Flame and Smoke Detection in Substation Based on Wavelet Analysis and Convolution Neural Network

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ABSTRACT

In this paper, a fire detection method based on color features, wavelet analysis, and convolution neural network is proposed. Firstly, the candidate region of flame is extracted by color segmentation method, and then the candidate region of smoke is generated by the background fuzzy model based on wavelet analysis. Then the candidate region is filtered by the trained CNN model, and the position of flame and smoke in a picture is located. Finally, a large number of fire pictures in different scenes are used to test the algorithm. The results show that this method can detect the location of flame and smoke accurately and quickly from images or videos, and can be applied to fire detection tasks in substation scenarios.

CCS Concepts

Computing methodologies → Object detection

Keywords

fire detection; substation; smoke detection; color characteristics

1. INTRODUCTION

There are inflammable and explosive devices such as transformers, capacitors and high voltage switches in substations, which have strong electromagnetic interference and are prone to fire. Fire protection in substations directly affects whether the substation can operate safely.However, the traditional fire detection technology mainly uses sensors to identify the flame and temperature. Each sensor can only detect the local space around the control points, which is difficult to play a role in special occasions such as open space. At the same time, there will be false alarm or missed alarm. Because these methods can only sense the occurrence of fire when the fire spreads to a certain extent, it will inevitably cause some losses. In order to reduce the loss caused by fire, it is necessary to detect flame and smoke in the early stage of fire occurrence and exterminate the fire in the bud.With the development of digital image processing technology in computer field, image-based fire detection technology is more and more widely used in the field of fire detection. Different smoke and flame detection algorithms are constantly proposed [1-4].In smoke image processing, Shu Xueming and others[5] proposed a fire detection method based on particle imaging system, light scattering system and smoke channel system .Xie Zhenping[6]uses Bayesian decision-making method to detect video smoke . Gomez-Ro-driguez F et al. [7] extract the moving region by optical flow method, and then detect the smoke by using wavelet method combined with the motion characteristics of smoke.Yuan [8-9] uses cumulative motion direction model to detect smoke. However, estimating the direction of motion by simple pixel summation method will lead to inaccurate estimation of direction.Then Yuan uses the double mapping structure to extract shape invariant features and combines them with AdaBoost classifier to detect video smog in [10].In [11], the author uses the pixel-level classification algorithm based on histogram to detect flame and smoke. The video sequences containing flame and smoke are used as training samples, and the regions with reduced high frequency energy components in images are recognized as smoke by wavelet transform. Phillips [12] et al. applied color histogram model based on Gauss distribution to flame detection. In [13], the author detects the flame by video analysis in wavelet domain, detects the flame flicker by one-dimensional time wavelet transform, and detects the color change of the flame moving region by two-dimensional space wavelet transform.

According to the high randomness of fire detection in complex and changeable environment, a new fire detection method based on color feature, wavelet analysis and convolution neural network is proposed in this paper. The candidate area of flame is generated by the color feature of flame, and the candidate area of smoke is generated by the background fuzzy feature. Candidate areas are filtered by carefully designed small CNN models, and the positions of flame and smoke are detected. The experimental results show that the method can detect flame and smoke in different scenes through real-time monitoring of specified scenes, and achieve the purpose of early detection of fire and accurate location of fire.

This paper is organized as follows.The next section analyzes the image features of flame and smoke and introduces the generation method of flame and smoke candidate region.Section III describes the proposed CNN architecture. In Section IV, results of this method are described. this paper is concluded in the last section.

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2. GENERATION OF CANDIDATE AREAS FOR FLAME AND SMOKE

2.1 Flame Detection Model

Flames usually appear red. As we know, RGB color model has less computational complexity than other color models. However, HIV and HSV color models are often used in flame image recognition, because their description of color is more suitable for human perception of the color of the objective world. Firstly, the flame images in different scenarios are sampled, and then the RGB spatial flame color feature model is established by analyzing the R, G, B mean values of the flame area.Figure 1 shows a partially sampled image .Table 1 shows the R, G, B statistical mean values of flame images in each sample of Figure 1.

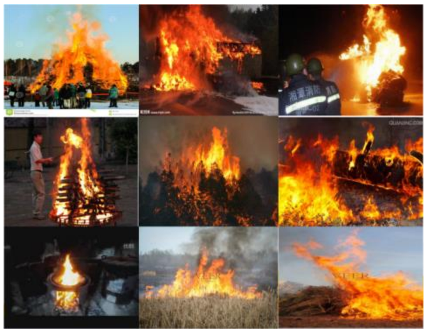

Figure 1. Part of sampling images

Table 1. Sampling values of flame image in RGB space

Image sequence number	B	G	R
1	98	230	250
2	56	145	200
3	88	188	230
4	38	129	213
5	49	130	247
6	108	219	219
7	76	234	240
8	71	225	251
9	60	164	253

Table 1 shows that the value of R channel is larger in most flame regions and the value of B channel is the smallest. In this paper, the RGB color feature model of flame is expressed as follows:

$$\begin{aligned}&(i) R >= G >= B \\ &(ii) R >= mean(R), G >= mean(G), B >= mean(B)\end{aligned} \qquad (1)$$

The mean (R), mean (G) and mean (B) in the above formula represent the mean of RGB channels of all the pixels in a picture, RGB color space is often used in display system, which is not suitable for image segmentation and analysis. Only using RGB color model to segment flame will produce a large number of false flame areas. The effect of flame segmentation is very unsatisfactory. Therefore, it is necessary to transform the image into HSV space to extract the flame area.

The flame detection proposed in this paper is aimed at the early stage of fire, when the flame area is small, it is R > G > B in RGB space and saturation in HSI color space. The smoke image is transformed from RGB space to HSI space, and the color model of flame image in HSI color space is obtained, which is expressed as follows:

$$\begin{aligned}&S = 1 - 3 \times (\min(\min(r, g), b) / (r + g + b)) \\ &S >= (255 - r) \times \frac{sTh}{rTh}\end{aligned} \qquad (2)$$

In the above formula, H represents the H component in HSI space, S represents the S component in HSI space. By adjusting the parameters rTh and sTh, the number of flame candidate areas can be changed. The smaller the ratio of rTh to sTh, the more flame candidate areas can be obtained, and the more false alarms can be obtained. In order to detect all flame regions, rTh = 200 and sTh = 5 are set in this paper.

2.2 Background Fuzzy Model

Current smoke detection methods are mostly based on smoke, temperature, light and composite detectors. Because these detectors rely on by-products of combustion process to detect smoke, they can only effectively detect smoke near flame and smoke source. For large space or outdoor places, the reliability of detection is low.

In order to improve the real-time and reliability of smoke detection, image processing technology should be used in smoke detection research. From the perspective of image processing technology, smoke can be detected by using the characteristics of background ambiguity, diffusivity, principal direction angle and so on. After synthetically comparing the difficulty and accuracy of various methods, we decided to use the background ambiguity of smoke to detect smoke.

Mean Background Model is a commonly used background ambiguity model, which regards moving objects as noise and eliminates them by means of cumulative averaging. The background image is obtained by averaging the sequence images of moving objects running for a period of time. It can be defined by the expression：

$$\text{Background}(x, y) = \frac{1}{N}\sum_{i=1}^{N} img_i(x, y) \qquad (3)$$

Mean background model is relatively simple to implement. It needs to read every frame of image, and then sum and average the corresponding pixels of each frame. In this paper, a three-dimensional matrix $\mathbf{mat}(x, y, k)$ is used to store the gray value of each frame image, where is a fixed value, which can be the whole video or a sequence image for a period of time.

2.3 Smoke Detection Model

Smoke can partially occlude other objects in general. In spatial domain, the background becomes blurred, and in frequency domain, the high frequency signal attenuates. According to the characteristics of smoke, we can use two-dimensional discrete wavelet transform to extract the texture features of smoke image and distinguish the texture blurring characteristics, so as to detect the existence of smoke.

The main feature of wavelet transform is that it can fully highlight some aspects of the image characteristics, and can localize the time (space) frequency analysis. The signal is refined at multi-scale by scaling translation operation, and the result of time subdivision at high frequency and frequency subdivision at low frequency is achieved.

An image can be decomposed into four parts after two-dimensional discrete wavelet transform: a low-frequency (cA) component sub-image and three high-frequency component sub-images. Among them, three high-frequency component sub-images contain texture information in horizontal direction (HL), vertical direction (LH) and diagonal direction (HH). When there is smoke in the image, the energy value of these three high-frequency component sub-images is usually reduced.

Suppose $\mathrm{w}_n(x,y)$ represents a composite image consisting of the sum of the energy values of three high frequency component subimages:

$$\mathrm{w}_n(x,y) = \left|LH_n(x,y)\right|^2 + \left|HL_h(x,y)\right|^2 + \left|HH_n(x,y)\right|^2 \quad (4)$$

The composite image is decomposed into sub-blocks of size $(K1, K2)$. The energy $\mathrm{e}_i(l_1,l_2)$ of the sub-block i is:

$$\mathrm{e}_i(l_1,l_2) = \sum_{(x,y)\in R_i} w_n(x,y) \quad (5)$$

In the formula above, R_i is the i sub-block with the size of (K1, K2) in the composite image $w_n(x,y)$, and (l_1,l_2) represents the corresponding position of the energy sub-block in the composite image. In this paper, the size of the block is 4x4.

The local high frequency energy of the current image after wavelet transform is compared with that of the background image after wavelet transform. If the energy value of the sub-block at (l_1,l_2) decreases, it means that the texture or edge of the current image is no longer as sharp as that of the background image, and there may be smoke in this area.

In order to improve the recognition rate, two thresholds of 0 < T1 < T2 < 1 are set. In this paper, T1 = 0.6 and T2 = 0 are selected. If smoke in the image results in the reduction of high frequency energy of the wavelet, it should satisfy the following requirements:

$$\mathrm{e}_i(l_1,l_2)^{\bullet} \times T2 < \mathrm{e}_i(l_1,l_2) < T1 \times \mathrm{e}_i(l_1,l_2)^{\bullet} \quad (6)$$

represents the sub-block energy value of the composite image at.If the energy value of the sub-block satisfies the condition of Eq.(6), all the pixel values in the sub-block are replaced by 0.The original image is restored by inverse wavelet transform. At this time, the original image is missing the pixel value of the identified smoke area. Then, by constructing the binary image of the image, all connected areas are found as candidate areas of the smoke area.

3. CNN FOR VIDEO FIRE AND SMOKE CLASSIFICATION

3.1 CNN Structure

The concept of convolutional neural network was first proposed by Fukushima [14]. He built a hierarchical neural network architecture inspired by Hubel's research work [15]. Leunun [16] successfully applied them to digital classification and built Letnet neural network to recognize handwritten numerals. In convolutional neural networks, each layer acts as a filter to extract the specific features in the original image. The shallow feature map of CNN is mainly used to extract those relatively obvious image features.

Through color segmentation of the original image in RGB space and HSV space, the candidate areas of flame can be extracted. The background ambiguity method based on wavelet analysis can be used to extract candidate areas of smoke. Because of the complexity of image background, the extracted candidate regions may contain some false-detection image blocks. The candidate regions of flame and smoke can be filtered out by carefully designed CNN classifier. At the same time, in order to achieve real-time speed of detection algorithm, a small CNN network is designed. The network consists of three convolution layers, three pooling layers and two full connection layers. The size of the model is 391k. Among them, the convolution kernel size of the first two convolutional layers is 3×3, and the convolution kernel size of the third convolutional layer is 2×2.Each convolution layer is followed by a pooling layer and a PReLu activation function. The output feature dimension of the first fully connected layer is 128, and the output feature dimension of the second fully connected layer is 3, and the final softmax layer can calculate the probability of the input image blocks belonging to flame, smoke, and background, respectively.

3.2 Training Process

The purpose of designing CNN classifier is to filter candidate areas of flame and smoke, so as to filter out false candidate targets. There are three types of training samples: flame samples, smoke samples and background. The production process of training samples is as follows: 1. Marking the flame and smoke areas of the collected fire images with image annotation tools; 2. Cutting any size image blocks randomly from the fire images according to the annotation information and scaling them to 24*24 size; 3. Background samples were randomly clipped from images without flame or smoke, and scaled to 24 x 24 size. The training set contains 60,000 images, and the number ratio of flame samples, smoke samples and background samples is 1:2:3. In the training process, 60% of the images are used as training set, 20% as verification set and 20% as test set. We use the SGD method to train the network. The batch size is 256, and the weights of the CNN network are randomly initialized. The initial learning rate was 0.01 and the momentum was 0.9. At the same time, in order to prevent the CNN network from over-fitting, Dropout layer is added after the two full connection layers, and dropout_ratio is 0.5. We trained the network for roughly 1000 cycles.

4. EXPERIMENTAL SIMULATION

4.1 Fire Data Set

Because pyrotechnic experiments are not allowed in substations, it is difficult to obtain ideal experimental video data. In view of the experiment of flame detection, our team has set up a flame data set, and collected 3000 flame pictures in different environments and scenarios, including some substation flame pictures, forest flame pictures, grassland flame pictures, urban flame pictures and so on. For the smoke detection experiment, this paper tests on eight smoke videos. Four of the videos contain smoke, which is used to test the recognition accuracy of the algorithm. The other four videos do not contain smoke, which is used to test the false detection rate of the algorithm.

4.2 Experimental Results

For flame detection, P_{rec} (precision)、 P_{TPR}(true positive rate), and P_{FPR} (false positive rate) are used to quantify the performance of the algorithm.

The experiment is compared with [17-19]. [17] uses the Gauss mixture model to detect the flame foreground, extracts color features from a large number of forest flame samples and finally detects the flame. In [18], color features are extracted from a large number of flame images, motion features are obtained by cumulative geometric independent component analysis (C-GICA), and flame recognition is achieved by back propagation neural network (BP).[19] extracts brightness and color features based on visual saliency, uses principal component analysis to reduce dimensionality, and combines dynamic and static features through linear weighting. The final experimental results are as follows:

Table 2. Results of various flame detection algorithms

Flame detection method	P_{rec}	P_{TPR}	P_{FPR}	**processing Time(ms)**
The proposed method	0.882	0.791	0.002	80
[17]	0.855	0.786	0.008	120
[18]	0.832	0.769	0.03	100
[19]	0.866	0.790	0.004	200

It can be seen from Table 2 that compared with the other three flame detection methods, the flame detection algorithm of this paper can not only ensure the accuracy of flame detection, but also the average detection time is the least, which can meet the real-time requirements of substation flame detection. The following is the actual detection effect of the partial flame picture.

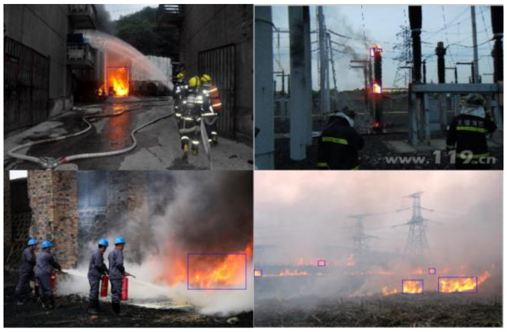

Figure 2. Flame image detection results

For smoke detection, this paper has been tested on 8 segments of video, and compared with the smoke detection algorithms in [3] and [8]. The experimental results are shown in Table 3 and Table 4.

Table 3.Comparison of video frames in which smoke is first detected

Video sequence	**Total number of frames**	**The proposed method**	**[3]**	**[8]**
1	1127	272	312	339
2	2889	77	93	120
3	347	200	--	230
4	933	66	74	110

Table 4.Comparisons of frames misdetected in smokeless video

Video sequence	**Total number of frames**	**The proposed method**	**[3]**	**[8]**
5	4536	3	12	20
6	1000	0	0	1
7	3000	0	0	3
8	700	0	2	6

For the smoke video in Table 3, the proposed algorithm can detect smoke earlier than the algorithms in[3] and [8]. For video 1, this algorithm detects smoke in frame 272,[3] detects smoke in frame 312, [8] detects smoke in frame 339; for video 3, this algorithm detects smoke in frame 200, [3] detects smoke in frame 230, and [2] has not detected smoke. For the four smokeless videos in Table 4, the error detection of this algorithm is the least. For video 5, there are 3 frame errors in this algorithm, 12 frame errors in [3] and 20 frame errors in [4]. For video 6-8, there is no false alarm in this algorithm, while the algorithms in [4] have false alarm in video 6-8. Through comparison, it is found that the proposed algorithm can detect smoke earlier, and the false detection rate is low. Figure 3 below is a screenshot of smoke detection results in this paper.

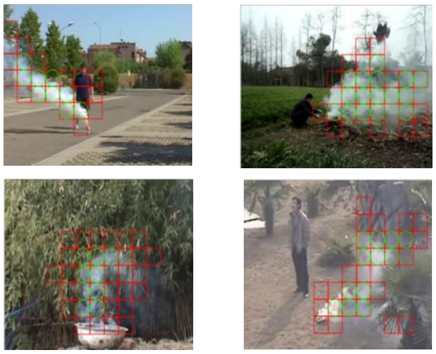

Figure 3. Screenshots of test results in this paper

5. CONCLUSION

This paper proposes a fire detection method based on color feature, wavelet analysis, and convolutional neural network for substation environment. Firstly, the candidate regions of flame and smoke are extracted by color segmentation method and background blur model respectively, and then the candidate regions are screened by CNN classifier, and the positions of flame and smoke are quickly and accurately located. The experimental results show that the proposed algorithm can detect flames and smoke in similar substation scenarios, which can meet the requirements of rapid and accurate substation fire detection.

6. ACKNOWLEDGMENTS

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