A Flame Detection Method Based on Fusion Feature and SVM for Substation Inspection

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Abstract. For the safety inspection of substation, this paper proposes a flame image detection method based on the combination of fusion feature and support vector machine (SVM). Firstly, the suspected flame area is detected by motion detection and flame color model. Then, four features of B-channel color variation coefficient, roughness, flicker frequency and flame area change rate are extracted. Finally, four features are sent to SVM to learn the flame classifier and used in video flame detection. The experimental results show that the proposed method can effectively identify the flame.

1. Introduction

Flame image detection technology is one of the key technologies in substation safety inspection [1, 2]. Flame detection technology based on video image processing, which needs to set up a camera outside, and automatically analyze and process the captured image within the monitoring range to determine whether there is flame [3, 4, 5]. According to the different types of cameras, they are divided into infrared cameras and ordinary cameras. According to the difference between flame and non-flame imaging in infrared band, infrared camera is used for analysis and processing, so as to realize flame detection. Ordinary cameras usually analyze and process the static features such as the color, brightness, sharp angle, shape of the flame or the dynamic features such as stroboscopic, deformation and displacement, so as to realize the detection of the flame. Celik [6] established a rule-based color model of flame pixel classification in YCrCb space. This method can achieve high accuracy and low false alarm rate for real-time flame in color video sequence. The author of [7] combined the significance detection technology and unified local two value mode to distinguish the flame area and non-flame area. Borges [8] combined Bayesian classifier to recognize the flame area by analyzing the inter frame changes of the potential fire area in the specific low-level features.

These methods play an important role in flame detection technology. Based on the study of the above flame detection methods, this paper puts forward a flame detection method based on fusion feature and SVM under the ordinary camera, which combines the static and dynamic features of the flame, and can accurately detect the flame target.

The rest of this paper is organised as follows. The extraction of suspicious fire areas is proposed in Section 2. In Section 3, the Multi-features extraction of flame is discussed. Flame detection method based on fusion feature and SVM is proposed in Section 4. In Section 5, the performance is discussed. Finally, conclusion is given in Sections 6.
2. Extraction of suspicious fire areas
Firstly, the region of the moving pixel of the image is determined by using the frame difference method. The frame difference method can get the track of target motion by eliminating the fixed or less changed objects in the background between two frames, which is expressed by (1) and (2):

\[
D_n(x, y) = |I_n(x, y) - I_{n-1}(x, y)|
\]

\[
P_n(x, y) = \begin{cases} 1 & D_n(x, y) \geq T \\ 0 & D_n(x, y) < T \end{cases}
\]

where \(I_n(x, y)\) is the gray value of pixel point \((x, y)\) in frame \(n\), \(I_{n-1}(x, y)\) refers to the gray value of pixel points \((x, y)\) in frame \(n-1\). \(T\) is the threshold value of the gray difference. If the difference is greater than the threshold value, it indicates that the pixel meets the motion characteristics, and the pixel is set as the foreground, otherwise it is set as the background. The foreground image may contain flame and non-flame images. The flame is usually red. In flame image recognition, because each color component in his space is independent of color information, it is suitable for color detection and analysis. Based on this, we establish a flame color model based on his color space. Each flame pixel should meet the following conditions:

\[
0 \leq H \leq 60^\circ \\
0 \leq S \leq 60 \\
127 \leq H \leq 255
\]

After motion detection and color model selection of the image, we then carry out morphological processing such as corrosion and expansion on the pixels that meet the requirements, and get the next more suitable flame suspected area for flame feature extraction.

3. Multi-features extraction of flame

3.1. Flame color feature
Assuming that there are \(K\) pixels in the suspected flame area, we can calculate the mean value of color component \(B\), and the standard deviation can be expressed as:

\[
B_{\text{mean}} = \frac{\sum_{i=1}^{K} B(x_i, y_i)}{K}
\]

\[
B_{\text{std}} = \left[ \frac{\sum_{i=1}^{K} (B(x_i, y_i) - B_{\text{mean}})^2}{K-1} \right]^{1/2}
\]

where \(B(x_i, y_i)\) represents the value of color component \(B\) at pixel point \((x_i, y_i)\). We divide the mean value by the standard deviation to obtain the coefficient of variation of color component \(B\), which is expressed as:

\[
B_s = B_{\text{mean}} / B_{\text{std}}
\]

3.2. Roughness feature of flame boundary
There are many methods to represent the shape of the fire area, such as geometric parameter method, Fourier shape descriptor method, shape invariant matrix method, boundary feature method, etc. For
the flame shape feature, the Fourier descriptor can represent the shape of the object very well, but the disadvantage of this method is that it is very time-consuming. Since fire has no specific boundary when it occurs, we are more concerned with the randomness of the flame and the roughness of the shape than with the shape itself.

Through observation, it can be found that the shape of the flame is affected by the environmental factors. Moreover, its shape is irregular, and changes with time. The uniqueness of the flame image can be expressed by the boundary roughness, which can effectively determine the shape of the fire region and reduce the time complexity of the algorithm. Therefore, the ratio of the perimeter of the convex hull of the candidate region to the perimeter of the flame is used to describe the roughness of the boundary. The flame roughness $BR$ is defined as:

$$BR = \frac{P}{P_{CH}}$$

where $0 < BR \leq 1$. $P$ is the perimeter of the suspected fire area. $P_{CH}$ refers to the perimeter of the convex hull in the fire zone. Convex hull refers to the smallest convex polygon that can contain fire area.

### 3.3. Feature of flame area change

Fire is a continuous process from the beginning to the end, and the characteristics of flame diffusion and spread are expressed in the image as the area of flame is constantly changing, and the area is constantly increasing in the continuous image frames. Therefore, we use it as a criterion for the determination of flame. We define the rate of area change as:

$$A_r = \frac{|S_{N+1} - S_N|}{S_N}$$

where, $S_N$ and $S_{N+1}$ respectively represent the area size of the adjacent two flame regions.

### 3.4. Flame stroboscopic feature

In the process of combustion, the flame will show the characteristics of continuous flicker, which is an important feature to distinguish the flame from the non-flame. In the process of the flame beating continuously, the area of the flame will also change continuously with the flicker of the flame, and its changing law has a direct correspondence with the flicker frequency of the flame, and there is a big difference with the interfering object. According to this feature, we set a counter $SUM$ to analyze the flame flicker feature of an image with a given length sequence $N$. In the experiment, the value of length sequence $N$ is 25. If the product of the area difference between two adjacent frames in three consecutive frames is less than 0, $SUM$ plus 1, otherwise plus 0. The formula is expressed as:

$$SUM(n) = \begin{cases} SUM(n-1) + 1 & d < 0 \\ SUM(n-1) & d \geq 0 \end{cases}$$

where $d = (S_{n+2} - S_{n+1}) \times (S_{n+1} - S_n)$. The value of $SUM$ is used to approximate the flicker characteristic $F_k$ of flame to exclude the influence of other interfering objects.

### 4. Flame detection method based on fusion feature and support vector machine

Support vector machine (SVM) is a new machine learning method widely used in the field of image processing and pattern recognition. Its core idea is to map the linearly indivisible feature vectors in the low-dimensional space to the high-dimensional space and find the optimal hyperplane in the high-dimensional space, so as to achieve the goal of linear separability. Considering the limited flame samples in this paper, we decided to use support vector machine to learn and classify features. In the process of mapping transformation, the selection of kernel function is very important. In this paper, the
radial basis function is selected as the kernel function after a large number of experiments, and its
definition is expressed as:

$$K(x, x) = \exp \left( \frac{||x - x'||^2}{2p^2} \right)$$

(10)

where $p$ is the width of the kernel function. In the process of flame detection, we first train the flame
detection classifier. In this paper, a 4-dimensional fusion feature vector $X$ is constructed according to
the color, shape and dynamic features of the flame, and the fusion feature vector $X = [B_s, BR, A, F_t]$ is
sent into the support vector machine for training to obtain the classifier. For the image to be
recognized, the feature vector is calculated and input to the trained classifier for classification.

5. Performance evaluation

5.1. Validity of flame detection method

![Flame video and non-flame video](image)

Figure 1. Flame video and non-flame video

| Proposed method      | CDR | EDR |
|----------------------|-----|-----|
| non-flame videos     | 96.2| 3.8 |
| flame videos         | 96.4| 3.6 |

Table 1. Performance comparison of the proposed method.

In order to verify the effectiveness of the proposed flame detection method, this paper selects 3 flame
videos and 3 non-flame videos from the self-built video library for our experiment. The videos are
shown in Figure 1. The videos 1, 2 and 3 are flame videos, and the videos 4, 5 and 6 are non-flame
videos. The correct detection rate (CDR) and error detection rate (EDR) of the flame were used as the
evaluation criteria for flame detection, which are expressed respectively as:

$$CDR = \frac{CD}{N} \times 100\%$$

(11)

$$EDR = \frac{ED}{N} \times 100\%$$

(12)

where $CD$, $ED$ and $N$ represent the number of correctly detected video frames, the number of
wrongly detected video frames and the total number of video frames, respectively.
As can be seen from Table 1, the method presented in this paper can accurately detect the flame in the flame region and well overcome the influence of interferers. This shows that the flame detection method is robust.

5.2. Accuracy of flame detection method
In order to verify the effect of this algorithm, experiments are carried out on all the videos in the test video set. In order to investigate the performance of fusion features in flame detection, the contribution of fusion features in flame detection is evaluated. The method adopted in this paper is to exclude one of the four characteristics one by one, and then calculate the above indexes. If there is a large decrease in the above index value after excluding a certain feature, it indicates that the excluded feature has a greater effect on the index, and vice versa. The experimental results are shown in Table 2.

| Method                              | CDR  | EDR  |
|-------------------------------------|------|------|
| Proposed method with four features  | 96.3 | 3.7  |
| Proposed method without BR          | 88.8 | 11.2 |
| Proposed method without $A_r$       | 86.4 | 13.6 |
| Proposed method without $F_i$       | 82.5 | 17.9 |
| Proposed method without $B_s$       | 85.3 | 14.7 |

It can be seen from Table 2 that $F_i$ has a great contribution to the proposed algorithm in this paper. When any one of these features is excluded, the CDR value decreases and the EDR value increases. As a result, the performance of the algorithm is reduced. When all four features are retained, CDR and EDR reached 96.3% and 3.7%, respectively. Therefore, the proposed algorithm in this paper achieves the best results. The above experiments show that the four characteristics have great contributions to flame detection.

6. Conclusion
In this paper, an unsupervised foreign object detection algorithm based on K-Means and GMM is proposed and verified on the first kind of image. In this paper, bird’s nest is used as a foreign object. For the first kind of image, the preprocessing is carried out firstly, that is to remove the interference and leave the nest branches. Then, the line is extracted by the Progressive Hough transform. Aiming at the specific goal of bird’s nest, the length histogram and direction histogram of bird’s nest branches are designed. Finally, the purpose of unsupervised bird’s nest recognition is realized by PCA. Experimental results show that the proposed algorithm can achieve good recognition effect.

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