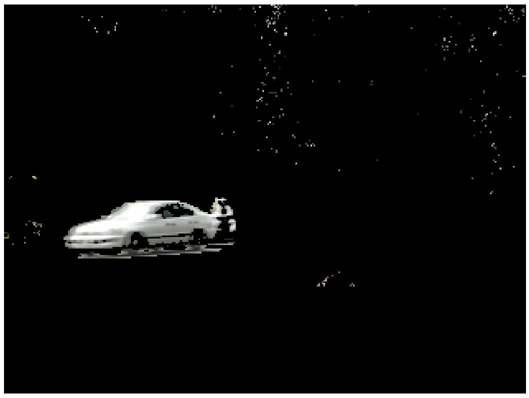
The temporal difference method was implemented by subtracting frame $t-1$ from frame t and regions with obvious intensity variation were considered foreground regions. Background subtraction involves a similar method, but in this study, a constructed background image instead of the frame $t-1$ was used. We applied the most common and robust method for background construction, the Gaussian Mixture Model (GMM) [34], which models each pixel as a Gaussian mixture using an online EM algorithm to update the model. Figure 4 shows the foreground segmentation achieved by background subtraction using the GMM model.

Tracking smoke targets by foreground segmentation is a necessary step in an object-based approach to temporal smoke analysis. However, smoke regions appear and disappear frequently because of a special particle property exhibited during ignition and combustion (as shown in Figure 5); therefore, tracking or analyzing the target using an object-based method is inefficient. Therefore, a block-based technique provides a more effective method for solving this problem.

(a) Video sequence

(b) GMM background image

(c) Current image



(d) Foreground image

FIGURE 4. Foreground segmentation using background subtraction (GMM)

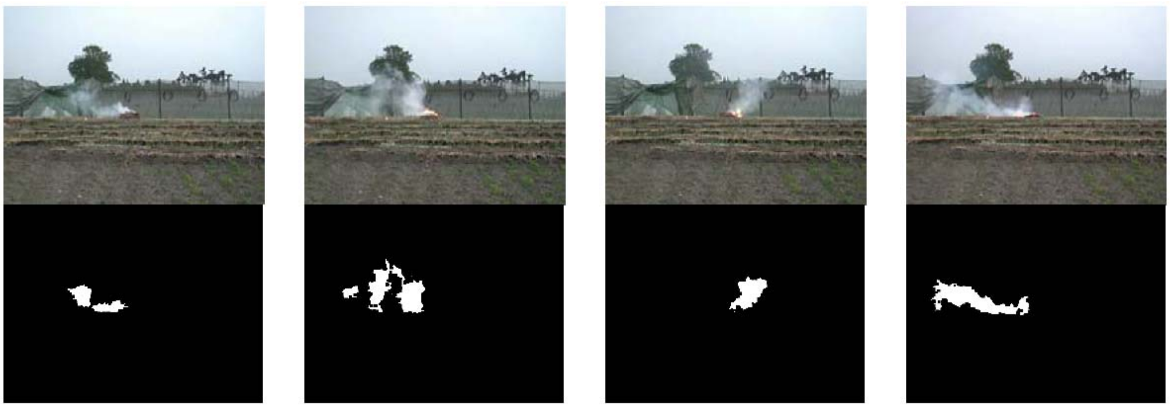


FIGURE 5. Smoke regions appear and disappear continuously

Figure 6 shows that only background subtraction values and temporal differences larger than the predefined thresholds are regarded as candidates containing moving objects, which reduces the computational cost. Further analysis of these moving regions is necessary to determine whether the motion is due to smoke or ordinary moving objects [8].

2.3. **Feature extraction.**

2.3.1. *2-D spatial wavelet analysis.* Smoke is semi-transparent, so the edges of image frames can lose their sharpness and this leads to a decrease in the high frequency content of an image. To identify smoke in a scene, the background was estimated and any decrease

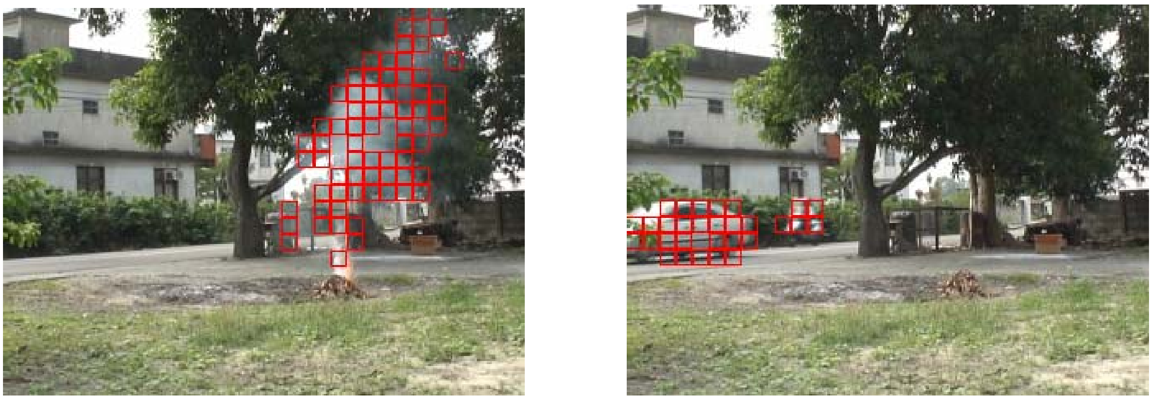
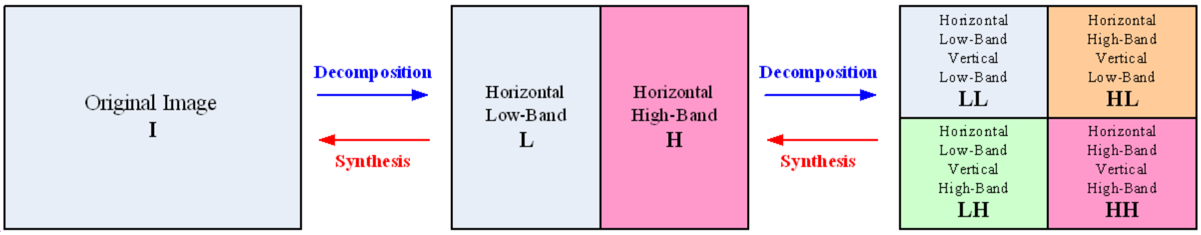


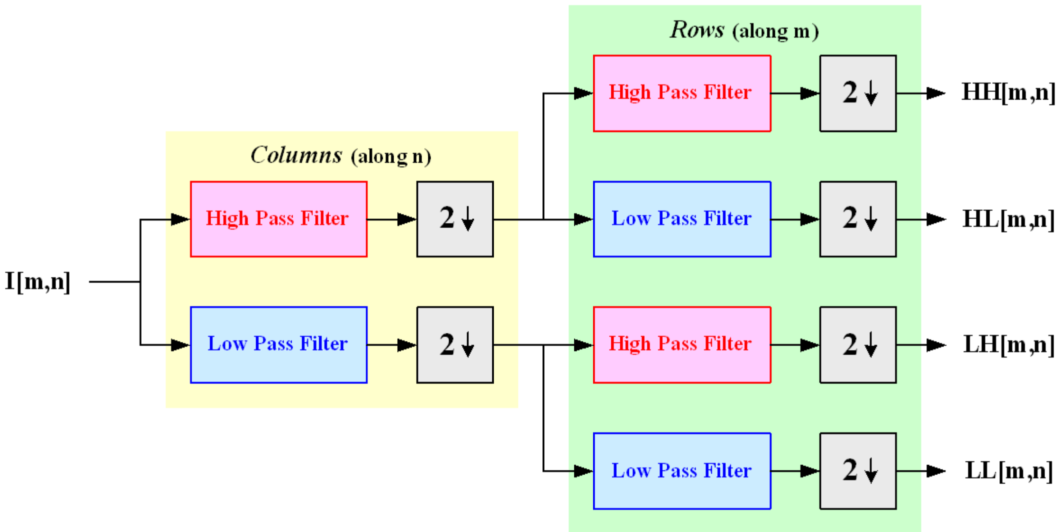
Figure 6. Results of block processing

in high-frequency energy was monitored using a spatial wavelet transform of the current and background image [8,9].

The whole 2-D spatial wavelet transform can be decomposed as the horizontal and vertical wavelet transforms shown in Figure 7(a). The direction from left to right is called "decomposition", while the reverse direction is called "synthesis".



(a) 2-D wavelet transform



(b) Coefficients of the 2-D wavelet transform

Figure 7. 2-D wavelet transform and coefficients

We use L and H to represent the low-band and high-band information, respectively. Following the 2-D spatial wavelet transform, the whole image is separated into four regions: horizontal low-band vertical low-band (LL), horizontal low-band vertical high-band (LH), horizontal high-band vertical low-band (HL), and horizontal high-band vertical high-band (HH).

Research has shown that wavelet sub-images contain the texture and edge information of the original image. Edges produce local extremes in wavelet sub-images [27,35,36]. The wavelet sub-images LH, HL and HH contain horizontal, vertical, and diagonal high-frequency information from the original image, respectively. If smoke covers one of the edges of the original image, then the edge initially becomes less visible and it may disappear from the scene after some time as the smoke thickens [8,9]. Figure 8 shows the original image and the single level wavelet sub-images.

(a) Frame without smoke

(b) Frame with smoke

FIGURE 8. Original image and single-level wavelet sub-images

The edges and texture contribute to the high-frequency information of the image; thus, the high-frequency information becomes even less visible as the smoke obscures part of the scene. This characteristic property of smoke is an accurate indicator of its presence in video frames, which also increases the possibility of determining the presence of smoke using wavelet sub-images, as shown in Figure 8. The spatial energy is evaluated block-wise by dividing the image into regular blocks of a fixed size and summing the squared contribution from each coefficient image, as shown in Figure 7(b) [19,26].

$$E\left(B_k, I_t\right) = \sum_{m,n \in B_k} \left[LH\left(m,n\right)^2 + HL\left(m,n\right)^2 + HH\left(m,n\right)^2\right] \tag{1}$$

where B_k is the kth block of the scene and I_t is the input image at time t.

The energy value of a specific block varies significantly over time in the presence of smoke. This energy drop can be further emphasized by computing the ratio α between the image energy of the current input frame I_t and that of the background model BG_t. The energy ratio has the advantage of normalizing the energy values and it allows a fair comparison between different scenes when the block energy can itself vary significantly. The ratio of the block B_k is given by

$$\alpha\left(B_k, I_t, BG_t\right) = \frac{E\left(B_k, I_t\right)}{E\left(B_k, BG_t\right)} \tag{2}$$

2.3.2. *1-D spatial-temporal energy analysis.* Smoke is semi-transparent during the early stages of a fire and it becomes less visible as time elapses. Thus, an instantaneous disappearance or appearance of a wavelet extremum in the current frame cannot be attributed to smoke. This type of change corresponds to an ordinary moving object covering an edge in the background or boundary of a moving object; hence, such changes are ignored. In this study, a one-dimensional temporal wavelet analysis of the spatial energy ratio α is proposed as an indicator of this phenomenon. As shown in Figure 9, after applying the 1-D wavelet transformation to the signal S, the high-band (details) and low-band (approximations) information can be obtained and they are denoted as D and A, respectively.

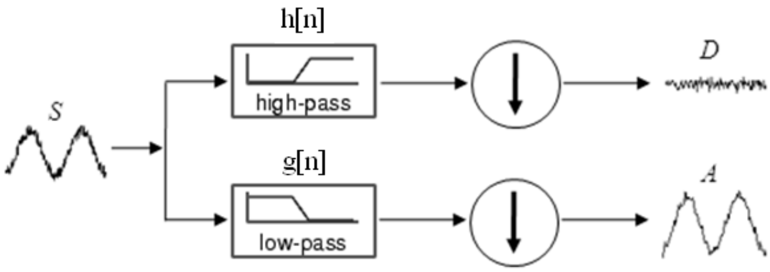


FIGURE 9. Block diagram of 1-D wavelet transform

Figure 10 shows the results of a comparison of the energy analysis for an ordinary moving object and smoke. As shown in Figure 10(c), ordinary solid moving objects produce a great quantity of variations in the energy ratio. In contrast, smoke has a smoother variation in the energy ratio, as shown in Figure 10(d).

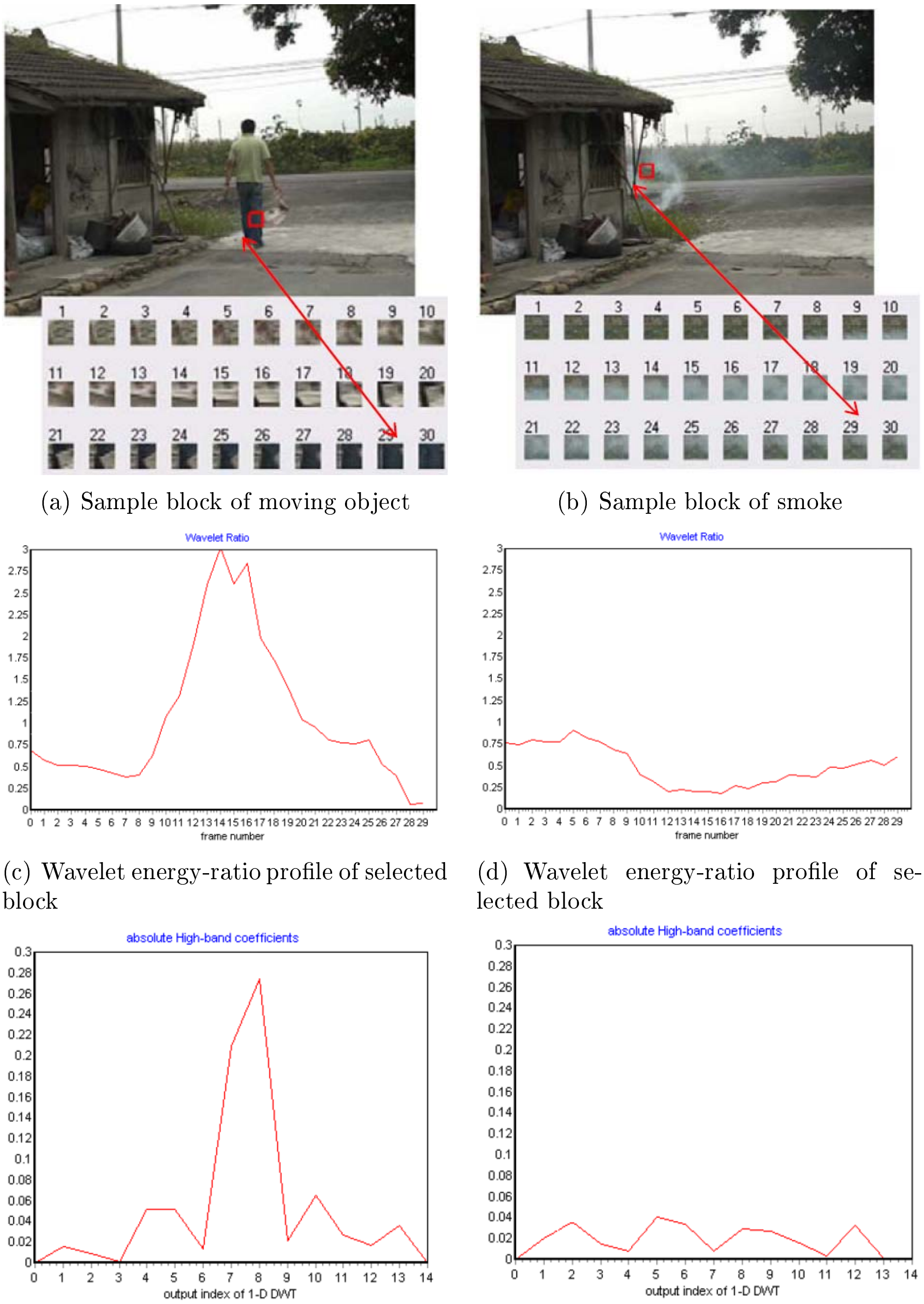
Figures 10(e) and 10(f) show that an appropriate threshold can be used to determine if the candidate region is smoke. The likelihood of a candidate block being a smoke region is inversely proportional to the parameter β:

$$\beta\left(B_k\right) = \frac{\sum_n |D[n]|}{N} \tag{3}$$

where $D[n]$ is the high-frequency information of the energy ratio α and N is a number representing the amount of time with a nonzero value for the details.

2.3.3. *1-D temporal chromatic configuration analysis.* In this study, color information was used as the third characteristic for identifying smoke in a video. Smoke is semi-transparent when it initially starts to expand, which leads to a decrease in the chrominance values of pixels. This provides another sign allowing the differentiation between smoke and ordinary moving objects.

Photometric invariant features are functions used for describing the color configuration of each image coordinate while discounting local illumination variations, and the normalized-RGB color space is commonly used for photometric invariant features. Therefore, the normalized-RGB color space was used in this study for smoke-detection analysis.



(a) Sample block of moving object

(b) Sample block of smoke

(c) Wavelet energy-ratio profile of selected block

(d) Wavelet energy-ratio profile of selected block

(e) Details of wavelet energy ratio

(f) Details of wavelet energy ratio

FIGURE 10. Comparison of energy analysis for ordinary moving object and smoke

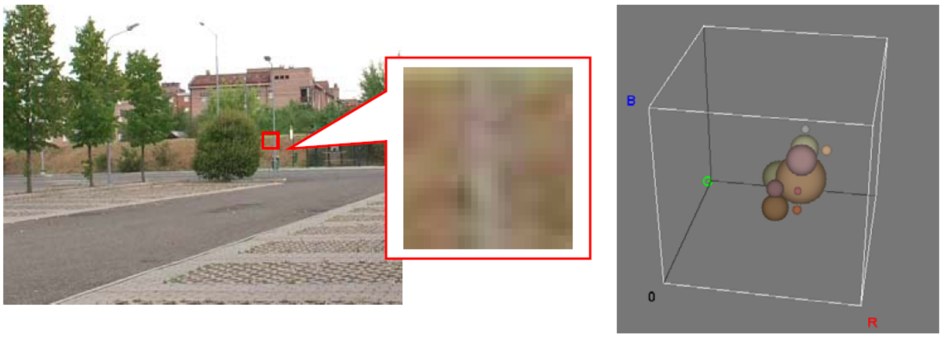
The normalized-RGB color space is obtained by dividing the R, G, and B coordinates by their total sum, as shown in (4), which projects a color vector in the RGB cube onto a point on the unit plane given by $r + g + b = 1$.

$$r = \frac{R}{R+G+B}, \quad g = \frac{G}{R+G+B}, \quad b = \frac{B}{R+G+B} \tag{4}$$

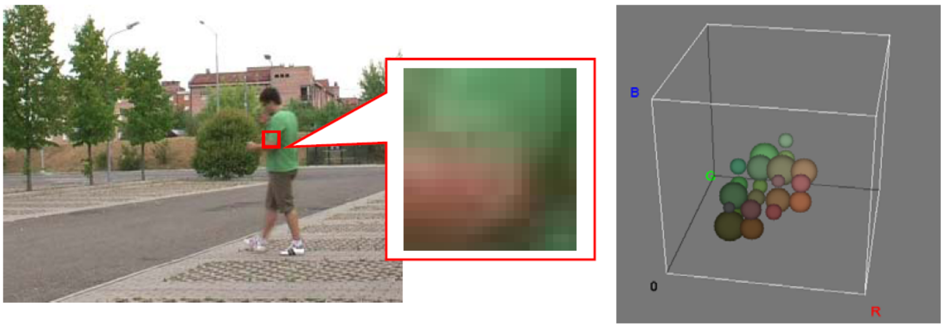
Based on the empirical analysis, smoke affects every component in the RGB color space of the obscured point, but it does not drastically change the configuration of the rgb color system. This constraint can be represented by

$$\begin{aligned} r\left(B_k, I_t\right) &\cong r\left(B_k, I_{t+\Delta t}\right) \\ g\left(B_k, I_t\right) &\cong g\left(B_k, I_{t+\Delta t}\right) \\ b\left(B_k, I_t\right) &\cong b\left(B_k, I_{t+\Delta t}\right) \end{aligned} \tag{5}$$

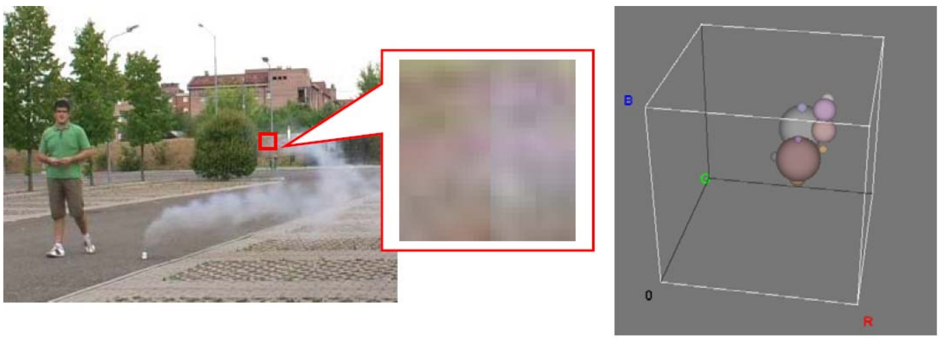
when candidate blocks are obscured by a smoke region instead of ordinary moving objects. This investigation drew the *RGB* color histogram of a specific block from three different positions in a video sequence to characterize the presence or absence of smoke. The color histogram distribution in Figure 11(c) is similar to that in Figure 11(a). However, the presence of a pedestrian produces very different color histogram distributions, as shown in Figures 11(b) and 11(a).



(a) Original image



(b) Image obscured by ordinary moving objects



(c) Image obscured by smoke

FIGURE 11. *RGB* color histogram of a specific block

Figure 12 shows the details (high-frequency information) of the three channels in the *rgb* color space using 1-D DWT. Figures 12(g) and 12(h) show that more details are produced when the selected block is obscured by ordinary solid moving objects than when the selected block is obscured by smoke, in which case there is a smooth variation in the rgb color space with few details. Therefore, it is easy to select an appropriate threshold value for identifying whether a candidate region contains smoke. In this study, we chose ρ as the color feature descriptor, which is calculated by

$$\rho(B_k) = \max_{n \in \text{interval}} \|(D_r[n], D_g[n], D_b[n])\|_2 \tag{6}$$

where $D_r[n]$, $D_g[n]$ and $D_b[n]$ represent the details of the r, g and b channels, respectively. Again, the likelihood of the candidate block being a smoke region is inversely proportional to the parameter ρ.

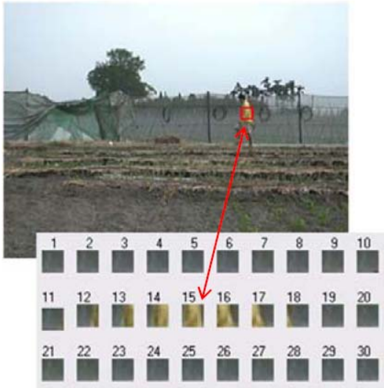
2.4. **Classification and verification.** The three features described in the previous subsection are partially complementary, but they have different physical meanings. The 2-D spatial wavelet feature in (2), α, distinguishes high-texture objects from smoke. The 1-D temporal energy feature in (3), β, distinguishes objects that suddenly change texture in the candidate block. The 1-D temporal chromatic configuration feature in (6), ρ, distinguishes objects that suddenly change their color structure in the candidate block. In this subsection, these three proposed features are combined as a feature vector $x = [\alpha, \beta, \rho]$ for each candidate block before being classified using a SVM. Furthermore, a verification process is proposed to reduce the false-alarm rate.

2.4.1. *Support vector machines.* SVMs have considerable potential as classifiers for sparse training data because they were developed to solve classification and regression problems. SVMs have similar roots to neural networks, and they can provide universal approximations for any multivariate function to any desired degree of accuracy. Instead of minimizing an objective function based on training, SVMs attempt to minimize a bound for the generalization error. SVMs have gained wide acceptance because of their high generalization ability over a wide range of applications [37] and their improved performance over traditional machine-learning methods, such as radial basis function networks [38] and back-propagation neural networks [39]. More details on SVM implementations are found in [40].

The proposed system used LIBSVM tools [41] to train the classifier for smoke detection. We randomly selected 1000 candidate blocks, i.e., 500 as the training sample set and the remainder as the test sample set. The feature vector $\mathbf{x}_i = [\alpha_i, \beta_i, \rho_i]$ was found for the i-th candidate block. Training data were manually labeled and a Gaussian kernel function was selected. Two crucial parameters were required. The first was the gamma $(-g = -1/\sigma)$ value of the kernel function, while the second was the cost $(-c)$ value of a penalty for the misclassified data. This study performed a ten-fold cross-validation to avoid an over-fitting situation. The parameters for our training data were $-g = 8$ and $-c = 32768$. We also selected thirty-five support vectors (SVs) for our model on the basis of the SVM training results. Figure 13 shows the online blockwise output data from SVMs after offline training. Solid blocks represent the possible regions of smoke objects, while hollow blocks represent the possible regions of non-smoke objects. These classified blocks were submitted to the next stage where connected blocks were labeled before further verification.

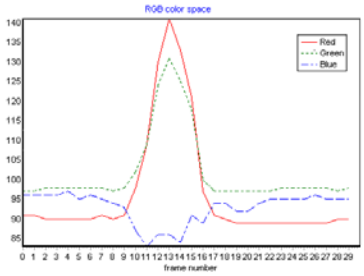
2.4.2. *Connected block labeling.* Connectivity between pixels is a fundamental concept that simplifies the definition of numerous digital image concepts, such as regions and boundaries [42]. We further verified the presence of smoke using the connected-block-labeling technique, which scans an image and groups its blocks into components on the basis of block connectivity, which is similar to connected components labeling. Figure 14 shows the results of the connected-block-labeling process.

When the ratio between the number of smoke blocks and the number of total blocks in a specific label is larger than a predefined value, all blocks in this label are colored "red" to

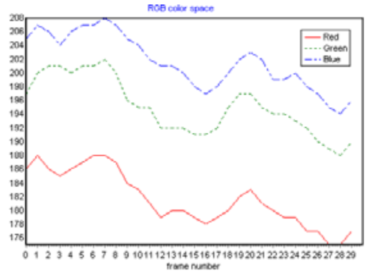


(a) Sample block of moving object

(b) Sample block of smoke

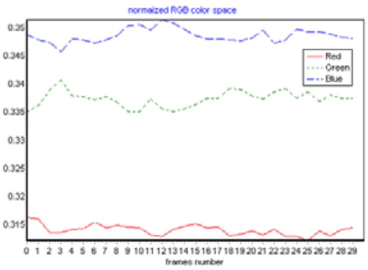


(c) RGB profiles of selected block

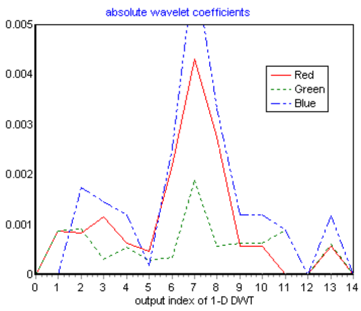


(d) RGB profiles of selected block

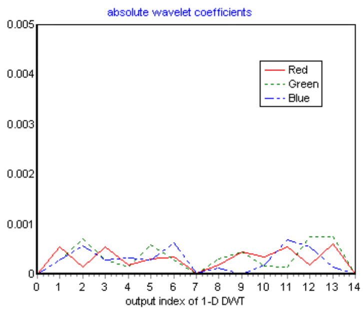
(e) RGB profiles of selected block



(f) RGB profiles of selected block



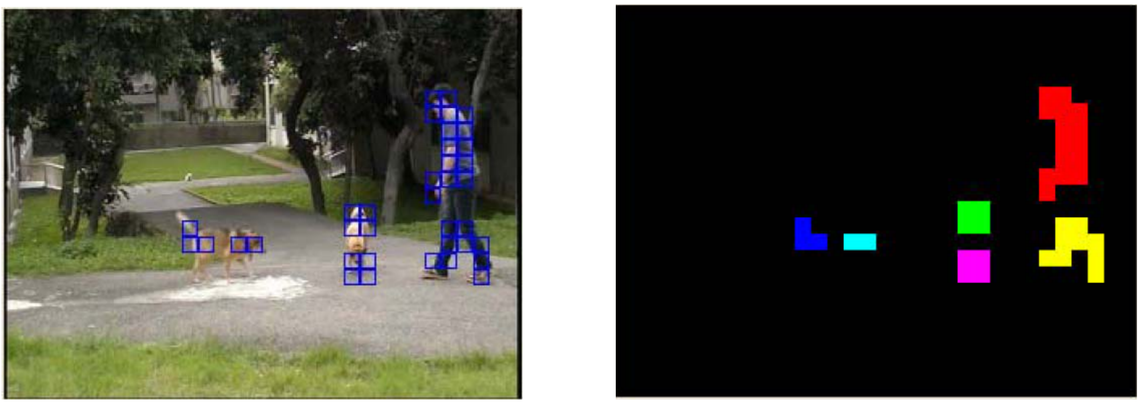
(g) Details of RGB in selected block



(h) Details of RGB in selected block

FIGURE 12. Comparison of color analysis for ordinary moving object and smoke

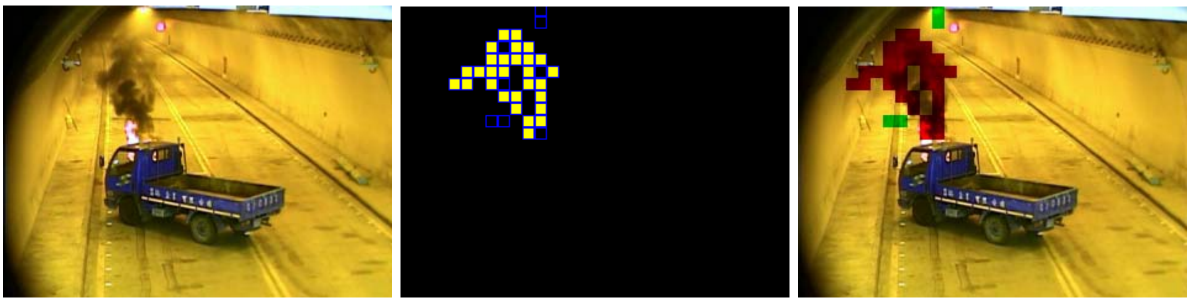
FIGURE 13. Blockwise output from SVM classifiers



(a) Sample block of moving object (b) Connected-block-labeling result of (a)

FIGURE 14. Connected-block-labeling results

indicate smoke regions and "green" to indicate non-smoke regions, as shown in Figure 15. This verification can eliminate falsely detected candidate blocks inside ordinary moving objects and smoke regions.



(a) Sample frame (b) Block labeling (c) Detection result

FIGURE 15. Illustration of smoke detection based on area ratio

2.4.3. *Alarm decision unit.* Occasionally, video surveillance systems place a camera too close to a road. In this situation, the presence of a large vehicle produces an exposure adjustment (as shown in Figure 16), which is done by a photoelectric device that automatically controls the photographic exposures due to the overall brightness of the image.

Figure 16. False alarms caused by exposure adjustment (Red indicates blocks with smoke and green indicates non-smoke blocks)

The final verification for our proposed system is based on the temporal consistency of smoke. The ADU provides a coherent description of segmented smoke over time. The goal is to track smoke from frame to frame, and to establish a correspondence between the smoke instances over time. Figure 17 shows that the ADU gathers statistical alarm data from video sequences and calculates the ratio between the alarm issue and total number of video sequences.

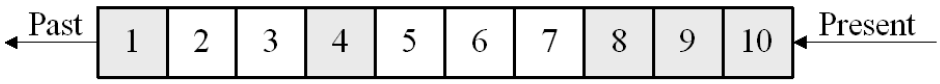
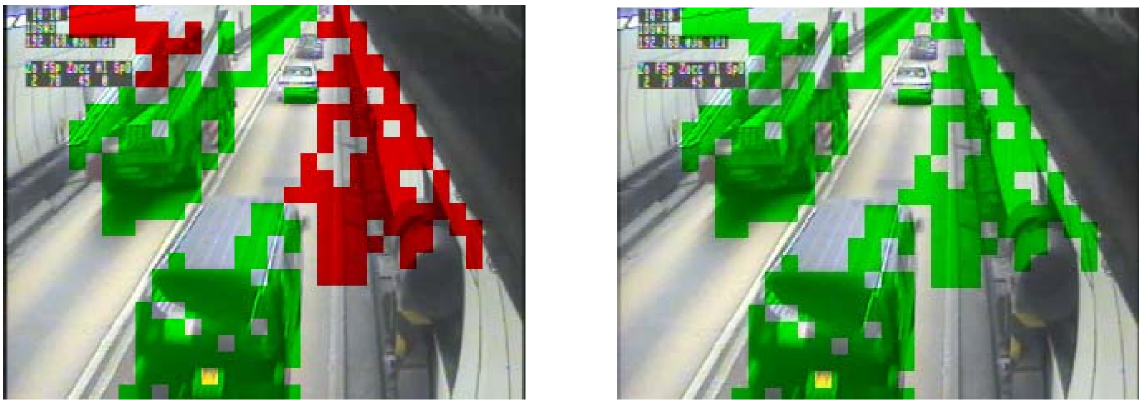


Figure 17. Illustration of alarm decision unit (ADU)

If an alarm is required for over 50% of a predefined time interval, the smoke-detection system sends out a real alarm. This approach deals better with sudden photo-timer changes or transient noise caused by cameras. Figure 18 shows the smoke-detection results with and without the ADU. The smooth filter eliminates miscalculations or transient noise and enhances system stability.



(a) Smoke-detection results without ADU

(b) Smoke-detection results with ADU

Figure 18. Illustration of smoke-detection results with and without ADU (Red indicates blocks with smoke and green indicates non-smoke blocks)

3. **Experimental Results.** This section reports the performance evaluation of the proposed smoke-detection technique and provides a quantitative comparison based on indices for the detection rate, false-alarm rate, and reaction time.

To evaluate the effectiveness of the proposed algorithm, we implemented the system on a PC with an Intel® Core^{TM}2 Duo CPU (2.2 GHz) and 2 GB RAM. The software platform was based on Borland C++ 6.0 and we used LIBSVM tools [41] to train the classifier for smoke detection. In addition, Table 2 shows that an extensive experimental dataset of recorded videos was used to evaluate the efficacy and efficiency of the system in many real-world scenarios, including indoor, outdoor, and tunnel environments. The average processing time was 32.27 ms per frame; i.e., the proposed algorithm can process 30.98 frames per second. In other words, the proposed smoke-detection method can be used in real-time VSD applications. Video demos of the proposed smoke-detection system are available online [43].

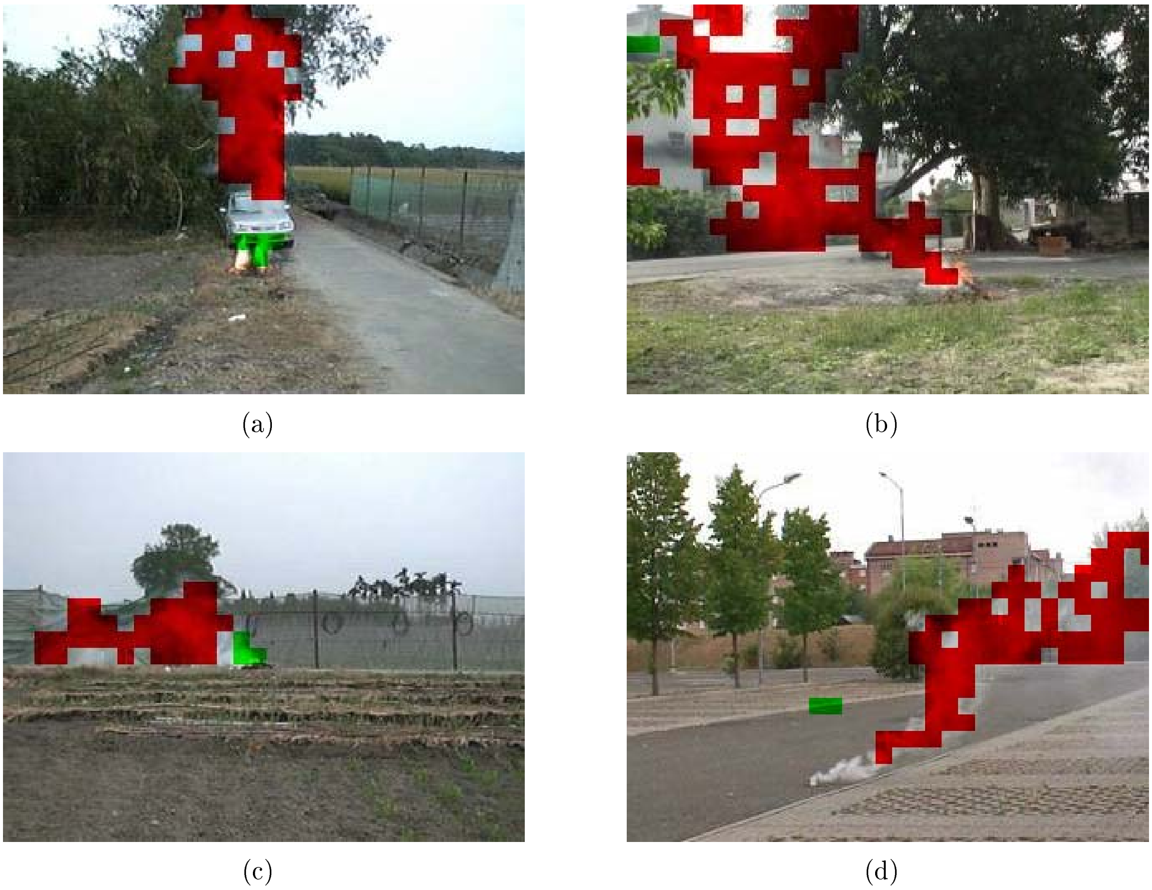
Table 2. Properties of the test video

Movie List	Description
Movie_01	Light smoke with a pedestrian
Movie_02	Light smoke with pedestrians, bicycles, cars, and swaying leaves
Movie_03	Fast-moving smoke with a pedestrian
Movie_04	Light smoke with a pedestrian and a car
Movie_05	Pedestrians walking through smoke
Movie_06	Light smoke with pedestrians and a car
Movie_07	Dark smoke with pedestrians and a car
Movie_08	Light smoke with pedestrians
Movie_09	Smoke in a room
Movie_10	Smoke in a room with a pedestrian
Movie_11	Light smoke in a tunnel with pedestrians
Movie_12	Dark smoke in a tunnel with pedestrians
Movie_13	Trailer towing away a truck with pedestrians
Movie_14	Cars with a dark shadow
Movie_15	Cars in a tunnel during daytime
Movie_16	Cars in a tunnel at night
Movie_17	Cars in a tunnel with photo timer adjustment
Movie_18	Cars in tunnel entrance with sunlight variations
Movie_19	Cars in tunnel entrance with sunlight variations
Movie_20	Cars in tunnel exit with sunlight variations

3.1. **Performance of the proposed system.** Figures 19-21 show test images where the proposed smoke-detection system achieved perfect detection results. Red blocks indicate smoke regions and green blocks indicate non-smoke regions. Figure 19 illustrates an outdoor environment situation. No wind was blowing in the case of Figure 19(a), but wind was blowing hard in the case of Figures 19(b)-19(d), and smoke was floating steadily in the air. The features were not affected by the external environment and smoke regions were detected correctly.

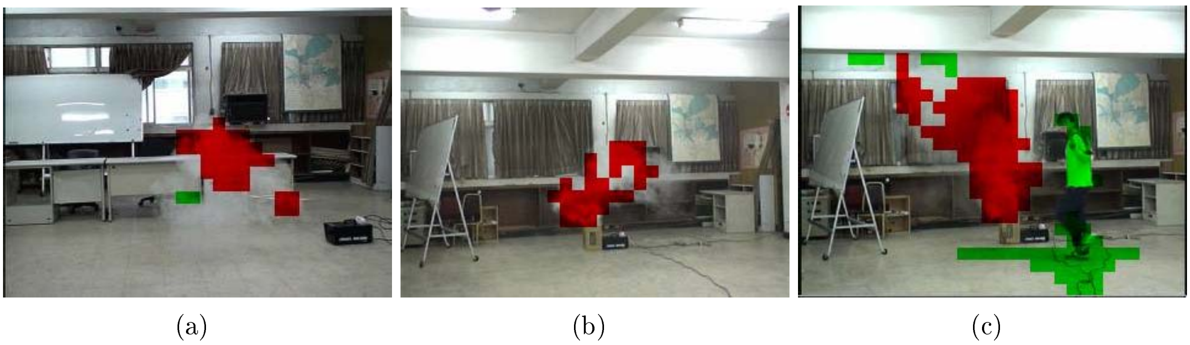
Figure 20 shows indoor environmental situations. Smoke regions could be detected correctly even with people walking around.

Figure 21 shows an outdoor environment with ordinary moving objects. Smoke regions were detected correctly with pedestrians, cars, motorcycles, and bicycles in our test data, as shown in Figures 21(a)-21(f).



(a) (b) (c) (d)

FIGURE 19. Smoke-detection results in diverse outdoor environments



(a) (b) (c)

FIGURE 20. Smoke-detection results in indoor environment

The following section discusses the test results for real traffic situations in tunnels. Several traffic conditions were found in the test videos, including traffic jams and large tour buses. The total length of the test videos was four hours and smoke regions were detected correctly. However, test results also included a small number of false alarms, as shown in Figure 22(f). Figures 22(a) and 22(b) illustrate the tunnel environment with smoke objects. The proposed algorithm detected smoke correctly and emitted alarms in sufficient time. Figure 22(c) shows different vehicles in a tunnel that did not activate the alarm system. Figure 22(d) shows cars in a tunnel at night, whereas Figure 22(e) shows cars in the same tunnel during the daytime.

The proposed system successfully sent alarms for smoke events in every test video. We propose a frame-based criterion to quantitatively evaluate a VSD system. Table 3 lists

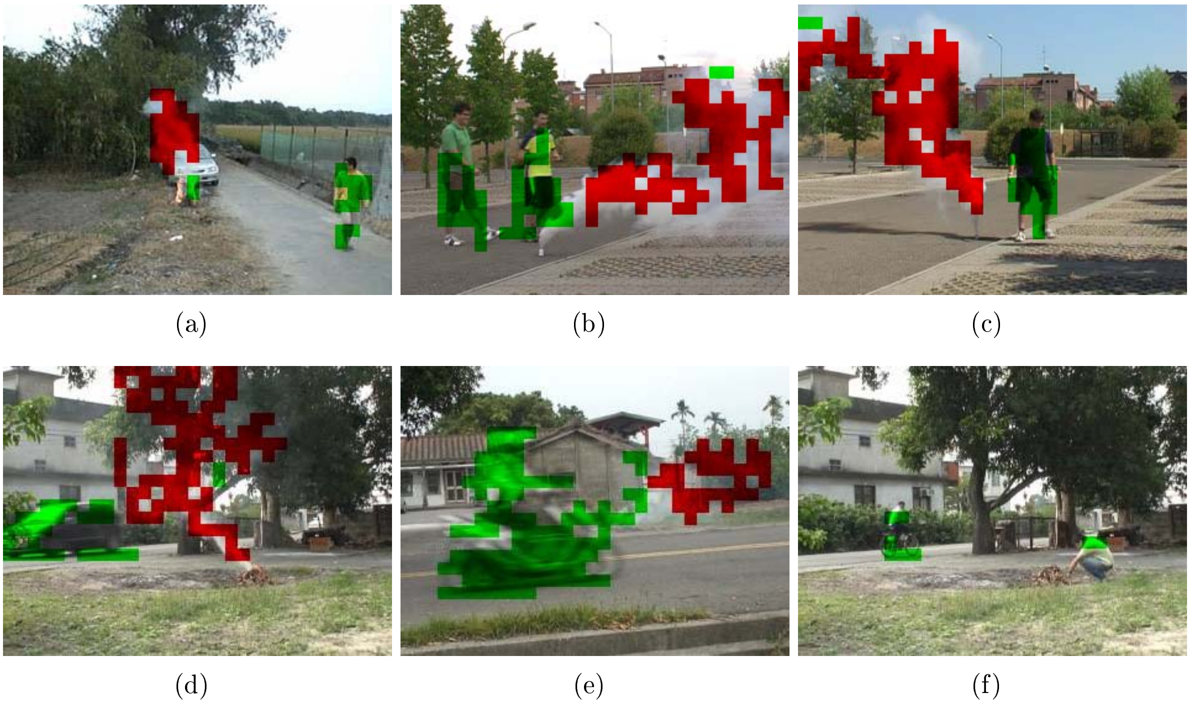


FIGURE 21. Smoke-detection results in outdoor environment containing moving objects

the quantitative evaluations for each feature and the combined features with and without the ADU. The detection rate and false-alarm rate are calculated as

$$\text{Detection Rate} = \frac{N_{\text{detected}}}{N_{\text{smoke}}} \times 100\% \tag{7}$$

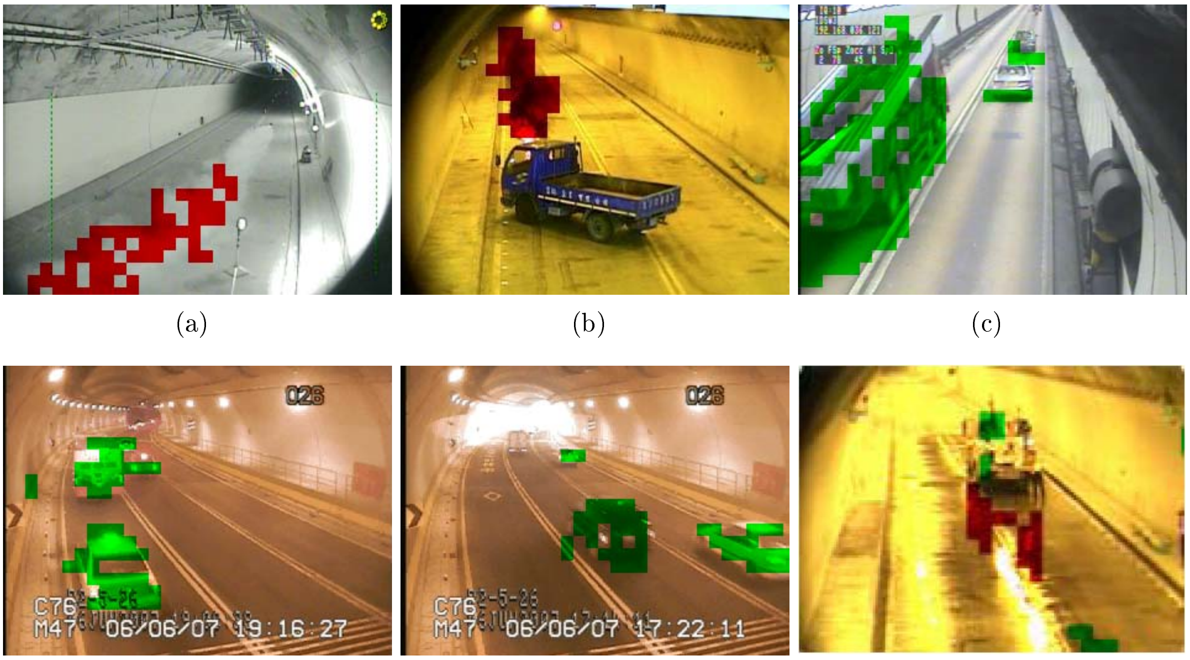
$$\text{False Alarm Rate} = \frac{N_{\text{false detected}}}{N_{\text{non-smoke}}} \times 100\% \tag{8}$$

Table 3 shows that the SVM classifier learnt the complementary relationships among the three features and achieved a low false-alarm rate of 1.7%. Furthermore, the combined features with the ADU results show that the ADU further decreased the false-alarm rate from 1.7% to 0.1%, while slightly decreasing the detection rate.

TABLE 3. Frame-based results of the proposed features

	Detection Rate	False-Alarm Rate	Reaction Time (sec)
2-D Spatial Wavelet Analysis	93.5 %	38.0 %	–
1-D Spatial-temporal Energy Analysis	91.7 %	13.1 %	–
1-D Temporal Chromatic Configuration Analysis	85.5 %	11.2 %	–
Combined Feature Analysis	**85.2 %**	**1.7 %**	**0.86**
Combined Feature Analysis + ADU	**83.5 %**	**0.1 %**	**1.34**

3.2. **Comparison.** The use of consistent evaluation criteria is essential to ensure that the comparisons between different approaches are accurate and unbiased. In the past, some studies [8,9] have applied video-based criteria. One smoke video usually contains one smoke event. Another criterion was frame-based [13,28]. Generally, video-based criteria can objectively evaluate the detection rate of a smoke-detection system, while frame-based



(a) (b) (c)

(d) (e) (f)

Figure 22. Smoke-detection results in real traffic situations in tunnels (Red indicates blocks with smoke and green indicates non-smoke blocks)

criteria indicate the sensitivity of a system. This study used both video-based and frame-based criteria. Based on the video-based criteria, we calculated the number of detected smoke videos and falsely detected non-smoke videos in a video dataset containing smoke and non-smoke clips. Based on the frame-based criteria, we calculate the average reaction time for detected smoke events using each smoke-detection system.

The test videos used for comparison are listed in Table 2. The test video dataset contained 12 smoke videos and 8 non-smoke videos. This study was compared with other approaches, including the wavelet-based method proposed by Toreyin et al. [9] and a method based on motion features proposed by Yuan [20]. Table 4 shows a comparison of the results with the three different smoke-detection methods.

Table 4. Comparison of results using different approaches

Methods	Reaction time (sec)	# of detected smoke videos	# of false alarmed videos
F. Yuan [20]	1.2	12	6
Toreyin et al. [9]	1.7	10	2
This study	**1.34**	**12**	**1**

The motion-based method proposed in [20] detected all smoke videos with the shortest reaction times. Unfortunately, any environment with upward moving objects, such as tunnels, caused false alarms. Figure 23 shows a false alarm case detected with the motion-based method. Upward motions caused by vehicles were as strong as those caused by smoke. Table 4 shows that the results for [20] contained the most false alarms.

The method used in [9] was composed of spatial and temporal features calculated by wavelets. The wavelet-based method proposed in [9] produced few false alarms but failed to detect smoke in two videos. Smoke was very thick in an indoor environment in the

(a) Motion orientation map

(b) Histogram of motion accumulation

FIGURE 23. Experimental result in tunnel using smoke-detection method proposed in [20]

two undetected smoke videos, as shown in Figure 20. Therefore, the texture of smoke area and the temporal variance for each pixel value was very low. The wavelet-based temporal feature proposed in [9] was calculated pixel by pixel, so it was not easy to extract the slow-changing texture of the smoke characteristics. However, our study proposed spatial-temporal analyses to temporally calculate the variance of spatial features in each block area. Thus, the proposed spatial-temporal feature can provide higher resolution for modeling slow-changing phenomena pertaining to smoke. As a result, our proposed smoke-detection method detected all smoke videos with appropriate reaction times and only one false alarm.

4. **Conclusions and Future Works.** Smoke detection is a crucial task for many video surveillance applications, and it could have a great impact on raising the safety levels in urban areas. The visual features of video fire and smoke detection used in previous studies can be divided into four categories: (1) motion, (2) appearance, (3) color, and (4) energy (texture). However, none of these features is perfect because each feature produces false alarms in certain situations. Therefore, no existing algorithms are sufficiently robust and flexible enough to overcome all the problems faced by the automatic video fire and smoke-detection systems, such as lighting conditions, scene complexity, and shadows. This study developed a novel smoke-detection approach using spatial and temporal analyses, which was based on a block-processing technique. Motion features were used to extract the candidate regions. The energy-based and color-based features of the candidate regions were then analyzed in their spatial, temporal, and spatial-temporal domains before all the proposed features were further combined using a SVM classifier. To decrease the false-alarm rate and maintain a high detection rate with a short reaction time, a temporal-based alarm decision unit (ADU) was developed. An extensive experimental analysis of recorded videos evaluated the efficacy and efficiency of the system in many real-world scenarios, including indoor, outdoor, and tunnel environments. Our experimental results showed that the proposed algorithm can detect smoke with a low false-alarm rate and a short reaction time.

The experimental results show that the proposed smoke-detection algorithm can work very well in various conditions in real environments. However, there are still some shortcomings in the proposed method, such as light reflections from wet ground and the continuous adjustments of the exposure value by the camera. Therefore, we need to make further improvements in the near feature. To overcome these critical problems, a global feature-verification scheme will be introduced in our future study, which will tentatively be based on the area ratio, contour analysis, region analysis, and other methods.

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