Fire Surveillance Method Based on Quaternionic Wavelet Features

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Abstract. Color cues are important for recognizing flames in fire surveillance. Accordingly, the rational selection of color space should be considered as a nontrivial issue in classification of fire elements. In this paper, quantitative measures are established using learning-based classifiers to evaluate fire recognition accuracy within different color spaces. Rather than dealing with color channels separately, the color pixels are encoded as quaternions so as to be clustered as whole units in color spaces. Then, a set of quaternion Gabor wavelets are constructed to establish an comprehensive analysis tool for local spectral, spatial and temporal characteristics of fire regions. Their quaternion Gaussian kernels are used to represent the spectral distribution of fire pixel clusters. In addition, a 2D band-pass filter kernel contained in the quaternion Gabor extracts spatial contours of fire regions. Another 1D temporal filter kernel is enforced to capture random flickering behavior in the fire regions, greatly reducing the false alarms from the regular moving objects. For early alerts and high detection rate of fire events, smoke region is also recognized from its dynamic textures in the proposed fire surveillance system. Experimental results under a variety of conditions show the proposed vision-based surveillance method is capable of detecting flame and smoke reliably.

Keywords: Fire Surveillance, Quaternionic features, Flame recognition, Smoke detection.

1 Introduction

Early fire detection is vital to insure human's safety and prevent hazards before fire gets out of control. Conventional sensor-based fire alarm systems detect chemicals by either ionization or photometry, overlooking the physical presence of combustion material at the location of the sensor. This requirement makes these systems dependent on the distance to fire source as well as sensors' positional distribution. To provide quick responses to fire and gain capability in monitoring open spaces, vision based fire surveillance systems are developed to efficiently identify the danger of flame or smoke with early alerts in areas previously deemed to be impractical for sensor-based systems.

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Color cues are important for recognizing flames in fire surveillance. Various color spaces have been used to perform flame pixel classification, including RGB[1][2], YUV[3], HIS[4] and YCbCr[5]. Fire color models are trained in the specified color space for flame detection. However, the color space is selected in an ad hoc manner without foundation of quantitative analysis.

Most of current fire detection methods focus on the feature description of flames [1-6]. The superior ones take into account the disordered spatial features and temporal flickering features to characterize the fire regions. Shape complexity is commonly used to depict the spatial fire features [7][8]. However, it is difficult to figure out the contour finely for fire regions. In addition, rather a long time is needed to detect temporal periodicity of fire flickering behavior [5][7]. Thus, the classification approach with low computational cost is preferred. Smoke is another important element to indicate fire appearance. It is assumed that smoke's color varies within the range from black-grayish to black [2]. However, the smoke color might reflect the color of the background due to semi-transparent property. The shape of the smoke is also considered in some research works [9]. These approaches are dependent on the assumption that smokes have distinct contours, which is not the fact for the thin smokes. Texture features are effective to extract smoke regions. Cui's approach [10] demonstrated high detection accuracy but should extract at least 48 features from each candidate smoke region for final discrimination.

Dynamic characteristics of flame and smoke are important clues to reduce search range of candidate fire regions. Frame differencing is commonly used to filter out the moving regions. But it still needs other decision rules to remove unwanted dynamic features and noises. Flames and smokes are always pointed at the top and spread upward by hot airflows. This is an important visual feature of fire. Yuan performed the orientation analysis using integral image to find candidate fire regions [11]. The block-wise orientation analysis in this method is not quite precise.

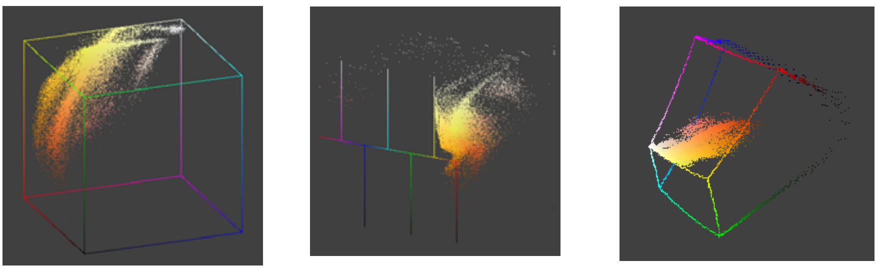
In this paper, a unified detection scheme of flames and smoke is presented. It is highlighted in three aspects: (1) Quantitative measures are established to evaluate the flame classification accuracy within the commonly-used color spaces, including RGB, HIS, YCbCr and LAB color spaces. (2) A set of quaternion Gabor wavelets are constructed to establish an comprehensive analysis tool for local spectral, spatial and temporal characteristics of fire regions, where the color cues, contour cues and turbulent motion cues are treated altogether in the filtering process. (3) Motion history image (MHI) analysis combined with statistical texture description and temporal wavelet transform is used to reliably recognize smoke regions.

The content is organized as follows. Section 2 evaluates the impact of color space selection, e.g. RGB, HIS, YCbCr and LAB, on flame element classification. In learning-based clustering process, quaternion representation is adopted to cluster color pixels as units in the color spaces. Section 3 presents a novel quaternionic Gabor filtering method to detect fire region. These quaternion Gabors are capable of conducting spectral analysis together with spatio-temporal wavelet filtering, resulting in reliable fire region detection. A cost-effective framework of smoke detection is given in Section 4. Then section 5 presents experimental comparison with the state-of-the-art methods. Finally, conclusion remarks are drawn in Section 6.

2 Color Space Selection for Flame Detection

Color cues are important for recognizing flames in fire surveillance. In previous works, various color spaces are selected to perform flame classification in an ad hoc way, including RGB[1][2], YUV[3], HIS[4] and YCbCr[5] color space. In this section, we establish a foundation of quantitative analysis of flame recognition accuracy in these commonly-used color spaces. Two of the most popular classifiers based on machine learning model, i.e. Adaboost and SVM, are used to extract the flame-colored regions. It is interesting to show that comparable detection rates and false alarm rate are achieved in these four color spaces if the fire color model is trained with parameter optimized in the specified color space.

Most flame pixels have color components of red, orange and yellow. We collect fire pixels from 19 fire video sequences and compute the spectral distribution of these pixels. Fig.1 illustrates the fire color distribution in RGB, HIS and Lab color spaces.



(a)RGB (b) HIS (c) Lab

Fig. 1. Spectral distribution of fire pixels gathered from 19 video sequences

Most former researches select HIS, YCbCr and Lab color spaces rather than RGB color space, assuming more independence among the three channels results in better classification performance. Here we rely on the quantitative analysis to evaluate the flame classification results under different selection of color spaces. We gather non-fire color samples from 15 videos of indoor and outdoor scenes, and classify them against fire colors via Support Vector Machine (SVM) and Adaboost. Each color pixel is represented by a pure quaternion[12], i.e. $x.i + y.j + z.k$, where $i^2 = j^2 = k^2 = -1$, $i.j = -j.i = k$ and imaginary parts x, y, z denote the color channels. Rather than treating each color channel independently, quaternion encodes color pixel as an entity, well preserving interrelationship between three color channels. Quantitative analysis for the classification results is listed in Table 1 and Table 2, respectively obtained by SVM and Adaboost approach. It is observed that comparable detection rates and false alarm rates are achieved in different color spaces if the fire color model is trained with parameter optimized in the specified color space. Thus, the selection of any commonly-used color spaces is reasonable in fire surveillance task. In the following content, we adopt quaternion to represent RGB color vector without additional explanation.

Table 1. Classification results using SVM

Color Spaces	RGB	HIS	YCbCr	Lab
Accuracy	95.4%	96.9%	95.7%	95.9%
False Alarm	10.67%	10.86%	9.46%	10.62%

Table 2. Classification results using Adaboost

Color Spaces	RGB	HIS	YCbCr	Lab
Accuracy	96.17%	96.17%	96.21%	96.04%
False Alarm	9.96%	10.18%	8.86%	10%

We conduct experiments to classify fire color produced by different inflamers using color models trained above. Different kinds of inflamers generate fires with different colors. Still, we can segment fire-color regions (labeled with green pixels) from non-fire color regions successfully no matter what inflamer is, as shown in Fig.2.

(a) Fire of ignited paper (b) Iron fire (c) Forest fire

Fig. 2. Classification Results of fire colors generated by different inflamers

3 Construction of Quaternionic Wavelet Filters

In vision-based fire surveillance system, detection of inherent features is fundamental for the whole surveillance performance. Spectral distribution is dominantly exploited as an essential static property to recognize existence of fire. In the state-of-the-art methods, flickering analysis is effective to depict dynamic features of fire elements [4][5]. As for the current fire surveillance systems, they conduct spectral, spatial and temporal analysis sequentially. Multiple threshold constraints should be established by learning-based techniques or empirical experience. In this section, we construct a set of quaternion Gabor wavelets to establish an comprehensive analysis tool for local spectral, spatial and temporal characteristics of fire regions, where the color cues, contour cues and turbulent motion cues are treated altogether in the filtering process. As a result, unitary threshold constraint is available in such an analysis scheme. These quaternion Gabors consist of three components, namely quaternion Gaussian kernel, bandpass filter kernel and temporal filter kernel, respectively responsible for spectral analysis, spatial contour filtering and temporal flickering detection,

3.1 Quaternion Gaussian Kernel for Spectral Analysis

As shown in Fig.3, 20 quaternion Gaussian kernels are utilized to represent the spectral distribution of fire pixels in RGB color space. Given mean value m_q^i and standard deviation σ_q^i $(i=1,\ldots,20)$, we can formulate the quaternion Gaussian kernels as,

$$G_q^i\left(\mu, m_q^i, \sigma_q^i\right) = \exp\left(-\frac{\left(\mu - m_q^i\right)^2}{2.\left(\sigma_q^i\right)^2}\right),\ (i=1,\ldots,20) \tag{1}$$

where m_q^i is a pure quaternion and located at ith cluster center of fire colors. Around each cluster center, the spectral probability density is represented by a quaternion Gaussian kernel with standard deviation σ_q^i. When the quaternion color vector μ falls into any one Gaussian envelope, we can estimate the probability of current pixel to have a fire color. Otherwise, we remove current pixel from candidate fire regions.

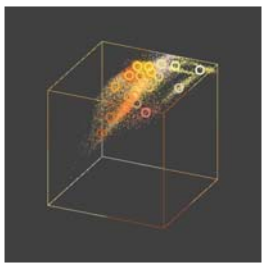


Fig. 3. 20 cluster centers of fire colors in RGB space, circled with different colors

As listed in Table 3, parameters of 20 quaternion Gaussian kernels are provided. In the extensive tests of fire region classification, it is noted that non-fire pixels usually fall into 3 Gaussian envelopes (marked with red cells in Table 3), increasing false alarms in the fire surveillance. These quaternion Gaussians contain the color of sky, road and brilliant yellow objects. In the following classification tests, we assign these Gaussian kernels with lower confidence to greatly reduce the false alarms.

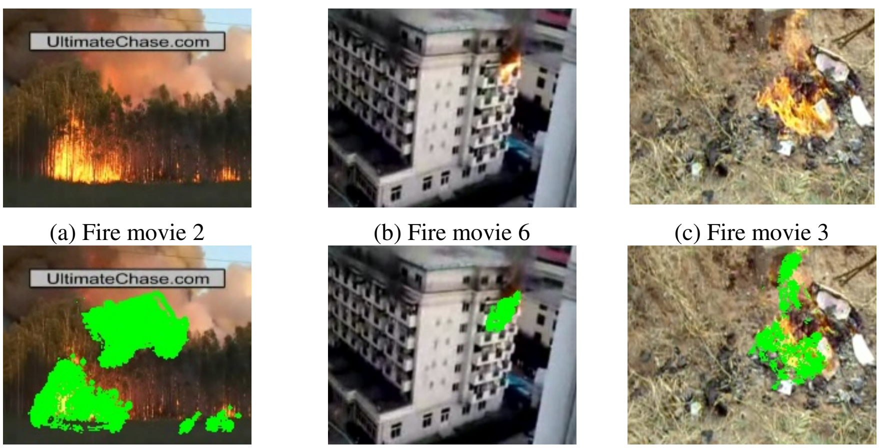
3.2 Band-Pass Filter Kernel for Spatial Contour Filtering

Fire is a complex natural phenomenon involving turbulent flow. The turbulent flames due to an uncontrolled fire expose a flickering characteristic. At the boundary of a flame region, pixels appear as fire elements at a certain flickering frequency. Considering extensive variations of the size and contour orientation of fire regions, we set up a set of band-pass filter kernels to conduct multi-scale and multi-orientation contour analysis. They are formulated as the real part of complex Gabor filter,

$$G_{u,v}(x,y) = \frac{f_m^2}{2^u\sigma^2}\exp\left(-\frac{f_m^2}{2^{u+1}\sigma^2}\left(x^2+y^2\right)\right)\left[\cos\left(\frac{f_m}{2^{0.5u}}\left(x\cos\frac{v}{N}+y\sin\frac{v}{N}\right)\right)-\exp\left(-\frac{\sigma^2}{2}\right)\right] \tag{2}$$

Table 3. Parameters of Quaternion Gaussian Kernels

m_q^1	σ_q^1	m_q^2	σ_q^2	m_q^3	σ_q^3
0.24i+0.76j+0.95k	0.06183	0.42i+0.81j+0.98k	0.04769	0.13i+0.65j+0.93k	0.07479
m_q^4	σ_q^4	m_q^5	σ_q^5	m_q^6	σ_q^6
0.39i+0.62j+0.78k	0.10804	0.44i+0.72j+0.9k	0.06713	0.35i+0.7j+0.97k	0.0535
m_q^7	σ_q^7	m_q^8	σ_q^8	m_q^9	σ_q^9
0.86i+0.94j+0.94k	0.08257	0.11i+0.34j+0.71k	0.12228	0.27i+0.63j+0.87k	0.07861
m_q^{10}	σ_q^{10}	m_q^{11}	σ_q^{11}	m_q^{12}	σ_q^{12}
0.22i+0.48j+0.94k	0.06608	0.71i+0.78j+0.87k	0.08201	0.41i+0.5j+0.9k	0.09518
m_q^{13}	σ_q^{13}	m_q^{14}	σ_q^{14}	m_q^{15}	σ_q^{15}
0.52i+0.82j+0.92k	0.05826	0.33i+0.87j+0.93k	0.05341	0.43i+0.89j+0.93k	0.04847
m_q^{16}	σ_q^{16}	m_q^{17}	σ_q^{17}	m_q^{18}	σ_q^{18}
0.28i+0.59j+0.98k	0.04847	0.65i+0.93j+0.95k	0.06505	0.36i+0.8j+0.91k	0.04967
m_q^{19}	σ_q^{19}	m_q^{20}	σ_q^{20}		
0.12i+0.41j+0.87k	0.08967	0.52i+0.92j+0.96k	0.05528		



(a) Fire movie 2 (b) Fire movie 6 (c) Fire movie 3

(d) Detected fire in movie 2 (e) Detected fire in movie 6 (f) Detected fire in movie 3

Fig. 4. Fire region detection using spatial filtering (labeled with green color in subfigures (d)-(f))

$$6\sigma \frac{f_m}{2^{0.5u}} = M \tag{3}$$

where (x, y) is the 2D spatial location of current color pixel, f_m denotes the central frequency of the filter with the smallest scale. Parameter u indicates the number of scales and N is the orientation number of the filters. The formulation in (3) is enforced to obtain octave bandwidth filters. Parameter M is a constant, enumerating the number of sinusoidal oscillations within the spatial Gaussian envelope. Denotation σ

is the standard deviation of the Gaussian envelope. Because of the substantial power at low frequencies in natural signals, DC sensitivity is eliminated by the term in the square bracket to avoid a positive bias of the response.

In the experiments, we conduct spatial filtering for fire region detection at **4** scales and **8** orientations. In Fig.4, intermediate filtering results with strong responses are illustrated as candidate fire regions.

3.3 Temporal Filter Kernel for Flickering Detection

In this section, we analyze flickering behavior of fire using temporal filtering method. Similar to the spatial filter kernel, temporal wavelet filters are formulated as the product of a Gaussian window and a sinusoid function. To obtain octave bandwidth property, we construct a set of filters according to (4) and (5),

$$G_{\sigma_T}(t) = \frac{k_T^2}{\sigma_T^2}\exp\left(-\frac{k_T^2 t^2}{2\sigma_T^2}\right)\left[\cos\left(k_T t\right) - \exp\left(-\frac{\sigma_T^2}{2}\right)\right], T = 0,\ldots S-1 \quad (4)$$

$$6\sigma_T k_T = M_T \quad (5)$$

where t indicates the frame time of current color pixel, S is the temporal scale number of the filters. Given an arbitrary filter in the set, which has a Gaussian envelope with standard deviation σ_T and central frequency k_T, constant number M_T of sinusoidal oscillations is observed within the spatial Gaussian envelope. Also, DC sensitivity is eliminated to avoid a positive bias of the response.

(a) (b) (c)

Fig. 5. Fire area detection results (a) not using analysis of temporal features (b) using analysis of temporal features

Finally, we can form a set of quaternion Gabor wavelets to perform comprehensive analysis of spectral, spatial and temporal features of fire regions. The representation of these quaternion Gabors can be formulated as,

$$G_W = G_q^i . G_{u,v}\left(x, y\right) \otimes G_{\sigma_T}(t) \quad \left(i = 1,\ldots,20, u = 0,\ldots,3, v = 0,\ldots,7, T = 0,\ldots,3\right) \quad (6)$$

where symbol '$\otimes$' denotes tensor product operator.

The related fire detection results are shown in Fig.6. The flowchart of our fire detection scheme is depicted in Fig.7.

In our fire detection framework, one threshold constraint is established for the level crossings in the comprehensive analysis of fire regions. It is noted that the search range of fire regions is greatly reduced by a preprocessing step of dynamic object

(a) Fire scenes in Movie 4 (b) Fire scenes in Movie 5 (c) Fire scenes in Movie 6

Fig. 6. Fire detection using comprehensive analysis of spectral, spatial and temporal features based on quaternion Gabor filtering

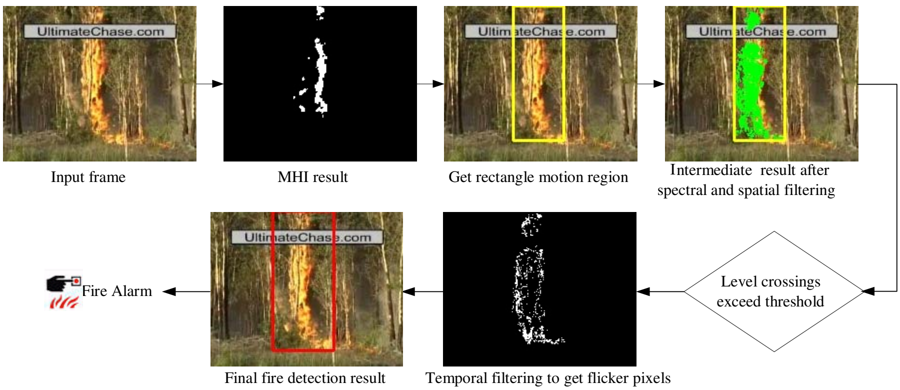


Fig. 7. Our fire Detection framework

extraction. The computation time is reduced to 20% of the time needed in the operation without motion filtering. The motion areas are extracted by Motion History Image (MHI) approach [13][14]. The following discussion of smoke detection is also based on MHI motion filtering method.

4 Smoke Region Detection

As mentioned in section 3.3, we extract moving objects as candidate fire regions using MHI method. Smokes always move upwards because of hot airflow. Hence, we indicate a moving object as smoke candidate if its main orientation points to the positive vertical component. Spectral features are not considered in our smoke detection framework, since semi-transparent smokes always reflect the color of background. Similar to flame regions, flicker process inherent in fire can be used as a clue for smoke detection. An instance of smoke flicker is shown in Fig.8. A similar technique modeling flicker behavior proposed in section 3.3 is developed to detect smoke flicker. Then, we use the GLCM-based texture descriptors in Cui's work [9], i.e. Entropy, Contrast, Angular Second Moment, Inverse Difference Moment and Image pixel correlation to match smoke regions with high confidence.

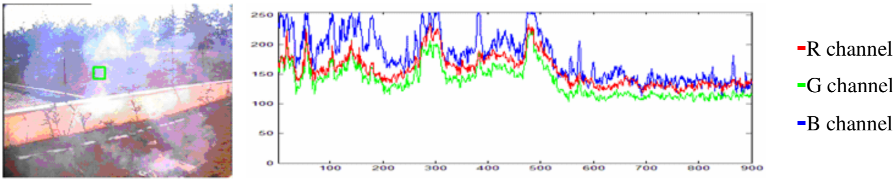


Fig. 8. An instance of smoke flicker (a) Smoke pixel at position (134, 85) (b) Temporal flicker behavior at the smoke pixel

These 5 GLCM features together with the mean value of the candidate smoke region are used to train a robust smoke texture model. As shown in Fig.9, candidate smoke regions are first extracted based on MHI method and flicker analysis. Then they are segmented into small blocks to check if the textures of these blocks are smoke-like ones, where the trained SVM classifier distinguishes smoke textures from other ones.

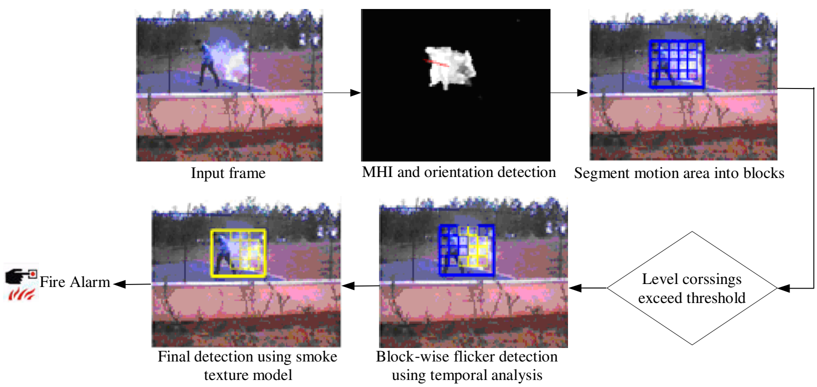


Fig. 9. Smoke Detection framework

5 Experimental Results

The proposed flame detection framework using Quaternionic features is implemented on a PC with an Intel Core Duo CPU 1.86GHz processor. We testify our framework on 12 sample videos. Fire movies 3, 6 are downloaded from Internet. The other fire movies are obtained from the following website: http://www.ee.bilkent.edu.tr/~signal/VisiFire/. The database of ordinary scenes is available at URL: http://homepages.inf.ed.ac.uk/rbf/CAVIAR/.

Some detection results are shown in Fig.10, where fire region is bounded by the red rectangle. It is observed in subfigures (h)~(l) that false alarms are alleviated in the cases of flashlight, illumination variations and clutters in the fire color regions. As compared with the state-of-the-art methods, including Toreyin's Method [4] and Ko's method [5] (Only fire detection results of movie 1,2,5,8 are available in [5] for these

(a) Movie 1 (b) Movie 2 (c) Movie 3 (d) Movie 4 (e) Movie 5 (f) Movie 6
(g) Movie 7 (h) Movie 8 (i) Movie 9 (j) Movie 10 (k) Movie 11 (l) Movie 12

Fig. 10. Test videos and our flame detection results, Movie description: (a) Burning tree; (b) Forest fire; (c) Burning paper; (d) Fire in garden; (e) Burning box; (f) Building fire; (g) Burning bin; (h) Car crash in tunnel; (i) Lighting dynamo; (j) Warm-toned store; (k) Hall of pedestrians; (l) Shining patio

two methods.), our framework outperforms these methods both in true positive and false positive, as listed in Table 4. True positive means the rate of correctly detecting a real fire as a fire and false positive means the rate of recognizing a non-fire as a fire, while missing means the rate of not recognizing a real fire.

Table 4. Comparison of fire detection results

Movie	**Frame number**	**Toreyin's Method**		**Ko's method**		**Our method**	
		TP	FP	TP	FP	TP	FP
1	245	82.6	4.9	77.7	0.0	100.0	0.0
2	199	63.7	10.0	97.9	0.0	95.2	0.0
3	128					83.6	0.0
4	545					93.6	1.3
5	1200	7.1	44.1	56.3	0.0	97.2	0.0
6	635					95.5	3.4
7	696					78.2	0.0
8	375	100.0	0.0	97.5	1.5	100.0	0.0
9	143					100.0	0.0
10	284					100.0	0.0
11	2226					100.0	0.0
12	1147					100.0	6.9

For an image of 200*160 pixels, the processing time per frame in flame detection scheme is about 50ms-200ms. For such an image, our smoke detection method takes about 90ms-200ms per frame. As shown in Fig.11, the motion regions which are

(a) Smoke movie 1 (b) Smoke movie 2 (c) Smoke movie 3

Fig. 11. Test videos and our smoke detection results

detected as smoke is bounded in the yellow frame. Subfigures (b) and (c) show that our method can detect thin smoke, which is available for early alerts for fire accidents.

6 Conclution

Instead of selecting color spaces for flame analysis in an ad-hoc manner, in this paper, quantitative measures are established to evaluate the flame classification accuracy within the commonly-used color spaces, including RGB, HIS, YCbCr and LAB color spaces. It is interesting to find that using different kinds of color space is all reasonable if the fire color model is trained with parameter optimized in the specified color space. More important, a new fire surveillance framework available for flame and smoke detection is presented, where a comprehensive analysis tool is established for local spectral, spatial and temporal characteristics of fire regions based on quaternion wavelet filtering method. Compared with the state-of-the-art method, better detection rate and lower false alarm rate is acquirable in our fire detection scheme.

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