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강인한 움직임 영역 검출과 화재의 효과적인 텍스처 특징을 이용한 화재 감지 방법

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Fire Detection Approach using Robust Moving-Region Detection and Effective Texture Features of Fire

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요 약

본 논문은 그레이 레벨 히스토그램을 이용한 움직임 영역 검출, 퍼지 클러스터링을 이용한 칼라 분할, 그레이 레벨 동시발생 행렬을 이용한 특징 추출 및 서포터 벡터 머신을 이용한 화재 분류 등과 같은 다중 이종 알고리즘을 포함하고 있는 효과적인 화재 감지 방법을 제안한다. 제안한 방법은 움직임 영역을 검출하기 위해 그레이 레벨 히스토그램에 기초한 최적의 임계값을 결정하고 난 후, CIE LAB 칼라 공간에서 퍼지 클러스터링을 적용하여 칼라 분할을 수행한다. 이러한 두 단계는 화재의 후보 영역을 기술하는데 도움이 된다. 다음으로 그레이 레벨 동시발생 행렬을 이용하여 화재의 특징을 추출하고, 이러한 특징들은 화재인지 아닌지를 분류하기 위해 서포터 벡터 머신의 입력으로 사용된다. 제안한 방법을 평가하기 위해 기존의 두 알고리즘과 화재 검출율 및 오류 화재 검출율에서 비교하였다. 모의실험결과, 제안한 방법은 97.94%의 화재 검출율 및 4.63%의 오류 화재 검출율을 보임으로써 기존의 화재 감지 알고리즘보다 우수성을 보였다.

▸ Keywords : 화재 감지, 움직임 영역 감지, 그레이 레벨 동시발생 행렬, 서포터 벡터 머신

Abstract

This paper proposes an effective fire detection approach that includes the following multiple heterogeneous algorithms: moving region detection using grey level histograms, color segmentation

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using fuzzy c-means clustering (FCM), feature extraction using a grey level co-occurrence matrix (GLCM), and fire classification using support vector machine (SVM). The proposed approach determines the optimal threshold values based on grey level histograms in order to detect moving regions, and then performs color segmentation in the CIE LAB color space by applying the FCM. These steps help to specify candidate regions of fire. We then extract features of fire using the GLCM and these features are used as inputs of SVM to classify fire or non-fire. We evaluate the proposed approach by comparing it with two state-of-the-art fire detection algorithms in terms of the fire detection rate (or percentages of true positive, PTP) and the false fire detection rate (or percentages of true negative, PTN). Experimental results indicated that the proposed approach outperformed conventional fire detection algorithms by yielding 97.94% for PTP and 4.63% for PTN, respectively.

▸ Keywords : Fire detection, Moving region detection, Grey level co-occurrence matrix, Support vector machine

I. Introduction

With the fast and advanced pace of technology, especially, in video surveillance, a new period of early warning and fire detection is opening. Compared to traditional fire detection systems which mostly use sensors and make decisions based on them, video-based fire detection systems use digital camera technology and video processing techniques. These video-based techniques have advantages over traditional methods with respect to response time and space.

Until now, many algorithms based on recognizing color and/or motion were introduced either as decision rules, probability models or as multiple layer filters [1-3]. These algorithms are simple, and real-time, however, they lack robustness. Consequently, in order to enhance performance, recent algorithms combine analysis techniques with classification techniques to find more specific fire parameters that distinguish between fire and non-fire situations. For instance, Borges and others analyzed frames to extract changing features of fires such as color, boundary, roughness and skewness for a Bayer classifier and made decisions about whether fires happened or not [4]. In addition, several researchers applied discrete wavelet transforms to extract features for classification [5-7].

To improve the classification performance of fire detection, this paper proposes an effective fire detection approach using heterogeneous image processing techniques: moving-region detection using grey level histograms, color segmentation in the CIE LAB color space using the FCM, feature extraction using the GLCM, and fire classification using SVMs. Experimental results show that the proposed approach outperforms two conventional algorithms with respect to percentages of true positive and true negative.

The rest of this paper is organized as follows. Section II introduces the proposed fire detection approach and Section III illustrates experimental results and evaluates the classification performance of the proposed approach. Finally, Section IV concludes the paper.

II. Proposed fire detection Approach

The proposed approach is illustrated in Fig. 1. In this paper, we use multiple heterogeneous methods for fire detection.

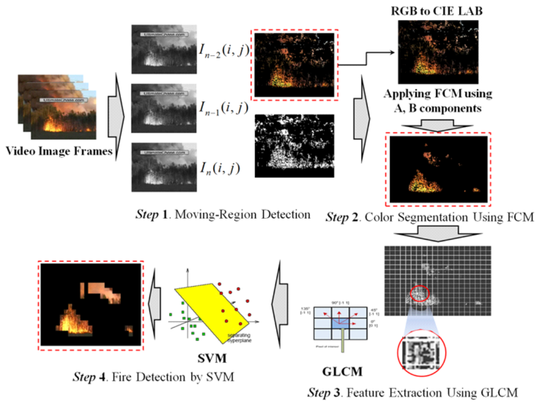


그림 1. 다중 이미지 처리 알고리즘을 사용한 제안한 화재 감지 방법
Fig. 1. The proposed fire detection approach using multiple image processing algorithms.

In the first two steps, we detect moving regions and perform color segmentation in the CIE LAB color space to specify candidate regions of fire. Then, we extract features of fire using the grey level co-occurrence matrix (GLCM) and finally determine whether or not there is fire in the current video image frame by using these features as inputs of support vector machine (SVM). More details about this procedure is described in the following sections.

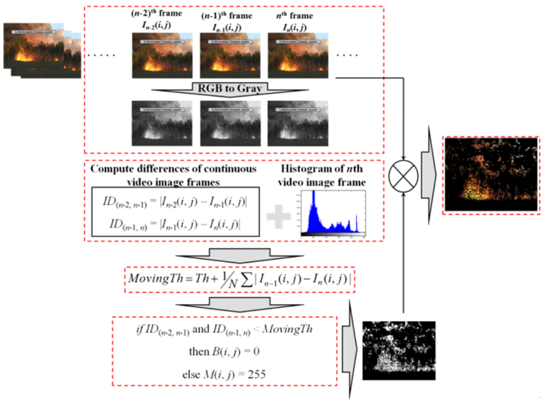


그림 2. 움직임 영역을 검출하기 위한 절차
Fig. 2. The procedure for detecting moving regions

1. Moving Region Detection and Color Segmentation

Turbulent flames have a characteristic flicker frequency of around 10 Hz and this stochastic motion behavior of flame is especially useful for recognizing fires [5]. Thus, this paper first detects moving regions in video image frames, which enables higher performance in detecting fires.

Fig. 2 shows the procedure for detecting moving regions. To detect moving regions, this paper uses three successive video frames [8]. Moving region detection is essentially composed of the following five steps:

Step 1: Convert input video frames in the RGB color space to grey level video frames.

Step 2: Let $I_{n-2}(i,j)$, $I_{n-1}(i,j)$ and $I_n(i,j)$ represent intensity values of the three consecutive video image frames, where $I_{n-2}(i,j)$ and $I_{n-1}(i,j)$ are the intensity values of the previous video frames, and $I_n(i,j)$ denotes the intensity values of the current video frame. Then, we can compute grey scale differences between two adjacent video frames as follows:

$$\begin{aligned} ID_{(n-2,n-1)} &= \sum \left| I_{n-2}(i,j) - I_{n-1}(i,j) \right| \\ ID_{(n-1,n)} &= \sum \left| I_{n-1}(i,j) - I_n(i,j) \right|. \end{aligned} \tag{1}$$

Step 3: Calculate a moving threshold to distinguish the moving regions from the background using (2):

$$MovingTh = Th + \frac{1}{N} \sum \left| I_{n-1}(i,j) - I_n(i,j) \right|, \tag{2}$$

where MovingTh is the moving threshold for detecting moving regions, $\frac{1}{N} \sum |I_{n-1}(i,j) - I_n(i,j)|$ denotes image changes in overall light and N is the number of pixels in the frame, and Th is an additional threshold value depending on the environment. We also investigate the impact of Th for fire detection and more details about Th threshold values are given in Section 3.2.

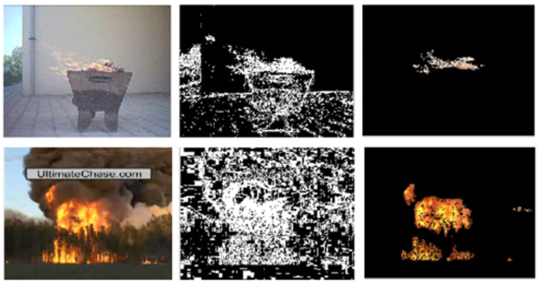
Step 4: To specify the moving region and background region, we use the following rule:

$$\begin{aligned} &\text{if } ID_{(n-1,n-2)} \text{ and } ID_{(n-1,n)} < MovingTh \\ &\text{then } B(i,j) = 0 \text{ else } M(i,j) = 255, \end{aligned} \tag{3}$$

where B(i, j) and M(i, j) represent the background region and moving region after determining the difference, respectively.

Step 5: Finally, we perform an AND operation between the current RGB video frame and the resulting frame in order to obtain the moving region in the RGB color space as shown in Fig. 2.

Since the moving region includes the region of several moving objects (e.g., fire, people, vehicle, and cloud) as well as the changing background areas, the proposed approach performs color segmentation to specify more effective candidate regions of fire by applying the fuzzy c-means clustering (FCM) algorithm [9]. To do this, we first convert the RGB color space to the CIE LAB color space which is one of the most effective color spaces for classifying illumination components, where L indicates the lightness of a pixel, and A and B indicate the colors of the pixel [10]. In this paper, we only use the A and B components of the resulting frame as inputs to FCM because environmental light can affect the detection of the moving regions if we use illumination components. To apply FCM to the proposed approach, we set the degree of fuzzification to 2 and the termination threshold to 0.001. This is because Bezdek et al. experimentally determined the optimal intervals for the degree of fuzzification and the termination threshold, and found them to range from 1.1 to 5 and from 0.01 to 0.0001, respectively [11]. Figure 3 depicts the result of moving region detection after these two steps mentioned above.



(a) (b) (c)

그림 3. 움직임 영역 검출 결과. (a) 원본 비디오 프로임, (b) 세 프레임 차이 방법을 이용한 움직임 영역, (c) 퍼지 클러스터링을 사용한 칼라 분리 수행후의 움직임 영역

Fig. 3. Results of moving region detection. (a) original video image frames, (b) moving regions using three frame differencing method, and (c) moving regions after performing color segmentation using fuzzy c-means clustering

2. Feature Extraction and Classification of Fire

After the first two steps, a certain number of non-fire pixels can be removed. However, the candidate region still has non-fire pixels because there can be moving reddish objects. Therefore, it is necessary to obtain more information about fires. The proposed approach utilizes the grey level co-occurrence matrix (GLCM) to extract features of fires, where the properties of fires are specified by calculating energy, contrast, and homogeneity for four directions (e.g., 0°, 45°, 90°, 135°) with 16x16 blocks of the video image frame as follows [12]:

$$\begin{aligned} Energy &= \sum_{i,j} p(i,j)^2 \\ Contrast &= \sum_{i,j} |i-j|^2 \, p(i,j) \\ Homogeneity &= \sum_{i,j} \frac{p(i,j)}{1+|i-j|}, \end{aligned} \tag{4}$$

where p(i,j) is the (i,j)th entry in a normalized GLCM.

Finally, to determine whether or not the candidate region includes fire, this paper employs a support vector machine (SVM) [13,14]. After the feature extraction step, we select 12 features specifying the characteristic of fire (e.g., energy, contrast, and homogeneity for four directions) and use them as inputs to the SVM. Due to the similarity between fire and non-fire features, it is difficult to ensure linear separation. Thus, to classify fire from the candidate moving region, we use the non-linear SVM with Gaussian radial basis kernel function which performs better than other kernels [7]:

$$K(x_i, x_j) = \exp\left(\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), \tag{5}$$

where $K(x_i,x_j)$ is the kernel function, x_i and x_j are the input feature vectors, and σ is a parameter to be set by the user, which determines the width of the effective basis kernel function. If small σ values are used, overtraining occurs with the basis function wrapped tightly around the data points. In contrast, if large σ values are used, the basis function draws an oval around the points without defining the shape or pattern. Consequently, σ values can affect the classification performance and we experimentally selected σ as 0.1 yielding the highest performance.

Furthermore, we first performed moving region detection and color segmentation with each frame of the video clips to train SVM. We then obtained candidate regions of fire, and divided each candidate region into 16x16 blocks. Finally, we extracted texture parameters from 2,500 fire-containing and 1,500 non-fire-containing blocks, respectively, and trained SVM by utilizing these texture parameters as inputs of it.

III. Experimental Result

1. Experimental Environment

To implement and evaluate the performance of the proposed fire detection approach and two conventional algorithms, we use MATLAB 7.5 on a Pentium Quad-Core 2.8 GHz PC platform. We use nine videos with 320x240 image size in this study as shown in Fig. 4. Movies 1-5 are outdoor fire videos and Movies 6 and 7 are indoor fire videos. Movie 8 shows a car accident in a tunnel without fire and Movie 9 is an outdoor video including reddish moving objects such as red cars and flags.

그림 4. 성능 평가를 위한 대상 비디오의 예
Fig. 4. Examples of target videos for performance evaluation

2. Selecting Threshold Values for Moving Region Detection

As mentioned in Section 2.1, Th threshold values can affect the performance of moving region detection in video frames. Thus, we investigate the impact of the threshold value by changing the threshold values with Movies 1, 3, 5, and 7 because, regardless of the threshold value, the performance was good enough for Movies 2, 4, and 6. Table 1 shows the experimental results, where TP (or true positive) is the number of frames that accurately recognize a real fire as a fire for all frames that fire candidates are correctly detected in the movie, and the percentage of TP (PTP) is the overall fire detection rate.

As shown in Table 1, we get different results by selecting different threshold values, and observe that the threshold values are closely related to the

표 1. 움직임 영역 검출을 위한 경계값의 결과
Table 1. The results of the threshold value for detecting moving regions

Movie	Number of frames	Th = 3		Th = 7		Th = 10		Th = 13	
		TP (frame)	PTP (%)	TP (frame)	PTP (%)	TP (frame)	PTP (%)	TP (frame)	PTP (%)
Movie 1	201	144	71.64	182	90.55	188	93.53	**192**	**95.52**
Movie 3	201	195	97.01	194	96.52	197	98.01	**201**	**100**
Movie 5	201	**187**	**93.03**	175	87.06	174	86.57	167	83.08
Movie 7	201	**201**	**100**	109	54.23	28	13.93	12	5.97

표 2. 제안한 알고리즘과 기존 알고리즘을 사용한 화재 감지율의 비교
Table. 2. Comparison of the fire detection rate using the proposed and conventional algorithms.

Movies	Number of frame	Algorithm 1 [5]		Algorithm 2 [6]		Proposed	
		TP (frame)	PTP (%)	TP (frame)	PTP (%)	TP (frame)	PTP (%)
Movie 1	201	185	92.04	184	91.54	188	93.53
Movie 2	201	192	95.52	190	94.53	201	100
Movie 3	201	188	93.53	187	93.03	201	100
Movie 4	201	194	96.52	193	96.02	199	99
Movie 5	201	192	95.52	194	96.52	198	98.51
Movie 6	188	181	96.28	179	95.21	188	100
Movie 7	201	190	94.53	191	95.02	201	100
Average			**94.85**		**94.55**		**98.74**

표 3. 제안한 알고리즘과 기존 알고리즘을 사용한 오류 화재 감지율의 비교
Table. 3. Comparison of false fire detection rate using the proposed and conventional algorithms.

Movies	Number of frame	Algorithm 1		Algorithm 2		Proposed	
		TN (frame)	PTN (%)	TN (frame)	PTN (%)	TN (frame)	PTN (%)
Movie 8	188	10	5.39	9	4.79	11	5.85
Movie 9	90	4	4.44	5	5.62	3	3.41
Average			**4.88**		**5.17**		**4.63**

light complexity of the background of the video image frames. Consequently, we select threshold values using histogram information of video image frames with the following rules: Th=13 when histograms are distributed in the range from 15 to 80(see Movies 1 and 3) and Th=3 when histograms are distributed in the range from 81 to 167 (see Movies 5 and 7). Furthermore, when we tested other videos, it was reasonable to set the threshold value to 10 when the histogram was distributed in the range from 167 to 245. The threshold value can be automatically set by monitoring the histogram information of the video image frames.

3. Performance Evaluation

To evaluate the performance of the proposed fire detection approach, we compared the proposed approach with two state-of-the-art fire detection algorithms. The comparison results are presented in Tables 2 and 3.

As shown in Table 2, all algorithms resulted in low accuracies for Movie 1. This is because Movie 1 is blurred and flickering. Notwithstanding the flicker of Movie 1, we achieved higher accuracy of fire detection than those of other algorithms by utilizing an adaptive threshold based on histogram information for detecting movement-containing regions. As a result, the proposed approach outperformed the other algorithms in terms of PTP by giving an average detection rate of 97.94% versus 94.85% and 94.55%, respectively.

Moreover, Table 3 represents an additional experimental result showing the accuracy of fire detection in two non-fire videos, where TN (or true negative) is the number of frames that recognize a non-fire as a fire for all frames that non-fire candidates are correctly detected in the movie, and the percentage of TN (PTN) is the overall false fire detection rate. The non-uniform characteristic of the moving regions in Movie 8 is similar to the color of fire so that the false rate is a bit high when we compare to that of PTN of Movie 9. For Movie 9, the false fire detection rate is small for all algorithms because the uniform characteristic of the moving regions differ from the non-uniform characteristics of fire. Likewise, our analytical results shows that the false fire detection rate increases when many pixels of car brake lights in Movie 8 are included in the 16x16 block for feature extraction.

IV. Conclusions

This paper presented the proposed fire detection approach which includes the following multiple image processing algorithms: grey level histograms for moving region detection, FCM for color segmentation, GLCM for feature extraction, and SVM for fire detection. First, we specified candidate regions of fire by combining moving region detection with color segmentation using the FCM. Then, to obtain more refined candidate regions of fire, we extracted fire features by using the GLCM. Finally, we determined whether or not there is fire in the current video frame by using these features as inputs for support vector machines. To evaluate the performance of fire detection, this paper compared the proposed approach with two state-of-the-art fire detection algorithms based on the fire detection rate (PTP) and false fire detection rate (TPN). The proposed method outperformed these comparison algorithms with results of 97.94% for PTP and 4.63% for PTN, respectively.

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