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Research Article

Video Based Fire Detection with Color and Geometric Features of Flames

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Abstract

Recently, video based flame detection technologies have become an important approach to the early detection of potential fire disasters. The recognition accuracy of most of the existing approaches for video based flame detection is not satisfactory. In this paper, we develop a new video based flame detection algorithm that can accurately recognize flames in video sequences based on color and geometric features extracted from regions that may contain flames in the video images. In addition to the traditional color and morphological features of flame regions, we develop a new feature to describe the color features of flame regions. All these features are then processed by a support vector machine (SVM) based classifier to determine whether a video sequence contains flames or not. Our testing results show that this new approach can effectively detect interference sources that are similar to flame regions in color and shape and achieve a high detection rate and good reliability.

Keywords: Video Based Flame Detection; Flame Color model; Flame Features; Support Vector Machine (SVM)

1. Introduction

Fire disasters often impose serious threats to the safety of human beings, it directly endangers the lives and properties of people. Therefore, it is of great practical value to detect fires before they become out of control. At present, some relatively mature methods of fire detection have been extensively used, such as smoke, temperature and light sensors. These sensors measure the concentration of smoke particles, the temperature and the intensity of light in its surrounding environment to detect the presence of fire.

However, these traditional fire detection equipments can be disturbed in certain environments,

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which may bring certain difficulties to fire detection. In addition, these traditional equipments issue fire warnings only when the concentration of the measured physical quantity has reached a certain level, which often occurs when the fire has been out of control. It is thus highly desirable to develop methods that can detect fires when they are still in their early stages.

Recently, video based fire detection technologies have gradually become an important alternative approach for the detection of fire. Video based fire detection technologies detect fire by analyzing the video images obtained from a surveillance video camera. Using algorithms in digital image processing, the video images can be processed in a real-time fashion and the presence of flames can be detected based on the features associated with regions that contain flames. The recognition accuracy and computational efficiency of the algorithm used to process the video images thus determines the performance of a video based fire detection system.

Researchers from the areas of computer vision and fire safety have done a lot of research work on the development of efficient and accurate algorithms for the detection of fire flames. With the continuous improvement of the algorithm for recognizing flames, the technology of image fire flame identification is under continuous development (Cheng et al., 1999; Noda and Ueda, 1994; Chen et al., 2004; Wu et al., 1997; Chen et al., 2004; Li et al., 2004; Celik et al., 2007; Fan et al., 2005). So far, features associated with the color and geometric shapes of regions that may contain flames have been used to recognize flames in video images (Noda and Ueda, 1994; Chen et al., 2004; Wu et al., 1997; Celik et al., 2007). However, most of the existing approaches are unable to accurately recognize flame regions when the video images also contain interference sources that have colors similar to those of flames. These approaches thus have high false positive and false negative rates when the video images contain other interference sources. An algorithm that can accurately recognize the flame regions from video images that may contain other interference sources is thus highly desirable to further improve the recognition accuracy of the existing video based fire detection systems.

In this paper, we develop a new approach that can accurately identify flame regions from video images. Specifically, we propose using a few new features to accurately describe the distribution of colors in a flame region. These new features are computed based on the first, second and third moments of the H components of pixels in a suspected region. These features and the circular degree of the region are then combined and processed by a Support Vector Machine (SVM) based classifier to determine whether the region indeed contains flames or not. Our testing results show that this new approach is able to achieve high recognition rates in the videos where the approach has been tested.

2. Detection of Suspected Flame Regions

Since the colors in a flame region are the most obvious features that can separate regions that contain flames from those that do not, we use the colors of flames as the first criterion to obtain the pixels that are probably in flame regions. This approach can effectively remove most of the regions that do not contain flames, the remaining pixels have colors that are similar to those of flame pixels and are analyzed in the subsequent steps to determine whether they are indeed flame pixels or not. The color of each pixel in a video image contains three components R, G, B, which represent the red, green and blue components in the color of the pixel. However, since the color (Hue), saturation

(Saturation) and brightness (Intensity) is more suitable for the description of the people's visual perception of color, we use a combination of the corresponding RGB-HSI color models to determine whether a pixel is a potential flame pixel or not. The conversion from the RGB space to HSI space is shown in equation (1), (2), and (3) (Liu, 2007):

$$H = \arccos\left[\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right] \qquad R \neq G \text{ or } R \neq B$$

$$H = 2\pi - \arccos\left[\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right] \qquad B > G \tag{1}$$

$$S = 1 - \frac{3}{R+G+B}\left[\min(R,G,B)\right] \tag{2}$$

$$I = \frac{R+G+B}{3} \tag{3}$$

The HSI color space has two characteristics. Firstly, the I component is independent of the color information of the pixel; secondly, and the H and S components of a pixel are closely related to the color felt by human beings, which makes the HSI color space very suitable for analyzing and processing images based on people's color perception. Our approach combines the components of both the RGB and HSI models to determine the flame region. Specifically, to be a potential flame pixel, its R component must be at least 180, the value of H component is between 0 and 2.093, the value of S component is between 20 and 100, and the value of I component is between 100 and 255. Based on these criteria, the potential flame pixels in an image can be effectively obtained. Figure 1 shows an example on using the RGB-HSI model to recognize potential flame regions in an image.

Fig. 1. The effect of flame detection with the RGB-HSI color model

3. Extraction of Features for Potential Flame Regions

3.1 Color Moment of Pixels in a Potential Flame Region

Histograms, color moments, color aggregation vectors are the tools that are often used to describe the color features of an image. We select to use the color moment, which is mainly used to describe the distribution of the color of the pixels in a suspected region. The distribution of the color can be described by the moments of the first, second and third orders of the *H* components computed with equation (1) for all pixels in a suspected region. The values of these moments can be computed with equations (4), (5), and (6) respectively (Zhang, 2001; Li et al., 2004).

$$K_1 = \frac{1}{N}\sum_{i=1}^{N} H(p_i) \tag{4}$$

$$K_2 = \left[\frac{1}{N}\sum_{i=1}^{N}\left(H(p_i) - K_1\right)^2\right]^{\frac{1}{2}} \tag{5}$$

$$K_2 = \left[\frac{1}{N}\sum_{i=1}^{N}\left(H(p_i) - K_1\right)^3\right]^{\frac{1}{3}} \tag{6}$$

where *N* represents the total pixels of the suspected region, $H(p_i)$ is the *H* component of pixel p_i in the suspected region, the summation is performed over all pixels in the region. For a suspected region, the first, second and third order color moments of the suspected region are calculated. To show how these moments can be used to recognize flame regions from those interference sources that have colors similar to flames, we calculate and compare the first color moments of three regions in video images that contain fire flames, a lamp bulb and candle lights respectively. Figure 2 shows the results of comparison.

As can be seen from Figure 2, the first order color moments of flame regions are significantly different from those of lamp bulbs and candle lights. The figure shows clearly that the first order color moments of flame regions fluctuate around a value of 2.5 and remain above 2.0, while those obtained on lamp bulbs rise from 0.25 to 1.25 and remain to be 1.25 after that. The first order color moments of candle lights fluctuate around 1.0 initially and suddenly change to a value around 1.8 and fluctuate around this new value in the remaining frames of the video. It is also clear from the figure that the final values of the moments obtained on fire flames and candle lights are not significantly different. This suggests that other features are needed to accurately recognize fire flames from interference sources that resemble fire flames in nature, such as the candle lights.

3.2 Circular Degrees of Fire Flames

Circular degree is a feature related to the geometric shape of an object. The geometric shapes of most of the interference sources (such as sunlight, lights, candle flame and so on) are usually of high regularity. However, the geometric shapes of fire flames are often of much lower regularities. The circular degree of a region is often used as a measure of the regularity of its shape. Therefore, a new criterion for recognizing fire flame regions is the circular degree of the region. As shown in equation (7), the circular degree of a closed region can be computed based on the ratio of the area of the region to the circumference of its boundary.

Error! Reference source not found. $\quad i = 1,2,\cdots,n$ (7)

where M_i is the circular degree of region i, A_i is the area of the region and P_i is its perimeter.

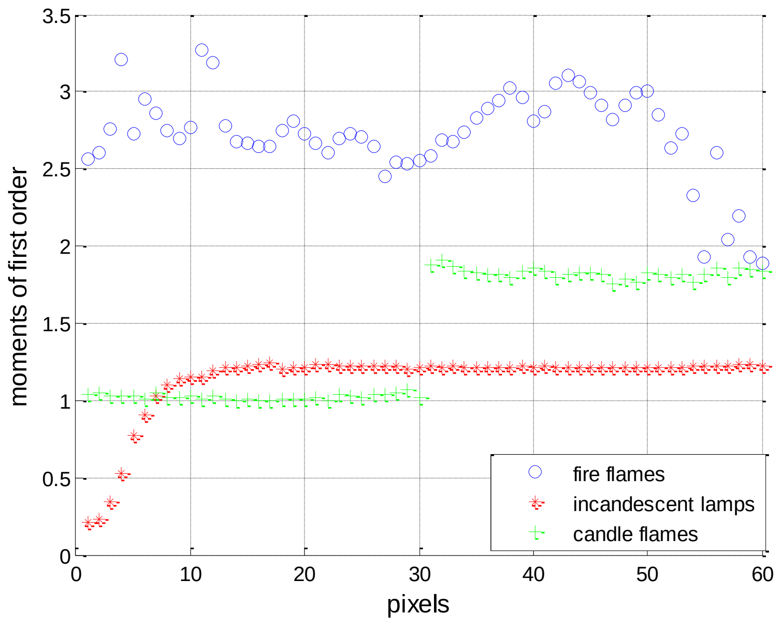

Fig. 2. The moments of first order computed for the colors of pixels in fire flames and other disturbance sources

To compute M_i with equation (7), we use the number of pixels in region i to represent A_i. The perimeter P_i is the length of the region's boundary, which can be obtained from the boundary chain code. Specifically, the boundary of a region can be obtained by applying a high-pass filter operator. The length of one step in the vertical or horizontal direction is considered to be the unit length, the length of a step along a diagonal line is then $\sqrt{2}$ of the unit length. It is straightforward to see that two consecutive steps that are perpendicular to each other along the boundary chain can be reduced to a single diagonal step, and the step size is also $\sqrt{2}$ of the unit length. The length of the boundary can be computed by traversing the boundary chain code as described above. In general, the roundness of a region is larger if its geometric shape is more complex. Figure 3 shows the circular roundness values computed based on the same videos where we have tested the first order color moments. It can be seen from the figure that the circular roundness values of a flame region fluctuates around 16.5, while those of candle flames and incandescent lamps fluctuate around 16.0 and 14.5 respectively.

From Figure 3, we can see clearly that the circular degrees of a flame region are not concentrated and the changes in their values across different frames in a video are relatively larger. On the other hand, those of the interference sources such as candle flames and incandescent lamps are relatively more concentrated. The circular degrees of video images can therefore be used as an effective criterion for early detection of fire flames.

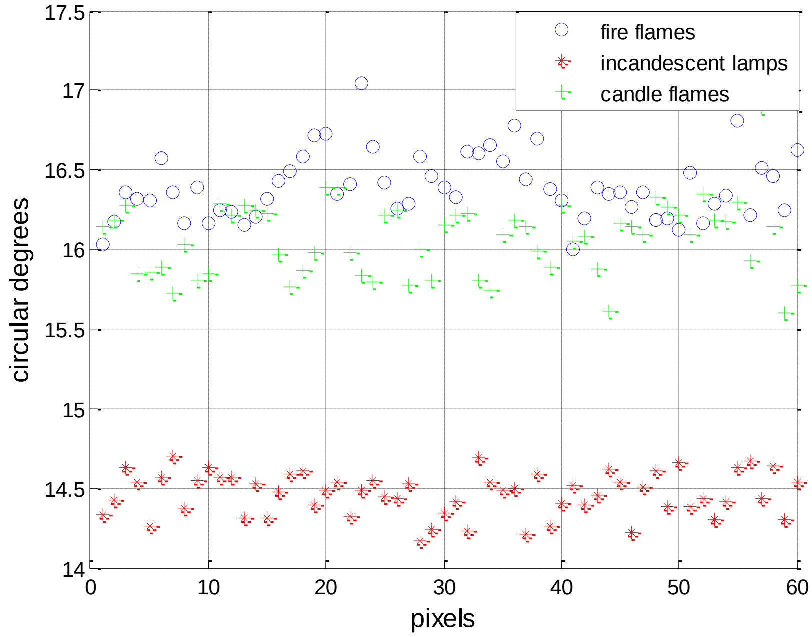

Fig. 3. The circular degrees computed for fire flames, candle flames and incandescent lamps respectively

4. Testing Results

We have implemented our approach and tested its performance on a few testing images. In the experiment, 60 images of the early fire image and the interference source images are selected. Each image is segmented based on the RGB-HSI color model and regions that potentially contain flames are obtained. The first, second and third order color moments and the circular degree of each region are then computed and combined together as a feature to represent the region. We choose 40 groups of the 60 images as the training sample to train the SVM based classifier. The outputs of the classification can be 1 or 2 (1 and 2 are used to represent fire flames and interference sources respectively). The remaining 80 groups are used as the testing data to evaluate the recognition rate and reliability of the method. Testing results are shown in Figure 4.

The blue empty circles in Figure 4 represent the actual classifications of fire flames and other interference sources while the red asterisks show the predicted classification results with our approach. It is clearly shown in the figure that the recognition accuracy of our approach is high. Specifically, a closer analysis of the testing results show that the overall recognition rate is around 93.75%; 87.5% of the fire flames and 100% of the interference sources in the testing images are correctly recognized by our approach. We believe that, since the flame regions in the early stage of a fire is in general small, the recognition accuracy of fire flames is relatively lower.

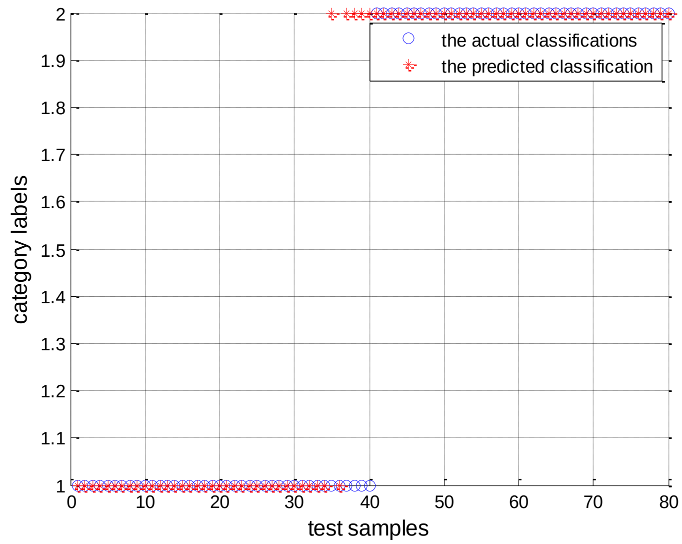

Fig. 4. Testing results on the recognition of fire flames from other interference sources

5. Conclusions

In this paper, we develop a new approach that can accurately recognize fire flames in video images. We develop new features to describe the distribution of the color in a flame region and combine these new features with the circular degree of a region into a feature vector to represent a suspected region. A SVM based classifier is then used to process the feature vector and a decision on whether the region contains fire flames or not is made based on the output of the classifier. Our testing results show that this new approach can detect regions that contain fire flames with high accuracy.

In addition to the static features of a suspected region, dynamic features may also carry important information that distinguishes fire flames from other interference sources. An important direction of our future work is thus to develop algorithms that can accurately extract dynamic features of a suspected region from video images and further improve the recognition accuracy with these dynamic features.

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Conflict of Interest

None

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