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A convolutional neural network-based flame detection method in video sequence

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Abstract

Computer vision-based fire detection is one of the crucial tasks in modern surveillance system. In recent years, the convolutional neural network (CNN) has become an active topic because of its high accuracy recognition rate in a wide range of applications. How to reliably and effectively solve the problems of flame detection, however, has still been a challenging problem in practice. In this paper, we proposed a novel flame detection algorithm based on CNN in real time by processing the video data generated by an ordinary camera monitoring a scene. Firstly, to improve the efficiency of recognition, a candidate target area extraction algorithm is proposed for dealing with the suspected flame area. Secondly, the extracted feature maps of candidate areas are classified by the designed deep neural network model based on CNN. Finally, the corresponding alarm signal is obtained by the classification results. The experimental results show that the proposed method can effectively identify fire and achieve higher alarm rate in the homemade database. The proposed method can effectively realize the real-time performance of fire warning in practice.

Keywords Convolutional neural network · Flame detection · Feature maps · Deep learning

1 Introduction

Conventional point smoke and fire detectors typically detect the temperature and the presence of certain particles generated by smoke and fire by ionization or photometry [1, 2]. However, alarm is not issued unless temperature and particles reach the sensors to activate them. Furthermore, many such detectors may not effectively detect in large space and outdoor environments. Therefore, fire is one of the common happening events, whose detection at early detection of fire is extremely more important than anything else to minimize loss of lives and property damage [3]. According to Jiu Yuan Zhuang Bei Web site of China (JYZBW) report 2017, a total of 205 fires occurred only in China, resulting in 2.17 million loss, 263 civilian fire injuries, this is just public statistics [4]. With the rapid development in computer performance and video processing techniques, there is a significant tendency to replace standard flame detectors. Since the video-based fire detection (VFD) can availably reduce detection time compared to the currently available sensors [5], the effective VFD method has become a hot topic in modern surveillance system [5, 6].

To effectively detect fire in real time, the traditional flame recognition algorithm mostly adopts the manual features which are color [2], shape [8], texture [7, 9] and motion [9, 10]. However, the extraction of uni-feature of flame cannot meet the high flame detection rate. Some researchers have proposed many flame detection models and algorithms based on multi-feature [11]. To improve the performance of probabilistic methods in flame detection, an improved probabilistic model is proposed based on color and motion features, which can generate candidate fire shapes more

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reasonable [12, 13]. To improve the video fire detection rate, a robust fire detection algorithm based on color and motion model without static background is proposed, which proved a satisfactory fire detection rate for different fire scenes [14, 15]. To reduce the number of false alarms, a new flame detection algorithm based on color and texture features is proposed, which can ensure the accurate classification of positive samples [16, 17]. However, most manual features have no invariance of translation, scale and rotation. Moreover, the flame has greatly difference under different external conditions, especially illumination, wind, burner and the distance from the camera, so most manual characteristics are designed based on statistical in certain circumstances.

Nowadays, a variety of deep learning algorithms are widely used in many application [18, 19], such as back propagation (BP) [20], bayes neural network (BNN) [21] and convolutional neural network (CNN) [22, 23]. To enhance the fire video detection performance, some experts use deep learning model to extract the useful features for detecting fire in video sequence. To effectively recognize the wildfire smoke, a smoke detection method based on BP is proposed, which can improve the accuracy of flame early warning [24]. To solve the difficult described problem of fire by mathematical model, a fire detection model based on fuzzy neural network (FNN) is proposed, which makes fire signal processing has self-learning and adaptive abilities [25]. To improve the accuracy of flame early warning, a CNN model is proposed for identifying fire and smoke videos [26]. Moreover, CNN is proved that can achieve better performance on fire videos with the smaller number of parameters [27]. Due to the advantage of CNN, we extensively studied CNN for flame detection at early stage. The main contributions of this article are summarized as follows:

1. Considering the efficiency of recognition, we presented a candidate target area extraction algorithm based on RGB model for dealing with the suspected flame area.
2. To achieve higher the alarm rate of flame detection, the normalized candidate fire feature maps are classified by the proposed neural network based on CNN.
3. The proposed framework improves the fire detection accuracy and reduces the number of false alarms compared to our previous studies.

The structure of our paper is: flame video image database is introduced in Sect. 2, extraction of fire features and classification of fire video images are described in Sect. 3, experiment results are provided in Sect. 4, discussion and conclusion are given in Sect. 5.

2 Flame video images acquisition

A flame video database from various online resources is acquired by camera in this paper. The current database contains 100 videos acquired in some kinds of environments, including 75 positive (fire) sequences and 25 negative (no-fire) sequences. The resolution of video is 1920×1080. The environments of extracting flame samples are shown in Fig. 1a. To train image-based fire classifier, a homemade program is designed to extract images from the videos with a sample rate of 25.

Due to the scale variation of flame shapes in video database, flame video images include positive samples and negative samples, which are, respectively, resized in 227×227, as shown in Fig. 1b. The statistics of the used train and test video images are shown in Table 1.

3 The proposed method

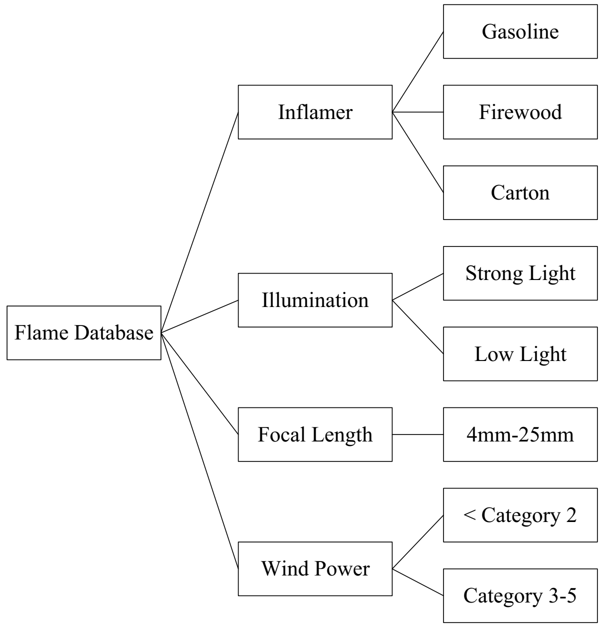
Our goal is to improve the performance of detecting fire, and an effective method is presented using deep neural network. The algorithm can be divided into two major phases: First, a color model is proposed to accurately segment fire candidate areas in video sequence based on a variety of environments. Second, the normalized candidate areas are identified by a novel structure based on CNN. Finally, the corresponding alarm is given by the identification results. The algorithm schematic diagram is shown in Fig. 2a.

3.1 Candidate flame area extraction method

Since the fire is extremely harmful, the sooner the warning, the smaller the loss which is caused by the fire. Therefore, the real-time requirement of the flame recognition algorithm is important in practical fire engineering.

The traditional deep learning methods of target detection are mostly based on multi-scale sliding window [28, 29]. However, these methods greatly reduce the efficiency of the algorithm. In this paper, the computation speed of the algorithm is improved by adding the fire color feature model. Since RGB model has less computation complexity than other color models [30], the proposed RGB model is adopted to extract fire color feature. At first, the original images are segmented to obtain the candidate area using the flame color model. Based on the statistical experience data, our experiment results show that each RGB pixel of fire should satisfy the following conditions:

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



(a)

(b)

Fig. 1 The environments and samples of flame database. **a** The environments of extracting flame video sequence. **b** Positive samples and negative samples

Table 1 Statistics of the proposed fire detection image database

	Images	Positive images	Negative images
Train set	40,000	20,000	20,000
Test set	4000	2000	2000

Here, $M(x, y)$ denotes 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 areas of neural network 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 Fig. 3a.

3.2 The proposed neural network structure

As we know, the structure of convolutional neural network (CNN) is divided into three parts: convolution layer, pooling layer and fully connected layer. The function of these three parts is the robust characteristics extraction, the feature dimension reduction and classification, respectively [31, 32].

According to the structure of CNN, we propose a novel convolutional neural network structure which is more suitable for fire detection. The proposed structure is shown in Fig. 3b.

3.2.1 Convolutional layers

It is the core of the proposed neural network. To effectively discriminate fire and distraction like fire, these layers consist

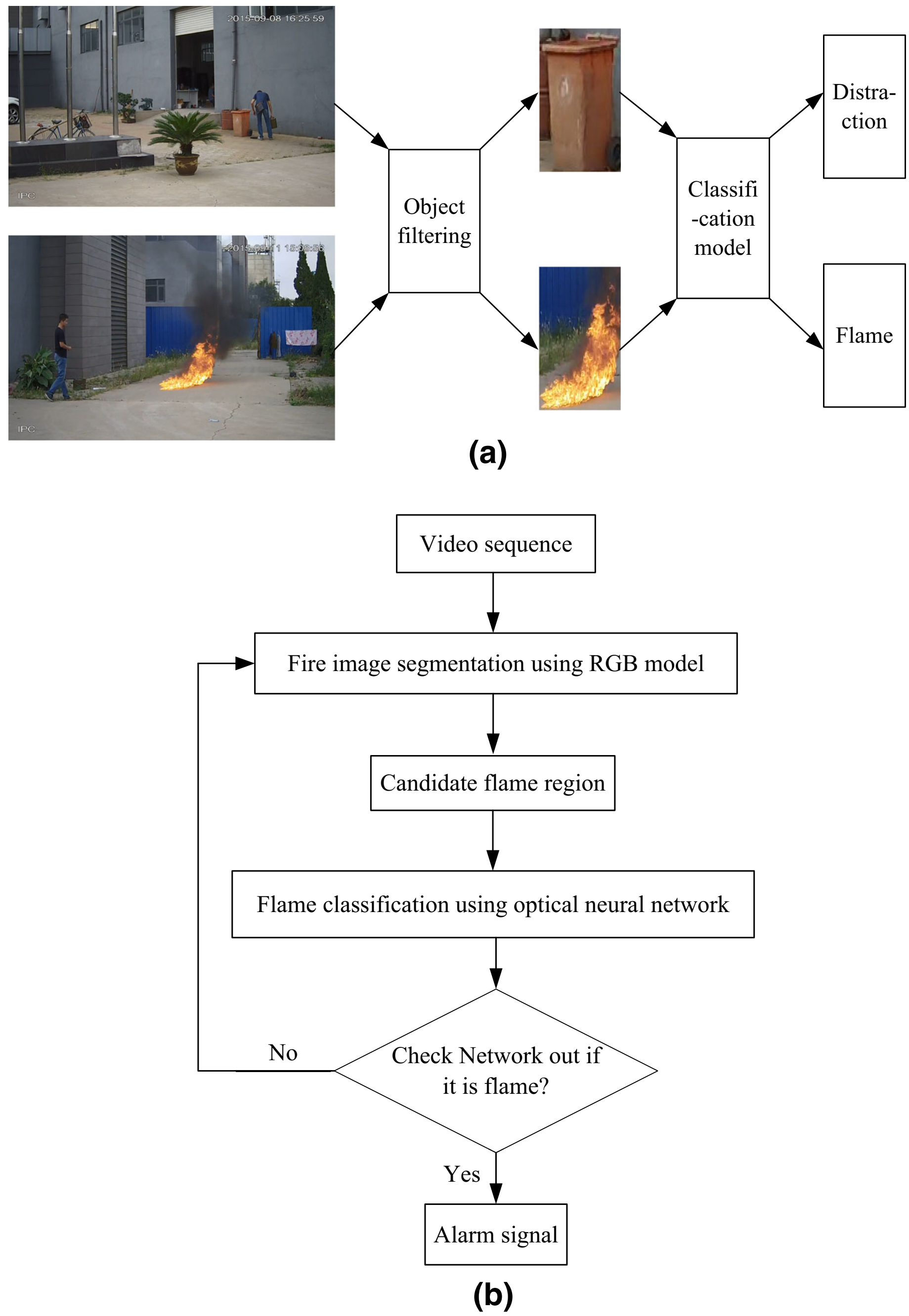


Fig. 2 The algorithm scheme and flow. **a** The algorithm schematic diagram. **b** The algorithm flowchart

of a rectangular grid of neurons which make the classification more robust. In convolutional layers, A RGB model-based fire image goes through three convolutional operations with kernel size $11 \times 11, 5 \times 5, 3 \times 3$, respectively. As we all know, the ReLU function $\Phi(x)$ has some advantages which are unilateral inhibition, wide excitation boundary and sparse activation, so a ReLU function $\Phi(x)$ is adopted after each convolutional layer and shown as:

$$\Phi(x) = \max(0, x) \tag{2}$$

Here, $\max(\cdot)$ denotes the larger value between 0 and x.

The visualization of convolution kernel function in the first layer is shown in Fig. 4a. As shown in the figure, the convolutional filters of the first-layer neural network model mainly detect low-order characteristics, such as edge, angle and curve. Then, the convoluted feature maps of the first layer are visualized with kernel size 11×11 and shown in Fig. 4b. From right figure, the different characteristics are detected by different filters.

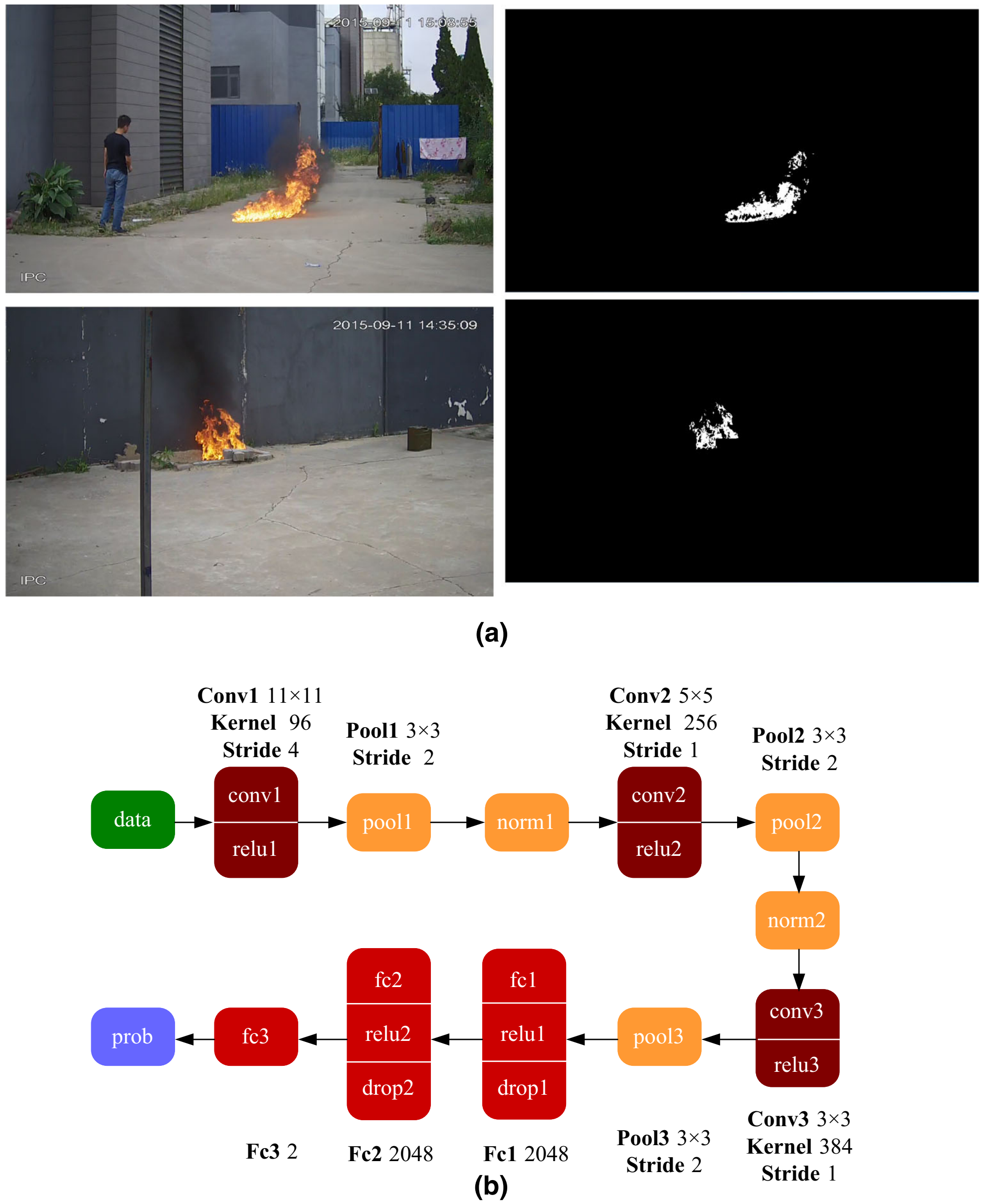


Fig. 3 Flame area extraction and schematic of neural network. **a** The images of candidate areas with different external scene (left: original images, right: the binary images based on color modal). **b** The schematic of proposed neural network

3.2.2 Pooling layers

After first three ReLU functions $\Phi(x)$, the processed data are downsampled in pooling layers. Here, to reduce the cost of more parameters, we adopt a window for max pooling, whose size is 3×3. To improve the generalization ability of the proposed structure and avoid the fitting phenomenon, the data are normalized by norm theory at first two pooling layers. The normalization functions are, respectively, shown as:

$$\begin{aligned} ||x||_1 &= |x_1| + |x_2| + \cdots + |x_n| \\ ||x||_2 &= (|x_1|^2 + |x_2|^2 + \cdots + |x_n|^2)^{\frac{1}{2}} \end{aligned} \quad (3)$$

Here, $||\cdot||_1$ and $||\cdot||_2$ represent L_1 norm and L_2 norm, respectively, x represents the convolution feature vector of fire candidate areas.

3.2.3 Fully connected layers

Finally, after the third pooling layer, the function of fully connected layers is to cascade fire feature images. In order to reduce over-smoothing phenomenon, the dropout method [33] is adopted after the last two ReLU functions $\Phi(x)$. It consists of setting to zero the output of each hidden neuron in chosen layer with some probability.

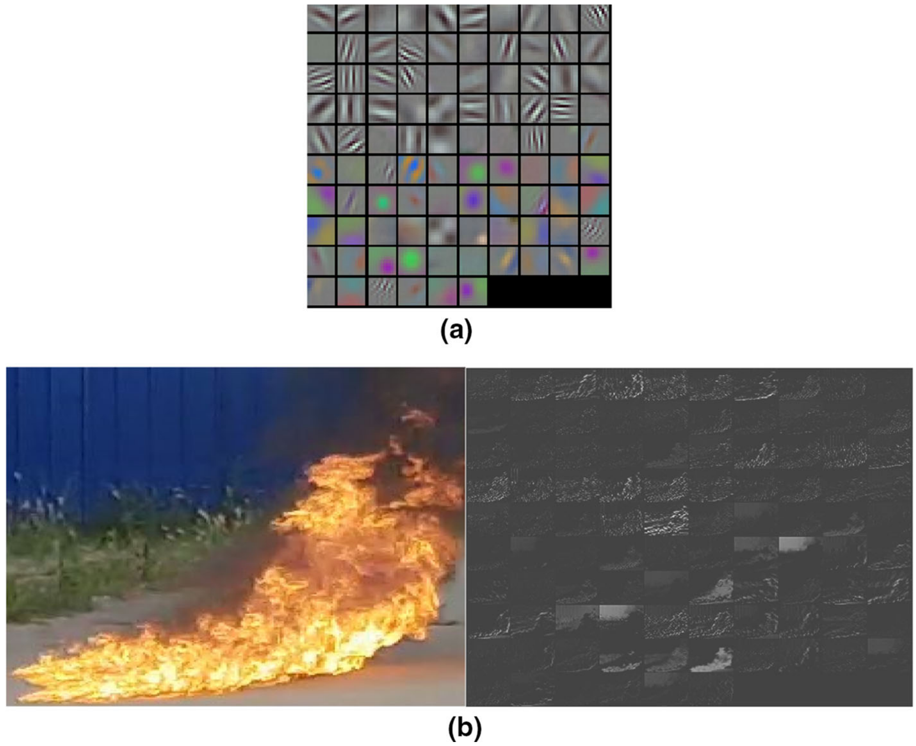


Fig. 4 The visualization in the first layer. **a** Convolution kernel function. **b** Left: original image, right: the convoluted feature maps are obtained by different filters

4 Experimental results and discussion

The proposed algorithm based on convolutional neural network (CNN) is implemented in C language and Caffemodel on a standard desktop PC which is equipped with a Octa-Core, CPU 3.6 GHz and 8 GB RAM. The flowchart of the method is shown in Fig. 2b.

In the processing of training neural network model, the training of convolutional layer is to train some convolutional filters, which have high activation of the unique mode to achieve the purpose of CNN. The more convolutional layers, the more complicate features. In this paper, to train the better convolutional kernels and obtain the more effective combination mode of these convolutional kernels, the optimal parameters are obtained by the proposed model, and then test samples are effectively classified by optimal parameters. The loss function curve of train set and test set are shown in Fig. 5a. From this curve, we can see that as the number of training and testing iterations increases, the loss functions all decrease and then the curves tend to stabilize. The test accuracy curve is shown in Fig. 5b. From this curve, we can see that as the number of training iterations increases, the test accuracy improves and then the curve reaches highest accuracy which is 97.64% when the number of iterations is 50,000.

In the previous studies [16, 34], different color spaces were used to extract flame color features, these methods have achieved good results. However, the processes of color space transformation and feature extraction are too complicated to meet the real-time requirements. Due to the high intensity of the flame area based on near-infrared image, the researchers present a lot of fire detection algorithms based on near-infrared image [35, 36]. The methods reduce the highlighted interference and obtain better results, but the requirement of hardware equipment is higher. According to the advantages of flame detection based on near-infrared video images, the researchers proposed a dual-spectrum flame feature detection method [37, 38], which combines the flame features of visible video images with the flame features of near-infrared video images. This method can effectively eliminate the small hole phenomenon in the segmentation area.

To evaluate the performance of the proposed method, experimental results were compared with obtained by the flame detection methods in the same scene, as shown in Fig. 5c. The first recognition method is based on color video image. The color model is used in our previous study and shown as:

$$\begin{cases} 0 < R - G < 120 \\ 60 < R - B < 160 \\ 10 < G - B < 120 \end{cases} \tag{4}$$

Here, R, G and B represent the value of R channel, G channel and B channel, respectively. The thresholds are determined by empirical values.

The second recognition method is based on near-infrared video image, and the flame area is extracted by the regional

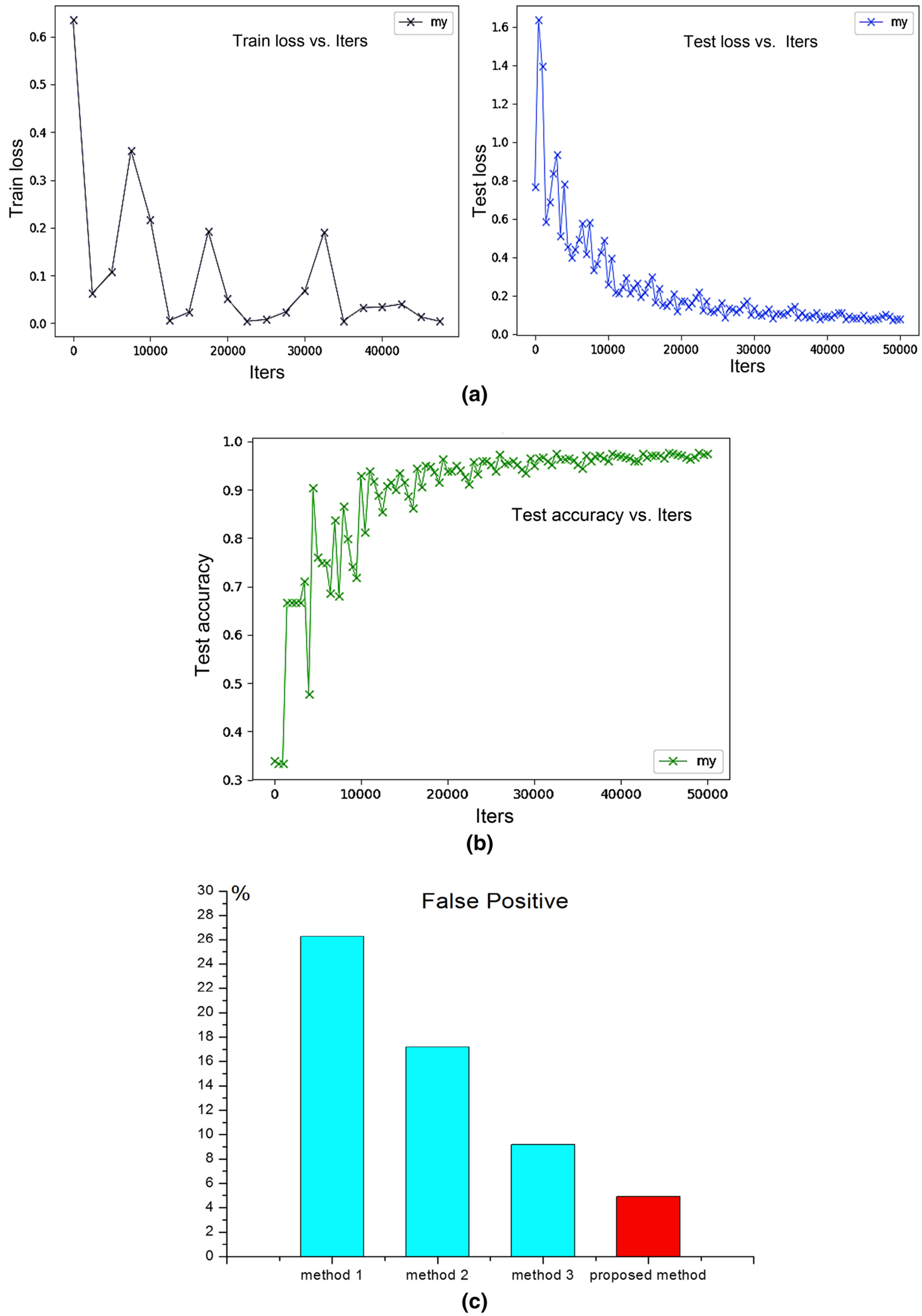


Fig. 5 Results and comparisons of different methods. **a** The loss function curve based on proposed method of train set and test set. **b** The test accuracy curve based on proposed method. **c** The comparison results of different methods

Table 2 The comparison performances of different methods

	Method 1	Method 2	Method 3	The proposed method
False positive (%)	26.3	17.2	9.2	4.9
Speed (fps)	15	20	12	30

growth algorithm [39], which is suitable for flame segmentation. The selection regulation of pixel is shown as:

$$R(x, y) = \begin{cases} 1, & R_1(x, y) * R_2(x, y) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Here, $R_1(x, y) = \begin{cases} 1, & f(x, y) \geq T_{\text{gray}} \\ 0, & \text{otherwise} \end{cases}$, $R_2(x, y) = \begin{cases} 1, & |f_t(x, y) - f_{t-1}(x, y)| \geq T_m \\ 0, & \text{otherwise} \end{cases}$, T_{gray} denotes the threshold of pixel intensity, $f_t(x, y)$ and $f_{t-1}(x, y)$ denote video images at t and $t-1$, respectively, T_m denotes the threshold of frame difference between $f_t(x, y)$ and $f_{t-1}(x, y)$. Then, the four-neighborhood growth mode is adopted to obtain the whole area of flame.

The third recognition method is used in our previous study which combines the first two methods, and the last method is proposed method. However, flame detection rates of first three methods are quite lower than the proposed detection rate. The comparison of computation speed of different methods is present in Table 2.

5 Conclusion and future works

In this paper, a new color fire feature detection and recognition scheme based on convolutional neural network has been proposed. First, the color feature of fire image is extracted to obtain the candidate area by the proposed RGB-based model. Second, the neural network is proposed to classify the normalized feature maps. Finally, the alarm signal is obtained by the classification result of convolutional neural network and test the performance of the proposed neural network. Experimental results have shown that the proposed algorithm achieves a superior performance in improving the fire color feature recognition based on RGB model accuracy as well as efficiency.

This work mainly focuses on the detection of flame, with comparatively little emphasis on fire location and understanding the objects and scenes under observation. Future studies may focus on realizing the fire location and detection only by neural network architecture, which can replace the process of extracting the suspected flame areas with empirical values, and we should further enrich the database with a variety of scenes to ensure the practicability of the algorithm.

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