Low-Light Forest Flame Image Segmentation Based on Color Features

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Abstract. For some forest fire images with low light intensity, the traditional segment algorithm is not very good. To solve this problem, this paper proposes a low-light forest fire image segmentation method based on color features. In order to increase the brightness of the image, equalization is performed on the V channel in HSV color space. The distribution of flame pixels in RGB color space and YCbCr color space are analyzed. Based on this characteristic, the flame is segmented and the whole flame is extracted. Experiment results showed that the proposed algorithm in this paper had higher detection rate of flame pixels, better segmentation effect, and good anti-interference performance.

1. Introduction
In recent years, forest fire detection technology based on computer vision has begun to replace the traditional forest fire detection method [1]. In the forest fire detection field, many scholars have proposed various algorithms for detecting fire in images or video sequences. Most of these methods are used to deal with fire images in general environments and ignore the low-light forest fire. When the camera is working in the forest, due to insufficient lighting conditions, often too dark video sequences are collected, resulting in low illumination images [2-3]. To solve this problem, the histogram equalization processing is performed on original image in the luminance channel of the HSV color space. Since the image quality and contrast is improved, the subsequent flame image segmentation is facilitated.

There are many flame segmentation algorithms based on color features. Ono et al. [4] proposed that background image of the red component were employed to extract features of potential regions in 2006. This method has high accuracy, but the training process of the neural network is more complex and the training time of the algorithm is longer. Celik et al. [5] collected 150 fire pictures from the Internet in 2007 and generated a set of rules for RGB color space. This method has good segmentation effect on the flame segmentation in normal environment, but it is not ideal for the flame segmentation effect in low illumination environment. Chen Tianyan et al. [6] analyzed the distribution of flame pixels in YCbCr space in 2011, summed up the color decision of the flame. This approach has high detection rate. However, variable thresholds are introduced in the decision conditions, which results in poor reliability and high requirements on the segmentation environment, especially for low-illumination flame images. The distribution of flame pixels in RGB color space and YCbCr color space are analyzed in this paper. The decision conditions under the two color spaces are fused to obtain a complete flame image.
2. Forest Fire Pixel Distribution Characteristics

2.1. Low Light Forest Fire Image Preprocessing
There are a large number of cameras in the forest, parks and other environments. The common disadvantage of the images they captured on cloudy days and nights is the low illumination. For the usual algorithm, these images cannot be processed directly, so the original image needs to be preprocessed to improve the contrast of the image. As shown in Fig. 1 (a) and (b), the flame image has a lower overall luminance value.

![Flame image](image-a)

![Brightness value](image-b)

![Preprocessed flame image](image-c)

![Histogram](image-d)

**Figure 1.** Brightness value of flame image.

The HSV model is a subjective model. The color parameters in this model specifically refer to Hue, Saturation, and Value. In order to facilitate the subsequent flame segmentation, gray-scale histogram equalization is performed on the V-channel in HSV color space [7]. Then the noise points are removed on the basis of median filter algorithm and the results are shown in Figure 1 (c) and (d).

It is shown in Figure 1 that after being pre-processed, the contrast of the image is obviously improved, and the visual effect is more obvious, which satisfy the needs of the subsequent image processing.

2.2. The Distribution of Flame Pixels in YCbCr Color Space
According to the characteristics of the YCbCr color space, the luminance channel is separated from the chrominance image, as shown in Figure 2. Where the (a), (b), (c) and (d) represent the original image, \( Y \), \( Cb \), \( Cr \) channel of the flame image, respectively.
In order to describe the characteristics of the flame pixels in each color channel more vividly, the flame pixel values in each channel are compared with the average pixel in corresponding channel as shown in Figure 3. Where the (a), (b) and (c) represent the $Y$, $Cb$, $Cr$ channel of flame pixel, respectively.

Figure 2. YCbCr color space separation image.

Figure 3. The pixel values in $Y$, $Cb$, $Cr$ channels and their mean values.
Figure 3. Compare the flame value with the average pixel in corresponding channel.

It can be seen from the Figure 3 that in Y channel, the pixel value of the flame area is significantly larger than that of the entire image; in the blue component Cb channel, the pixel value of the flame area is smaller than that of the entire image; while in the red component Cr channel, flame area pixel value is larger than that of the entire image. The above distribution rule can be expressed by equation (1):

\[
\begin{align*}
Y(i,j) &> Y_{\text{mean}} \\
Cb(i,j) &< Cb_{\text{mean}} \\
Cr(i,j) &> Cr_{\text{mean}}
\end{align*}
\]  

(1)

Where \(Y_{\text{mean}}, Cb_{\text{mean}}, Cr_{\text{mean}}\) represent the average pixel values on the corresponding channel.

2.3. The Distribution of Flame Pixels in RGB Color Space

The color characteristics of the flame are more obvious and change from red to yellow [8]. Through the human's intuitive understanding of the flame, it is also found that the red component of the flame pixel is larger than its green component. In this paper, 270 low-illumination forest fire images are studied. The pixel values of the flame pixels of an image on the R and G channels are shown in Figure 4.
Figure 4. Comparison of Pixel Values of Flames in R and G Channels.

It can be seen from Fig.5 that the pixel value of the flame pixel on the R channel is larger than the pixel value on the G channel. This rule is expressed mathematically as equation (2):

$$ R(i,j) > G(i,j) $$

where $R(i,j)$ and $G(i,j)$ represent the pixel value of the corresponding position, respectively.

3. The Algorithm Flow

The low light forest fire image segmentation algorithm based on color features proposed in this paper can be divided into three parts. The first part is about image preprocessing. For the low-illumination flame image, the histogram equalization processing is performed on the V channel of the HSV color space, and a median filter operation is performed to improve the image contrast. The flames are then extracted according to the flame pixel distribution rules in the RGB and YCbCr color spaces, respectively. Finally, the two results are processed by ‘and’ operator to obtain a complete flame image. The algorithm flow chart in this paper is shown in Figure 5.

Figure 5. Flow chart of the proposed algorithm.
4. Analysis of Experiment Results

This paper focuses on the flame image under low illumination. In order to illustrate the applicability of this algorithm, HAF[9] and MCC are employed to analyze the results in Figure 6.

**Figure 6.** This is the segmentation results. The left column is the original image. The central column is ground truth image which means a manually segmented flame image based on the measure supposed by Martin D [10]. And the right column is the results from the proposed algorithm. In addition, the segmentation results are compared with the algorithm proposed by Celik et al. [5] and Chen Tianyan et al. [6].

4.1. HAF

This indicator can quantify the quality of the region segmentation algorithm. It not only includes the measurement of the overlap between the measured segmentation result and the reference result, but also includes the penalty for over segmentation and under segmentation. First, a match index is defined:

\[
M = \sum_{j \in \text{max}, \text{Card}(R_{i\text{ref}}^j \cap R_{j\text{seg}}^j)} \frac{\text{Card}(R_{i\text{ref}}^j \cap R_{j\text{seg}}^j)}{\text{Card}(R_{i\text{ref}}^j \cap R_{j\text{seg}}^j)} \times \rho_j
\]  

Where \( \text{Card} \) represents the number of objects, specifically the number of pixels; \( \rho_j \) represents the weight, that is, the proportion of the closed area in the segmentation result; \( R_{i\text{ref}}^j \) represents the \( i \)-th region in the manually segmented image; \( R_{j\text{seg}}^j \) represents the \( j \)-th region in the segmentation result. Equation (3) expresses the morphological relationship between the two regions. By considering the most important overlapping surfaces, each region in the segmentation results is compared with the corresponding region in the manual segmentation result.

Second, consider over-segmentation and under-segmentation and define the following indicators:

\[
\eta = \begin{cases} 
\frac{\text{NR}_{\text{ref}}}{\text{NR}_{\text{seg}}}, & \text{if } \text{NR}_{\text{seg}} \geq \text{NR}_{\text{ref}} \\
\log \left( 1 + \frac{\text{NR}_{\text{seg}}}{\text{NR}_{\text{ref}}} \right), & \text{otherwise}
\end{cases}
\]  

(4)
The final evaluation index $HAF$ is defined as equation (5):

$$HAF = \frac{M+m \times \eta}{1+m}$$  \hspace{1cm} (5)

Where $m$ is a weighting factor. When the over-segmentation and under-segmentation results are serious, the value of $\eta$ decreases, and the value of the evaluation index $HAF$ is reduced. In general, the value of $m$ is 0.5. It plays a decisive role for over-division and under-segmentation in the judgment process.

The $HAF$ evaluation index of the segmentation results in Figure 6 is shown in Table 1.

From the data in Table 1, we can see that under the conditions of over-segmentation and under-segmentation, the algorithm still has advantages, and the segmentation result still has good anti-interference performance.

**Table 1. $HAF$ evaluation of segmentation results in Figure 6.**

| No. | Celik    | Chen    | This paper |
|-----|----------|---------|------------|
| 1   | 0.0879   | 0.1244  | 0.6897     |
| 2   | 0.0936   | 0.1333  | 0.8528     |
| 3   | 0.1073   | 0.1143  | 0.8750     |
| Average | 0.0963 | 0.1240  | 0.8058     |

4.2. $MCC$

The Matthews correlation coefficient ($MCC$), proposed by Matthews, is often used as a binary classification test to verify the balance of results. This parameter is based on the PRAS parameter, and the evaluation of the results is more balanced and has a higher accuracy ratio. As we all know, TP, FP, TN, and FN indicate true positives, false positives, true negatives, and false negatives, respectively. The $MCC$ is the geometric mean of the regression coefficient and its dual, as shown in equation (6):

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TN+FN)(TN+FP)(TP+FN)(TP+FP)}}$$  \hspace{1cm} (6)

The $MCC$ evaluation index of the segmentation result in Figure 6 is shown in Table 2.

According to the data in Table 2, the average accuracy of our algorithm is 93%. Compared with other scholars’ algorithms, the accuracy of flame segmentation is improved.

**Table 2. $MCC$ Evaluation of Segmentation Results in Figure 6.**

| No. | Celik    | Chen    | This paper |
|-----|----------|---------|------------|
| 1   | 0.6218   | 0.8167  | 0.9338     |
| 2   | 0.7193   | 0.8456  | 0.9194     |
| 3   | 0.6817   | 0.8312  | 0.9452     |
| Average | 0.6743 | 0.8312  | 0.9328     |

5. Conclusion

The characteristics of each color space is employed innovatively in this paper, the distribution characteristics of flame pixels in different color spaces are analyzed, and three different evaluation indicators are applied to evaluate the results objectively, which verifies the feasibility of the algorithm. Compared with other scholars’ algorithms, this method is simple and can extract the pixels of the flame effectively. The experimental data show that the proposed algorithm has higher detection rate, lower false positive rate and stronger anti-interference.

6. References

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