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Dangerous smoke classification using mathematical model of meaning

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Abstract

Fire accident remains a problem in modern society. This leads great efforts in finding ways to prevent, detect and control it. Conventional fire detection systems are mostly point detectors, which have limitation for early smoke detection, especially in a high-ceiling atrium. A video-based smoke detection system is an interesting alternative approach. It has better area coverage and detecting smoke faster. In this work, a video-based smoke detection system was developed with two main processes, *i.e.* moving objects segmentation with Gaussian Mixture Models (GMM) and smoke classifications with Mathematical Model of Meaning (MMM). In the MMM model, the interpretation of dangerous smoke is based on the context provided. Then the classification results are compared with conventional smoke detector. The results show that MMM can recognize the dangerous smoke faster than conventional smoke detectors.

Keywords: Mathematical model of meaning (MMM); Gaussian mixture model (GMM); Smoke detection

1. Introduction

Fire is an important element in our life but it also can be a destructive element. Fire disasters frequently occur sometimes with huge loss of properties, life and environmental damages. Fire and smoke detection systems play a key role in controlling the effectiveness of protection system and life safety measures for building occupants. Nevertheless, in some cases, the conventional fire detection devices are not too effective in detecting fire accident. The example of conventional – point based fire detection devices are optical based smoke detectors. The responses of point detectors are depend upon their locations. Thus, larger room requires more detectors to be installed. Adding new features into the CCTV as smoke detectors could provide opportunity to detect smoke in larger area faster.

Video based early fire warning systems have caught many researchers' attention nowadays. There are many research activities about this system, as shown in Verstockt et al. [1]. Many video based systems are able to detect if there is smoke or not in the video sequences. But, when and how the smoke images should be classified as dangerous smoke is still need further studies. This paper presents a new approach in designing video based fire warning system including features to define a dangerous smoke condition.

The remainder of this paper is organized as follows. Section 2 discusses about object segmentation using Gaussian Mixture Model (GMM), and the explanation on how the GMM works. Analysis of dangerous smoke will be discussed in Section 3. While Section 4 discusses about classification of dangerous smoke using Mathematical Model of Meaning

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(MMM) based on analysis in Section 3. How MMM model works will also be explained in this section. Section 5 discusses about experimental result using MMM as classification method. Section 6 concludes the earlier sections. Fig. 1 shows the block diagram of the proposed smoke detection method.

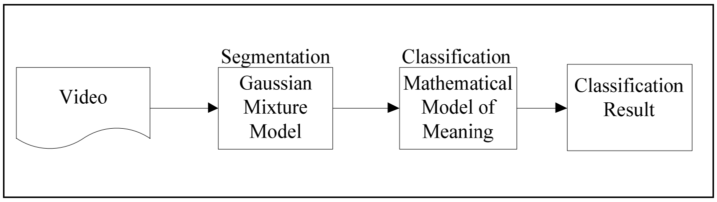


Fig. 1. The block diagram of the proposed smoke detection method.

2. Segmentation using Gaussian mixture model

Segmentation is a process of separating moving objects/foreground from background image in video sequence. This process is an important component in the integrated system since it extracts smoke images and features as moving objects in the video. Segmentation method used in this paper is based on the Gaussian Mixture Model (GMM). This method was proposed by Stauffer [2, 3]. Those papers showed that GMM approach was excellent against many environmental conditions. The GMM approaches are applicable for detecting transparent moving such as smoke [4, 5].

Motivation of using GMM as a segmentation method is because GMM are able to detect complex object, and it is robust against light changing and scene changing in a long time. These advantages have potential use for detecting smoke objects in video because smoke is complex object, and also occurring in a long time.

In an earlier work [6], Ardiansyah applied the GMM and Bayesian approaches to separate smoke image with the background of about 7 smoke video records. Typical results showing the real smoke image, expected area, and outcomes of GMM and Bayesian approaches are presented as Fig. 2. In general, the GMM model provides better results than the Bayesian approach.

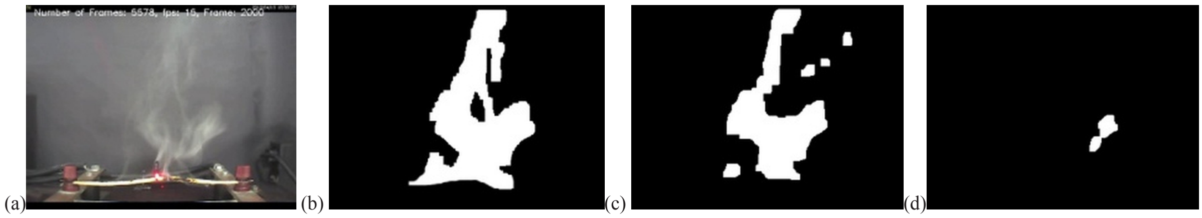


Fig. 2. Visual comparison between GMM and Bayesian approaches: (a) real image, (b) expected area of the smoke by an observer, (c) GMM result, and (d) Bayesian result [6].

The idea behind GMM model is that each pixel is assumed normally distributed or Gaussian Distribution. Pixels whose gray value not changing significantly are predicted as background, while other pixels are predicted as a foreground or moving objects. Each pixel is given a weight. Weight shows how long pixel appears in the video. The longer a pixel in the video, the larger weight that pixel have. Pixels that have a large weight are predicted as a background images. The details of GMM are explained in the following paragraphs.

Each pixel is modeled by a mixture of K Gaussian distribution. Here, K is how many pixels that will be used for predicting mean and covariance parameters in Gaussian distribution. It ranges between 3 and 5, but for the efficient computation, it is wise to use 3 components. The probability of a certain pixel has a gray value of X_t at time t, can be written as follows:

$$P(X_t) = \sum_{i=1}^{K} w_{i,t}\eta(X_t;\mu_{i,t},\Sigma_{i,t}) \tag{1}$$

where $w_{i,t}$ is the weight parameter of the i^{th} Gaussian component at time t. While $\eta(X_t;\mu_{i,t},\Sigma_{i,t})$ is the normal distribution of i^{th} component at time t. It can be written as

$$\eta(X_t;\mu_{i,t},\Sigma_{i,t})=\frac{1}{(2\pi)^{\frac{n}{2}}\left|\Sigma_{i,t}\right|^{\frac{1}{2}}}e^{-\frac{1}{2}(X_t-\mu_{i,t})^T\Sigma_{i,t}^{-1}(X_t-\mu_{i,t})} \tag{2}$$

where $\mu_{i,t}$ is the mean and $\Sigma_{i,t}=\sigma_i^2\mathbf{I}$ is the covariance of the i^{th} component at time t and $\mathbf{I}$ is the identity matrix.

The K distributions are ordered based on value w_k/σ_k and the first B distributions are used as a model of a background in the image. The following formula estimates the value for *B*.

$$B=argmin_b\left(\sum_{j=1}^{b}w_j>T\right) \tag{3}$$

The threshold T is the minimum fraction of the background model. The index b is the smallest index that satisfies the Eq. (3). Background subtraction is performed by choosing foreground pixel that have more than 3.5 standard deviations from any pixel which predicted as background pixel, in other word, pixels that in *B* distributions. Then the Gaussian component (weight $w_{k,t}$, mean μ_t and variance σ_t^2) that matches the test value (foreground pixels) will be updated in the new frame using the following equations

$$w_{k,t}=(1-\alpha)w_{k,t-1}+\alpha(M_{k,t}),\text{ where } M_{k,t}=\begin{cases}1;\ matched\\0;\ others\end{cases} \tag{4}$$

$$\begin{aligned}\mu_t&=(1-\rho)\mu_{t-1}+\rho X_t\\ \sigma_t^2&=(1-\rho)\sigma_{t-1}^2+\rho(X_t-\mu_t)^T(X_t-\mu_t)\\ &\text{where } \rho=\alpha\eta(X_t\mid\mu_k,\sigma_k^2)\end{aligned} \tag{5}$$

where α is the learning rate and $1/\alpha$ defines the time constant which determines change and $\rho=\alpha\eta(X_t\mid\mu_k,\sigma_k^2)$ is the learning factor for adapting the current distribution . Using Eq. (4) every matched pixel will be updated so it maintains the background's properties of the pixels which have large weight and small variances. A typical result of GMM approach is given in Fig. 3. Once an object is detected in the video, there are many features which can be used for defining dangerous smoke criteria. The proposed features like area, velocity, height, width, and center point of the objects will be explained in Section 3.

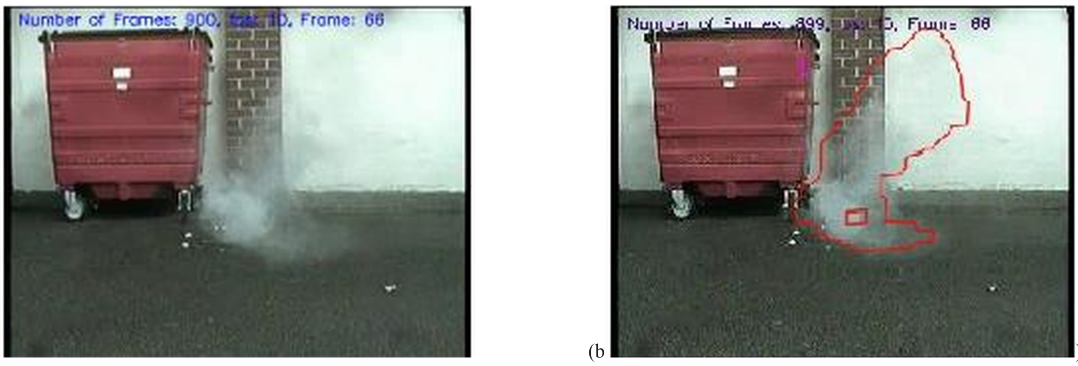
(a)  (b)

Fig. 3. (a) Original image, (b) segmented image.

3. Dangerous smoke criteria

Criteria of dangerous smoke have been suggested by Nugroho et al. [7], and Dharsono [8]. Smoke features like area, centroid point, and optical density are considered as factors that can be used to determine whether smoke is dangerous or not. Direct comparison with optical based smoke detector is also suggested for evaluating the performance of overall system. By using GMM model one can extract smoke features as follows:

Extracted features are summarized as follows:

- Center Point

By finding the maximum and minimum of x and y in the objects, one can easily calculate the center point of objects. Assumed that $x_{min}, y_{min}, x_{max}$ and y_{max} is the minimum and maximum of x and y in objects, meanwhile, (x_{cent}, y_{cent}) is the center point of objects. Then center point is calculated using following equations

$$x_{cent} = x_{min} + \left(\frac{x_{max} - x_{min}}{2} \right)$$
$$y_{cent} = y_{min} + \left(\frac{y_{max} - y_{min}}{2} \right) \quad (6)$$

This center point will be useful for calculating velocity of the objects.

- Height

Object's height is calculated between y_{max} and y_{min}.

- Width

Object's width is subtracted between x_{max} and x_{min}.

- Area

Object's area is how many pixels contained in the objects. Area represents how large objects are.

- Velocity

Velocity is described as the velocity of the centre point of the segmented smoke images. As the captured smoke image approaches the ceiling, the upward velocity of its center-point is decreasing. It becomes zero when smoke fills the ceiling area. But if smoke is continuously being produced by the burning materials, then the smoke layer is descending. This defines the dangerous condition of the smoke in a room fire. Velocity is calculated using center point of the objects between the current frame and the previous frame. It's calculated using Euclidean distance. Assume (x_{cent}, y_{cent}) is the center point of objects in current frame and (x_{cent1}, y_{cent1}) is the center point of objects in previous frame. Then distance (d) between that point is calculated using Euclidean distance in the following formula:

$$d = \sqrt[2]{(x_{cent} - x_{cent1})^2 + (y_{cent} - y_{cent1})^2} \quad (7)$$

Then velocity is calculated by dividing distance with time which can be easily calculated as $1/fps$ where *fps* is frame per second of the videos. Then the velocity (v) is calculated with:

$$v = \frac{d}{t} = \frac{d}{1/fps} = d.fps \quad (8)$$

These five features will be used to analyze when smoke becomes dangerous in a room fire.

4. Classification using mathematical model of meaning

In order to complement with GMM method, the Mathematical Model of Meaning (MMM) is then used to classify the dangerous smoke. This model is proposed by Kitagawa in [9] for searching data in heterogeneous multidatabase which ambiguity is the main problem for this database. Based on user searching's context, this model can give the actual meaning on what user want. There are 2 examples in [9] which give us views how MMM works. When user search using keyword computer with context os, database and compiler, MMM shows that computer has a closer meaning to software than hardware. In the next example, users search using the same keyword, but change the context to architecture, CPU, and I/O devices. MMM shows computer has a closer meaning to hardware than software. This model also used to search image based on the context in [10] and creating an automatic decorative multimedia using kansei factor in [11].

MMM formulation was explained in the following step:

- Creating Data Matrix

Data matrix is created by using video training that will be used for determine dangerous of smoke. Features of when smoke becomes dangerous in each training video is extracted and labeled 1. Then 2 features vectors when smoke is firstly see and halfway to dangerous is extracted and labeled 0. For one video training there will be 3 feature vectors, 2 vectors are "smoke" labeled (label 0) and 1 vector is "dangerous smoke" labeled (label 1). Data matrix $(\mathbf{B})$ can be seen in the following matrix:

$$\begin{array}{cccccc} \mathbf{B} & y & t & l & A & v \\ \mathbf{b}_1(k_1) & y_1 & t_1 & l_1 & A_1 & v_1 \\ \mathbf{b}_2(k_2) & y_2 & t_2 & l_2 & A_2 & v_2 \\ \mathbf{b}_3(k_3) & & & \vdots & & \\ \vdots & & & \vdots & & \\ \mathbf{b}_i(k_i) & & & \vdots & & \\ \vdots & & & \vdots & & \\ \mathbf{b}_m(k_m) & y_m & t_m & l_m & A_m & v_m \end{array} \tag{9}$$

where:

$y =$ center point of smoke

$t =$ height

$l =$ widht

$A =$ area

$v =$ velocity

$\overline{\mathbf{B}} = \{\mathbf{b}_1(k_1), \mathbf{b}_2(k_2), \ldots, \mathbf{b}_m(k_m) | k = 0,1\}$

$\mathbf{b}_i(k_i) = i^{th} object\, with\, label\, k, 1 \le i \le m$

$k_i = \begin{cases} 0 & If \quad smoke \\ 1 & If \quad dangerous \quad smoke \end{cases}, 1 \le i \le m$

Set $\overline{\mathbf{B}}$ is a collection of feature vectors in $\mathbf{B}$. In this work, the data matrix has 18×5 size, e.g. for 18 feature vectors and 5 features for each vector.

- Define Semantic

Correlation Matrix from data matrix $(\mathbf{B})$ in step 1 is calculated with $\mathbf{B}^T\mathbf{B}$. This matrix will be square matrix size $n \times n$, with n is how many feature we use in data matrix. Then we do eigenvalue decomposition method to the correlation matrix,

$$\mathbf{B}^T\mathbf{B} = \mathbf{Q}\begin{pmatrix} \lambda_1 & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \ddots & & & & \vdots \\ \vdots & & \lambda_v & & & \vdots \\ \vdots & & & 0 & & \vdots \\ \vdots & & & & \ddots & \vdots \\ 0 & \cdots & \cdots & \cdots & \cdots & 0 \end{pmatrix}\mathbf{Q}^T, \text{ where } 0 \le v \le n \tag{10}$$

The Eigen value and Eigen vector of the above matrix can be found easily with a commercial software like MATLAB software, where orthogonal matrix $\mathbf{Q}$ is defined by

$$\mathbf{Q} = (\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_n)$$

is the matrix which its column are eigenvector corresponding to the eigenvalue in diagonal matrix.
Semantic space $(\mathcal{S})$ is a vector space which spanned by non zero eigenvector.

$$\mathcal{S} := span(\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_v)$$

where $\{\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_v\}$ are orthonormal bases in semantic space $\mathcal{S}$

- Define Semantic Projections

Semantic projections is a mapping from semantic space to semantic subspace.

$$\mathbf{P}_{\lambda i} : \mathcal{S} \mapsto span\{\mathbf{q}_i\}$$

Then we define a set of semantic projections $\mathbf{\Pi}_v$ as follows

$$\mathbf{\Pi}_v = \{0, \mathbf{P}_{\lambda 1}, \mathbf{P}_{\lambda 2}, \ldots, \mathbf{P}_{\lambda v},$$

$$\mathbf{P}_{\lambda 1}, +\mathbf{P}_{\lambda 2}, \mathbf{P}_{\lambda 1} + \mathbf{P}_{\lambda 3}, \ldots, \mathbf{P}_{\lambda v-1} + \mathbf{P}_{\lambda v},$$

$$\vdots$$

$$\mathbf{P}_{\lambda 1}, +\mathbf{P}_{\lambda 2} + \ldots + \mathbf{P}_{\lambda v}\}$$

The number of elements in $\mathbf{\Pi}_v$ is 2^v, and it shows there is 2^v meaning can be expressed by this formulation.

- Creating Semantic

Given context $s_l = (\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_l)$ and real positive number $0 < \varepsilon < 1$. Semantic operator determines which subspace will be projected based on context provided, or in other words, which semantic projections will be used for calculating distance between new feature vector with feature vectors in matrix data. Semantic Operator can be written as follows:

$$S_p : T_l \mapsto \mathbf{\Pi}_v$$

where T_l is the set sequence of l objects and $T_l \subset \overline{\mathbf{B}}$. In this research, dangerous smoke label ($k_i = 1$) is used as a context. It is written in a mathematical notation as $s_l = \{\mathbf{b}_i(k_i) \mid \mathbf{b}_i(k_i) \in \overline{\mathbf{B}} \text{ and } k_i = 1\}$. This context was selected to detect dangerous smoke in the training video.

Operator S_p consists of the following process

1. Fourier expansion of each $\mathbf{u}_i (i = 1, 2, \ldots, l)$

Define $\hat{\mathbf{u}}_i \in \mathcal{S}$ is the Fourier expansion where

$$\hat{\mathbf{u}}_i = (u_{i1}, u_{i2}, \ldots, u_{iv})$$

$$u_{ij} = \langle \mathbf{u}_i, \mathbf{q}_j \rangle \text{ where } j = 1, 2, \ldots, v$$

Fourier expansion is used for mapping arbitrary vectors to semantic space $\mathcal{S}$.

2. Computing semantic center $\mathbf{G}^+(s_l)$

Semantic center is calculated by sum up all Fourier expansion of context vector. Then divide it by its infinite norm.

$$\mathbf{G}^+(s_l) = \frac{\hat{\mathbf{u}}_{total}}{\left\| \hat{\mathbf{u}}_{total} \right\|_\infty} \tag{11}$$

where

$$\hat{\mathbf{u}}_{total} = \sum_{i=1}^{l} \hat{\mathbf{u}}_i \tag{12}$$

3. Determining the semantic projection $\mathbf{P}_\varepsilon(s_l)$.

Semantic projection is the function that mapped the given context to which semantic subspace has a meaning according to the context.

$$\mathbf{P}_{\varepsilon}(s_l) = \sum_{i \in \Lambda_{\varepsilon}} \mathbf{P}_{\lambda_i} \in \mathbf{\Pi}_v \tag{13}$$

where

$$\Lambda_{\varepsilon} = \{i \mid \left|(\mathbf{G}^{+}(s_l))_i\right| > \varepsilon\} \tag{14}$$

- Finding the Nearest Feature Vector in Data Matrix Creating Semantic

When semantic projections have chosen with context provided, feature vectors from objects in new video, will be extracted. MMM will be calculating distance between new feature vectors ($\mathbf{b}$) that extracted using GMM and feature vectors in data matrix $\mathbf{B}$. Then the nearest distance feature vector's label in the data matrix, will be assigned to the new feature vectors in test video. It can be written as follows

$$\min_{\mathbf{b}_i(k) \in \mathbf{B}} \left\| \mathbf{P}_{\varepsilon}(s_l)(\mathbf{b} - \mathbf{b}_i(k)) \right\|, 1 \le i \le m \tag{15}$$

Figure 4 gives the Diagram of Mathematical Model of Meaning.

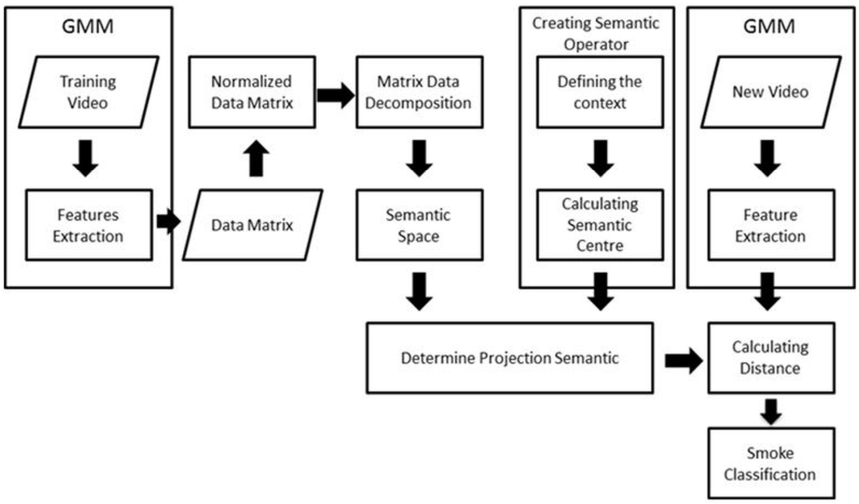
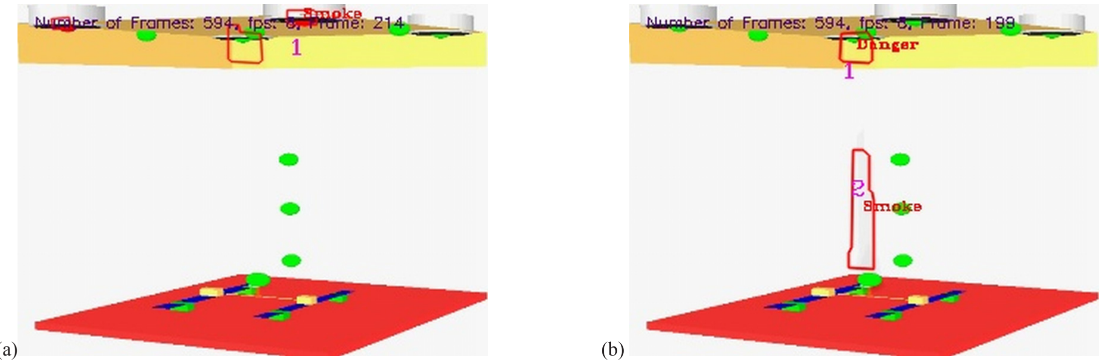


Fig. 4. Diagram of mathematical model of meaning.

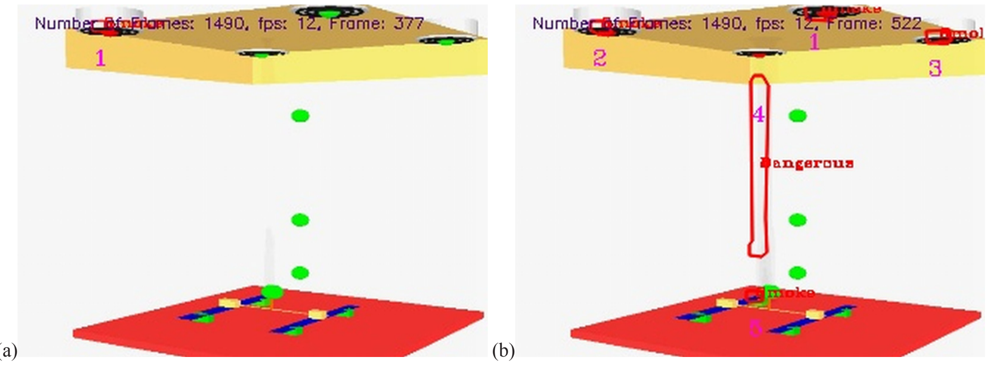
5. Experimental set up and result

The proposed method is implemented in a computer with processor Inter Core 2 Duo 1.66 GHz and 4 GB of RAM DDR 2. This system tested only with video containing smoke. Video capture was resized to 320 × 240 pixels, and the fps set to 8-12. This system using 18 experimental fire videos laboratory [12, 13], which every 3 videos is using a different material. Those materials are cigarette, PVC, paper, wood, rubber, and foam. One video from each material was taken as a training video, which features extracted from that video will be used for data matrix **B** that explained in section 4. Matrix Data will be used in MMM for training. Then a testing video will be used to test the model. Six testing video was made using Fire Dynamic Simulator (FDS) [7] and also use six material as we described before. In that simulation video, a conventional smoke detector was attached as a comparison to the classification model with MMM. The use of 4 detectors and thermocouples are for measuring the optical density and temperature of smoke. They were installed to make sure whether there are significant changes in gas temperature profiles. The dangerous condition was defined when more than one detector went off. Fig. 5 shows the typical result which is then summarized in Table 1. In general it was shown that in most cases, the MMM approach (column 7 of Table 1) detected dangerous smoke faster than that of the conventional smoke detector (column 5).



(a) (b)

Fig. 5. Simulation of burned foam material using FDS. (a) smoke detectors alarmed; (b) MMM alarmed.



(a) (b)

Fig. 6. Simulation of burned cigarette material using FDS. (a) smoke detectors alarmed; (b) MMM alarmed.

Table 1. Comparison between smoke detector and MMM when dangerous smoke criteria is matched

Material	Total Frame	Frame per Second (fps)	Smoke Detector Alarmed		MMM alarmed	
			Frame	Second	Frame	Second
Foam	594	8	214	26.75 s	199	24.88 s
Cigarette	1490	12	377	31.42 s	522	43.50 s
Wood	1610	12	283	23.58 s	100	8.33 s
PVC	1586	12	300	25.00 s	220	18.33 s
Paper	1970	12	350	29.17 s	300	25.00 s
Rubber	1670	12	200	16.67 s	150	12.50 s

Although Table 1 shows that MMM is faster in detecting dangerous smoke than conventional detector. Nevertheless for a cigarette material the MMM approach requires longer time for reaching the dangerous criteria (Fig. 6). Compared to other materials, cigarette material produces less smoke. This is clearly shown by a delay in detecting the dangerous smoke by both MMM approach and using conventional detector.

Figure 6 shows the image of burning cigarette material. Although, the smoke image is relatively small, conventional smoke detectors are able to detect dangerous smoke condition by triggering the alarm in the left front detector (Fig. 6(a)). But, MMM model fails to detect it as dangerous smoke. About 12 s later, as shown in Fig. 6(b), the smoke area become larger by time and approaching the ceiling. At this stage the condition was detected by MMM model as dangerous condition. This is supported by the activation of more than one alarm.

6. Conclusions

A video based smoke detection system was developed by combining the GMM model for segmentation of moving objects and the MMM methods for classification of the objects. MMM classifies the objects based on dangerous smoke context, type of smoke that detected in video. Using smoke images produced by FDS modeling works, it was found that for most cases, the MMM approach detected dangerous smoke faster than that of the conventional smoke detector.

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