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# 조기 화재 경보 시스템을 위한 비디오 기반 연기 감지 방법

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## 요 약

본 논문은 조기 화재 경보 시스템에서 예측하지 못한 위험요소들의 이벤트에 즉각 응답하는 비디오 기반의 효과적인 4단계 연기 감지 방법을 제안한다. 첫 번째 단계에서는 근사 미디언(approximate median) 방법을 사용하여 비디오의 현재 프레임에서 움직이는 영역들을 분리한다. 두 번째 단계에서는 연기의 칼라 기반 분리 기법을 사용하여 이러한 움직이는 영역들로부터 후보 연기 영역을 선택한다. 세 번째 단계에서는 특징추출 알고리즘을 사용하여 연기의 움직임이나 지역 불규칙성과 같은 후보 연기 영역들의 특징을 분석하여 연기의 다섯 가지 특징 파라미터를 추출한다. 네 번째 단계에서는 추출된 다섯 가지 특징 파라미터를 K-nearest neighbor (KNN) 알고리즘의 입력으로 사용하여 후보 연기 영역이 연기인지 아닌지를 구분한다. 모의실험 결과, 제안하는 4 단계 연기 감지 방법은 기존의 연기 감지 알고리즘들과 비교하여 연기감지의 정확도에서 우수한 성능을 보였고, 또한 오픈된 넓은 공간에서도 높은 신뢰성과 낮은 오류 경보율을 보였다.

**키워드 : 비디오기반 연기 감지, K-nearest Neighbor(KNN) 알고리즘, 조기 화재경보 시스템**

# A Smoke Detection Method based on Video for Early Fire-Alarming System

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## ABSTRACT

This paper proposes an effective, four-stage smoke detection method based on video that provides emergency response in the event of unexpected hazards in early fire-alarming systems. In the first phase, an approximate median method is used to segment moving regions in the present frame of video. In the second phase, a color segmentation of smoke is performed to select candidate smoke regions from these moving regions. In the third phase, a feature extraction algorithm is used to extract five feature parameters of smoke by analyzing characteristics of the candidate smoke regions such as area randomness and motion of smoke. In the fourth phase, extracted five parameters of smoke are used as an input for a K-nearest neighbor (KNN) algorithm to identify whether the candidate smoke regions are smoke or non-smoke. Experimental results indicate that the proposed four-stage smoke detection method outperforms other algorithms in terms of smoke detection, providing a low false alarm rate and high reliability in open and large spaces.

**Keywords : Video-based Smoke Detection, K-nearest Neighbor Algorithm, Early Fire-alarming Systems**

## 1. Introduction[1)]

Smoke detection has become more appealing because of its important application in surveillance systems. Several traditional methods have been proposed to detect smoke and fire [1],[2]. The existing methods are based on particle sampling, temperature sampling, relative humidity sampling, air transparency testing, and analysis of temporal or spatial characteristics of smoke. However, most of these methods require a close proximity to the source of 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 weaknesses, video smoke detection has recently received more attention as it is effective in a particular environment [3],[4].

A number of smoke detection algorithms with video have been proposed. Some of these were applied to real surveillance systems and achieved considerable successes. A fast accumulative motion model based on the integral

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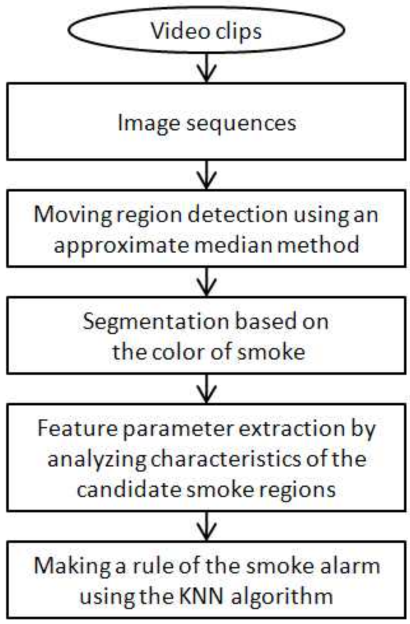
image for video smoke detection was proposed in [3]. This model use chrominance detection along with the fast estimation of the motion orientation of smoke. In addition, orientation data is accumulated over time to improve performance. In [4], two decision rules were used to make a smoke alarm: (1) the chromatic decision rule, deduced by analyzing the color of smoke, and (2) the dynamic decision rule that is dependent on the spreading attributes of smoke. Visual-based smoke detection using support vector machines (SVM) was proposed in [5]. In this method, additional universal features, such as the changing unevenness of density distribution and the changing irregularities of the contour of smoke, were suggested. These features were then used to distinguish between smoke and non-smoke by employing SVM. In [6], smoke detection in video using wavelets and support vector machines was proposed. The features of smoke were extracted using wavelets, and then these features were used as an input for SVM to distinguish between smoke and non-smoke. An efficient target-tracking based early fire smoke detection in video was proposed in [7]. In this algorithm, three effective static and dynamic smoke visual features were used in addition to combination of temporal and spatial characteristics of smoke. However, the authors only assessed the brightness consistency of smoke. In [8], the transparent feature of smoke was utilized, such as the edge blurring value of the background object in the wavelet domain. In addition, the contour characteristic of smoke was incorporated to improve the accuracy of smoke detection [9].

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 color filters based techniques applied on smoke color attributes, and (3) other algorithms that only extract features from moving objects and then make a smoke alarm based on the classifier. These algorithms have limited application and insufficient robustness. To eliminate these shortcomings and to enhance the performance of smoke detection, an effective smoke detection method that utilizes a combination of static and dynamic features of color smoke in addition to a K-nearest neighbor (KNN) algorithm.

The rest of this paper is organized as follows: Section II introduces characteristics of smoke. Section III presents the proposed smoke detection method. Section IV describes analysis, and a performance comparison of the proposed method with other conventional methods. Section V concludes this paper.

## 2. Characteristics of Smoke

Investigation of smoke characteristics plays an important role in the development of smoke detection system because these characteristics are used to distinguish between smoke and non-smoke. By analyzing several video clips that contain smoke or non-smoke, important characteristics of smoke in color and region are obtained. The color of smoke ranges from bluish-white to white when the temperature is low, and from grayish-black to black when the temperature rises until fire ignites. When smoke appears, it usually rises from a stable position on the screen, drifting upward in a diffuse manner. The area, size, and number of smoke regions are varied and change from frame to frame [3]. The surface and boundary of the smoke regions are usually rough and coarse [4].




(Figure 1) A flowchart of the proposed smoke detection method

## 3. The Proposed Smoke Detection Method

A flowchart of the proposed smoke detection method with video is depicted in (Figure 1). The method is composed of four stages: (1) moving region detection using an approximate median method, (2) color segmentation of smoke to select candidate smoke regions, (3) feature parameter extraction by analyzing characteristics of the candidate smoke regions, (4) making a rule of the smoke alarm using the K-nearest neighbor

(KNN) algorithm. The proposed smoke detection method is presented in detail in the following sections.

### 3.1 Moving Region Detection

Moving region detection is a fundamental task in video smoke detection, which is the first stage of our method. A number of methods were proposed to detect moving regions in video from static cameras: temporal differencing, background subtraction, optical flow, and so on. Among these methods, the background subtraction has been commonly used because of its simplicity and effectiveness. This method separates the foreground objects from the background in a sequence of video frames. Many different methods have been proposed in the background subtraction in which each method has different strengths and weaknesses in terms of performance and computation time [10]. In this study, an approximate median method is used to detect moving regions because it provides high efficiency with low computational time. A detailed description of this method is given in [11].

In this stage, the approximate median method utilizes only the gray image. Let $I_n(i, j)$ represents the intensity value of the pixel at the location $(i, j)$ in the $n^{th}$ video frame. The estimated background intensity value at the same position, $B_{n+1}(i, j)$, is calculated as follows:

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

where $B_n(i, j)$ is the previous estimate of the background intensity value at the same pixel position. From (1), we observe that the background is updated after every frame. In this way, the background eventually converges to an estimate where half of input pixels are greater than the background, and half are less than the background. 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:

$$|I_n(i,j) - B_n(i,j)| > T, \quad (2)$$

where $T$ is a predetermined threshold.

(Figure 2) shows original images with detected moving regions using the approximate median method. The moving regions include smoke or non-smoke, such as people or objects. Color segmentation of smoke is then utilized to select only candidate smoke regions from these moving regions.

### 3.2 Color Smoke Segmentation

The color of moving objects is different from that of smoke. We investigated the characteristics of the smoke color in Section 2.1: (1) the smoke color ranges from grayish-black to black, and (2) it also ranges from bluish-white to white. When the smoke color ranges from grayish-black to black, the intensity value, $I$, of its gray image ranges from the threshold values, $TH_1$ to $TH_2$ (where $TH_1$ = 80 and $TH_2$ = 150). For its true-color pixels of smoke, three components R, G, B of each pixel have the same value each other, and we assume that |max(R, G, B) - min(R, G, B)| < $TH_3$, where we set $TH_3$ equals to 40. On the other hand, if the color of smoke ranges from bluish-white to white, we assume that B = max(R, G, B), |R - G| < $TH_4$ (where $TH_4$ = 35), and the intensity value, $I$, of its gray image ranges from $TH_5$ to $TH_6$ (where $TH_5$ = 180 and $TH_6$ = 230). With these rules, we select candidate smoke regions.

### 3.3 Feature Extraction of Smoke

#### 3.3.1 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 characteristic, 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

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

(Figure 2) Results of moving region detection using the approximate median method: (a) an original smoke image, (b) the resulting smoke image, (c) an original image of human walking, and (d) the resulting image of human walking 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:

$$\triangle A_n = |A_n - A_{n-1}| \ , \tag{3}$$

where $\triangle A$ is the size difference between consecutive $A_n$ and $A_{n-1}$, which is the areas of candidate regions in the $n^{th}$ and $(n-1)^{th}$ frames, respectively. Using all the $\triangle As$ between the previous frames and current frame, the mean value ($M_A$) and variance value ($V_A$) are calculated using the following equations [4, 5]:

$$M_A = \frac{1}{n}\sum_{i=1}^{n}\triangle A_i \ \text{and} \tag{4}$$

$$V_A = \frac{1}{n}\sum_{i=1}^{n}|\triangle A_i - M_A|^2 \ . \tag{5}$$

Although this feature can be used to distinguish between rigid body objects and smoke motion, but it is difficult to distinguish between non-rigid body objects and smoke motion according to size variation due to the distance between a camera and an object.

### 3.3.2 Determining the Smoke Origin

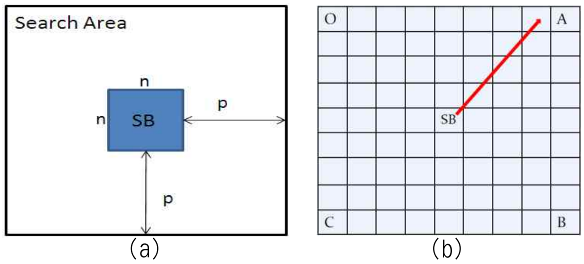
Unlike other moving objects, the origin of smoke is continued for the subsequent frames in video, and it drifts upward in a way of the diffusion process. Using this feature of smoke, we make a parameter that classifies between smoke and non-smoke for each frame. To generate the parameter, a square box $S_1$ of $RxR$ in (Figure 3) is generated from the smoke origin (or centroid), where the smoke origin is decided if the number of boundary pixels from a candidate moving region are large enough. Then, if the number of pixels within the square for each frame is $(RxR)/2$ pixels, we decide that the frame includes smoke. Otherwise, it can be concluded that the objects in the candidate moving regions are non-smoke. The feature parameter, $R_S$, of $S_2$ to $S_1$ is defined as follows, where $R_S$ is the ratio of the number of pixels within the square box ($S_2$) over that of the square ($S_1$):

$$R_S = \frac{S_2}{S_1} \ . \tag{6}$$

### 3.3.3 Motion Estimation

One of the most important features of smoke is spreading out and drifting upward in the diffusion process. Thus, we use a block motion estimation model to extract the feature of smoke from the candidate smoke regions and suppose that all pixels in the same block have the same motion parameters. As shown in (Figure 4(a)), a search block is defined as $n$ x $n$ pixels, and the searching displacement ($p$) needs to be discretized at each direction.

(Figure 3) An example of determining the smoke origin



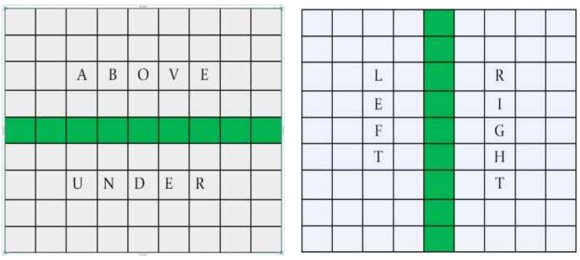

(Figure 4) Search area and search points of a square block

From (Figure 4(b)), for example, we can calculate a motion vector of the matched search block (MSB), where we assume that $n$=8 and $p$=4. Let the coordinates of O, A, B, C and the center of the search block are (-4, -4), (4, -4), (4, 4), (-4, 4), and (0, 0), respectively. The motion vector of the matched search block is (3, -4).

Depending on the location of the matched search block, we can calculate the number of the matched search blocks within four different sections based on the center of the coordinate as shown in (Figure 5): $MSP_{AS}$ (the number of MSBs in the above section), $MSP_{US}$ (the number of MSBs in the under section), $MSP_{LS}$ (the number of MSBs in the left section), and $MSP_{RS}$ (the number of MSBs in the right section). We then calculate two parameters to be used as an input for the KNN algorithm: $R_{AU}$ (the rate of $MSP_{AS}$ versus $MSP_{US}$) and $R_{LS}$ (the rate of $\min(MSP_{LS}, MSP_{RS})$ versus $\max(MSP_{LS}, MSP_{RS})$), which are defined as follows:

$$R_{AU} = \frac{MSP_{AS}}{MSP_{US}} \quad (7)$$

$$R_{LR} = \frac{Min(MSP_{LS},\ MSP_{RS})}{Max(MSP_{LS},\ MSP_{RS})} \quad (8)$$




(Figure 5) Four devided sections to calculate the number of matched search blocks

To provide more accurate values of these two parameters, $R_{AU}$ and $R_{LS}$, as an input of the KNN algorithm, we use an accumulate matrix (AM) that accumulates the number of the matched search blocks within the four different sections among several frames, shown in (Figure 6).

With 240 frames, (Figures 6(a)) and 6(b) show the accumulative matrix of the number of the matched search blocks and the accumulation of the number of the matched search blocks within four different sections, respectively.

These two parameters are used as an input for the KNN algorithm, which is described next, to distiguish between smoke and non-smoke.

### 3.4 Making the Rule of Smoke Alarm Using a K-Nearest Neighbor Algorithm

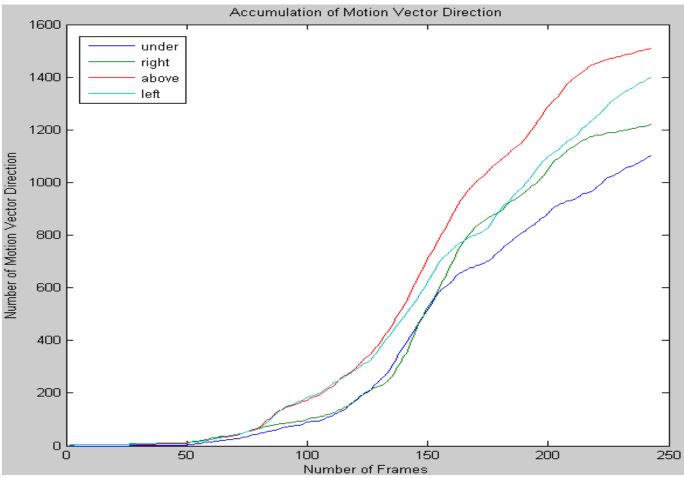
From Section 3.3, we can extract a feature vector of each frame that consists of five parameters, such as $X_i = \{M_A, V_A, R_S, R_{AU}, R_{LR}\}$. This feature vector is used as an input for the K-nearest neighbor (KNN) algorithm to distinguish between smoke and non-smoke. The KNN algorithm is a supervised learning technique that has been widely used in many applications in the field of data mining, image processing, computer vision, and pattern classification [13],[14]. Let $\{X_1, X_2, \cdots, X_N\}$ be the training samples which are extracted from training video clips, where $N$ is the number of training samples. Also, let $Y$ be the category of training data set. For example, $Y$ equals to 0 when smoke is not detected, and $Y$ is equals to 1 when smoke is detected. If a new feature vector, $X_j$, is given as an input of the KNN algorithm, it is distinguished between smoke and non-smoke by the following steps:

1) Determine the parameter $K$ which is the number of the nearest neighbours.
2) Calculate the distance between $X_j$ and all the training samples using the Euclidean distance.
3) Sort the Euclidean distance and determine the nearest neighbours based on the $K$ minimum distance.
4) Collect the category $Y$ of the nearest neighbours.
5) Use simple majority of the category $Y$ in order to decide the category of new data point.

If $Y$ of the new data point, $X_j$, equals to 1, a smoke alarm is made. In this case, an error rate may be higher since only a single frame is evaluated. To solve this

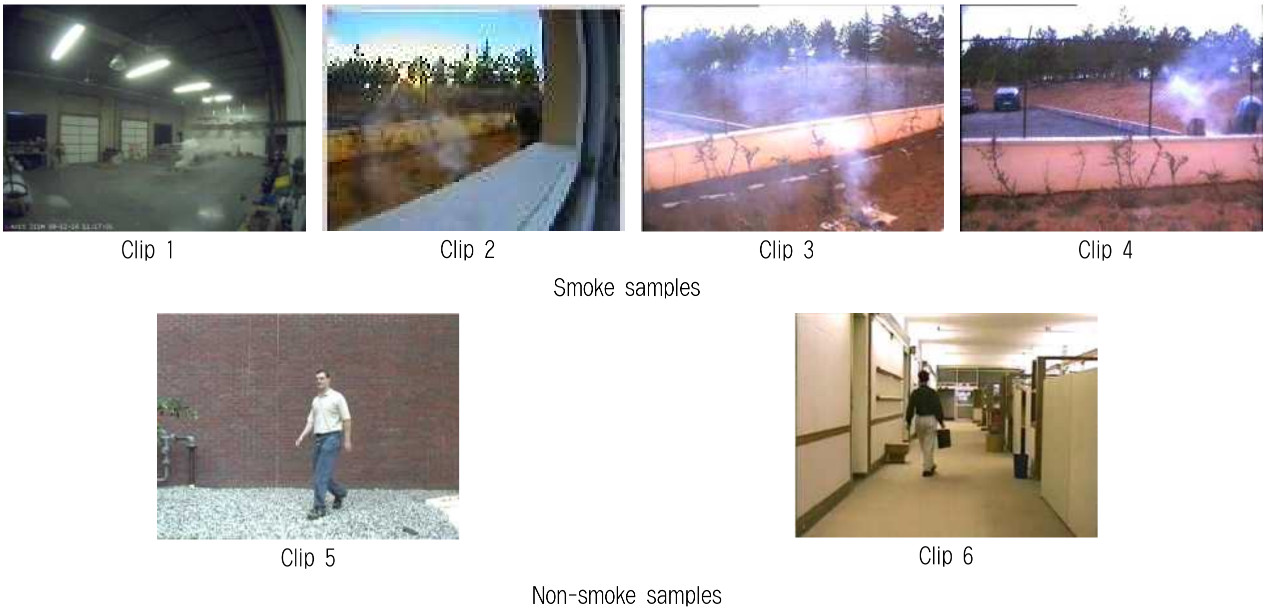
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 256 | 46 | 40 | 77 | 99 | 48 | 51 | 39 | 233 |
| 34 | 23 | 19 | 10 | 28 | 19 | 13 | 19 | 33 |
| 35 | 19 | 22 | 9 | 25 | 16 | 19 | 12 | 36 |
| 31 | 11 | 12 | 21 | 72 | 28 | 12 | 15 | 26 |
| 52 | 61 | 35 | 51 | 0 | 60 | 44 | 48 | 76 |
| 33 | 9 | 20 | 47 | 52 | 15 | 8 | 9 | 16 |
| 33 | 15 | 34 | 25 | 20 | 12 | 15 | 10 | 35 |
| 41 | 25 | 20 | 16 | 23 | 7 | 11 | 11 | 28 |
| 147 | 31 | 26 | 51 | 56 | 41 | 34 | 27 | 100 |

(a)




(b)

(Figure 6) Accumulation of the matched search blocks: (a) accumulative matrix of the matched search blocks and (b) accumulation of the matched search blocks within the four different sections

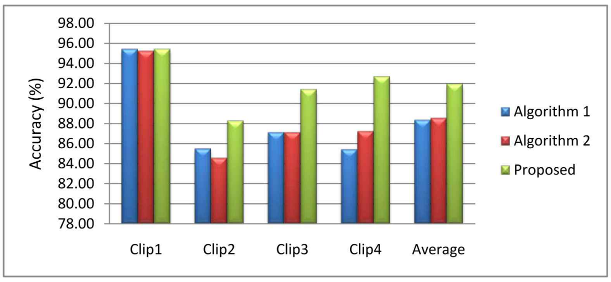



(Figure 7) Examples of test video clips

problem, we employ an accumulative variable (ACC). For example, if ACC equals to 10 (10 consecutive frames with $Y$ = 1), the smoke alarm is made.

## 4. Experimental Results

In this section, we evaluate the performance of the proposed smoke detection method and compare with that of other two state-of-the-art smoke detection algorithms, called Algorithm1 [4] and Algorithm2 [5]. These algorithms are implemented with MATLAB software tool on a PC platform. The resolution of each video frame is 320x240 pixels. With many simulations in several video clips, we select optimal parameters for the proposed method as follows: the threshold $T$ equals to 5, and the number of nearest neighbours equals to 9. For this study, we extract 5000 training samples from several different kinds of video clips, such as smoke (called positive video), non-smoke (called negative video), indoor smoke, and outdoor smoke. In addition, we evaluate the performance of the proposed algorithm with six different video clips as shown in (Figure 7).



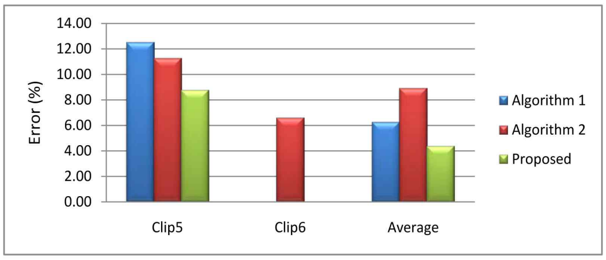

(Figure 8) The comparison of smoke detection accuracy using the proposed method and other two algorithms with smoke (positive) video clips

<Table I> The Comparison of Smoke Detection Accuracy using the Proposed Method and Other Two Algorithms with Smoke (Positive) Video Clips

| | Number of frame | Algorithm 1 | | Algorithm 2 | | Proposed | |
|---|---|---|---|---|---|---|---|
| | | TP(frame) | PTP(%) | TP(frame) | PTP(%) | TP(frame) | PTP(%) |
| Clip1 | 1060 | 1012 | 95.47 | 1010 | 95.28 | 1012 | 95.47 |
| Clip2 | 214 | 183 | 85.51 | 181 | 84.58 | 189 | 88.32 |
| Clip3 | 140 | 122 | 87.14 | 122 | 87.14 | 128 | 91.43 |
| Clip4 | 165 | 141 | 85.45 | 144 | 87.27 | 153 | 92.73 |
| Average | | | 88.40 | | 88.57 | | 91.99 |

<Table II> The Comparison of Smoke Detection Error using the Proposed Method and Other Two Algorithms For Non-Smoke (Negative) Video Clips

| | Number of frame | Algorithm 1 | | Algorithm 2 | | Proposed | |
|---|---|---|---|---|---|---|---|
| | | TN(frame) | PTN(%) | TN(frame) | PTN(%) | TN(frame) | PTN(%) |
| Clip7 | 80 | 10 | 12.50 | 9 | 11.25 | 7 | 8.75 |
| Clip8 | 152 | 0 | 0.00 | 10 | 6.58 | 0 | 0.00 |
| Average | | | 6.25 | | 8.91 | | 4.38 |




(Figure 9) The comparison of smoke detection error using the proposed method and other two algorithms for non-smoke (negative) video clips

<Table I> and (Figure 8) show the comparison of smoke detection accuracy using the proposed method and other two algorithms [4],[5], where TP stands for true positive which is the number of detected smoke frames correctly, and PTP is the percentage of smoke detection correctly. The smoke detection accuracy of the proposed method is higher than that of other two algorithms (92% versus 88.4% and 88.6%).

<Table II> and (Figure 9) represent the error of the proposed method and other two smoke detection algorithms for negative (non-smoke) video clips, where TN stands for true negative which is the number of incorrectly detected frames of smoke, and PTN is the percentage of smoke detection incorrectly. The proposed method shows only an error of 4.4% of smoke detection. This is in contrast to other two algorithms, which show an error of 6.25% and 8.9% of smoke detection, respectively.

Overall, the proposed method outperforms other two algorithms in terms of consistently increasing the accuracy of smoke detection.

## 5. Conclusion

In this paper, an effective, four-stage smoke detection approach with video was proposed for early fire-alarming systems. The proposed approach employs an approximate median method to segment moving regions in each video frame in the first stage, a segmentation method to select candidate smoke regions from these moving regions in the second stage, a feature extraction method to extract feature parameters of smoke in the third stage, and the K-nearest neighbor (KNN) method to identify whether the candidate smoke regions are smoke or non-smoke in the final stage of the proposed approach. Experimental results showed that the proposed approach outperforms other two state-of-the-art smoke detection algorithms in terms of smoke detection accuracy. It can also detect both indoor and outdoor smoke with high reliability and low false alarm rate.

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