Early Flame Detection in Video Sequences based on D-S Evidence Theory

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***Abstract*—A multi-feature fusion early flame detection algorithm based on D-S evidence theory is proposed. In this algorithm, first the method based on YcbCr and RGB color spaces is used for extracting the flame region of interest. Then flame classifiers based on flame flicker frequency and flame image correlation between frames are selected as two features of D-S feature fusion, the basic probability assignment functions of two features are defined. Finally, the combination discipline of D-S evidence theory is used to determine the final result of all the feature classifiers. Experiments show that the proposed detection algorithm gives 89.5% correct flame rate with a 4.5% false alarm rate and the method is efficient and fast with wide application prospects in fire detection.**

***Index Terms*—computer vision, fire detection, feature fusion; D-S evidence theory**

I. Introduction

Due to the rapid developments in video monitoring system and computer vision techniques, computer vision-based flame detection systems have been got more and more attentions all over the word. Currently, researches of flame detection based on video always focus on following features which are widely applied on flame detection both domestic and overseas: fleam color features, fleam morphological features, fleam dynamic features and the combinations of these features. Definitely, color features are widely used in fire detection systems based on video which apply different color spaces [1]. Toereyin et al. [3] employed raw R, G, and B information and developed a set of rules to classify the flame pixels along with motion information and Markov field modeling of the flame flicker process. Wang Ying et al. [5] used combinations of RGB and HSV and YCbCr color models for the representation of fire region of interest, then use the feature of fire correlation between frames, experiments proved that the algorithm has very good efforts, which can completely extract fire area and reduce the interferences from changes of brightness in images. Zhang et al. [9] applied combination of color feature and fire flicker feature from time series analysis of fire high changes. Cheong et al. proposed a new vision sensor-based fire monitoring system apply two additional methods to candidate fire pixels, luminance map and Support Vector Machine (SVM).removed non-fire pixels using the luminance map make a temporal fire model for two-class SVM classifier with radial basis function (RBF) kernel [10]. Chao-Ching Ho et al. used temporal probability density which 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 is employed to provide feedback of the flame and smoke real-time position at a high frame rate [11]. B. Ugur Töreyin et al. [12] extracted the flame region of interest (FROI) through flame motion feature and luminance detection, and then wavelet analysis and variation analysis of temporal information were employed to confirm the existence of flame.

There are still plenty of problems needed to be solved in the vision-based fire detection technology: (1) Characteristics of flame pixels in visible image and infrared image are different, so it is hard to extract the FROI accurately through the same method or algorithms based on flame color features. (2) There are many disadvantages of single feature flame detection. Static characteristics of the flame: Although the color feature detection using a simple model, false detection rate of interference videos is high, and can only detect red or yellow flame, hardly rule out interferences which is similar with flame and requirements of equipment is high.

Manuscript received January 6, 2012;
Nation Nature Science Foundation: No 60873147; Science and Technology Development Program of Jilin Province: No 20060527
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doi:10.4304/jcp.8.3.818-825

Dynamic feature of the flame always detect after the detections of static characteristics, so results of them depend on the accuracy rate of FROI extraction. (3) Combinations of features are applied in fire detection field. Voting method is widely used to reduce interferences. But, flame detection sensitivity is also reduced accordingly. Can't meet the requirements of engineering application which need the high detection rate is and low false detection rate.

In this paper, early fleam detection in video sequences based on Dempster [13]-Shafer [14] (D-S) evidence theory is proposed, we apply the YCbCr and RGB color spaces to construct a generic chrominance model for flame pixel classification. Most of the works on flame pixel classification in color video sequences are rule based Turgay Celik [2], Wang [5] and Shen [6]. Then two flame detection algorithms of different features which based on flame flicker and flame image correlation were used as classifiers. Finally the results of two classifiers are integrated through the D-S evidence theory. Experiments shows that the proposed model gives 89.5% correct flame rate with a 4.5% false alarm rate. This is a significant improvement over other methods used in the literature.

II. Flame Region of Interest Extraction

Improving the accuracy of flame region of interest extraction can significantly improve the detection rates of subsequent flame feature detection algorithms. Color feature is an essential feature of the flame, which is often used to extract the FROI of video sequences. We experiment three different FROI algorithms, and test different rules of flame extraction, whose color space are RGB [1][3], YcbCr[2], HSI[3]. Comparison of results is shown in Figure.1. The best rules are selected to extract flame (Rule1-Rule6).

$$\begin{cases} \text{Rule1:}\ \ R \ge G \ge B, \\ \text{Rule2:}\ \ R \ge R_{mean} \\ \text{Rule3:}\ \ Y(x,y) > Cb(x,y), \\ \text{Rule4:}\ \ Cr(x,y) > Cb(x,y), \\ \text{Rule5:}\ \ F_\tau(x,y) = \begin{cases} 1 & if \quad \begin{matrix} Y(x,y) > Y_{mean}, \\ Cb(x,y) < Cb_{mean}, \\ Cr(x,y) > Cr_{mean} \end{matrix} \\ 0 & \text{otherwise} \end{cases} \\ \text{Rule6:}\ \ F_\tau(x,y) = \begin{cases} 1 & if\ |Cb(x,y) - Cr(x,y)| \\ & \ge \tau \\ 0 & \text{otherwise} \end{cases} \end{cases} \tag{1}$$

$$Fire\_Fr_n(x_i) = \begin{cases} 255 & Rule1 - Rule6 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

For a given image, we can define the mean values of the four components in RGB and YCbCr color space as

$$R_{mean} = \frac{1}{K}\sum_{i=1}^{K} R(x_i, y_i)$$

$$Y_{mean} = \frac{1}{K}\sum_{i=1}^{K} Y(x_i, y_i)$$

$$Cb_{mean} = \frac{1}{K}\sum_{i=1}^{K} Cb(x_i, y_i) \tag{3}$$

$$Cr_{mean} = \frac{1}{K}\sum_{i=1}^{K} Cr(x_i, y_i)$$

where (x_i, y_i) is the spatial location of the pixel, R_{mean}, Y_{mean}, Cb_{mean}, and Cr_{mean} are the mean values of red, luminance, ChrominanceBlue, and ChrominanceRed channels of pixels, and K is the total number of pixels in image. τ is a constant value which is used to distinguish the flame and inferences from analyzing a variety of images including ones with changing illumination and lighting. Furthermore, the images are selected so that fire-like colored objects are also included in the set. They are collected from the internet and test video library. Images are both indoor and outdoor environments.

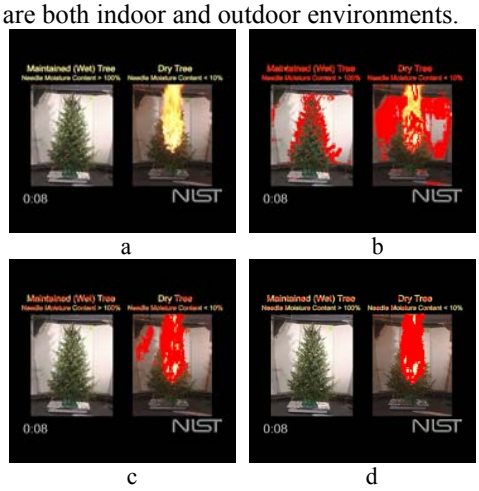

Figure 1. Comparison of suspected flame area extraction algorithms

(a) Original image, (NIST "comparison_wetdry.avi" frame 350th) (b)red regions is FROI which is extracted by the rules of HSI color model based methods of Wen-Bing Homg [3], (c)red regions is FROI which is extracted by methods of K.H. Cheong [1] (d) red regions is FROI which is extracted by Eq. (1) and (2).

III. A Novel Representation of Irregular Rectangles

A. Feature Based on Flame Flicker Frequency

Flame flicker feature is one of common flame characteristics used in fire detections. As we all known, flame height changes violently when flame flickering. There is a link between flame height changing frequency and flame flicker frequency. Most interference as walking people wearing red coat and sun in images doesn't have this feature. Based on method of [7], firstly connected domains of FROI and heights of their minimum enclosing rectangles are calculated. Then heights are stored in the flame height sequence HN. Finally, Discrete Cosine Transform (DCT) is applied on HN. For a certain height sequence, $h_i(n) = H\left(C_i^N\right)$, it's DCT model is defined as

$$A_i(0)=\frac{1}{\sqrt{N}}\sum_{n=0}^{N-1}h_i(n) \tag{4}$$

$$A_i(k)=\sqrt{\frac{2}{N}}\sum_{n=0}^{N-1}h_i(n)\cos\frac{(2n+1)k\pi}{2N}, \quad k=1,\ 2,\ 3,\ \cdots,\ N-1 \tag{5}$$

where H^N is height sequences of FROI sequences C_i^N. There could be several FROI in a frame, i stands for the number of FROI, and N is the size of sequences. Fire events occur in succession, and interferences may happen intermittently and randomly. Variances of $A_i(k)$ is more distinguishable than employing only $A_i(k)$ in flame detection. Flame model based on flame flicker feature is defined as follow, where l is the length of flame height of DCT model (FHDCTM) sequence.

$$f_d(A_i)=\sum_{k=1}^{l-1}\frac{A_i(k)*A_i(k)}{l-1} \tag{6}$$

B. Feature Based on Flame Image Correlation Between frames

Research shows that flame has continuous oscillation feature because of influences from gas plume entrainment and air flow. Based on this feature, we employ Shen's [6] method as a classifier of fusion method based on D-S evidence theory. the base theory of image correlation is:

$$C(n_1,n_2)=\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}X_k(x,y)X_{n+k}(x+n_1,y+n_2) \tag{7}$$

For a series of images, $X_k(x,y)$ is the intensity of pixel (x, y) in the kth frame N1, N2 is the width and height of image, n1, n2 describe offsets. Eq.8 is used for the normalization of Eq.7 in order to rule out the noises between frames.

$$\bar{C}(n_1,n_2)=\frac{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}\left[X_k(x,y)-\bar{X}_k\right]\cdot\left[X_{N+k}(x+n_1,y+n_2)-\bar{X}_{N+k}\right]}{\sqrt{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}\left[X_k(x,y)-\bar{X}_k\right]^2}\cdot\sqrt{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}\left[X_k(x,y)-\bar{X}_{N+k}\right]^2}} \tag{8}$$

where $\bar{X}_k$, $\bar{X}_{N+k}$ is the mean intensity value of all pixels in the kth and N+kth frame. N is the length of correlation value sequence.

$$\bar{X}_k=\frac{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}X_k(x,y)}{N_1\times N_2},\quad \bar{X}_{n+k}=\frac{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}X_{N+k}(x,y)}{N_1\times N_2} \tag{9}$$

Eq.10 is the correlation value when $n_1=0,n_2=0$ in Eq.8 which are used in detecting flame.

$$\bar{C}(0,0)=\frac{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}\left[X_k(x,y)-\bar{X}_k\right]\cdot\left[X_{N+k}(x,y)-\bar{X}_{N+k}\right]}{\sqrt{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}\left[X_k(x,y)-\bar{X}_k\right]^2}\cdot\sqrt{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}\left[X_k(x,y)-\bar{X}_{N+k}\right]^2}} \tag{10}$$

IV. Flame Detection Algorithm of Multi-Feature Fusion base on D-S Evidence Theory

We define environment Θ={everything in a frame of video sequence}={flame, smoke, Christmas tree et.al}. Definitely, the environment is a mutually exclusive set and the elements of which is limited. Ignorance hypothesis and contradiction hypothesis needn't to be given a certain trust value. Rather than give the Mass to the subsets or elements which you want to assign. In this paper we give the Mass to the flame event of video. And the others of Mass assign to the entire environment. There may be some flame events that not be assigned trust value. Therefore, the employment of D-S evidence theory can allocate trust value to the flame which is not be detected by classifiers. Due to this the correct flame detection rate of proposed method is higher than other flame detection algorithms. We introduce the process of our method as follow.

Process 1: The basic probability assignment of Feature1-flame Detection algorithm based on flame flicker

Step 1. Find the max area of connected domains of FROI in N consecutive frames.

Step 2. Calculate the variances of all values in flame height of DCT model (FHDCTM) sequences by using Eq.5.

Step 3. If the value of max area in Step1 is zero or flame height sequence H^N is not fulfilled, then Set FHDCTM value of current frame to 0, store it in FHDCTM sequence.

Step 4. DCT processing for flame height sequence H^N, store it in FHDCTM sequence.

Step 5. Calculate the variances of FHDCTM of current frame (results of Step 4) by using

$$fh=\sum_{i=1}^{l-1}\frac{H(i)^2}{\text{maxArea}}$$

where l is length of H^N, H (i) is the ith value of H^N.

Step 6. if the variances of FHDCTM of current frame is greater than a fixed threshold then it shows there is flame in current frame, and return 1.

Step 7. Store the return value of Step6 in sequence F^N.

Step 8. The basic probability assignment functions of Feature1:

$$\begin{cases} Mass_{dct}(Fire)=\dfrac{n_{dct}}{l_{dct}}, if \quad \text{variances}>\tau_{dct} \\ Mass_{dct}(\Theta)=\dfrac{l_{dct}-n_{dct}}{l_{dct}}, if \quad \text{variance}\le\tau_{dct} \end{cases} \tag{11}$$

where l_{dct} is the length of F^N, and n_{dct} is the numbers

of elements whose value is 1 in F^N after Step7 .

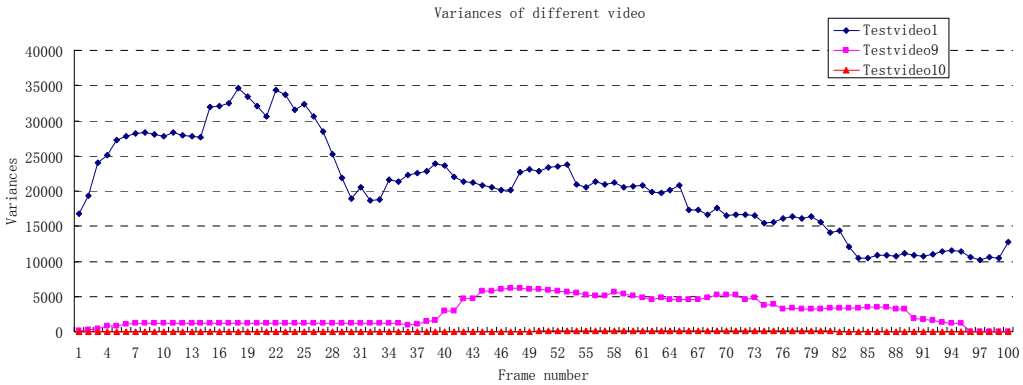

Figure 2. Variances comparison of different videos

Process 2: The basic probability assignment of Feature2-flame Detection algorithm based on image correlation between frames

Initialization:

Step 1. Store the binary digital images of FROIs in sequence $F_{cor}{}^N$ whose length is l_{cor} .

Step 2. Calculate all pixel in 1st image of sequence $F_{cor}{}^N$, then calculate the intensity of pixels which satisfy Eq.2the others pixels intensity are set to 0 .

Step 3. After pixels traversal calculation for the entire image through Step2, we get the mean intensity value of entire image and the part of $\sqrt{\sum_{x=0}^{N_1-1}\sum_{y=0}^{N_2-1}\left[X_k(x,y)-\bar{X}_k\right]^2}$ in Eq.8 can be calculated.

After initialization, the following steps are used to deal with the others elements in sequence $F_{cor}{}^N$:

Step 4. Get the mean intensity value of current frame by using Step2 and Step3.

Step 5. Calculate the correlation coefficient c of pixels by using Eq.8

Step 6. Record the number of correlation coefficient whose value is negative, stored in negativeNum.

Step 7. Calculate the difference of correlation coefficient between frames, the correlation coefficient is oscillating if c_c-$c_p > \tau_{\text{cor}}$, and record the correlation coefficient oscillation times of $F_{cor}{}^N$ by using parameter csum, otherwise set $c_p = c_c$, where c_c , c_p are correlation coefficient value of current frame and previous frame.

Record the values of negativeNum and csum, values of csum are stored in sequence $F_{csum}{}^N$.

Step 8. Compare the oscillation frequency of correlation coefficient between frames, if $csum_p$ is equal to $csum_c$, describe there is no oscillation of value csum, then record the times of no oscillation ncctimes in $F_{csum}{}^N$, where $csum_c$, $csum_p$ are correlation coefficient oscillation times of current frame and previous frame.

Step 9. The basic probability assignment function of Feature2:

$$\begin{cases} Mass_{cor}(Fire) = \dfrac{l_{cor} - ncctimes}{l_{cor}}, if & ncctimes < \tau_{cor} \\ Mass_{cor}(Fire) = 0 & ,if \quad ncctimes = N \\ Mass_{cor}(\Theta) = \dfrac{csum}{l_{cor}} & ,if \quad ncctimes \geq \tau_{cor} \end{cases} \tag{12}$$

The value of csum of flame videos and interference videos may be at the same range, flame and interferences can hardly be distinguished by using csum. So that ncctimes in step8 are used. Figure.3 shows ncctimes of continuous 100 frames in different videos.

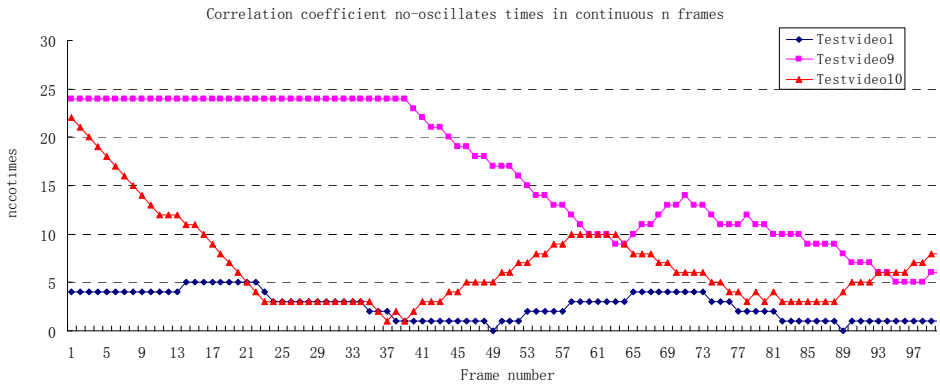

Figure 3. Correlation coefficient oscillation times

Process 3: Features fusion based on D-S evidence theory

Bel_{dct}, Bel_{cor} are defined as belief functions in same frames of discernment Θ, where the Bel_{dct}, Bel_{cor} is based on Feature1 and Feature2.. m_{dct} , m_{cor} are the basic probability assignment functions are given at Step8 in Process1, and Step9 in Process2. $m_{dct\&cor}$ is the basic probability assignment functions after feature fusion. The focal elements are X_1, X_2, …, X_M and Y_1, Y_2…, Y_N. $fire \subseteq \Theta$ is used for describing flame event in videos. Features fusion based on D-S evidence theory is defined as:

$$m_{dct\&cor}(fire) = m_{dct}(fire) \oplus m_{cor}(fire) = \frac{\sum_{X_i \cap Y_j = fire} m_{dct}(X_i) m_{cor}(Y_j)}{K} \quad (13)$$

where,

$$K = 1 - \sum_{X_i \cap Y_j = \varphi} m_{dct}(X_i) m_{cor}(Y_j) \quad (14)$$

In Figure.4 flame and interference can be distinguished by $m_{dct\&cor}(fire)$, The value of $m_{dct\&cor}(fire)$ in Testvideo9 is close to Testvideo1, so Eq.14 is used to detect flame in test videos.

$$IsFire_n = \begin{cases} 1 & m_{dct\&cor}(fire) \geq th\_fire \\ 0 & m_{dct\&cor}(fire) < th\_fire \end{cases} \quad (15)$$

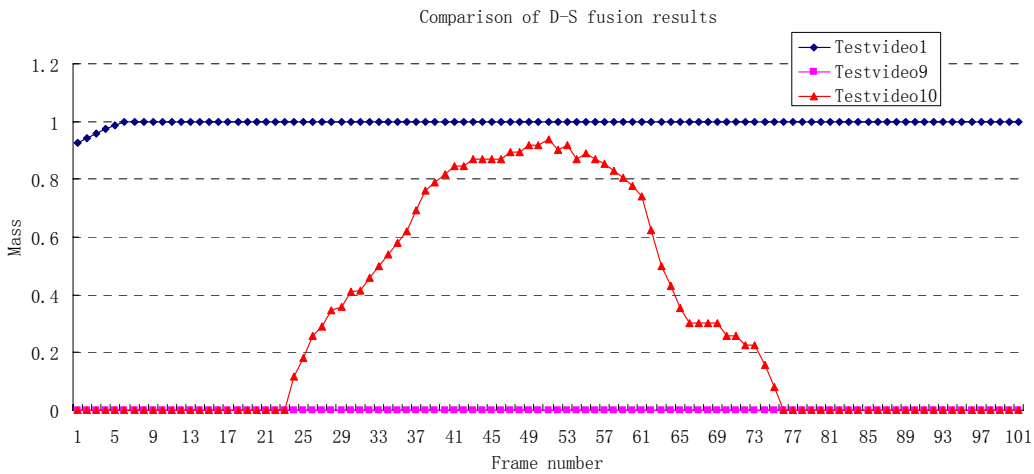

Figure 4. Comparison of D-S fusion

V. Experiments and Results

Experiments are performed on an Intel Core i3 540 computer running at 3.07 GHz. A general digital color video camera (logitech QuickCam 300, 000 pixels) is used to capture several flame sample image sequences with the format of pixel resolutions of 320×240 and 176×144. In general, experimental verification of a fire detection system is very difficult task. There are few standard datasets, thus some of test videos in this paper can be downloaded from National Institute of Standards and Technology, (http: //www.fire.nist.gov/tree_fire.htm) and Toreyin's test videos (http: //signal.ee.bilkent.edu.tr/VisiFire/), the others are from internet and capture from our general camera (testvideo1, 2, 3, 5, 6, 7, 11, 12, 13, 14). Flame videos (Testvideo1-Testvideo8) and interference –videos (Testvideo9-Testvideo16). Continuous 100 frames of each video are selected for the experiments of single feature algorithm testing, proposal method testing and comparisons of proposal method and others methods introduced in this paper. Figure 5 is scenes of test video library and Table 1 is introductions of test video library.

Figure 5. Scenes of test video library

There are no widely ''agree-upon'' evaluation criteria.

Thus, to validate the effectiveness of the proposed approach, correct flame detection rate r+ (Eq.16), and false alarm rate of interferences r- (Eq.17) are applied to measure results of algorithms.

Correct flame detection rate:

$$r_{+} = \frac{n_f}{n_{tf}} \tag{16}$$

False alarm rate of interferences: $r_{-} = \frac{n_i}{n_{ti}}$ (17)

where n_f is numbers of flame frames detected by algorithms, n_{tf} is total numbers of flame frame in each test video, and n_i is numbers of flame frames detected by algorithms in interference videos, n_{ti} is total numbers of each interference video.

Experiment 1.

Different results of various τ

Flame in videos will show different color features in different environments, such as environments of Test video 4, 8 are outdoor, due to the impacts of sunlight the flames in these videos are translucent, and have low flame color saturation. While testvideo1, 3, 5 are indoor flame videos and flame color saturation are higher than Testvideo4, 8. Various τ in Eq.1 will result in different detection results. Table 2 is detection results of test video testing in various τ . Experiment shows that result is the best one when τ =50. Therefore τ is set to 50 in the following-up experiments.

Experiment 2.

Results of dynamic feature detection algorithms and proposed method

TABLE I
TEST VIDEO DETAILS

Video type	Video	Description	Size
Fire viedo	Testvideo1	Indoor fire, burning paper	320×240
	Testvideo2	Indoor fire, burning Christmas tree	320×240
	Testvideo3	Indoor fire, buring paper	320×240
	Testvideo4	Outdoor fire, weather conditions is windy	320×240
	Testvideo5	Indoor fire, buring paper	320×240
	Testvideo6	Indoor fire, buring paper	176×144
	Testvideo7	Indoor fire, buring paper	176×144
	Testvideo8	Outdoor fire, weather conditions is sunny	320×240
Interference video	Testvideo9	Outdoor light interference (car lights)	320×240
	Testvideo10	Moving objects (people wearing red pants walk back and forth)	320×240
	Testvideo11	Fire-like colored objects (Shaking CD under sunlight)	176×144
	Testvideo12	Light dramatic changes (a flowing white curtains)	176×144
	Testvideo13	A fire-like colored bottle before a rocking fan	176×144
	Testvideo14	Interference of TV program (fire in TV program)	320×240
	Testvideo15	Moving objects (people wearing red coat walk)	320×240
	Testvideo16	Car headlights, red tail lights and lighting in the tunnel	320×240

TABLE II.
RESULTS OF DIFFERENT τ

Fire video	20	30	40	50	60	Interference video	20	30	40	50	60
Testvideo1	92	91	100	100	49	Testvideo9	0	90	0	0	0
Testvideo2	0	12	88	84	2	Testvideo10	17	0	0	0	0
Testvideo3	100	82	100	100	100	Testvideo11	0	0	0	0	0
Testvideo4	98	51	72	73	0	Testvideo12	0	0	0	0	0
Testvideo5	72	70	100	100	0	Testvideo13	0	0	0	0	0
Testvideo6	99	59	94	94	10	Testvideo14	0	94	37	36	0
Testvideo7	100	62	100	100	32	Testvideo15	100	0	0	0	0
Testvideo8	0	0	34	65	52	Testvideo16	0	0	0	0	0
Total	561	427	866	716	245	Total	117	184	37	0	0
r+	70.12%	53.38%	86.00%	89.50%	30.63%	r-	14.63%	23.00%	4.63%	4.50%	0.00%

Feature1 is flame detection algorithm based on flame flicker feature which we describe the feature by calculating the variances of fire high sequences after the operation of DCT. Feature2 is the feature of flame image correlation between frames. Table III is the comparison of Feature1, Feature2, and fusion results of two features by voting method and D-S evidence theory.

Experiment 3.Algorithm comparison

Table 4 is the comparison of algorithm results of [6], [7], [12] and proposed method under the same conditions. The correct flame detection rate of methods in [6] is the lowest one in four methods, and interferences such as car lights and walking people on red coat in Testvideo9 and 10 cannot be excluded. The correct flame detection rates of methods in [7] is 4.75% lower than proposed method, but it's false alarm rate of interferences is 4% higher than

proposed method, interference of car lights in Testvideo9 can't be completely ruled out .Although the correct flame detection rate of algorithms in [12] is 100%, but the false alarm rate of interferences is high too. Robustness of the algorithm proposed in this paper is high, good at detecting early flame.

Experiment 4. Algorithm execution time

Table V is algorithm execution time, average processing time of videos with resolution of 320×240 is 31.58 milliseconds per frame, and videos of 176×144 is 14.62 milliseconds, achieve real-time processing goals.

TABLE III.
RESULTS OF PROPOSAL ALGORITHMS

Fire video	Feature1	Feature2	Voting method	Proposed method	Interference video	Feature1	Feature2	Voting method	Proposed method
Testvideo1	92	78	78	100	Testvideo9	20	30	0	0
Testvideo2	85	34	34	84	Testvideo10	0	11	0	0
Testvideo3	87	52	52	100	Testvideo11	0	0	0	0
Testvideo4	73	71	71	73	Testvideo12	0	0	0	0
Testvideo5	100	76	65	100	Testvideo13	0	4	0	0
Testvideo6	94	62	59	94	Testvideo14	48	72	17	36
Testvideo7	100	40	40	100	Testvideo15	0	0	0	0
Testvideo8	47	64	26	65	Testvideo16	0	0	0	0
Total	678	447	360	716	Total	68	117	17	36
r+	84.75%	55.88%	45.00%	89.50%	r-	8.50%	14.63%	2.13%	4.50%

TABLE IV.
ALGORITHM COMPARISON

Fire video	[6]	[7]	[12]	Proposed method	Interference video	[6]	[7]	[12]	Proposed method
Testvideo1	78	92	100	100	Testvideo9	30	20	100	0
Testvideo2	34	85	100	84	Testvideo10	11	0	100	0
Testvideo3	52	87	100	100	Testvideo11	0	0	100	0
Testvideo4	71	73	100	73	Testvideo12	0	0	64	0
Testvideo5	76	100	100	100	Testvideo13	4	0	63	0
Testvideo6	62	94	100	94	Testvideo14	72	48	100	36
Testvideo7	40	100	100	100	Testvideo15	0	0	100	0
Testvideo8	64	47	100	65	Testvideo16	0	0	100	0
Total	447	678	800	716	Total	117	68	727	36
r+	55.88%	84.75%	100%	89.50%	r-	14.63%	8.50%	90.87%	4.50%

TABLE V.
ALGORITHM EXECUTION TIME

Fire	execution time	Interference	execution time
Testvideo1	29.79ms	Testvideo9	33.78ms
Testvideo2	30.47ms	Testvideo10	31.13ms
Testvideo3	35.06ms	Testvideo11	14.75ms
Testvideo4	28.63ms	Testvideo12	12.04ms
Testvideo5	30.79ms	Testvideo13	14.47ms
Testvideo6	16.61ms	Testvideo14	36.47ms
Testvideo7	15.25ms	Testvideo15	30.69ms
Testvideo8	30.12ms	Testvideo16	30.46ms

VI. SUMMARY

In this paper, early fire detection in video sequences based on D-S evidence theory is proposed. We apply the YCbCr and RGB color spaces to construct a generic chrominance model for flame pixel classification. Then two flame detection algorithms of different features which based on flame flicker and flame image correlation were used as classifiers. Finally the results of two classifiers are integrated through the D-S evidence theory. The proposed model gives 89.5% correct flame rate with a 4.5% false alarm rate. This is a significant improvement over other methods used in the literature.

ACKNOWLEDGMENT

This work is supported by the grants from the National Natural Science Foundation of China [Grant No. 60873147].

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