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Flame Detection Using Generic Color Model and Improved Block-Based PCA in Active Infrared Camera

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In this paper, we proposed an all-weather flame detection algorithm which could make full use of active infrared cameras presently installed in many public places for surveillance purposes. Firstly, according to the different spectral imaging results in day and night, we propose a video type classification algorithm (VTCA) via imaging clues. VTCA could help us select different flame visual features in color image and infrared image. Secondly, we use a generic YCbCr-color-space-based chrominance model to extract regions of interest (ROI) of flame. Thirdly, two flame dynamic features are used to verify the candidate ROIs, which are common flame flicker feature and an improved block-based PCA in consecutive frames. The experimental results show that the proposed flame detection model has been successfully applied to various situations, including day and night, indoor and outdoor on our test video datasets, and it gives a better performance compared with other state-of-the-art methods.

Keywords: Active infrared camera; video-type classification; generic color model; dynamic flame feature.

1. Introduction

Recently, flame detection systems based on computer vision have gained more and more attentions. Most of the vision-based fire detection systems utilize common visible camera,[1,2,4,7–11,14,18,19,22,27,29] infrared camera,[28,20] thermal camera,[3] or long wave infrared (LWIR) thermal camera[21] as sensors. The common visible camera is usually used for detecting flame in well-lit areas, and other cameras are used in the dark, haze or dust environment. For flame detection algorithms, characteristics of

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color, shape, spatial variation, morphology are extensively used as flame visual features. Color is the widely used static feature in vision-based fire detection systems. For instance, characteristics of flame pixels presented in RGB,[1,3,22] HSI,[9,14] HSV,[22] and YCbCr[2,22,27] color spaces were used as clues to identify flame pixels correctly. Flicker is the most utilized dynamic flame feature. This feature is usually extracted using DCT, wavelet decomposition,[3,20] motion history detection[9] and flame image correlation.[18,22] Usually, there are several features as flame detection clues in one system, then decision fusion plays important rules in the systems. For examples, Fuzzy Logic,[14] Voting method, Choquet integral[22] and Dempster–Shafer theory[23] are reported for combinations of flame features in some researches to improve the accuracy of the vision-based flame detection systems. There are some representative researches about flame detection in videos:

Hou *et al.*[11] proposed a new updating target extraction algorithm for fire candidate regions segmentation, and then fire recognition algorithms, such as fuzzy neural network and Fuzzy GALSSVM are improved to detect fire. Experiments show that algorithms can be implemented for large space fire detection.

Ko *et al.*[14] proposed two algorithms which are based on Fuzzy+Gaussian and Fuzzy+Parzen to detect fire, and the latter algorithm produces better result. In the first place, they used a background model and a flame color model to detect candidate flame regions. Then, forming probability density functions for the intensity variation, wavelet energy, and motion orientation are changed into membership functions for fuzzy logic. At last, defuzzification step is applied to estimate fire appearance according to the probability value.

In Ref. 3, flame detection was achieved through a linear weighted classifier based on the following features: contrast enhancement by the local intensities operation, candidate region selection by thermal blob analysis and region shape regularity. Determined by wavelet decomposition analysis and region intensity saturation, the method can detect fire regions in thermal videos, which are in turn available in both outdoor and indoor environments.

A video-based fire detection system which utilized color, spatial and temporal information was proposed in Ref. 8. The system divided the video into spatial-temporal blocks and used covariance-based features extracted from these blocks to detect fire. The extracted features were trained and tested using a SVM classifier. The system can detect visible flame well by using nonstationary cameras.

Wirth *et al.*[27] used histogram back-projection in YCbCr color space in combination with a model image derived from known flame images to extract candidate flame pixel regions.

A feature-based multi-sensor fire detector operating on ordinary video and LWIR thermal images was proposed by Verstockt *et al.*[21] They extracted hot objects from the thermal images by dynamic background subtraction and histogram-based segmentation, and intensity-based dynamic background subtraction was utilized for extracting moving objects. The methods can detect invisible flame well via

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analyzation using a set of flame feature focusing on the distinctive geometric, temporal and spatial disorder characteristics of flame regions, in dark environment.

In Ref. 1, a probabilistic model for color-based fire detection was proposed. It could quantize the pixels into array of degrees of confdence for whether the corresponding pixel shows fire, and then analyze the interframe changes for specific low-level features describing possible fire regions. These features were color, area size, surface coarseness, boundary roughness, and skewness within suspected fire regions. The method can identify fire in video.

Wang *et al.*[22] used RGB, HSV and YCbCr color models in combination to represent possible fire regions. When they used the feature of fire correlation between frames, their experiments proved that the algorithm gives well performance, which can completely extract fire area and reduce the interferences from changes of brightness in images.

Ho *et al.*[9] used temporal probability density, represented by extracting the flickering area with level crossing and separating the alias objects from the flame and smoke region. Then, the continuously adaptive mean shift (CAMSHIFT) vision tracking algorithm was employed to provide feedback of the flame and smoke real-time position at a high frame rate.

Cheong *et al.*[4] proposed a new visual-sensor-based fire monitoring system, which applies two additional methods to candidate fire pixels: luminance map and support vector machine (SVM). The system removes nonfire pixels using the luminance map, and a temporal fire model was made for two-class SVM classifier with radial basis function (RBF) kernel.

Wu *et al.*[12] proposed a fire detection method by combining the characteristics of fire with human activity. This method specially focuses on early stage manmade fire, and performs well in the initial combustion which has small scale and short appearance.

In Ref. 20, Töreyin *et al.* extracted the flame region of interest (FROI) through flame motion and luminance detection. Wavelet analysis and variation analysis of temporal information were employed to confirm the existence of flame.

Dimitropoulos *et al.*[6] proposed a method for fire detection by spatio-temporal information. A nonparametric model is utilized to background subtraction and color analysis. After that, the fire behavior can be detected by employing various spatio-temporal features. And dynamic texture analysis is applied to further distinguish fire region.

Zhang *et al.*[29] applied a combination of color feature and fire flicker feature from time series analysis of fire height changes.

Toereyin *et al.*[19] employed raw RGB information and developed a set of rules to classify the flame pixels along with a motion information and Markov field modeling of the flame flicker process.

A multi-feature fusion early flame detection algorithm based on D-S evidence theory[5,15–17] is proposed in our previous work.[23] Flame flicker frequency based on

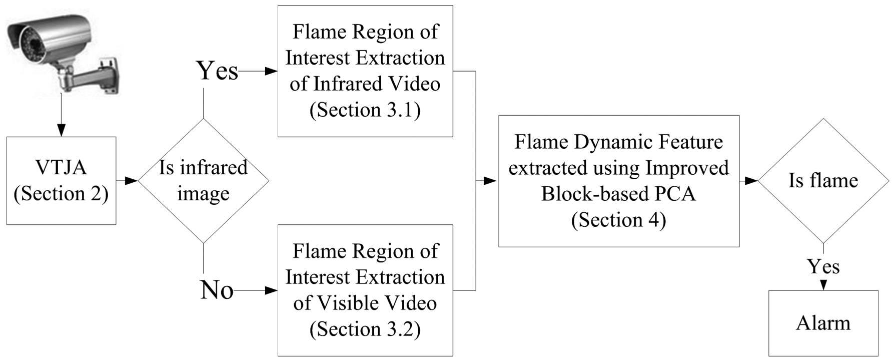

Fig. 1. Process of proposed method.

DCT and flame image correlation between frames are fused by D-S evidence theory to detect flame in visible images.

The remainder of this paper is arranged as shown in Fig. 1. In Sec. 2, we propose a video type classification algorithm (VTCA). In Sec. 3, we use the YCbCr color space to construct two generic chrominance model for visible and infrared flame pixel classification. In Sec. 4, flame detection using dynamic features are utilized as classifiers. Finally, we draw conclusions in Sec. 5.

2. Video Type Classification Algorithm

Active infrared cameras are widely used in existing vision-based surveillance systems. In order to make full use of these devices, we apply the active infrared cameras as environment sensors for flame detection. Usually, there is a photo resistor in an active infrared camera to control the infrared lights according to the environment illumination conditions, so characteristics of flame pixels in visible-light and infrared images are not the same caused by the captured images variation. In other words, it is hard to extract the flame ROI of visible and infrared accurately through a single color-feature-based algorithm. Background model,[14] dynamic background subtraction[21] and histogram-based segmentation methods[21] could handle with this problem, but they also introduce more interference. Although using sunrise–sunset times for a specific location could switch different imaging types for daytime and night time, it does not work for indoor environments where the illumination is irregular, especially at cinema and theatre. VTCA presented in this paper could classify the type of each frame capture from camera using image feature, and thus different ROIs extraction algorithm can be selected, respectively. The more accurate the VTCA classification is, the better performance of flame detection could be achieved. VTCA is a novel algorithm based on color histogram statistics in HSV color space. After analyzing the images from video libraries of PETS2001,[23] KMU CVPR Lab,[24] NIST,[13] VisiFire[25] and the video library in this

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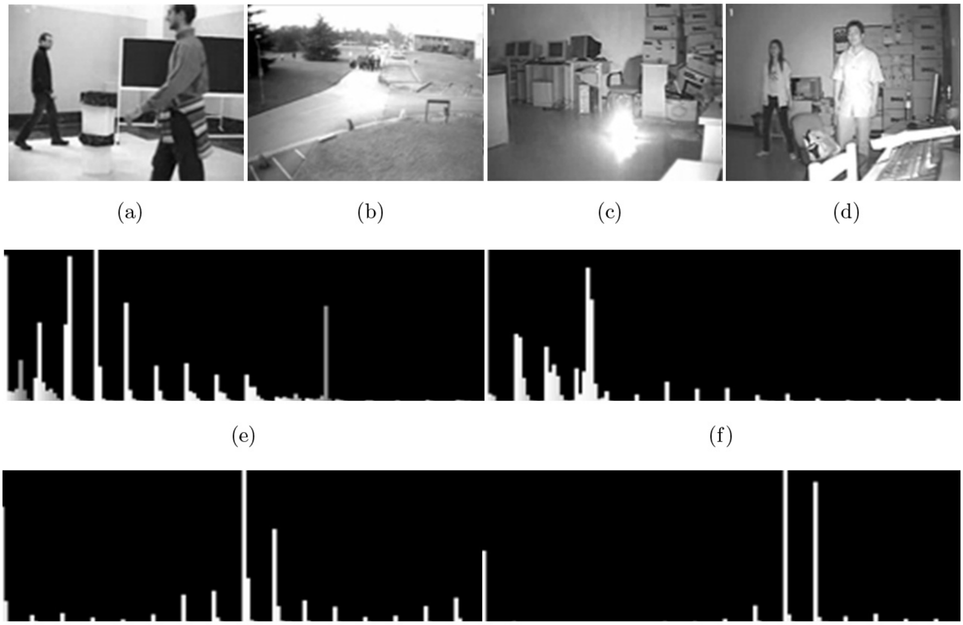

(a) (b) (c) (d)

(e) (f)

(g) (h)

Fig. 2. *H-S* histograms of visible images and infrared images. (a) is the image of visible-light video 14 in subclass 1 which is illustrated in Fig. 3, (b) is the image of visible-light video 7 in subclass 1, (c) is the image of infrared flame video inf_1 in subclass 3, and (d) is the image of infrared video ini_1 in subclass 3. (e) to (h) is the H-S histogram of (a) to (d), respectively.

paper, the number of colors in infrared images is less than visible images. That means that the H components in visible-light and infrared images (both in the HSV color space) are different. Besides, the color purity of infrared images is much lower than visible-light images. The S components in infrared and visible images are different too. Figure 2 can illustrate this idea well.

2.1. *Definition of the eigenvector* $\mathrm{HS_n}$ *and* H-S *histogram*

In order to visualize the HSV components of the image, we introduce the eigenvector $\mathrm{HS_n}$ and the H-S histogram, where n is the number assigned to each eigenvector. H component is divided into 16 levels $\{\mathrm{H_0}, \mathrm{H_1}, \ldots, \mathrm{H_{15}}\}$, each of $\mathrm{H_i}$ represents 22.5° difference of hue. Furthermore, every $\mathrm{H_1}$ component is divided into eight (sub)levels, representing saturation component $\{\mathrm{S_0}, \mathrm{S_1}, \ldots, \mathrm{S_7}\}$. In this way, an H-S histogram with 128 levels is created, and the H and S components of pixels can be mapped into eigenvectors $\mathrm{HS_n}$ and an H-S histogram. $\mathrm{H_xS_y}$ is defined as pixel which is in the yth S level of xth H level of H-S histogram, where n can be calculated by $n = 8x + y$, and hs_n is defined to be the value of each $\mathrm{HS_n}$. hs_n also means that there are hs_n pixels in level n. In order to express hs_n significantly in the H-S histogram, we normalize hs_n as follows:

$$\text{nor\_}hs_n = \frac{hs_n}{\text{Max}\{hs_1, hs_2, \ldots, hs_n\}}. \tag{1}$$

2.2. *Video type classification based on* H-S *histogram*

Plenty of experiments have been done on a large amount of visible-light and infrared images, taken from the test video library in this paper. Some of the images and their H-S histograms are illustrated in Fig. 2, the types of images can be classified by Eqs. (2) and (3).

$$\begin{cases} \text{Rule 1}: & \text{nor\_}hs_n \geq \text{Th\_}hs_n \\ \text{Rule 2}: & \text{Th\_}hl \leq \text{Num\_H} \leq \text{Th\_}hh\,. \\ \text{Rule 3}: & \text{Th\_}sl \leq \text{Num\_S} \leq \text{Th\_}sh \end{cases} \tag{2}$$

We can define visible images as

$$\text{IsVisible} = \begin{cases} 1 & \text{Rule 1}-\text{Rule 3} \\ 0 & \text{otherwise}, \end{cases} \tag{3}$$

where Th_hs_n is the threshold of hs_n. We only use the eigenvector HS_n whose hs_n value is above Th_hs_n for video type classification. Num_H and Num_S present the number of H and S components in H-S histogram, respectively. If the Num_H of an image is between Th_hl and Th_hh, and the Num_S is between Th_sl and Th_sh, the image is visible. To evaluate the performance of the proposed VTCA, we test it on video library in this paper. Detail results of VTCA are presented in Sec. 5.2.

3. Flame ROI Detection Using Generic Chrominance Model

Due to the imaging principles of active infrared camera, characteristics of flame pixels in the color image and infrared image are different, so it is hard to extract the FROI accurately via the same color clues. Naturally, visible and infrared candidate flame regions are initially detected using different methods. This process is essential for improving the flame detection performance and reducing the detection time on both types of videos.

3.1. *Detection of infrared FROI*

Brightness is the main feature of infrared flame. Infrared flame region of interest (IR-FROI) can be detected by extracting pixels that satisfy brightness features. Every image in red, green and blue (RGB) color space can be viewed as composition of three color planes: red, green, and blue. Nevertheless, although RGB color space can be applied for pixel classification, it has disadvantages of illumination

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dependence, thus if the illumination of image changes, the flame pixel classification rules cannot perform well. Furthermore, it is not possible to separate a pixel's value into intensity and chrominance. The chrominance can be used in modeling color of flame rather than modeling its intensity. It provides more robust representation for flame pixels. So it is needed to transform RGB color space to one of the color spaces where the separation between intensity and chrominance is more discriminate.[2] We use YCbCr color space to model flame pixels. The conversion of two-color space is linear, it is convenient to convert RGB space to YCbCr space. Y channel is luminance which is easy to represent the brightness feature of image pixels.

$$\begin{cases} \text{Rule 1}: & F(x,y) = \begin{cases} 1 & \text{if } Y(x,y) > Y_{\text{mean}} \\ 0 & \text{otherwise} \end{cases} \\ \text{Rule 2}: & F(x,y) = \begin{cases} 1 & \text{if } |\text{Cr}(x,y) - \text{Cr}_{\text{mean}}| < \tau_{\text{in}} \\ 0 & \text{otherwise} \end{cases} \end{cases}. \tag{4}$$

$$\text{InFire\_Fr}_n(x_i) = \begin{cases} 255 & \text{Rule 1 \& Rule 2} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

3.2. *Detection of visible FROI*

Color feature is an essential feature of the flame, and is often used to extract the FROI from videos. We experiment on three different FROI algorithms, and test different rules of flame extraction. The rules are based on YCbCr,[2] RGB,[4] and HSI.[10] We select four visible flame rules from Ref. 2 to extract flame in our experiments (Rule 1–Rule 4).

$$\begin{cases} \text{Rule 1}: & Y(x,y) > \text{Cb}(x,y) \\ \text{Rule 2}: & \text{Cr}(x,y) > \text{Cb}(x,y) \\ \text{Rule 3}: & F_\tau(x,y) = \begin{cases} 1 & \text{if } Y(x,y) > Y_{\text{mean}}, \text{Cb}(x,y) < \text{Cb}_{\text{mean}}, \text{Cr}(x,y) > \text{Cr}_{\text{mean}} \\ 0 & \text{otherwise} \end{cases} \\ \text{Rule 4}: & F_\tau(x,y) = \begin{cases} 1 & \text{if } |\text{Cb}(x,y) - \text{Cr}(x,y)| \geq \tau \\ 0 & \text{otherwise} \end{cases} \end{cases} \tag{6}$$

$$\text{Fire\_Fr}_n(x_i) = \begin{cases} 255 & \text{Rule 1} - \text{Rule 4} \\ 0 & \text{otherwise} \end{cases}. \tag{7}$$

(x,y) is the pixel location, Y_{mean}, Cb_{mean}, and Cr_{mean} are the mean values of luminance, Chrominance-Blue, and Chrominance-Red channel. In Ref. 2, τ is a constant value which is used to distinguish the flame and interference. τ is 40 in our experiments.

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4. Flame Dynamic Feature Extracted Using Improved Block-Based PCA

Although the detection of FROI using two color models is effective in videos containing flames, moving objects having similar flame features are also detected incorrectly. Various video flame detection algorithms have recently been proposed. There are more sophisticated video-based flame detection methods exploiting spatial-temporal characteristics of flames. Some of them are spatial features of flames, such as flame edge corner feature, flame height feature, flame centroid feature and flame area variation. Besides, the temporal features of flames are widely used in flame detection, such as flame flicker feature based on DCT, flame wavelet decomposition analysis and flame image correlation between frames, etc. Although dynamic features mentioned above are useful in visible images, however according to the infrared flame characteristics, there are few regular spatial features of flame in infrared images. So we proposed a better flame features which satisfy both visible flame detection and infrared flame detection. In this paper, we use features based on flame flicker which are applied by an improved block-based principle component analysis.

Firstly, a common flicker feature was used to get more accurate FROIs. As far as we know, flame height changes violently with flame flickering. Due to this feature, there are plenty of pixels changing from fire to nonfire or from nonfire to fire in sequential frames. So, flame can be detected by using this feature in a sequential flame video. We count the times a pixel (x, y) changes between extreme values in continuous frames. Whether the change count is greater than a fixed threshold is an evidence for judging pixel (x, y) belongs to an FROI or not.

Flame in videos has continuous oscillation feature because of influences from gas plume entrainment and air flow. Shen[18] and many other researches proposed a series of principles based on the oscillation feature. And we enhance this characteristic by using an improved frame correlation for fire detection. Considering the fire's shapes and area are not stable in different situations, we normalize the fire region and reduce the dimensionality of fire feature to guarantee that various fire images have the standardized feature dimensionality. A method called improved block-based principal component analysis (IBBPCA) is proposed to resolve the dimensionality reduction problem. The method is applied to the accurate FROIs target. When the FROI, which may contain a possible fire section, is to be extracted, IBBPCA segments the region into several small blocks. The bounding box of the motion region is calculated and divided into 30 sub-regions evenly as a 6×5 matrix in this paper. Every sub-region is regarded as a block and has a value which represents the composite degree of approximation to flame. The value V of each blocks are computed as Eq. (8).

$$V_k = \frac{\sum_{i=1}^{n} (Y_i + \omega \times |\mathrm{Cb}_i - \mathrm{Cr}_i|)}{n} \quad k = 1, \ldots, m, \tag{8}$$

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where m is the total number of blocks, and n denotes the number of pixels in each block. Y_i, Cb_i, Cr_i represent the value of YCbCr channel in the ith pixel of kth block, respectively, and ω is the weight. Then, a region could be represented by a set of invariant composed of color information, it can be represented as feature F in Eq. (9).

$$F = [V_1, V_2, V_3, \ldots, V_m]. \tag{9}$$

In this paper, we use a 6×5 matrix, so the value of m is 30. But m can be changed to adjust different situations. Then, IBBPCA applies traditional principal component analysis to complete further dimensionality reduction. We set up a fire image database for the training purpose. The training images in the database are segmented into 30 blocks as the previous method. Then, a training matrix is created where columns and rows denote each training picture and corresponding feature F, respectively. The eigenvalue and eigenvector are calculated from covariance matrix which is obtained from the training matrix. We use the eigenvector to handle the feature F, and reduce F into 10 dimensions from 30. According to Eq. (10), we can obtain the correlation via continuous frames' feature F.

$$C(p, q) = \frac{\sqrt[2]{\sum_{j=1}^{m} (V_p^j - V_q^j)^2}}{m}, \tag{10}$$

where p, q are the regions belonging to two successive frames in a video. V_p^j and V_q^j represent the jth invariants of p, q region's feature F, and m is the dimension of feature F. The result of Eq. (9) denotes the correlation between continuous frames, and this frame correlation can be used for detecting flame.

5. Experiment Analysis and Comparison

5.1. *Introduction of experiments and test video details*

Our flame detection system was implemented using Visual Studio 2005 environment, and experiments were conducted on a PC installed Windows XP operating system. A general active infrared camera (Web a DSP CCD camera, Model WB-335) was used to capture several flame sample videos. The resolutions of images are 320×240.

In general, experimental verification of a flame detection system is a very difficult task. Our test video library has been divided into four subclasses. Subclass 1 is used for testing the VTCA, subclass 2 is used for testing visible flame detection, subclass 3 is used for testing flame detection results under the nonvisible environments, and the videos in subclass 4 are captured from our flame detection system which monitored all-weather. Figure 3 show the scenes of test video library. Some of test videos in this Library are formerly proposed by others. 1–16 are from PETS 2001.[24] f_1-f_6, i_1-i_6 are cited from Ref. 14 and can be downloaded from website of KMU CVPR Lab.[13] f_7 is from National Institute of Standards and Technology.[25] f_8 is from Toreyin's test videos.[26] Others are captured from our general active infrared camera, such as

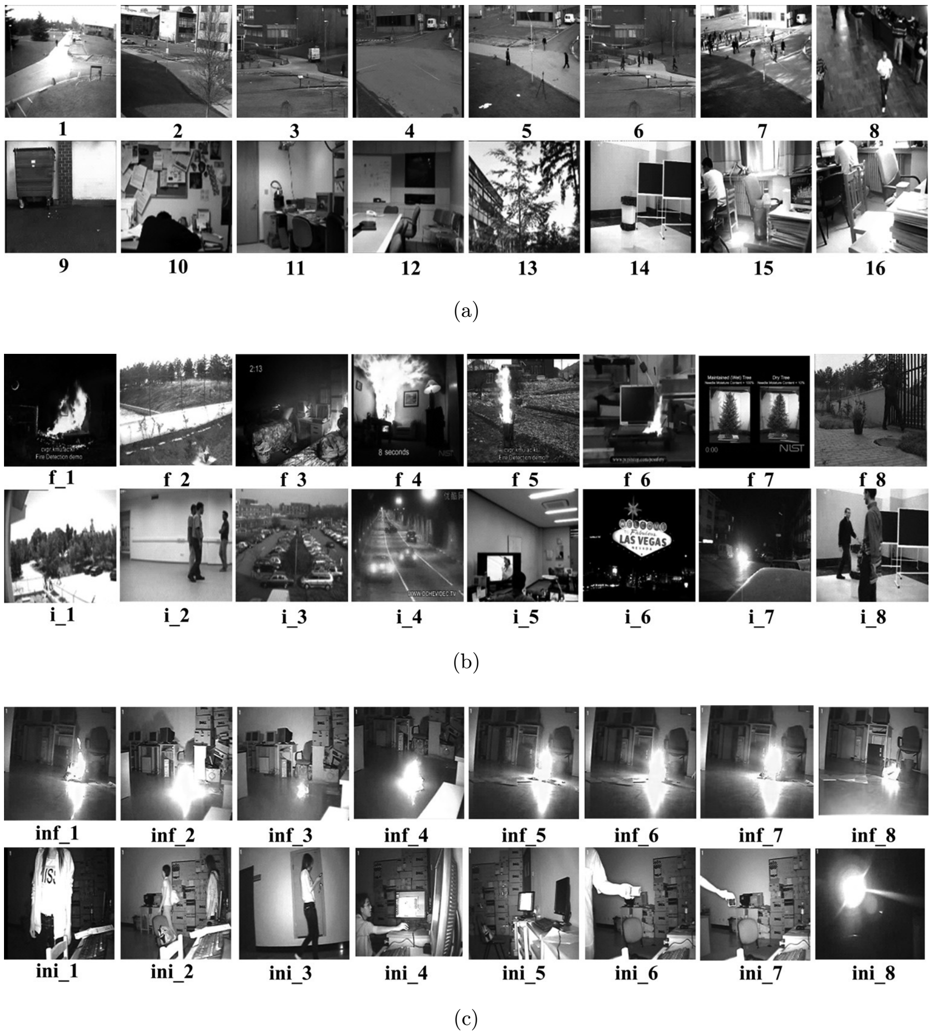

Fig. 3. Test video library. (a) Subclass 1, visible-light test video library. (b) Subclass 2, visible flame and interference test video library. (c) Subclass 3, infrared flame and interference test video library.

infrared test videos (inf_1-inf_8, ini_1-ini_8) in Fig. 3(c). To validate the effectiveness of the proposed approach. Flame detection rate r_+, and false alarm rate of interferences r_- are applied to measure results of algorithms.

To validate the effectiveness of the proposed approach. Flame detection rate r_+, and false alarm rate of interferences r_- are applied to measure results of algorithms.

$$\text{Flame detection rate} : r_+ = \frac{n_f}{n_{tf}}, \tag{11}$$

$$\text{False alarm rate of interference} : r_- = \frac{n_i}{n_{ti}}. \tag{12}$$

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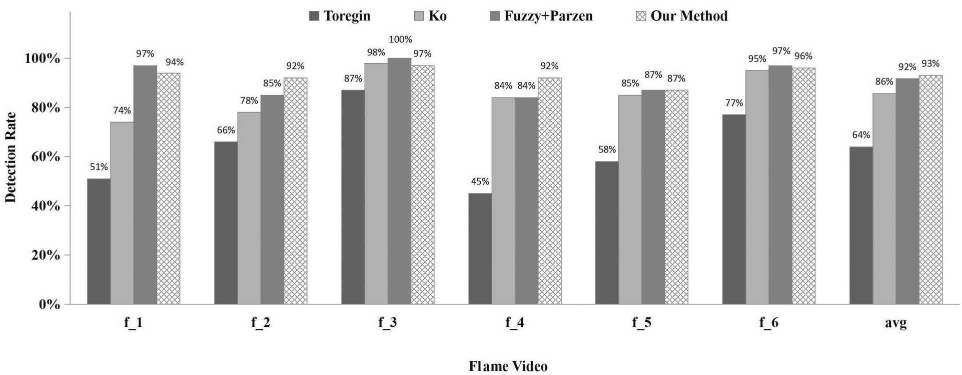
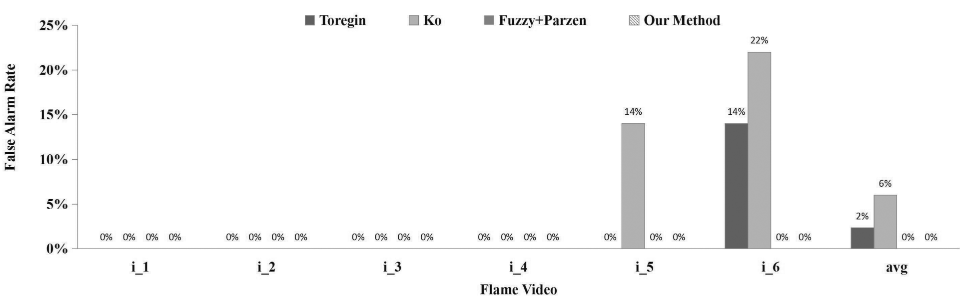
Table 1. Experimental results of VTCA.

Video	Frame Number	Accuracy Rate (%)	Video	Frame Number	Accuracy Rate (%)	Video	Frame Number	Accuracy Rate (%)
1	727	100	*f*_1	329	100	inf_1	2549	100
2	843	99.17	*f*_2	750	100	inf_2	750	99.87
3	727	100	*f*_3	892	100	inf_3	750	99.87
4	270	100	*f*_4	402	98.34	inf_4	1000	99.70
5	1490	100	*f*_5	645	100	inf_5	750	100
6	1490	100	*f*_6	549	100	inf_6	724	100
7	1576	100	*f*_7	2522	99.66	inf_7	775	100
8	5730	100	*f*_8	707	100	inf_8	750	100
9	899	98.99	*i*_1	314	100	ini_1	1250	100
10	3963	100	*i*_2	209	100	ini_2	1225	100
11	5090	100	*i*_3	304	90	ini_3	1300	100
12	3271	100	*i*_4	182	100	ini_4	425	100
13	540	100	*i*_5	540	99.75	ini_5	974	100
14	586	100	*i*_6	662	100	ini_6	924	100
15	2249	100	*i*_7	154	98.79	ini_7	799	100
16	538	100	*i*_8	586	100	ini_8	650	100



(a)



(b)

Fig. 4. Algorithms comparison. (a) Flame Detection Rate, (b) Interference False Alarm Rate, (c) Flame Detection Rate and (d) Interference False Alarm Rate.

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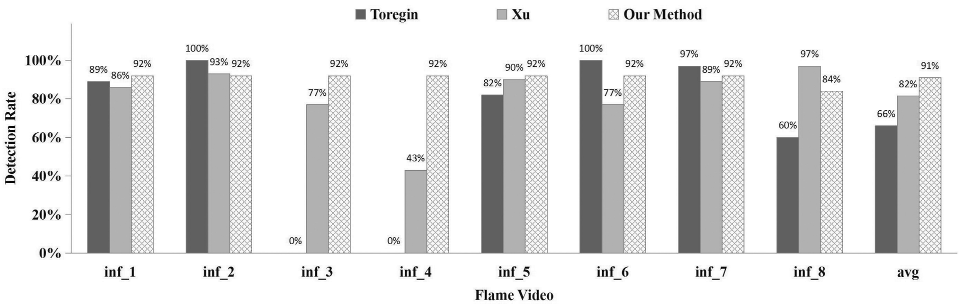
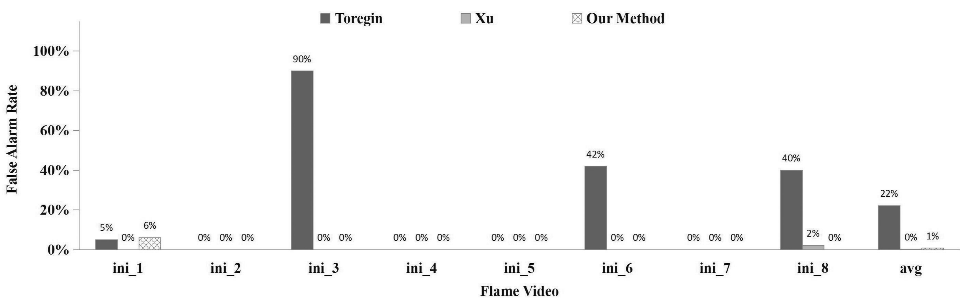


(c)



(d)

Fig. 4. (*Continued*)

5.2. *Results of VTCA*

VTCA can be used under both indoor and outdoor environments, different seasons, different illumination conditions. Table 1 shows the VTCA results of subclass 1 (visible light, different situations), subclass 2 (visible light, f_1 to f_8 are flame videos under both indoor and outdoor environments, and i_1 to i_8 are interference videos) and subclass 3 (infrared, inf_1 to inf_8 are flame videos under both indoor and outdoor environments, and ini_1 to ini_8 are infrared interference videos). Results show that the proposed VTCA is accurate and robust.

5.3. *Results and comparisons*

To evaluate the performance of our algorithm, Ko,[14] Xu[28] and Töreyin's[19,20] algorithms, which have been working well among existing algorithms, were compared with our method. The comparative results are presented in Fig. 4, with (a) and (b) being algorithm comparisons under visible flame and interference videos. In order to compare objectively, we cite part of results from Fig. 9 of Ref. 14. In Fig. 3(a), our methods outperformed Fuzzy+Parzen, Ko and Töreyin's[20] methods with an average flame detection rate (AFDR) of 93% compared to 92%, 86% and 64%, in Fig. 3(b), average interference false alarm rate (AIFAR) of 0% compared to 0%, 6%, and 2%.

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Figures 3(c) and 3(d) are algorithm comparisons under infrared flame and interference videos, in Fig. 3(c), proposed methods outperformed Xu and Töreyin's[1] methods with an AFDR of 91% compared to 82% and 66%, in Fig. 3(d), AIFAR of 0.75% compared to 0.25% and 22%, respectively.

6. Conclusions

In this paper, a flame detection algorithm using Generic Color Model and Improved Block-based PCA in Active Infrared Camera is proposed. Experiments show that the VTCA proposed in our essay gives accurate results. By experimenting on the test video dataset in this paper, the proposed model gets 93% correct rate of flame detection with a 0% false alarm rate in visible videos, and achieves 91% correct rate of flame detection with a 0.75% false alarm rate in infrared videos. The algorithm can make full use of present surveillance system. Afterwards, we will focus on the flame position based on computer vision, and improve the accuracy of extracting FROI.

References

1. P. V. K. Borges and E. Izquierdo, A probabilistic approach for vision-based fire detection in videos, *IEEE Trans. Circuits Syst. Video Technol.* **20**(5) (2010) 721–731.
2. T. Celik and H. Demirel, Fire detection in video sequences using a generic color model, *Fire Saf. J.* **44** (2009) 147–158.
3. M. I. Chacon-Murguia and F. J. Perez-Vargas, Thermal video analysis for fire detection using shape regularity and intensity saturation features, *3rd Mexican Conf. Pattern Recognition* (2011), pp. 118–126.
4. K. H. Cheong, B. C. Ko and J. Y. Nam, Vision sensor-based fire monitoring system for smart home, ICUT2007, *1st Int. Conf. Ubiquitous Information Technology and Applications(Conf.)*, Dubai, UAE, 2007.
5. A. P. Dempster, Upper and lower probabilities induced by a multi-valued mapping, *Ann. Math. Stat.* **38**(2) (1967) 325–339.
6. K. Dimitropoulos, P. Barmpoutis and N. Grammalidis, Spatio-temporal flame modeling and dynamic texture analysis for automatic video-based fire detection, *IEEE Trans. Circuits Syst. Video Technol.* **25**(2) (2015) 339–351.
7. P. Foggia, A. Saggese and M. Vento, Real-time fire detection for video-surveillance applications using a combination of experts based on color, shape, and motion, *IEEE Trans. Circuits Syst. Video Technol.* **25**(9) (2015) 1545–1556.
8. Y. H. Habiboğlu, O. Günay and A. Enis Çetin, Covariance matrix-based fire and flame detection method in video, *Mach. Visi. App.* **23**(6) (2012) 1103–1113.
9. C.-C. Ho, Machine vision-based real-time flame and smoke detection early flame and smoke detection, *Meas. Sci. Technol.* **20**(4) (2009) 045502-1–045502-13.
10. W.-B. Homg, J.-W. Peng and C.-Y. Chen, A new image-based real-time flame detection method using color analysis, networking, sensing and control, tucson, arizona, USA, *IEEE Comput. Soc. Press* (2005), pp. 100–105.
11. J. Hou, J. Qian, W. Zhang and Z. Zhao, Fire detection algorithms for video images of large space structures, *Multimedia Tools. Appl.* **52** (2011) 45–63.
12. W. Jiayun, Real-time visual detection of early manmade fire, *2015 IEEE Int. Conf. Information and Automation* (2015), pp. 993–997.

13. KMU CVPR Lab web page, http://cvpr.kmu.ac.kr/Dataset/Dataset.htm.
14. B. C. Ko, H.-J. Hwang and J.-Y. Nam, Nonparametric membership functions and fuzzy logic for vision sensor-based flame detection, *Opt. Eng.* **49**(12) (2010) 127202-1–127202-11.
15. S.-A. Liu, Z.-B. Zhang, L.-Y. Qi and M. Ma, A fractal image encoding method based on statistical loss used in agricultural image compression, *Multimedia Tools Appl.* **75**(23) (2016) 15525–15536.
16. S.-A. Liu, W.-N. Fu, L.-Q. He, J.-T. Zhou and M. Ma, Distribution of primary additional errors in fractal encoding method, *Multimedia Tools Appl.* **76**(4) (2017) 5787–5802.
17. G. A. Shafer, *Mathematical Theory of Evidence* (Princeton University Press, Princeton NJ, 1976).
18. S.-L. Shen, C.-Y. Yu and F.-N. Yuan, Renovated method for identifying fire plume based on image correlation, *J. Saf. Environ.* **7**(6) (2007) 96–99.
19. B. U. Töreyin, Y. Dedeoglu, U. Gueduekbay and A. E. Çetin, Computer vision based method for real-time fire and flame detection, *Pattern Recogn. Lett.* **27**(1) (2006) 49–58.
20. B. U. Töreyin, R. G. Cinbis, Y. Dedeoglu and A. E. Çetin, Fire detection in infrared video using wavelet analysis, *Opt. Eng.* **46**(6) (2007) 7204–7213.
21. S. Verstockt, A. Vanoosthuyse and S. V. Hoecke, Multi-sensor fire detection by fusing visual and non-visual flame features, *Int. Conf. Image and Signal Processing (ICISP 2010)* (2010), pp. 333–341.
22. Y. Wang and W.-H. Li, High-precision video flame detection algorithm based on multi-feature fusion, *J. Jilin Univ. (Eng. Technol. Ed.)* **40**(3) (2010) 769–755.
23. W. Li, P. Liu, Y. Wang, H. Li, B. Fu and H. Ni, Early flame detection in video sequences based on D-S evidence theory, *J. Comput.* **8**(3) (2013) 818–825.
24. Web page, http://www.hitech-projects.com/euprojects/cantata/datasets_cantata/dataset.html.
25. web page, http://www.fire.nist.gov/tree_fire.htm.
26. webpage, http://signal.ee.bilkent.edu.tr/VisiFire/.
27. M. Wirth and R. Zaremba, Flame region detection based on histogram back projection, *2010 Canadian Conf. Computer and Robot Vision* (2010), pp. 167–174.
28. Z. Xu, B. Han, J.-H. Song and W.-Y. He, Fire detection algorithm based on embedded system using infrared pictures, *Sci. Technol. Eng.* **8**(1) (2008) 96–100.
29. J.-H. Zhang, J. Zhuang, H.-F. Du and S.-A. Wang, Flame detection algorithm based on video multi-feature fusion, *J. XI'AN Jiao Tong Univ.* **40**(7) (2006) 811–814.

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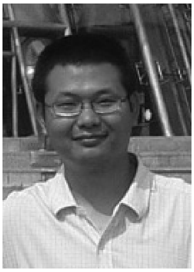

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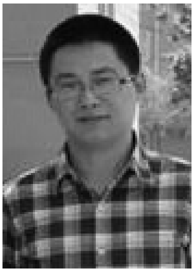

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