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Video Flame Detection Based on Color and Contour Features

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Abstract: In this paper, a video flame detection method combining fire color and contour features is proposed. Firstly, fire color areas are obtained using fire color detection rules based on RGB color space and HSI color space. Secondly, the whole continuous and close flame contours are extracted by applying the Chan-Vese model in fire color areas. Then the moving properties of flame contours are analyzed and those with characteristic displacement and vibration features are accepted as flame objects. Experimental results show the proposed approach can remove the static or dynamic non-flame objects and segment the flame area from the complex background, and also has a high time effectiveness.

Key Words: flame detection, fire color, Chan-Vese model

1 Introduction

Fire flame detection is a very important issue because it closely related to people's safety and property. In traditional fire protection systems, most sensors (such as smoke detector, flame detector, heat detector, etc.) require product of combustion from fire to reach the sensors before an alarm is issued. And these sensors are not suitable for open spaces as product of combustion tend to spread away which can reduce the detection. In contrast, vision-based flame detection systems offer several advantages [1], such as lower cost, faster response time, higher possibility of fire detection, etc. Thus many vision-based methods have been proposed to detect fires or smokes in many environments such as home, office, forest and so on.

According to most fire detection papers presented in the literature, fire has very distinct static and dynamic characteristics [1]. Fire color is the most powerful static feature for finding fire-like regions in video sequences. To define a real burning fire, in addition to using color, dynamic features are usually adopted to distinguish fire from non-fire objects. Examples of these fire dynamics include the change in shape, flame movement and flickering. For example, Chen et al. [2] used an RGB/HSI color model and dynamic analysis of flames that matches the disordered characteristic of flames with the growth of pixels to check for the existence of a fire. Liu et al. [3] utilized the shape and color features to detect an occurrence of fire in visual image sequences. Töreyin et al. [4] used fire-colored pixels in moving regions and a temporal/spatial wavelet analysis. Marbach et al [5] used the YUV color model, where time derivative of luminance component Y was used to detect the candidate fire pixels, and the chrominance components U and V were used to classify whether or not the candidate pixels were the true fire pixels. Lai et al. [6] used color and motion features for fire detection in early stages. Celik [7] developed a novel fire color model in CIE L*a*b* color space and applied motion detection to reduce false fire alarm.

As edge contour can be used to analyze the shape of the flame, a video flame detection approach combining fire color and contour features is proposed in this paper. Firstly, fire color regions are detected using fire color detection rules based on RGB color space and HSI color space proposed by Chen et al [5]. Secondly, the whole continuous and close flame contours are extracted by applying the Chan-Vese model [8] in fire color areas. Then the moving properties of flame contours are analyzed and those with characteristic displacement and vibration features are accepted as flame objects.

The remainder of this paper is arranged as follows. Section 2 presents the method for fire region candidates detection using color rules based on RGB color space and HSI color space. The flame contour extraction algorithm in successive frames is presented in Section 3. The moving properties of flame contours are analyzed and final fire region are marked out in Section 4. Section 5 provides experimental results on some fire video flips. The paper concludes in Section 6.

2 Fire Region Candidates Detection Using Color Rules

Although there are some statistical fire color models [9, 10], most of the works on fire color detection are rule-based. In this paper, we continue to adopt rule-based color detection approach proposed by Chen et al [2] as it is simple and effective. They used the RGB color space and HSI color space. In general the color of fire flames belongs to the red-yellow range. Thus for a given fire pixel, the value of red channel is greater the green channel, and the value of the green channel is greater than the value of blue channel. As red is the major component in a colorful image of fire, the value of red channel must be higher than a specified threshold. However, lighting conditions in the background may adversely affect the saturation values of flames resulting in similar R, G and B values which may cause non flame pixels to be considered as flame colored. Therefore, to avoid the effect of the background illumination on flame detection, the saturation value of fire pixel should be larger than a specified threshold. The whole rules are described as follows,

$$\begin{cases} \text{Rule1: } R>R_T \\ \text{Rule2: } R\geqslant G\geqslant B \\ \text{Rule3: } S\geqslant(255-R)S_T/R_T \end{cases} \quad (1)$$

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where R_T is the threshold of red component, ranging from 115 to 135, and S_T is the saturation threshold, ranging from 55 to 65. Pixels which are satisfied with all the three rules are regarded as fire pixels.

Fig. 1 shows an original frame (a) and the fire color pixel detection results (b). From the figure we can see that the wall, the ground and board blocks are also detected as the fire pixels, and there are some noises and isolated pixels. These noisy pixels will affect the feature extraction and decision speed afterwards. So we adopt morphological operators to remove them. As there are still some small regions in the image, which are not so important in our decision process, area rule is utilized, i.e., the regions whose areas are less than a predefined threshold are removed. The final processing result is show in Fig.1 (c).

(a) (b) (c)

Fig.1 Fire color region detection results: (a) original frame; (b) fire color pixel detection; (c) morphological processing and small region removing

3 Flame Contour Extraction Based on Chan-Vese Model

Notice that the rules above are very permissive and many non-fire regions may be included in the first step. Thus additional analysis is necessary to further refine the results. The moving property of flame shape is the most commonly used feature to distinguish the alias. As edge contour can be used to analyze the shape of the flame, in this second step, the edge contour in each fire region candidate is extract using the Chan-Vese model. Compared to classical edge detection operators, such as Roberts operator, Sobel operator, Prewitt operator, Log operator and Canny operator, Chan-Vese model can capture continuous and close edge contour [11]. Moreover, it is insensitive to image noise. This model is based on the theory of curve evolution implemented via level set [12] techniques. Its central idea is to follow the evolution of a function ϕ whose zero level set always corresponds to a closed curve which divided the image into internal and external homogeneous regions. The motion for this evolving function ϕ is determined by a partial differential equation, i.e.

$$\begin{cases} \dfrac{\partial \phi}{\partial t} = \delta(\phi)\left[\mu\kappa - \nu - \lambda_1 (I(x,y)-c_1)^2 + \lambda_2 (I(x,y)-c_2)^2\right] \\ \phi(x,y,t=0) = \phi_0(x,y) \\ c_1 = \dfrac{\iint_\Omega I(x,y)H(\phi)\mathrm{d}x\mathrm{d}y}{\iint_\Omega H(\phi)\mathrm{d}x\mathrm{d}y} \\ c_2 = \dfrac{\iint_\Omega I(x,y)(1-H(\phi))\mathrm{d}x\mathrm{d}y}{\iint_\Omega (1-H(\phi))\mathrm{d}x\mathrm{d}y} \end{cases} \tag{2}$$

where I(x,y) is the image intensity, $\kappa = \mathrm{div}\left(\nabla\phi / |\nabla\phi|\right)$ is the curvature. $\mu \geq 0$, $\nu \geq 0$, $\lambda_1, \lambda_2 > 0$ are fixed parameters. The Heaviside function H and the one-dimensional Dirac measure δ are defined respectively by

$$H(z) = \begin{cases} 1, & if\ z \geq 0 \\ 0, & if\ z < 0 \end{cases}, \quad \delta(z) = \frac{d}{dz}H(z). \tag{3}$$

In practical calculation, the Heaviside function and the Dirac function are computed as follows:

$$H_\varepsilon(z) = \frac{1}{2}\left(1 + \frac{2}{\pi} arctg\left(\frac{z}{\varepsilon}\right)\right), \quad \delta_\varepsilon(z) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + z^2} \tag{4}$$

where ε is a constant.

From equation (2), $I(x,y)$ is defined in the whole range of the image, and c_1, c_2 is also defined in the image domain with global characteristics. As a result, Chan and Vese emphasize the global optimization ability of this method. Just one initial closed contour can detect the targets with internal holes, without special process of detecting internal holes.

To discrete equation (2) we use a finite difference semi-implicit scheme as in [13]. Let h be the two dimension grid step size and Δt be the temporal step size. $(x_i, y_i) = (ih, jh)$, $1 \leq i$, $j \leq M$ is the grid coordinates. $\phi_{i,j}^n = \phi(n\Delta t, x_i, y_i)$ approximate $\phi(x,y)$ in grid (x_i, y_j, t_n). Let $\phi^0 = \phi_0$ and the finite differences of $\phi(x,y)$ are

$$D_x^{(-)}\phi_{i,j} = \phi_{i,j} - \phi_{i-1,j}, \quad D_x^{(+)}\phi_{i,j} = \phi_{i+1,j} - \phi_{i,j},$$
$$D_x^{(0)}\phi_{i,j} = \frac{\phi_{i+1,j} - \phi_{i-1,j}}{2}, \quad D_y^{(-)}\phi_{i,j} = \phi_{i,j} - \phi_{i,j-1},$$
$$D_y^{(+)}\phi_{i,j} = \phi_{i,j+1} - \phi_{i,j}, \quad D_y^{(0)}\phi_{i,j} = \frac{\phi_{i,j+1} - \phi_{i,j-1}}{2}.$$

The numerical solution of (2) is as follows:

$$\phi_{ij}^{n+1} = \phi_{ij}^n + \tau\delta_\varepsilon(\phi_{ij}^n)\left|\begin{matrix} \mu Q(\phi_{ij}^{n+1}) \\ +\max(F,0)\nabla^+ + \min(F,0)\nabla^- \end{matrix}\right| \tag{5}$$

where

$$\begin{aligned} Q(\phi_{ij}^{n+1}) = {} & D_x^{(-)}\left(\frac{D_x^{(+)}(\phi_{ij}^{n+1})}{\left[(D_x^{(+)}(\phi_{ij}^n))^2 + (D_y^{(0)}(\phi_{ij}^n))^2\right]^{\frac{1}{2}}}\right) \\ & + D_y^{(-)}\left(\frac{D_y^{(+)}(\phi_{ij}^{n+1})}{\left[(D_y^{(+)}(\phi_{ij}^n))^2 + (D_x^{(0)}(\phi_{ij}^n))^2\right]^{\frac{1}{2}}}\right) \end{aligned} \tag{6}$$

$$\nabla^+ = \begin{bmatrix} \max(D_x^{(-)}\phi_{i,j},0)^2 + \min(D_x^{(+)}\phi_{i,j},0)^2 \\ +\max(D_y^{(-)}\phi_{i,j},0)^2 + \min(D_y^{(+)}\phi_{i,j},0)^2 \end{bmatrix}^{\frac{1}{2}} \tag{7}$$

$$\nabla^- = \begin{bmatrix} \min(D_x^{(-)}\phi_{i,j},0)^2 + \max(D_x^{(+)}\phi_{i,j},0)^2 \\ +\min(D_y^{(-)}\phi_{i,j},0)^2 + \max(D_y^{(+)}\phi_{i,j},0)^2 \end{bmatrix}^{\frac{1}{2}} \tag{8}$$

$$F(x,y) = -\nu - \lambda_1 (I(x,y)-c_1)^2 + \lambda_2 (I(x,y)-c_2)^2 \qquad (9)$$

As in the first step fire candidate regions has been detected, we find that only a few iterations are required before convergence. In the Chan-Vese model, let $\lambda_1 = \lambda_2 = 1$, $\varepsilon = 1$ time step $\tau = 0.1$, $\mu = 250$, and the average convergence speed is about 10 second.

The final detected contours of three successive frames using the Chan-Vese model are showed with white curve in Fig. 2. From the figure we can see that there are three suspicious flame contours in each frame.

Fig. 2 Edge contour extraction results of three successive frames

4 Moving Properties of Video Flame Contours

After the above steps, the continuous close flame contours in each frame have been obtained. Next we turn to decide whether there is a fire using three successive frames by detecting the dynamic features derived from the frame contours. As the shape of a burning fire is continuous moving and expanding, the area and the perimeter of the flame contour will increase, that is to say, if $A_{i-2} \leqslant A_{i-1} \leqslant A_i$ and $P_{i-2} \leqslant P_{i-1} \leqslant P_i$, where A_i is the area involved by the flame contour in i frame and P_i is the perimeter of the flame contour in i frame, there is a fire in the frame i. As there may be some noises in the image and the contours of non-fire regions may also change in the three successive frames, we can make fire decision based on the following rule,

$$\begin{cases} \text{a fire occurs} & \text{if } |A_{i+1}-A_i| \geqslant A_T \ \& \ |P_{i+1}-P_i| \geqslant P_T \\ \text{no fire occurs} & \text{otherwise} \end{cases} \qquad (10)$$

where A_T and P_T are the thresholds of area and perimeter respectively, and they are diverse in different environments.

For the example in Fig. 2, there are three fire region candidates in each frame, but only the area and perimeter of the contours in the middle satisfied the above rule. So this region is regarded as the true fire region. Fig. 3 shows the final decision result, where the white rectangle marks out the fire region.

Fig. 3 Final flame decision

5 Experimental results

To verify the performance of the proposed method, a test set of four fire video clips are selected from Signal and Image Processing Group at Bilkent University in Turkey (http://signal.ee.bilkent.edu.tr/VisiFire/FireClips). The properties of video sequences are given in Table 2. The four movie sequences are outdoor fire videos. The frame rate of the video data varied from 15 Hz to 30 Hz, and the size of the input image was 320×240 pixels. The computing environment is CPU Intel Core（TM）2 Duo 2.83G，Memory 2GB，Matlab7.

Table 1 Properties of video sequences

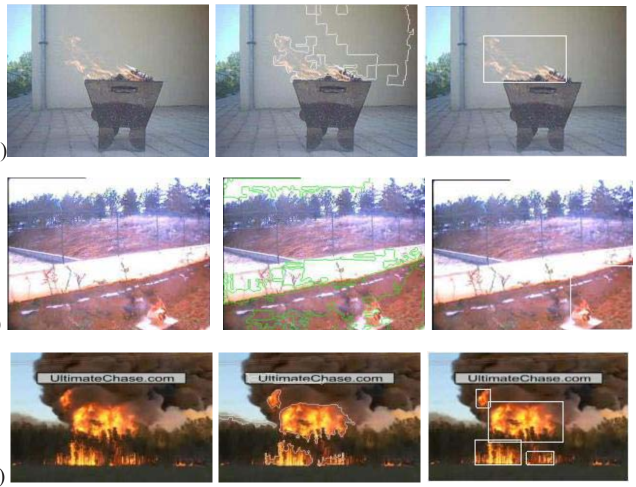
Name	Frame numbers	Description
Movie 1	510	Man in fire-colored shirt behind fire
Movie 2	368	Fire in box
Movie 3	213	Fire in garden
Movie 4	190	Fire in forest

Fig. 4 presents some examples of final fire region detection results of the other three video clips. The first column of the figure is one original frame from the video clips. The second column is the fire candidate contour extraction result. The third column is the final flame decision result, where the white rectangle marks out the fire region. From the results we can see that most of the fire regions in these video frames are marked out with our method.

(1)

(2)

(3)



(a)Original frame (b) fire contour extraction (c) final flame detection
Fig.4 Examples of flame detection results

The experimental results of the proposed flame detection method with comparison to the method in [10] are shown in Table 2, where F_t denotes the number of frames of a video sequence, F_f denotes the number of frames containing fire in a video sequence, and F_c denotes the number of frames that correctly classify the fire regions by the proposed algorithm. The detection rate R_d of a video is defined as

$$R_d = F_c / F_f \qquad (11)$$

Table 2 Experimental results

Name	F_t	F_f	Method of [10]		Our method	
			F_c	Rd(%)	F_c	Rd(%)
Movie 1	510	510	271	53.2	284	55.7
Movie 2	368	368	291	79.2	299	81.3
Movie 3	213	213	124	58.3	121	57.1
Movie 4	190	190	185	97.5	179	96.8

From Table 2 we can see that the detection rate of Movie 1 and 2 is a little better than the method of [10] and the detection rate of Movie 3 and 4 is a little less than the method of [10].

The false negative detection of our method are due to very small fire regions on the initial combustion in some of the video sequences. False positives are mainly caused by light reflection from a fire onto white smoke.

6 Conclusions

In this paper a video flame detection method combining fire color and contour features is proposed. Firstly the fire region candidates are detected according to fire color rules proposed by Chen et al. Secondly the continuous and close contours of these regions in each frame are extracted. If the area and perimeter of the contour in three successive frames are increased, the region is regarded as the fire flame region. Experimental results show our approach can detect fire flame objects from video sequences and remove the influence of non-fire disturbances. Moreover, our method is simple and has a high time effectiveness.

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