Fire Video Image Detection Based on a Convolutional Neural Network

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Abstract. Computer vision-based and real-time flame detection is very important in modern surveillance system. At present, convolutional neural network (CNN) has become a topic discussed by more and more researchers because of its high recognition accuracy and wide application. The preprocessind process of the traditional image processing method is complicated and the false positive rate is high. So, in this paper we proposed an algorithm for detecting flame in real time using CNN technology. Firstly, to improve the accuracy of detection, we proposed a suspicious target regions segmentation for disposing the suspected flame regions. This algorithm could locate the target area and segment the target area to improve the flame detection and recognition accuracy. Then, we designed a model based on CNN to classify the extracted feature maps of candidate areas. Finally, we could get the detection of flame according to the classification results. The experimental results show that the approach has high recognition accuracy.

1. Introduction

1.1. Background
In the past few decades, flame detection techniques have received increasing research attention. Fire detection can reduce casualties and economic losses, so the detection system requires higher detection speed [1]. To ensure the reliability of flame detection, the conventional flame detection methods usually extract the manual features which are color feature [2], form feature [3], texture feature [4] and motion [5]. The researchers combined these features to improve the accuracy of the tests. Ruchanurucks et al [6] defined a flame pixel color model based on RGB color space, which used the range of the value of each color component of the pixel, as well as the relationship between R and B, and increased the brightness characteristics of the flame pixel for segmentation, which achieved a good effect in the experiment. If only use the color features, the accuracy of flame detection will not high. So they combined the dynamics and foreground detection. Specifically, the flame area varies with the flow of air. Therefore, many present approaches [7], [8] uses a motion recognition step first to delete the static regions. It not only reduces the computational time but also mitigates the interference of noise and distractors. At present, a lots of deep learning methods are widely used in various applications [9-11], In order to improve the fire detection accuracy, some scholars used the deep learning model to extract
the useful functions of fire detection in image sequences [12]. They proposed a CNN model for video identification of fire and smoke. Because of the merit of CNN, we have done a lot of research on flame detection using CNN model.

1.2. Main Work of the Study
To improve flame detection, we proposed an improvement for flame detection. The specific work content was as follows:
a. Considering the efficiency of detection, we presented a candidate target area extraction approach for disposing the suspected obstacle area. And we could obtain a complete ROI region which is ready for the training of a CNN.
b. The proposed algorithm improves the fire detection accuracy and reduces the number of false alarms compared to other methods.

1.3. Organizational Structure
In the following, we introduced the CNN in Section 2. We propose a method of flame detection in Section 3. Next, the experimental results are provided in Section 4. Lastly, Section 5 concludes with a discussion and suggestions for future research directions.

2. Convolutional Neural Network

2.1. An introduction to convolutional neural networks
CNN is a neural network dedicated to processing and has similar network structured data, for example, time series data (which can be thought of as a 1-dimensional network that is periodically sampled on the time axis) and image data (which can be considered as 2-dimensional network). Since the convolutional neural network was proposed, models using CNNs, such as CIFAR and ImageNet, etc., have obtained achievements in many fields. To date, researchers have continued to study and propose many typical networks, such as LeNet, AlexNet, GoogLeNet and ResNet. Research based on convolutional neural networks continues, and it plays a significant role in various fields, for instance, speech recognition, surveillance scene recognition, and face detection.

2.2. The basic structure of convolutional neural networks
A CNN is a kind of feedforward neural network with a deep structure. Its basic components include the convolutional layer, pooled layer (also called sampling layer) and fully connected layer. Alex Net has five convolutional layers, three of which are followed by a maximum pooled layer and finally three fully connected layers. Such a structure makes it possible to learn the target features autonomously from the training set so that the acquired image features are richer than the artificially captured features and can more accurately express the essential attributes of the objects.

3. The proposed method
The overall scheme for flame detection in this paper is shown in figure 1. First, we propose a color segmentation model for flame candidate regions in video sequences based on multiple surroundings. Second, the CNN extracts the flame characteristics of the object. We train the proposed CNN according to the flame data set of the flame separated in the first step. And we extract the flame feature through the pool 1 network. Third, we use a rectangular frame to calibrate the flame position and the detection result is exported.

Figure 1. The overall scheme for flame detection
3.1. **Suspected fire zone extraction method**

Flames have unique visual characteristics. The flame color and the surrounding environment contrast characteristic is remarkable, plays the pivotal role in the fire detection. In our paper, a fire color feature model is designed to improve the calculation speed of the algorithm. RGB color space uses different proportions of RGB three primary colors mixed to express different colors. Because the computational complexity of RGB models is lower than other color models, the proposed RGB model is used to extract fire color features. The original image was segmented out of the candidate region using a flame color model. Our experimental results illustrate that each RGB pixel of the flame should meet the following conditions:

\[
M(x, y) = \begin{cases} 
1, & f_R(x, y) - f_B(x, y) > 60 \land f_R(x, y) > 200 \\ 
0, & \text{otherwise} 
\end{cases} 
\]  

(1)

Here, \(M(x, y)\) shows the segmented color binarization mask, \(f_R(x, y)\) is the value of channel R, and \(f_B(x, y)\) is the value of channel B.

Then, the normalized candidate regions of CNN are extracted by obtaining the external rectangle of the connected region, the binary images of the external rectangle regions with different external scenes are shown in figure 2.

![Figure 2. experimental results](image)

3.2. **Fire detection of deep neural network structure**

In order to reduce the complexity of convolutional neural network training, this paper increases the positioning of the Bounding Box and the ROI layer when designing the network, which improves the operation speed. According to the experience of previous research scholars, when the number of layers of the network is increased, the more characteristics of learning are learned. However, in many practical applications, there are many problems, such as the difficulty of training the network, the type of training test database, the test equipment, etc., and the detection effect of the model with many network layers is not very satisfactory.

As we all know, the structure of convolutional neural network includes three-part convolutional layer, pooled layer and fully connected layer. According to the structure of CNN, this paper proposes a CNN which is more suitable for flame detection. The structure, its network structure diagram is shown in figure 3. In essence, the CNN applied to flame detection is still to extract the flame features of the input image through the training network, and to extract the abstract flames layer by layer to obtain the global features that can be characterized. The high-level features, in turn, get the classification accuracy of the flame.

![Figure 3. The improved convolutional neural network structure](image)
4. Experimental Results and Discussion

4.1. The Training of Convolutional Neural Network
In this paper, the experimental operating system is Windows 10 with 16GB memory and i7-8700 CPU. And our data set is from video published by various research institutions on the Internet (http://www.ultimatechase.com/Fire_Video.htm, http://signal.ee.bilkent.edu.tr/Visi Fire), and the images from video are taken to create the data set of fire images. We trained the training data set, and the loss curve in the training process is shown in figure 4. From figure 4 we can find that the loose curve gradually converges with the increase in the number of iterations, showing a continuous decline and a state of approaching stability. The loss function calculation of the algorithm in this paper uses the following formula:

\[ L(x, c, l, g) = \frac{1}{N} \left( L_{\text{conf}}(x, c) + \alpha L_{\text{loc}}(x, l, g) \right) \]

Here, N is the default number of matched boxes, and x indicates whether the matched box belongs to a certain category, with a value of \{0, 1\}. l is the prediction box, g is the true value; c is the confidence that the selected target belongs to a certain category.

4.2. Flame detection
Figure 5 shows the flame detection effect under normal light. The detection of the flame by the proposed approach is highlighted by the blue rectangle inside the images. Our algorithm can accurately detect flame under normal light. Generally, our algorithm has a higher accuracy in identifying flames with a simple background under normal illumination. It can accurately identify flames.

Figure 6 shows the flame detection effect at nighttime. The experiment results have shown the adaptability and robustness of our proposed detection method under disparate scenes and light conditions. At the same time, the experimental equipment in this paper is simple. The cost compares with the traditional detection equipment is lower. We have farreaching significance for the practical application.
Figure 6. The flame detection effect at nighttime

4.3 Comparison experiment
In order to further manifest the accuracy of our algorithm, we choose the method with the multi-feature fusion based flame detection (method 1). This is a method of adaptive background update based on infrared video images which is used to detect suspected flame areas and introduces the flame detection method of multi-feature fusion fire detection based on the analysis method for improving hierarchical process.

Table 1. The comparison of recognition accuracy

| Method          | Recognition Accuracy (%) | Speed (fps) |
|-----------------|--------------------------|-------------|
| Method 1        | 95.9%                    | 0.75        |
| Our method      | 97.1%                    | 0.12        |

The recognition accuracy is shown in table 1. As can be seen from table 1, the proposed method is sensitive to flame images and has a high detection accuracy, and its speed is relatively fast.

5. Conclusion
This paper proposes a flame detection scheme based on a CNN. We propose a CNN model to learn the characteristics of different types of flames by using the structural advantages of CNN. Then the global features with representational meaning are extracted. The improved suspected fire zone extraction method is used to realize flame detection and recognition. Experimental results show that the algorithm is effective and has high recognition accuracy. In the future, it is necessary to improve the detection model and reduce the network complexity. However, the algorithm has some limitations. For example, when some lights appear, a false check can occur. We plan to make further study of this problem.

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