Video-Based Early Flame Detection for Vessels by Using the Fuzzy Color Clustering Algorithm

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ABSTRACT

This paper presents a video-based flame alarm detection method for vessels to detect the flames by using clustering algorithm. First, the dominant flame color lookup table (DFCLT) is created by using the fuzzy c-means clustering algorithm. Then, the changed video frames are automatically selected, and the changed regions are figured out from these frames. Finally, we announce elementary, medium, or emergency flame alarms by comparing the pixels of changed regions with the DFCLT. The experimental results indicate that the proposed flame detection approach can detect dangerous flames, effectively and efficiently.

1: INTRODUCTION

A vessel fire results in severe damage to the ship's equipments and injury to the people once the fire can not be detected and extinguished in time. Though new generation vessels are equipped with fire detecting facilities, such as a smoke sensor, a relative humidity sensor, and a temperature sensor, these equipments are easy to be fault alarm. Furthermore, the fire could not be immediately detected if it is far from the sensor, and the process of firing can not be recorded. To overcome the drawbacks of the traditional fire detecting equipments, the video-based flame alarm system is developed.

Noda and Ueda [1] use gray-scale images obtained from infrared cameras to detect flame in tunnels. Foo [2] presents methods for detecting flame in aircraft dry bays and engine compartments from gray-scale images. Color constitutes a powerful visual information and be used for the video-based flame detection algorithms. Healey et al. [3] present a flame detection system using color video input for a pre-allocated view on some ideal conditions. Yamagishi and Yamaguchi [4] also proposed a flame detection algorithm for color images based on the HSV color space and artificial neural networks. To reduce false flame alarms, in addition to the color feature, the characteristic of variation among contiguous frames is also considered. Phillips et al. [5] use color and motion information to locate flame. Chen et al. [6] apply decision rule method of color to distinguish flame pixels, and use the characteristics of growth and disorder of fire pixels to raise a flame alarm. In [7], a color histogram is used to detect moving fire pixels, and a wavelet domain approach is used to determine the temporal high-frequency activity in a pixel. However, the methods to locate flame regions and analyze its variation are complicated, and none of them can distinguish the burning degree of flame. Though [8] uses the variation of flame contours to estimate the burning degree of flames, two thresholds must be carefully selected.

To address the aforementioned problems, this paper presents a video-based flame alarm system for vessels to detect the flames by using clustering algorithm. The proposed method is composed of two parts: the DFCLT creation, and the dangerous flame detection. First, the DFCLT is created by using the fuzzy c-means clustering algorithm. Then, the changed regions are figured out from the changed video frames, and an elementary, medium, or emergency flame alarm is issued by comparing the pixels of changed regions with the DFCLT. The experimental results indicate that the proposed flame detection approach can detect dangerous flames, effectively and efficiently.

In the following section, the steps of the DFCLT creation are detailed. The dangerous flame detection approach is elaborated in Sec III. In Sec. IV, the experimental results are presented and analyzed. In the last section, we conclude this paper with possible research directions.

2: THE DFCLT CREATION APPROACH

To acquire the DFCLT for vessels, the video sequences of burning process are taken in a vessel under safety control. The burning materials are selected from paper, sawdust, pillows, gasoline, and diesel fuel, which are commonly used in a vessel. Ten firing video sequences are taken under lighting and unlighted circumstances from those materials. As illustrated in Fig. 1, the creation process of the DFCLT is composed of three phases: the frame selection phase, the region selection phase, and the fuzzy color clustering phase. Detail processes are described as follows:

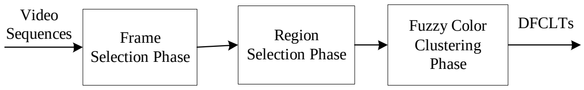


Fig. 1. The creation process of the DFCLT.

2.1: FRAME SELECTION PHASE

An early firing image and a fully firing image are selected from each video sequence. Therefore, twenty images are manually selected from the aforementioned ten video sequences. As shown in Fig. 2, (a), (b), (c), (d), and (e) are the firing images of paper, sawdust, pillows, gasoline, and diesel fuel, respectively. The early firing images are depicted in (a1), (a3), (b1), (b3), (c1), (c3), (d1), (d3), (e1), and (e3). The fully firing images are described in (a2), (a4), (b2), (b4), (c2), (c4), (d2), (d4), (e2), and (e4).

2.2: REGION SELECTION PHASE

To acquire the fire pixels precisely, fire regions are manually cropped as shown in Fig. 2 (r1), (r2),…, and (r20). We obtain 321,435 fire pixels to create the DFCLT.

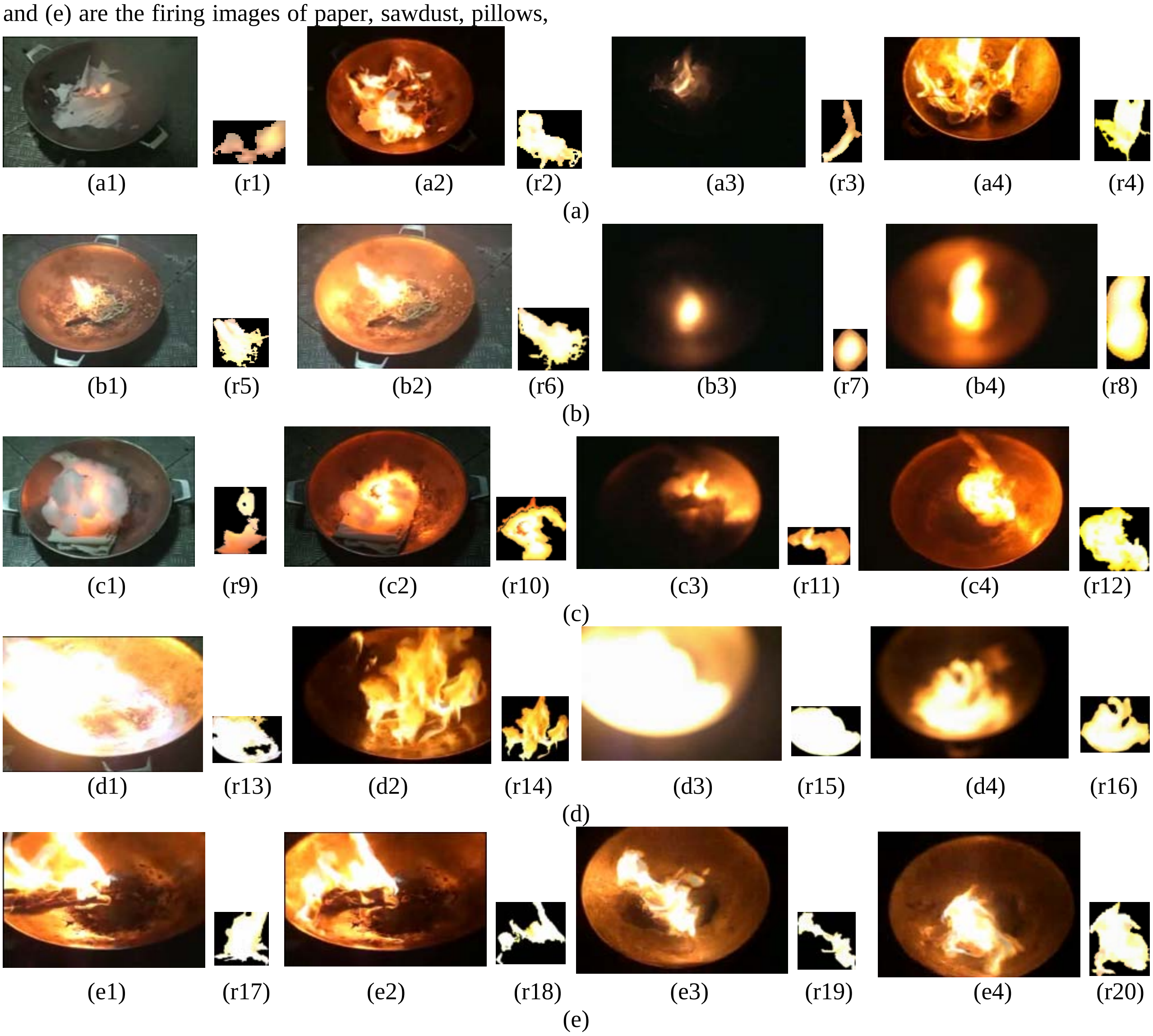


Fig. 2. The firing images and regions of (a)paper (b)sawdust (c)pillows (d)gasoline (e)diesel fuel.

2.3: FUZZY COLOR CLUSTERING PHASE

In this phase, the fuzzy c-means (FCM) algorithm is used to group pixels into clusters [9] according to RGB color features. The FCM_based clustering procedure iteratively minimizes the criterion function as shown in (A1). A detailed description of the clustering algorithm is given as follows:

The FCM Clustering Procedure

// The input values are RGB color features.
// The output values are clusters with pixels.
// *c* represents the number of clusters, *w* the exponential weight, and

//μ_{ik} ‘s (i=1,…,c, k=1,…,n) the membership values
Initialize parameters c and w; and then assign values to μ_{ik} ‘s using either a random function or an approximation method.
Do
    For each cluster c, update center using (A3) and
    μ_{ik} ‘s using (A2);
Until (all centers are stabilized)
Assign pixels to one cluster according to μ_{ik}’s.

In the simulation, w is 1.5, and c is set from 5 to 12. To distinguish the elementary, medium, or emergency fire-alarm, and to concern the computational complexity, five clusters (i.e. dominant fire colors) are accommodated to the proposed method. Table 1 demonstrates the DFCLT for vessels.

Table 1. The DFCLT for vessels.

	R	G	B
1	232	146	65
2	248	195	89
3	249	236	128
4	249	247	189
5	252	252	249

3: THE DANGEROUS FLAME DETECTION

Fig. 3 shows the process of the proposed dangerous flame detection approach. First, the changed video frames are automatically selected. Then, the changed regions are figured out from these frames. Finally, we announce elementary, medium, or emergency dangerous flames by comparing the pixels of changed regions with the DFCLT. Detail processes are described as follows:

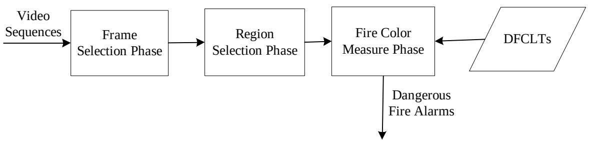


Fig. 3. The process of dangerous flame detection.

3.1: FRAME SELECTION PHASE

The luminance of video frames is increasing from non-flame to flame alarms issued. First, all video frames are converted to gray level images, and a smoothing filter is used for noise reduction. Second, a non-flame image is assigned to the reference image (I_0), and difference images (ID_1, ID_2,…) are obtained from the subtraction of consecutive images (I_1, I_2,…) and the reference image. Then, difference images are converted to binary images where 1 represents the pixel of changed region, and 0 represents the pixel of background. Finally, changed images are selected while the pixel number (PN) of 1 is greater than the threshold value of Ta. The experimental value of Ta is 25 pixels.

3.2: REGION SELECTION PHASE

In this phase, regions are segmented according to the selected binary images by using 8-adjacency connected components. We inspect each pixel of the binary image with value 1 by using 8-adjacency connected components from left to right, top to bottom. The changed regions are segmented as show in Fig. 4. Finally, the fire pixels of each region are obtained by the convolution of segmented binary image and selected image.

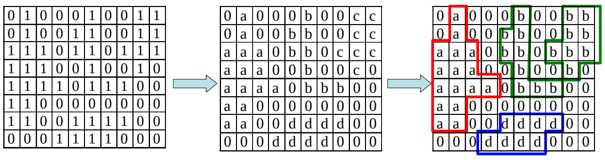


Fig. 4. The example of region segmentation.

3.3: FIRE COLOR MEASURE PHASE

We announce elementary, medium, or emergency dangerous flames by comparing the pixels of changed regions with the DFCLT. If the pixels of region belong to less than and equal to two dominant flame colors, non-flame alarm is issued for the region, e.g., the flame of lighter or candle. If the pixels of region belong to 3, 4, or 5 dominant flame colors, the elementary, medium, or emergency flame alarm is issued for the region, respectively. There are two steps to decide whether the pixel is belongs to the DFCLT.

First, pixel is temporarily assigned to one dominant color of DFCLT where the Euclidean distance between pixels of selected region and the dominant color of DFCLT is minimum as shown in (1), and the pixel is in the range of the dominant color. The range of each dominant color is computed as a circle where the center is

$$D_i(Q_i, I_j) = \sqrt{(Q_{Ri} - I_{Rj})^2 + (Q_{Gi} - I_{Gj})^2 + (Q_{Bi} + I_{Bj})^2} \qquad (1)$$

where $I_j=\{R_j,G_j,B_j\}$,j=1,2,…,n, is the pixels of selected region, $Q_i=\{R_i,G_i,B_i\}$, i=1,2,3,4,5, the values of the DFCLT.

Second, we check the assigned pixel whether it is in the range of the dominant flame color. The range of each dominant color is computed as a circle where the center (d_i) is the dominant flame color, and the radius (Rm_i) is the distance between the color of pixel and center. As shown in Fig. 5, though the sample pixel is near the fifth dominate flame color, it does not belong to any dominate flame color of the DFCLT for the reason of out of range of all dominate flame colors.

Only the region with the largest number of fire pixels represents the changed image. The number of the dominant flame colors of the changed frame decide which degree of flame alarm will be issued.

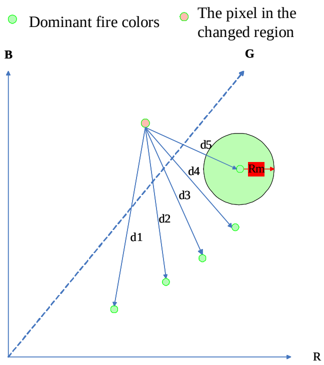


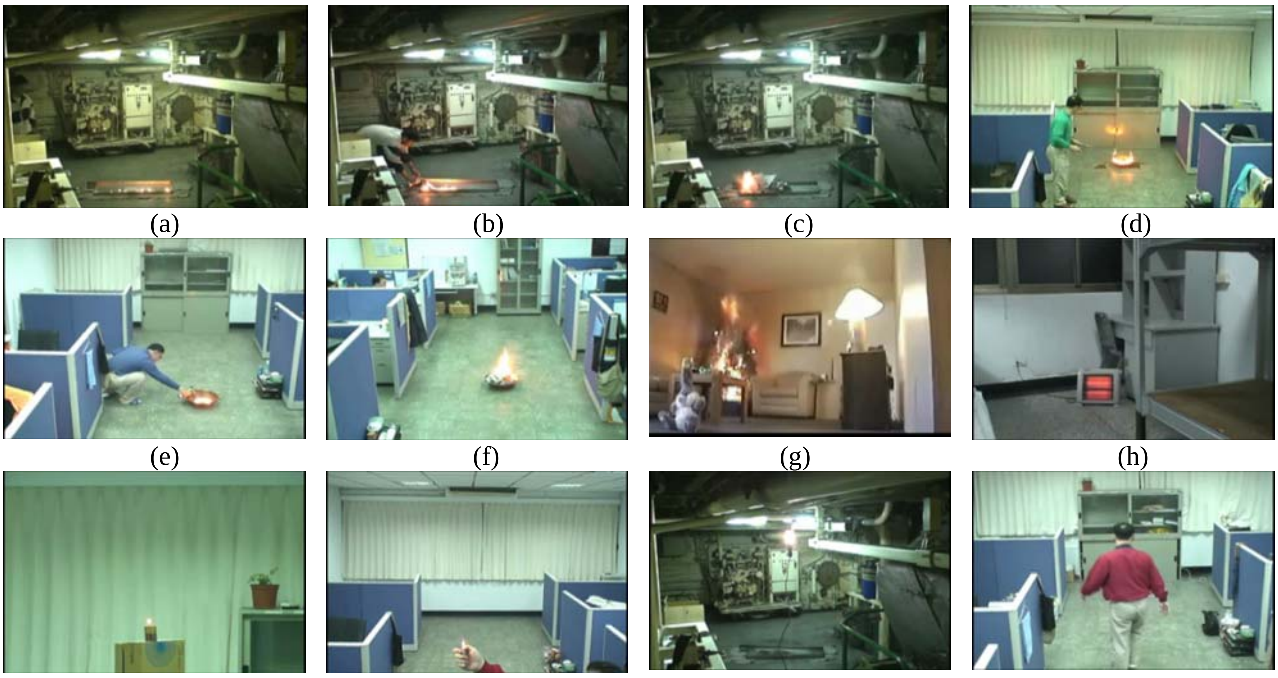
Fig. 5. The distance between the sample pixel and the dominate flame colors.

4: EXPERIMENTAL RESULTS AND ANALYSIS

The experimental environment is depicted as follows:

– Personal Computer : CPU-Pentium III 3.0G, RAM=1GB, Hard Disk=200GB
– Operation System : Window XP
– Development Tool : Matlab 7.0
– Image and Video Editing Tools : Photoshop 7 and Premiere Pro 1.5
– Camera : Single Static Camera, SONY PC-350

The experimental database consists of 16 video sequences which the frame rate is 30 frames per second, and the size is 720 by 480 pixels. To verify the early flame detection of the proposed method, the content of test firing video sequences must record the complete process of burning. However, these fire video sequences are not easily acquired. Most of the test video sequences are captured by ourselves under safety control. Only the video of burning Christmas tree is referred to [10]. The distance between the camera and the flame is at least three meters. The key-frames of the 12 video sequences for flame alarm detection are depicted as Fig. 6. Video sequences (a), (b), and (c) are made from the burning of gasoline, diesel fuel, and paper in a vessel, respectively. Video sequences (d), (e), and (f) are made from the burning of gasoline, diesel fuel, and paper in an indoor room, respectively. The content of video sequence (g) is the burning Christmas tree obtained form [10]. Video sequences (h), (i), (j), (k), and (l) are made from lighting up a candle and a lighter, turning on an electric radiator and a bulb, and a walking person with a red coat, respectively.



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)

Fig. 6. The key-frames of the 12 video sequences for flame alarm detection.

For the proposed method, the elementary, medium, or emergency flame alarm is issued while the pixels of changed regions conform to 3, 4, or 5 dominant flame colors of DFCLT. The dangerous flame detection results of the proposed method for the 12 video sequences as shown in Fig. 6 are depicted in Fig. 7.

The comparison of the proposed method and the decision rule method [5] for flame detection is shown in Table 2. For the dangerous firing video sequences 1 to 7, the proposed method can all distinguish flame alarm to elementary, middle, or emergency level of fire except the video sequence 4. Because the burning process of gasoline in the video sequence 4 is violent, the middle fire alarm is direct issued. On the contrary, the decision rule method can not detect flame for the video sequences 1, 3, 4, and 6. The reasons are that the growing rule is failed for the rapid and violent burning, e.g., the burning of gasoline in video sequences 1 and 4, and the variable rule is lost for the slowly burning, e.g., the burning of paper in video sequences 3 and 6. Furthermore, the real early flame in the video sequences 2 and 5 is near frame 453 and 720, respectively. It is verified that the proposed method is more suitable for the early flame detection than the decision rule method. For the non-flame video sequences 8, 9, 10, 11, and 12, the proposed method does not issued any flame alarm. On the contrary, a false flame alarm is made in the video 8 by the decision rule method.

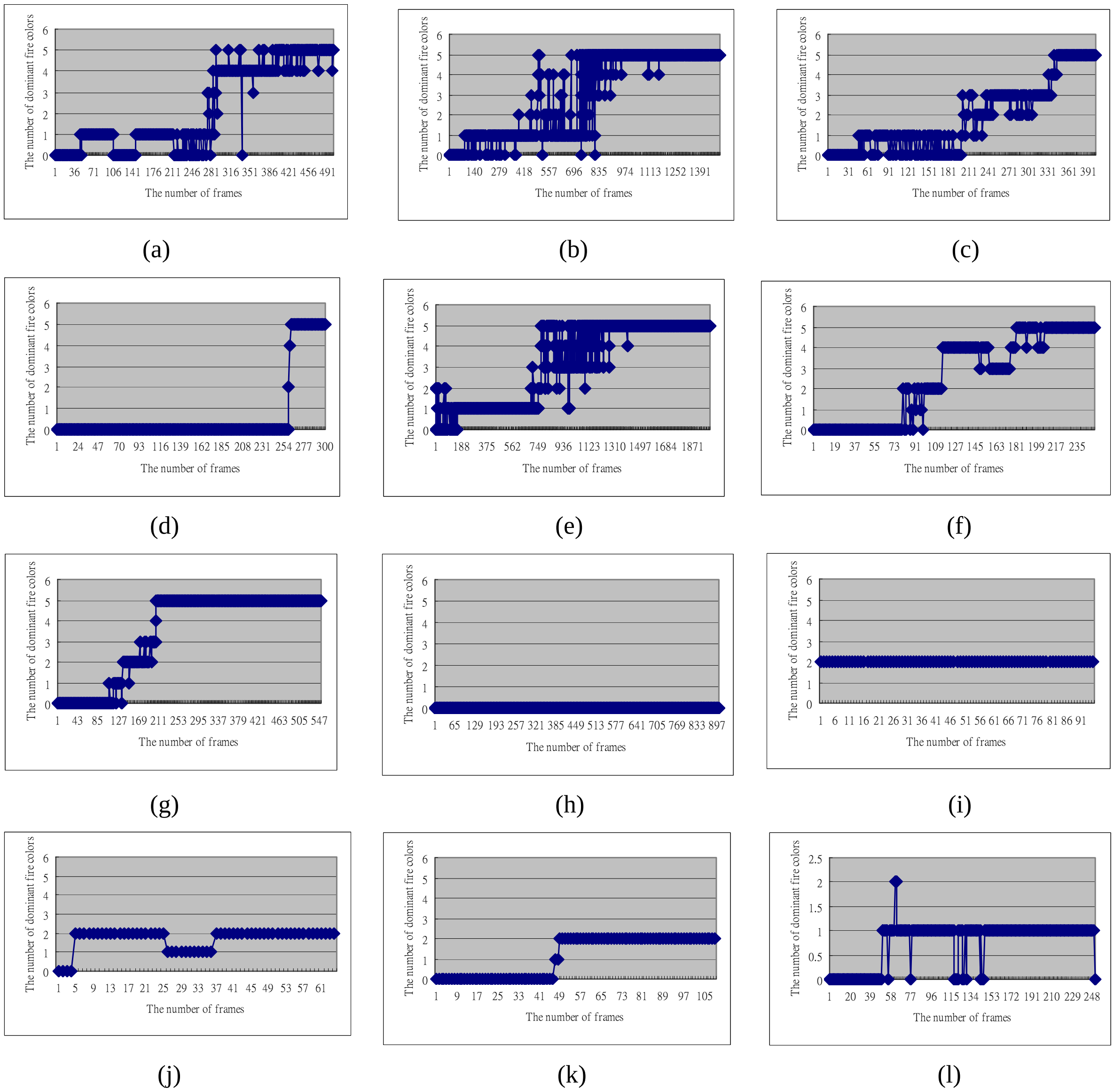


Fig. 7. The dangerous flame detection results of the proposed method for the 12 video sequences as shown in Fig. 6

5: CONCLUSION

In this paper, we proposed the FCM clustering algorithm to create the DFCLT for dangerous flame detection in a vessel, and three degree of flame alarms, elementary, middle, and emergency, are issued. The proposed method outperforms the decision rule method for the reducing of false flame alarms, and detecting of flame alarms, early and correctly.

Here we would like to mention the following areas of investigation which may merit further study.

1) Adjust the proposed method for panned cameras or multiple cameras to extend the detection area.
2) Combine the characteristics of color, shape, texture, and spatial relationships to improve the performance.
3) Apply the proposed method to other applications, such as to distinguish the ion of burning metal according to the burning flame color in Chemistry.

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Table 2. The comparison of the proposed method and the decision rule method for dangerous flame detection.

Video sequences	Length of Video	The proposed method			Decision rule method [5]	Video description
		Elementary flame alarm	Middle flame alarm	Emergency flame alarm		
1	500	275	284	290	X	Burning of gasoline in a vessel
2	1500	453	494	502	871	Burning of diesel fuel in a vessel
3	400	202	331	339	X	Burning of paper in a vessel
4	500	X	261	262	X	Burning of gasoline in an indoor room
5	2000	710	769	772	241	Burning of diesel fuel in an indoor room
6	250	148	115	181	X	Burning of paper in an indoor room
7	550	170	172	207	311	Burning of a Christmas tree
8	900	X	X	X	882	Turn on a warmer
9	95	X	X	X	X	Light a candle
10	65	X	X	X	X	Light a lighter
11	110	X	X	X	X	Lighting a lamp
12	250	X	X	X	X	People walking with a red coat

"X" represents no dangerous flame alarm

REFERENCES

[1] S. Noda, K. Ueda, "Fire detection in tunnels using an image processing method", IEEE Proceedings on Vehicle Navigation and Information Systems Conference, pp. 57-62, 1994.

[2] S. Y. Foo, "A machine vision approach to detect and categorize hydrocarbon fires in aircraft dry bays and engine compartments", IEEE Trans. Industry Applications, vol. 36, pp. 549-566, March/April 2000.

[3] G. Healey, D. Slater, T. Lin, B. Drda, and A. D. Goedeke, "A system for real-time fire detection", IEEE Proceedings on Computer Vision and Pattern Recognition(CVPR) , pp. 605-606, June 15-17, 1993.

[4] H. Yamagishi and J. Yamaguchi, "Fire flame detection algorithm using a color camera", in Proc. Int. Symp. Micromechanics and Human Science, pp. 255-260, 1999.

[5] Walter Phillips III, Mubarak Shah, and Niels da Vitoria Lobo, "Flame recognition in video", Pattern Recognition Letters, Vol. 23, Issue. 1-3, pp. 319-327, January 2002.

[6] T. H. Chen, P. H. Wu, and Y. C. Chiou, "An Early Fire-Detection Method Based on Image Processing ", IEEE International Conference on Image Processing (ICIP), vol. 3, pp.1707 - 1710, Otc. 2004.

[7] Y. Dedeoglu, B. U. Toreyin, U. Gudukbay, and A. E. Çetin, "REAL-TIME FIRE AND FLAME DETECTION IN VIDEO", IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), pp. 669-672, March 2005.

[8] W. B. Horng, J. W. peng, and C. Y. Chen, "A New Image-Based Real-Time Flame Detection Method Using Color Analysis", IEEE International Conference on Networking, Sensing and Control, Tucson, Arizona, USA, pp. 100-105, March 2005.

[9] A. K. Jain and R. C. Dubes, "Algorithms for Clustering Data", Prentice-hall, 1998.

[10] U.S. Fire Administration working for a fire-Safe America， " Holiday Fire Prevention "， http://www.usfa.fema.gov/safety/tips/treefir.shtm。

APPENDIX. FUZZY C-MEANS

The purpose of FCM [21] is to minimize the object function J(U,V):

$$J(U,V)=\sum_{i=1}^{c}\sum_{k=1}^{n}\mu_{ik}^{w}\left|\mathrm{x}_{\mathrm{k}}-\mathrm{v}_{\mathrm{i}}\right|^{2} \quad \text{(A1)}$$

where, c represents the number of clusters, n the number of data items, w the exponential weight, $\mathbf{X}=\{x_1,x_2,x_3,\ldots,x_n\}$ an n-dimensional data vector, V= $\{v_1,v_2,\ldots,v_c\}$ a vector of dimension c, U=(μ_{ik}) a $c*n$ matrix, where μ_{ik} represent the membership value of vector x_k in cluster i, and

$$0\leqq\mu_{ik}\leqq 1 \qquad i=1,2,\ldots,c;\ k=1,2,\ldots,n$$

$$\sum_{i=1}^{c}\mu_{ik}=1 \qquad k=1,2,\ldots,n$$

$$0\leq\sum_{k=1}^{n}\mu_{ik}\leq n \qquad i=1,2,..,c.$$

The minimization of the objective function with respect to membership values leads to

$$\mu_{ik}=\frac{\left[\dfrac{1}{\left|x_k-v_i\right|^2}\right]^{1/(m-1)}}{\sum_{j=1}^{c}\left[\dfrac{1}{\left|x_k-v_j\right|^2}\right]^{1/(m-1)}}$$

$$i=1,2,\ldots,c;\ k=1,2,\ldots,n. \quad \text{(A2)}$$

The minimization of the objective function with respect to the center of each cluster gives rise to the following equality

$$\mathrm{v}_{\mathrm{i}}=\frac{\sum_{k=1}^{n}\mu_{ik}^{m}x_{ik}}{\sum_{k=1}^{n}\mu_{ik}^{m}} \qquad i=1,2,\ldots,c. \quad \text{(A2)}$$