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# An effective four-stage smoke-detection algorithm using video images for early fire-alarm systems

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ABSTRACT

This paper proposes an effective, four-stage smoke-detection algorithm using video images. In the first stage, an approximate median method is used to segment moving regions in a video frame. In the second stage, a fuzzy c-means (FCM) method is used to cluster candidate smoke regions from these moving regions. In the third phase, a parameter extraction method is used to extract a set of parameters from spatial and temporal characteristics of the candidate smoke regions; these parameters include the motion vector, surface roughness and area randomness of smoke. In the fourth stage, the parameters extracted from the third stage are used as input feature vectors to train a support vector machine (SVM) classifier, which is then used by the smoke alarm to make a decision. Experimental results show that the proposed four-stage smoke-detection algorithm outperforms conventional smoke-detection algorithms in terms of accuracy of smoke detection, providing a low false-alarm rate and high reliability in open and large spaces.



## 1. Introduction

As fire accidents usually cause economic and environmental damage, including the loss of human lives, fire detection has become more appealing in surveillance systems. Several traditional methods have been proposed to construct automated fire-alarm systems. Existing methods are based on particle sampling, temperature sampling, relative humidity sampling, air transparency testing and analysis of temporal or spatial characteristics of smoke [1]. Smoke is the forecasting symbol of fire; therefore, smoke detection for early fire-alarm systems is highly attractive for personal safety and commercial applications. However, most of these methods require close proximity to the source of the smoke and are based on particle sensors. As a result, they cannot detect smoke in open or large spaces and cannot provide additional information about the process of burning. To overcome these problems, video-based smoke detection has recently received more attention since it is an effective and inexpensive method in open or large spaces.

A number of smoke-detection algorithms using video images have been proposed. Some of these have been applied to real systems and have achieved considerable success. Existing smoke-detection methods can be classified into three groups according to the means used for detection: (1) histogram-based smoke detection, (2) temporal-analysis-based techniques and (3) rule-based techniques [3]. Some methods utilize a combination of techniques to determine the presence of smoke in video images. In the first group, a histogram of smoke levels is used with some statistical measures to determine the probability of smoke presence. In the second group, temporal-analysis-based techniques utilize the differences between successive frames and the wavelet transform of temporal values of pixels to extract time-varying features. The third group of methods utilizes rules based on the knowledge of smoke tendencies to determine its presence.

Thou-Ho et al. [1] used two decision rules to make a smoke alarm: the chromatic decision rule, deduced by analyzing the colour of smoke, and the diffusion-based dynamic decision rule, which was dependent on the spreading attributes of smoke. However, only the chrominance and spreading attributes of smoke were considered.

A fast, accumulative motion model based on the integral image for video smoke detection was proposed in Ref. [3]. This model uses chrominance detection along with fast estimation of the motion orientation of smoke. In addition, orientation data was accumulated over time to improve performance. The algorithm used a chrominance detection protocol described previously [1]. Estimated motion orientation, however, is not precise enough when smoke is present in windy environments (e.g. outdoors).

An efficient target-tracking-based, early fire-detection algorithm using video images was presented in Ref. [2]. In this algorithm, three effective static and dynamic visual features of smoke were used in addition to combinations of temporal and

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spatial characteristics. However, only the brightness consistency of smoke was assessed.

Visual-based smoke detection using support vector machines (SVMs) was proposed in Ref. [4]. Additional universal features of smoke, such as the changing unevenness of the density distribution and the changing irregularities of the contour of smoke, were suggested in the method. After extracting these features, the method employed SVMs in order to distinguish between smoke and non-smoke. However, the authors overlooked colour as a distinguishing feature of smoke, and were unable to identify the difference between smoke and non-smoke using their algorithm.

In Ref. [5], an efficient video smoke-detection scheme using wavelets and an SVM classifier was proposed. Wavelets were used to extract the features of smoke, and SVMs were used to distinguish between smoke and non-smoke. Torein et al. [6] proposed a system using features of the partial transparency of smoke and implemented the scheme by extracting the edge blurring values of the background object in the wavelet domain. An enhancement of the system utilizing the contour characteristics of smoke was also proposed Ref. [7]. In Ref. [8], a single-stage wavelet energy and a back-propagation neural network were used on a small data set for smoke detection, but that system required a high processing power not available for the structure of generally used video surveillance systems with CCD cameras.

The algorithms discussed above can be classified into three groups: (1) those that make a smoke alarm by simply combining the rules related to smoke features, (2) those that utilize colour filter-based techniques applied to smoke colour attributes and (3) other algorithms that only extract features from moving objects and then make a smoke alarm based on the classifier. In order to enhance the performance of video smoke detection, this paper proposes an effective smoke-detection algorithm that utilizes a combination of the colour and dynamic features of smoke in addition to FCM clustering and an SVM (to improve accuracy).

The remainder of this paper is organized as follows. Section 2I provides background information for the proposed smoke-detection algorithm using video images. Section 3 presents the proposed smoke-detection algorithm using FCM and SVMs. Section 4 describes experimental results, analysis and a performance comparison of the proposed algorithm with other conventional methods. Section 5 concludes the paper.

## 2. Background information

### 2.1. Features of smoke

Investigation of the features of smoke plays an important role in the development of smoke-detection systems since these features are used to distinguish between smoke and non-smoke. In this study, important characteristics of smoke in colour and region are obtained with respect to the nine test videos studied. The colour of smoke ranges from bluish-white to white when the temperature is low, and from greyish-black to black when the temperature rises until a fire ignites. When smoke appears, it usually rises from a stable position on the screen, drifting upwards in a diffuse manner. The area, size and number of smoke regions are varied and change from frame to frame. The surface and boundary of the smoke regions are usually rough and coarse.

### 2.2. Fuzzy c-means algorithm

The FCM algorithm is an unsupervised clustering method developed by Dunn in 1973 [24], and then improved by Bezdek in 1981 [9]. This algorithm has been successfully applied to feature analysis, clustering and, especially, pattern recognition [10,11].

The FCM algorithm is an iterative method of clustering that allows one piece of data to belong to two or more clusters. Let an unlabelled data set $X=(x_1, x_2, x_3, \ldots, x_n)$ represent the pixel intensity, where $n$ is the number of pixels in an image. The FCM algorithm tries to sort the data set $X$ into $c$ clusters. The standard FCM objective function is defined as follows:

$$J_m(U,V)=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}d^2(x_j,v_i) \tag{1}$$

where $d^2(x_j, v_i)$ represents the distance between the pixel $x_j$ and the centre $v_i$ of the $i$-th cluster, and $u_{ij}$ is the degree of membership of the data $x_j$ in the $i$-th cluster, along with the constraint $\Sigma_{i=1}^{i=c}u_{ik}=1$. The parameter $m$ controls the fuzziness of the resulting partition with $m \geq 1$ and $c$ is the total number of clusters. Local minimization of the objective function $J_m(U,V)$ is accomplished by repeatedly adjusting the values of $u_{ij}$ and $v_i$ according to the following equations:

$$u_{ij}=\left[\sum_{k=1}^{c}\left(\frac{d^2(x_j,v_i)}{d^2(x_j,v_k)}\right)^{1/m-1}\right]^{-1} \tag{2}$$

$$v_i=\frac{\sum_{j=1}^{n}u_{ij}^{m}x_j}{\sum_{j=1}^{n}u_{ij}^{m}}, \quad 1 \leq \mathrm{i} \leq \mathrm{c} \tag{3}$$

The iteration of the FCM algorithm is terminated when the end condition $\max_{1 \leq i \leq c}\{\|v_i^{(t)}-v_i^{(t-1)}\|\} < \varepsilon$ is satisfied, where $v^{(t-1)}$ are the centres of the previous iteration and $\varepsilon$ is the predefined termination threshold. Finally, all pixels are distributed into each cluster according to the maximum membership, $u_{ij}$.

### 2.3. Support vector machines (SVMs)

Support vector machines (SVMs) are a set of supervised learning techniques introduced by Vapnik, which analyzes data and recognize patterns [12,13]. SVMs have been applied to numerous fields of classification and regression analysis, especially in pattern recognition [14]. The standard SVM is a non-probabilistic binary classifier. Given a set of training examples, each labelled as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. SVMs are capable of learning in high-dimensional spaces, and can provide high performance with a limited training data set. Several techniques have been proposed to improve the classification performance and the time cost of SVMs [15,16].

The basic principle of the SVM classifier is the use of a hyper-plane to divide a given data set into two classes while maximizing the margin. However, in many real-world applications, there are many data sets that are not linearly separable. There is likely no hyper-plane that can split the non-linear data sets into two classes. To deal with such cases, a soft margin SVM or a kernel function is used. The well-known kernels include radial basis, polynomial and sigmoidal.

### 2.4. Mean and variance values

Let $X=\{x_1, x_2, x_3, \ldots, x_n\}$ represent the data set. Mean and variance values of the data set are defined as follows:

$$M_x=\frac{1}{n}\sum_{i=1}^{n}x_i \tag{4}$$

$$V_x = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - M_x\right|^2 \quad (5)$$

where $M_x$ is the mean value of $X$ and $V_x$ is the variance value of the data set, $X$.

## 3. Proposed smoke-detection algorithm

A flowchart of the smoke-detection algorithm using video images is depicted in Fig. 1. The algorithm is composed of two phases: training and classification. In the training phase, the training data sets are extracted from the training videos and used to train the SVM. In the classification phase, the trained SVM is utilized to distinguish between smoke and non-smoke. In the following sections, the proposed smoke-detection algorithm is presented in detail.

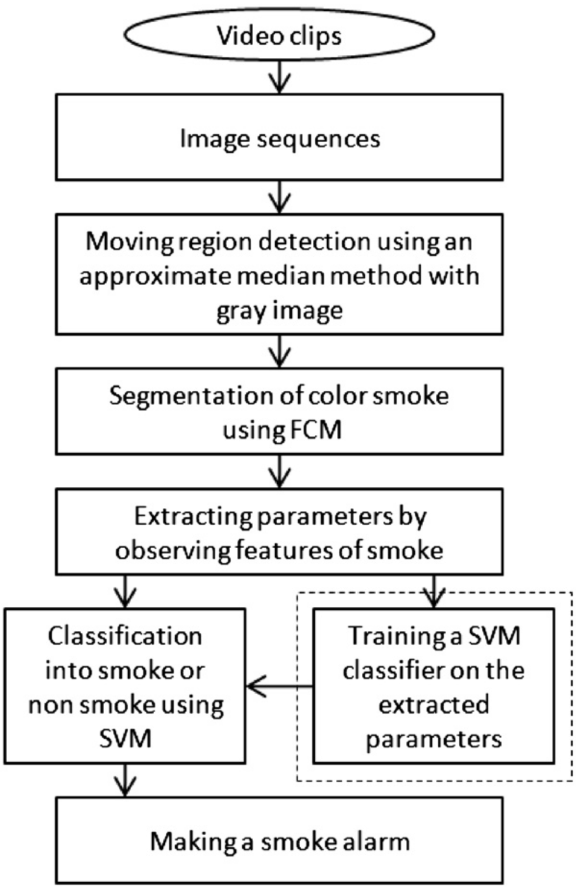


**Fig. 1.** Flowchart of the proposed smoke-detection algorithm using video images.

### 3.1. Moving-region detection using the approximate median method

Moving-region detection is a fundamental task in video smoke detection, and it is the first step of the proposed algorithm. A number of approaches have been proposed to detect moving regions in video images from static cameras: background subtraction, temporal differencing and optical flow. The background subtraction method is commonly used because of its simplicity and effectiveness. The method separates the foreground objects from the background in a sequence of video frames. Different methods in background subtraction have been proposed in which each method has different strengths and weaknesses in terms of performance and computation time [17]. In this study, an approximate median method is applied to the proposed algorithm due to its high efficiency with low computational resources. A detailed description of the method was given in Ref. [18].

In this stage, the proposed algorithm utilizes only the grey image. Let $I_n(i, j)$ represent the intensity value of the pixel at location $(i, j)$ in the $n$-th input video frame. The estimated background intensity value at the same position, $B_{n+1}(i, j)$, is recursively calculated as follows:

$$B_{n+1}(i,j) = \begin{cases} B_n(i,j)+1 & \text{if } I_n(i,j) > B_n(i,j) \\ B_n(i,j)-1 & \text{if } I_n(i,j) < B_n(i,j) \end{cases} \quad (6)$$

where $B_n(i, j)$ is the previous estimate of the background intensity value at the same pixel position in the preceding frame. From Eq. (6), it is noted that the background is updated after every frame. Initially, the value of $B_1(i, j)$ is set to the pixel intensity of the first image frame $I_1(i, j)$. A pixel positioned at $(i, j)$ is assumed to be moving if

$$\left|I_n(i,j) - B_n(i,j)\right| > T \quad (7)$$

where $T$ is a predetermined threshold.

Fig. 2 illustrates the step-by-step image results of the approximate median method for detecting moving regions. The original smoke image, grey smoke image and a resulting image of the moving region detected using the approximate median method are depicted in Fig. 2(a), (b) and (c), respectively. However, the moving regions include smoke or non-smoke, such as people or objects; FCM clustering is utilized to cluster only candidate smoke regions from these moving regions.

### 3.2. Segmentation of smoke colour using fuzzy c-means clustering

In practice, there are a number of moving objects in video images with smoke, e.g. people, vehicles and animals. However, the colours of these objects are different from the colour of smoke. Thus, segmentation of smoke based on the colour is considered. Smoke segmentation based on the colour requires two steps: (1) the pixels in the moving regions are distributed into groups and (2) groups having a similar colour of smoke are selected. To accomplish this, the well-known FCM algorithm is

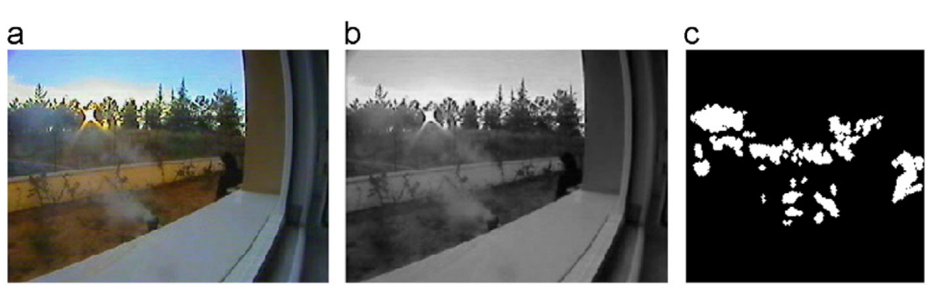


**Fig. 2.** Detection of moving regions using the approximate median method: (a) an original smoke image, (b) a grey smoke image and (c) the resulting image using the approximate median method.

employed. In addition, we use the CIE LAB colour space to construct a generic chrominance model for smoke pixel segmentation instead of red–green–blue (RGB) colour space. This was because RGB has the disadvantage of illumination dependence, even though it can be used for pixel classification. In addition, in contrast to RGB colour space, CIE LAB colour space is completely device independent and makes it possible to separate luminance/illumination from chrominance information. The conversion from RGB to CIE LAB colour space can be formulated as follows [19]:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (8)$$

where the $Y$ primary is intentionally defined to make closely to luminance, and $X$ and $Z$ primaries give colour information. Let $X_0$, $Y_0$ and $Z_0$ denote the $XYZ$ values for the reference white. For example, for the CIE standard illuminant $D_{50}$ (used in colour facsimile), $X_0=96.422$, $Y_0=100$ and $Z_0=82.512$. Then

$$L=116f(Y/Y_0)\text{-}16, \quad (9)$$

$$A=500[f(X/X_0)\text{-}f(Y/Y_0)], \quad (10)$$

$$B=200[f(Y/Y_0)\text{-}f(Z/Z_0)] \quad (11)$$

where

$$f(q)=\begin{cases} \sqrt[3]{q} & \text{if } q>0.008856 \\ 7.787q+\frac{16}{116} & \text{otherwise} \end{cases} \quad (12)$$

where $q$ is an argument of the function $f(\ )$. The CIE LAB colour space consists of three components $L$, $A$ and $B$, where $L$ indicates the lightness of pixels, and $A$ and $B$ indicate the chrominance of pixels. The chrominance components $A$ and $B$ are considered input for the FCM clustering algorithm. The output of the FCM algorithm is the clusters of pixels in the moving regions. The steps followed by the FCM algorithm are

1) Compute the number of groups $c$ and initialize centroid $V^{(0)}=\{v_1^{(0)}, v_2^{(0)}, \ldots, v_c^{(0)}\}$.
2) Compute the membership values, $u_{ij}$, for each data element using Eq. (2).
3) Update the values of the centroid using Eq. (3).
4) Evaluate the terminating condition, $\max_{1\le i\le c}\{\|v_i^{(t)}-v_i^{(t-1)}\|\}<\varepsilon$, where $\|.\|$ is the Euclidean norm. The iteration stops when it is satisfied, otherwise go to step 2.
5) Assign all pixels to each cluster according to the corresponding maximum membership values.

In order to improve the accuracy of clustering, it is necessary to compute the precise number of clusters, the initial values of the centroid of the clusters and the value of the threshold in the terminating condition. The empirical method shown in Ref. [20] was used efficiently for the initialization of the aforementioned parameters. The value of the centroid of each cluster is compared with the colour of smoke. The clusters with values of the centroid nearest to the colour of smoke are selected for the next step of the proposed algorithm. If there is no suitable centroid, it can be concluded that the objects in the moving regions are not smoke.

Fig. 3 shows segmentation results of smoke colour from the moving regions using the FCM algorithm. The original frame from the video clip and the moving regions selected by the approximate median filter method are shown in Fig. 3(a) and (b), respectively. The candidate regions of smoke are shown in Fig. 3(c), and (d) represents the non-smoke regions.

### 3.3. Parameters extraction

The selected candidate regions of smoke, shown in Fig. 3(c), can be smoke or non-smoke. By investigating several video images, we observed that the temporal and spatial features of smoke vary during the manifestation of smoke. The nature of the varying features of smoke is utilized in this study to detect smoke. Thus, we extract the following features of the candidate regions to identify either smoke or non-smoke.

#### 3.3.1. Motion vector

Motion plays an important role in video smoke detection, providing both spatial and temporal characteristics of smoke regions. Thus, some parameters are extracted from the motion feature of smoke. To do this, we first calculate the total area of candidate regions from an entire video frame by measuring the number of pixels. If the total area of candidate regions in each frame is larger than a set of threshold values derived from different smoke scenes, the centroid value of each candidate region is computed by averaging the coordinates of the boundary pixels of the candidate region. Otherwise, we assume that the candidate regions are non-smoke, and the frame cannot be used for further analysis. Fig. 4(a) and (b) shows an example of a coordinate system with an origin, $O_0$, and the corresponding candidate region, respectively.

Some characteristics are defined from the coordinate system for a candidate-moving region. The short distance ($SD$) is the distance from the centroid of the previous frame, $O_{n-1}$, to the centroid of the present frame, $O_n$. The long distance ($LD$) is the distance from $O_0$ to the centroid of the present frame, $O_n$, and $\alpha$ is

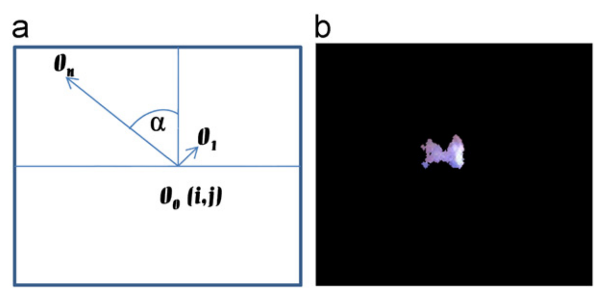


**Fig. 4.** Example of a coordinate system for a candidate-moving region: (a) coordinate system and (b) candidate-moving region of smoke.

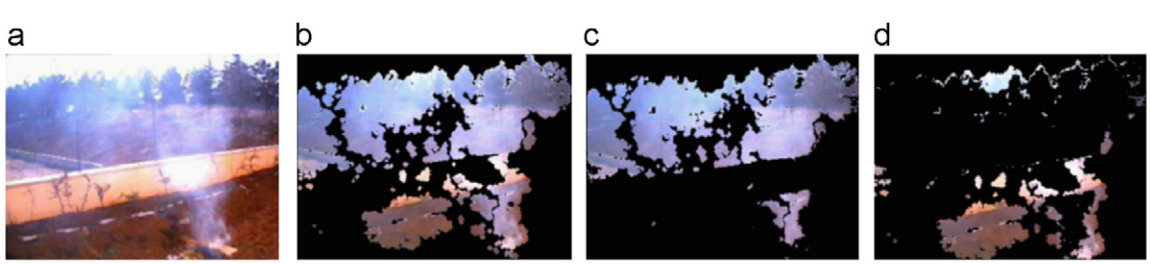


**Fig. 3.** Segmentation steps of smoke colour using the fuzzy c-means algorithm: (a) original image, (b) moving regions, (c) smoke regions and (d) non-smoke regions.

the angle between the vector, $O_0O_n$, and the vertical axis of the coordinate system.

For the parameters $SD$, $LD$ and $\alpha$ in each video frame, the mean ($M$) and variance ($V$) can be calculated using Eqs. (4) and (5). As a result, six parameters are extracted from the features of the motion vector for further analysis: mean of $LD$ ($M_{LD}$), variance of $LD$ ($V_{LD}$), mean of $SD$ ($M_{SD}$), variance of $SD$ ($V_{SD}$), mean of $\alpha$ ($M_\alpha$) and variance of $\alpha$ ($V_\alpha$). In this paper, we consider two kinds of motion vectors: global motion vector and local motion vector. The global motion vector is defined as a vector $O_0O_n$, in which $O_0$ is the origin and $O_n$ is the centroid of the present frame, as shown in Fig. 4(a). The local motion vector is defined as a vector $O_{n-1}O_n$, in which $O_{n-1}$ is the centroid of the previous frame.

### 3.3.2. *Surface roughness*

Unlike non-smoke moving regions with the same colour as smoke, the intensity of the smoke region pixels in a grey image is always non-uniform, and the surface of these smoke regions is coarse. Thus, for each frame, we can calculate feature parameters of the smoke (e.g. mean ($M_I$) and variance ($V_I$) of intensity of all the pixels in the candidate regions) using Eqs. (4) and (5).

### 3.3.3. *Area randomness*

The size of the smoke regions randomly changes from frame to frame. In contrast, non-smoke regions do not have a feature of such random changes in the size of candidate regions. Using this feature, we can extract two parameters, such as the mean and variance values, by calculating the difference in area between two consecutive frames and then accumulating these differences among the previous frames and the current frame. The changes in the size of candidate regions from frame to frame are calculated using the following rule:

$$\Delta A_n = |A_n - A_{n-1}| \quad (13)$$

where $\Delta A$ is the difference in size between consecutive $A_n$ and $A_{n-1}$, which are the areas of candidate regions in the $n$-th and $(n-1)$-th frames, respectively. Using all the $\Delta A$s between the previous frames and current frame, the mean value ($M_A$) and variance value ($V_A$) can be calculated using Eqs. (4) and (5).

## 3.4. *Smoke alarm decision using a support vector machine*

SVMs, supervised machine-learning techniques, have received much attention from the machine-learning community due to their robust performance with respect to sparse and noisy


**Fig. 5.** Example of test videos. Movies 1–6 are smoke videos; movies 7–9 are non-smoke videos; movies 3–7 and 9 are outdoor smoke videos; and the others are indoor smoke videos.

**Table 1**
Smoke-detection results of the proposed and conventional algorithms in positive videos.

| | Number of frames | Algorithm 1 | | Algorithm 2 | | Algorithm 3 | | Algorithm 4 | | Proposed | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | TP (Frame) | PTP (%) | TP (Frame) | PTP (%) | TP (Frame) | PTP (%) | TP (Frame) | PTP (%) | TP (Frame) | PTP (%) |
| Movie 1 | 1060 | 1012 | 95.5 | 1010 | 95.3 | 1011 | 95.4 | 1009 | 95.2 | 1012 | 95.5 |
| Movie 2 | 200 | 165 | 82.5 | 167 | 83.5 | 170 | 85.0 | 171 | 85.5 | 167 | 83.5 |
| Movie 3 | 214 | 183 | 85.5 | 181 | 84.6 | 177 | 82.7 | 174 | 81.3 | 189 | 88.3 |
| Movie 4 | 190 | 157 | 82.6 | 159 | 83.7 | 155 | 81.6 | 157 | 82.6 | 162 | 85.8 |
| Movie 5 | 140 | 122 | 87.1 | 122 | 87.1 | 117 | 83.6 | 119 | 85.0 | 128 | 91.4 |
| Movie 6 | 165 | 141 | 85.5 | 144 | 87.3 | 139 | 84.2 | 138 | 83.6 | 153 | 92.7 |
| Average | | | 86.5 | | 86.9 | | 85.4 | | 85.5 | | 89.5 |

data [22]. A set of ten parameters was extracted from the spatial and temporal characteristics of smoke: $\boldsymbol{sv}_i=[M_{LD}, V_{LD}, M_{SD}, V_{SD}, M_\alpha, V_\alpha, M_I, V_I, M_A, V_A]$. These ten parameters are used as input feature vectors to train the SVM classifier, which is then used to make a smoke alarm in the video frame. The Gaussian radial basis kernel function uses the following for mapping the input vector to a high-dimensional feature space, as an SVM performs better with the Gaussian radial basis kernel than with other kernels [23]

$$k(sv_i,sv_j)=\exp\left(-\frac{\|sv_i-sv_j\|}{2\delta^2}\right) \tag{14}$$

where $k(sv_i, sv_j)$ is the kernel function, $\boldsymbol{sv}_i$ and $\boldsymbol{sv}_j$ are the input feature vectors and $\delta$ is a parameter set by the user, which determines the width of the effective basis kernel function. If small $\delta$ values are used, overtraining occurs with the basis function wrapped tightly around the data points. In contrast, if large $\delta$ values are used, the basis function draws an oval around the points without defining the shape or pattern [23]. In this study, the best performance occurred if the standard deviation, $\delta$, was between 4 and 6. Thus, the default value for $\delta$ was set at 5.5. The SVM classifier was then used to distinguish between smoke and non-smoke. In order to reduce a false-alarm, an accumulation of alarms was used. In other words, only a smoke alarm that occurred for the last ten successive frames was considered a reliable alarm. Otherwise, it was declared noise.

## 4. Experimental results

### 4.1. Experimental environment

The performance of the proposed smoke-detection algorithm was compared with four, state-of-the-art algorithms: accumulative motion orientation model (*Algorithm 1*) [3], smoke detection based on video processing (*Algorithm 2*) [1], visual-based detection using SVMs (*Algorithm 3*) [4] and target-tracking-based detection in video images (*Algorithm 4*) [2]. The proposed and conventional algorithms were implemented using MATLAB and tested on a Pentium Quad-Core 2.8 GHz PC. In this study, we used the training data sets $\boldsymbol{SV}=\{\boldsymbol{sv}_1, \boldsymbol{sv}_2, \boldsymbol{sv}_3, \ldots, \boldsymbol{sv}_L\}$ extracted from training movies, where $\boldsymbol{sv}_i$ were the input feature vectors. The training movies included indoor smoke, outdoor smoke, non-smoke and moving objects with the colour of smoke. In addition, the test was performed using nine video sequences with a $320\times240$ image size, shown in Fig. 5. Movies 1–6 are smoke videos, and movies 7–9 are non-smoke videos. In addition, movies 3–7 and 9 are outdoor smoke videos, and the others are indoor smoke videos.

By observing several videos, we empirically set the feature parameter values for the proposed algorithm: the threshold $T$ value was 5 in Eq. (7), the fuzziness coefficient $m$ value was 2 in Eqs. (2) and (3), the terminal condition $\varepsilon$ value for FCM was 0.001 and the scaling factor $\delta$ value was 5.5 in Eq. (14).

### 4.2. 0 Performance evaluation

The comparison results are presented in Table 1 and Fig. 6, where the true positive (TP) is the number of overall smoke-detected frames and the percentage of TP (PTP) is the overall smoke-detection rate. For Movie 1, the accuracy of all the algorithms was the highest because it had clearly visible smoke in the indoor space. For Movie 2, since the smoke was blurred and the colour of smoke was similar to the colour of the wall, the accuracy of all the algorithms was relatively low. For movies 3, 4, 5 and 6, the smoke-detection accuracy of the proposed algorithm outperformed that of other algorithms on both indoor and outdoor test videos, showing an average detection rate of 89.5% versus 86.5%, 86.9%, 85.4% and 85.5%, respectively.

Three negative videos, including non-smoke were also tested. The comparison results are presented in Table 2 and Fig. 7, where the false positives (FPs) are those non-smoke events that an algorithm classifies as smoke and the percentage of FP (PFP) is the overall false smoke-detection rate. For Movie 7, the false

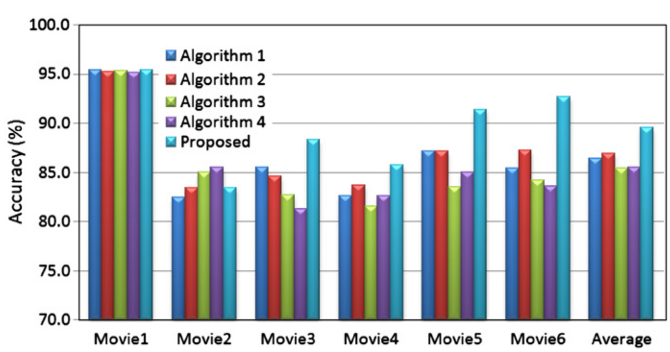


**Fig. 6.** Smoke-detection accuracy of the proposed and conventional algorithms in positive videos.

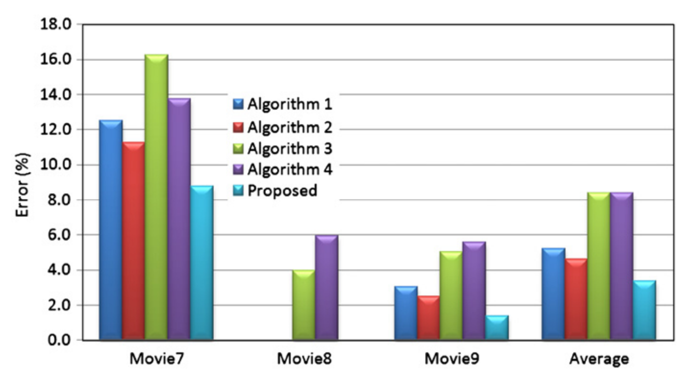


**Fig. 7.** False smoke-detection rate for the proposed and conventional algorithms in negative videos.

**Table 2**
False smoke-detection results for the proposed and conventional algorithms in negative videos.

| | Number of frame | Algorithm 1 | | Algorithm 2 | | Algorithm 3 | | Algorithm 4 | | Proposed | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | FP (Frame) | PFP (%) | FP (Frame) | PFP (%) | FP (Frame) | PFP (%) | FP (Frame) | PFP (%) | FP (Frame) | PFP (%) |
| Movie 7 | 80 | 10 | 12.5 | 9 | 11.3 | 13 | 16.3 | 11 | 13.8 | 7 | 8.8 |
| Movie 8 | 152 | 0 | 0.0 | 0 | 0.0 | 6 | 3.9 | 9 | 5.9 | 0 | 0.0 |
| Movie 9 | 360 | 11 | 3.1 | 9 | 2.5 | 18 | 5.0 | 20 | 5.6 | 5 | 1.4 |
| Average | | | 5.2 | | 4.6 | | 8.4 | | 8.4 | | 3.4 |

smoke-detection rate was greater than other movies for all algorithms, as one person was moving in the video and the colour of his trousers was similar to the colour of smoke. For other videos, there were no moving regions with a colour similar to smoke. The proposed algorithm outperforms the four conventional algorithms in terms of reducing the false smoke-detection rate, with a false rate of 3.4% versus 5.2%, 4.6%, 8.4% and 8.4%.

Overall, the proposed algorithm clearly outperformed the other conventional algorithms with consistently increasing accuracy of smoke detection and decreasing error of false smoke detection for each video.

## 5. Conclusions

In this paper, effective smoke detection in video images was proposed for early fire-alarm systems. The proposed algorithm employed FCM clustering to extract candidate regions of smoke from all of the moving regions. In addition, unlike other algorithms, the proposed algorithm utilized features of smoke, such as the motion vector, surface roughness and area randomness, to extract feature parameters for more accurate analysis. Moreover, these feature parameters were used as input feature vectors to train a support vector machine (SVM), which was then used to distinguish between smoke and non-smoke. Experimental results showed that the proposed algorithm outperformed other smoke-detection algorithms while consistently increasing the accuracy of smoke detection on both indoor and outdoor test videos. Thus, these results demonstrate that the proposed algorithm is a suitable candidate for early fire-alarm systems.

In the future, we will evaluate the performance of the proposed algorithm over a wider variety of video images and smoke scenarios, particularly those with different material, sources and ventilations. In addition, we will explore a different set of smoke features to enhance the performance of the proposed algorithm. Moreover, we will implement the proposed algorithm using typical DSP platforms available for CCD surveillance cameras.

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