Journal of Computers Vol. 32 No. 4, 2021, pp. 137-151
doi:10.53106/199115992021083204011

A Novel Hierarchical Wildfire Alarm System Based on Vegetation Features

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Received 5 January 2021; Revised 26 April 2021; Accepted 4 June 2021

Abstract. In recent years, frequent wildfires have not only severely damaged the environment and ecology, but also threatened the environment of human life. In order to enable fire alarms to detect fire disasters earlier, many related works have proposed image fire detection methods using global positioning systems (GPS) and unmanned aerial vehicle (UAV). These related work intends to make the fire detection method accurate and send early to reduce the threat posed by wildfire. The related work of fire detection is to use fire with high energy as the detection target. However, the work that only uses fire features to detect when used in fire alarms often produces false alarms. In order to understand the cause of the false alarm, we found one of the possible reasons from the fire-related report. The fire related report pointed out that the traditional fire triangle has been extended in time and space, and the original oxygen, fuel and heat sources have become climate, vegetation and ignition. Information related to climate features can already be obtained from existing equipment other than images. In related studies, the most frequently detected fire is the ignition that extends the fire triangle. The last fuel-extended vegetation is a feature that has not been used for image fire detection in related work. Therefore, based on the features of deep learning convolutional neural network (CNN), this article proposes a flame detection task that uses both vegetation and ignition features at the same time. And compare the experimental results with related work. The results of the comparison show that the features we proposed allow the fire alarm to achieve 100% true positive rate (TPR) as in the past, but also reduce the false positive rate from 40.47% to 4.15%. This experimental result shows that the features we propose can effectively assist the flame alarm system to reduce the chance of false alarms. At the same time, a method is proposed to further support the automated fire alarm system to effectively respond to wildfire threats.

Keywords: deep learning, hierarchical system, vegetation, wildfire

1 Introduction

When the fire source is out of control, the fire is a disaster [1]. From ancient times to the present, fire has the extreme power of destroying nature, environment and ecology. In order to reduce the property damage caused by fire, many researchers try to find the best way to detect fire and smoke as early as possible. They combined detection methods with automatic sprinkler systems to extinguish fires or provided disaster reports to experts to determine whether to evacuate.

In non-visual fire detection work, some works use non-visual sensors to analyze aerosol composition. Existing systems reduce false alarms and fire threats by analyzing the results [2-5]. Related work [6] uses the Internet of Thing (IoT) and non-visual sensors to analyze the fire field to provide decision-making information for escape. Related work [7-10] designed a detection system for fire in special situations to control the fire.

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In visual fire detection work, visible light is used in fire detection work to reduce threats. In the existing methods [11-25], they use the mid-frequency and high-frequency features of the image to achieve the purpose of fire and smoke detection. In related work using visible light, there is also a method of extracting fire pixels through a defined color range [18-36]. In addition, some existing works use image segmentation and morphology to find the position of candidate fires [17, 19, 32, 37-41]. In addition, related work [42-43] proposed an algorithm for calculating the fire position from satellite views. In recent years, deep learning has also been used in fire detection work [44-51].

Fig. 1 is the relationship diagram between the fire elapsed time and the traditional fire triangle model [52]. It illustrates the changes of the traditional fire triangle in time and space. Table 1 is the wildfire fuel table defined by U.S. Fire Administration [53-54]. When a wildfire occurs, most of the fuel burned by the fire is the Class A fuel in Table 1. At the same time, the factor corresponding to Fig. 1 for Class A fuel is Vegetation. Since the features of the Vegetation factor are quite susceptible to environmental changes, this factor is not considered in the existing research work. Although image-based fire detection can effectively detect fires through fire and smoke, the lack of Vegetation factor analysis results still makes fire alarms using existing methods produce false alarms.

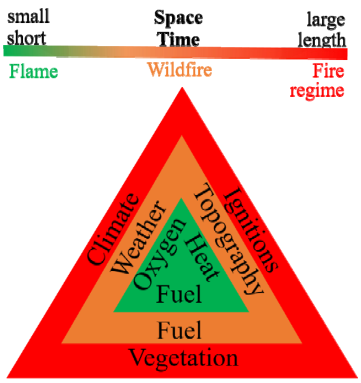


Fig. 1. An extension of the traditional fire triangle concept [52]

Table 1. Fire types of fire class [53-54]

Description	Europe	United States	Australian
Combustible materials (wood, paper, fabric, refuse)	Class A	Class A	Class A
Flammable liquids	Class B	Class B	Class B
Flammable gases	Class C	Class B	Class C
Flammable metals	Class D	Class D	Class D
Electrical fire	not classified (formerly Class E)	Class C	Class E
Cooking oils and fats	Class F	Class K	Class F

In order to effectively reduce the false alarms of fire alarms in specific situations, this article proposes an attempt to add Vegetation features to the images. However, as described above, the features of Vegetation factors are quite susceptible to environmental changes. For this problem, based on the analysis of the classifier in related work, this article selects the Convolutional Neural Network (CNN) [55-57] whose identification work is less affected by the environment to implement the proposed system. The difference from the related work performed using the CNN fire detection system [44-51] is that the proposed system further analyzes the features of vegetation. Improved the alarm system by adding fire detection with vegetation features.

The main contributions of this paper are summarized as follows:

1. This paper proposes vegetation features based on the traditional fire triangle model of temporal and spatial changes [52]. At the same time, according to the CNN features [55-57], which are less affected by the environment, the vegetation features are realized.

2. We propose an undiscovered problem in related work for the existing image-based fire alarm system. Design experiments based on problems and propose solutions.

3. This paper proposes to combine ignition and vegetation features in response to a problem not mentioned in the literature, and uses related work to confirm the existence of the problem. And in the experimental results, the method proposed in this article solves this problem that has not been mentioned in related work in the past, so as to improve the false alarm problem caused by the problem to the video fire alarm system.

The rest of this article is organized as described below. In Section 2 we introduce the existing related work of image fire detection using CNN. Section 3 indicates three subsections. The first subsection uses ignition features and vegetation features to illustrate the pre-classification of spread fire and non-spread fire. The next subsection introduces the network architecture that we use in deep learning training and system testing. The last subsection introduces the proposed system operation process that uses both the ignition feature and the vegetation feature at the same time. In Section 4, the experimental results and contributions of proposing the simultaneous use of ignition features and vegetation features are described and discussed. Section 5 summarizes the contribution and future work of this paper to the image-based fire alarm system.

2 Related Works

In this section, we introduce the flame detection related work on flame feature extraction and their results in recent years.

Huang and DU [58] used RS-SVM to classify in flame detection and proposed seven features of suspicious flames. They first select an appropriate RS-SVM kernel function, and project the training sample features into a high-dimensional space through nonlinear projection. Find the best hyperplane from the high-dimensional space, and map the hyperplane to the non-linear classification plane of the low-dimensional space. Their system flow chart is shown in Fig. 2. The specific implementation steps of their algorithm are as follows:

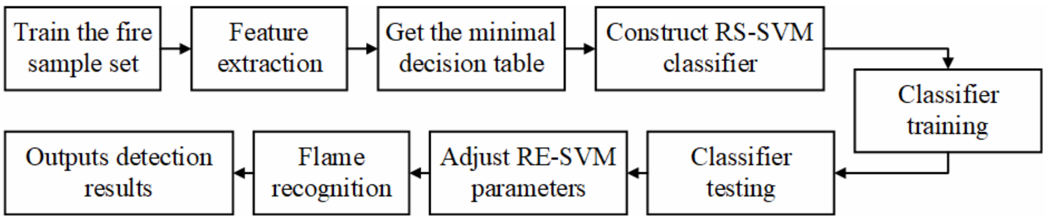


Fig. 2. Flow chart of the method proposed by Huang and DU [58]

1. Create a flame database. Collect video images of fires and shelters, and then extract seven features of suspicious fire areas from the images. Create a feature database based on the extracted features.

2. Construct a feature classification table based on the database in step 1, and then discretize the continuous attribute values of the flame sample set.

3. Use attribute reduction algorithms to perform attribute reduction processing on the fire information system, and obtain the corresponding two minimum decision tables and kernel attributes from the processing results.

4. Determine the parameters of the kernel function and the kernel function, and then train the classification model to use the obtained kernel attributes as the input vector.

5. Use well-trained SVM to detect flame test sample sets and analyze the identification results.

Huang and DU use the geometric and texture features of seven flames. These seven features are defined as similarity, area change rate, circularity, correlation coefficient, overall mobility features, R-G area-component ratio and number of pointed corners. The method of obtaining these features is to extract the pixel range of fire and smoke from the image, and then extract these features from the pixel range. In flame pixel analysis, Huang and DU segmented flame pixels from the three primary color distribution of flame in the image through formulas (1) and (2). Where, $R(x, y)$, $G(x, y)$, $B(x, y)$ are the RGB three primary color energy of the image at the coordinate (x, y). K is the total pixels of the flame image. R_mean is the average value of the main color energy of the flame image.

$$\begin{cases} R_{mean} = \dfrac{1}{K}\sum_{i=1}^{K} R(x_i, y_i) \\ R(x, y) > R_{mean} \\ R(x, y) > G(x, y) > G(x, y) \end{cases}, \tag{1}$$

$$R(x, y) > G(x, y) > B(x, y) \cap R(x, y) > 200, G(x, y) < 200, B(x, y) < 100. \tag{2}$$

In the smoke pixel analysis, they extracted the metric of similarity α from the three primary colors according to the formula (3). In the smog color model, the calculation result will eventually fall on $\alpha \in [0, 20]$.

$$\alpha = \max(|R-G|, |G-B|, |R-B|). \tag{3}$$

After confirming that the metric of similarity α of the pixels is consistent, the HIS color model is used to segment the smoke pixels through the formulas (4) and (5). Where, *h*, *i*, *s* are the energy values of the HIS color model.

$$D = \sqrt{(V_1 + V_2 + V_3)}, \tag{4}$$

$$\begin{cases} V_1 = (1-i)^2 \\ V_2 = S\cos H - s\cos h \times (S\cos H - s\cos h). \\ V_3 = S\cos H - s\cos h \times (S\cos H - s\cos h) \end{cases} \tag{5}$$

With the pixel range of fire and smoke, the seven features they actually use can be extracted from the pixel range. They finally verified the usability of the method through the comparison between the features and the comparison of multiple SVM kernel functions.

3 Methods

3.1 Ignition and Vegetation Data Pre-classification

In image processing related work [11-51], the methods used to identify fire and non-fire images have high accuracy. However, the flame detection work that only uses the ignition feature cannot fully automate the fire alarm system. This situation makes it necessary for firefighters to confirm the position of the flame and the surrounding conditions when a fire alarm is issued before the action assessment can be carried out. Generally, according to the elements in Fig. 1, ignition will deteriorate or self-extinguish depending on whether there is vegetation around. Therefore, we need an image-based feature that can not only detect the ignition, but also know whether there is vegetation around. According to the vegetation conditions around the ignition, the fire alarm system can more accurately reduce false alarms and prevent the loss of rescue time due to underestimation of the disaster.

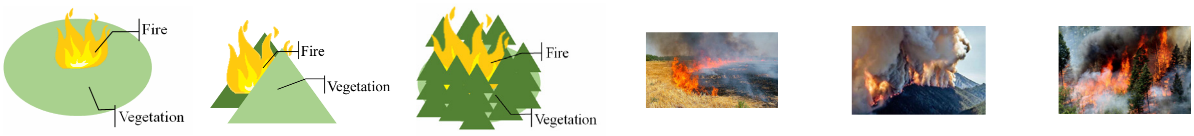
In order to detect the fire and analyze whether the surrounding vegetation is around, the method of this article is to further classify the flame image. Therefore, this section first introduces the pre-categorization of materials. In this section, we divide flame images into three categories: non-fire image, spread fire image and non-spread fire image. Fig. 3 shows three categories of images, respectively. Fig. 3(a) is nature image without fire; Fig. 3(b) is fire or smoke image with vegetation around it, which may make fire serious; Fig. 3(c) is fire or smoke image, but the fuel is blocked by non-inflammable material.

In this pre-classification, the fire category is different from previous works. As shown in Fig. 3(b) and Fig. 3(c), fire category is divided into spread fire and non-spread fire in detail. It is separated into two categories depending on whether it is a Class A combustion material. In the following we present the description of the two categories through Fig. 4 and Fig. 5 exhaustively.

(a) Normal (b) Spread Fire (c) Non-spread Fire

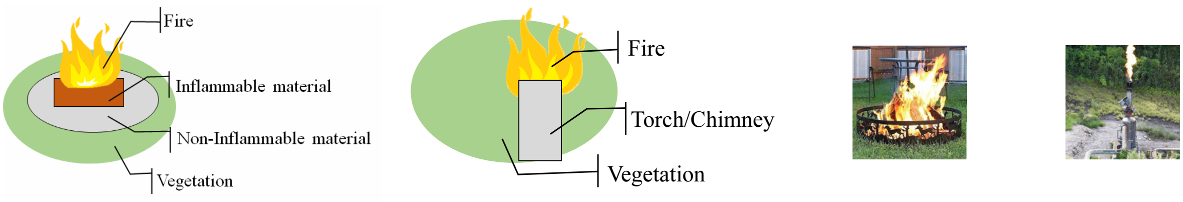
Fig. 3. The Classes of Proposed Fire Pre-classification

Fig. 4 shows the category that can cause severe wildfires. Fig. 4(a), Fig. 4(b) and Fig. 4(c) are schematic diagrams of grassland, mountain and forest vegetation, and Fig. 4(d), Fig. 4(e) and Fig. 4(f) are the corresponding actual images of Fig. 4(a), Fig. 4(b) and Fig. 4(c), respectively. Fig. 5(a) is a fire plugged with non-inflammable materials. Fig. 5(b) is an optical illusion image, in view of the chimney fire is projected onto the Class A vegetation. Fig. 5(c) and Fig. 5(d) are the relevant actual images of Fig. 5(a) and Fig. 5(b), individually.



(a) Glass Vegetation (b) Mountain Vegetation (c) Forest Vegetation (d) Ground truth of (a) (e) Ground truth of (b) (f) Ground truth of (c)

Fig. 4. Spread Fire Class Explanation



(a) Blocked Case (b) Columnar Case (c) Ground truth of (a) (d) Ground truth of (b)

Fig. 5. Non-spread Fire Class Explanation

3.2 The Deep Learning Convolutional Neural Network Model

This subsection introduces the two deep learning convolutional neural network (CNN) architectures that we employ to test our proposed system. One is AlexNet [59-60], and the other is GoogleNet [61]. The description of two architectures are as follows.

Input Layer. Source of input flame and natural image data in JPEG format collected from Google Image Search. The input data has been adjusted to the required size, AlexNet is 227×227 pixels, and GoogleNet is 224×224 pixels. In the input layer, the RGB data value is normalized to 0-1, and the minimum difference in pixel value is 0.00392157 (1/255), which corresponds to the value of the 8-bit image data value. Before network training, the training data is divided into two parts, where 80% of the data is training input, and 20% of the data is verification input.

Convolutional Layer. In Table 2 and Table 3, all layers defined as conv are convolution layers. This layer uses different kernel size filters and stride to extract image features named neurons. After the convolution layer, neurons are activated by the activation function layer. Rectified linear unit (ReLU) [62] is an activation function often used in recent CNN works.

Table 2. Modified AlexNet Architecture with MATLAB

Layers	Definition	Feature Maps	Activations	Kernel Size	Stride
0	data	3	227×227		
1	conv1	96	55×55	11×11	4
2	pool1	96	27×27	3×3	2
3	conv2	256	27×27	5×5	1
4	pool2	256	13×13	3×3	2
5	conv3	384	13×13	3×3	1
6	conv4	384	13×13	3×3	1
7	conv5	256	13×13	3×3	2
8	pool5	256	6×6	3×3	2
9	fc6 (Fully-connection)	Number of neurons: 4096			
10	fc7 (Fully-connection)	Number of neurons: 4096			
11	fc8 (Softmax)	Output layer neurons: α			

Table 3. Modified GoogleNet Architecture with MATLAB

Layers	Definition	Feature Maps	Activations	Kernel Size	Stride
0	data	3	224×224		
1	conv1	64	112×112	7×7	2
2	pool1 (Max pooling)	64	56×56	3×3	2
3	conv2	192	56×56	3×3	1
4	pool2 (Max pooling)	192	28×28	3×3	2
5	inception3a	256	28×28		
6	inception3b	480	28×28		
7	pool3 (Max pooling)	480	14×14	3×3	2
8	inception4a	512	14×14		
9	inception4b	512	14×14		
10	inception4c	512	14×14		
11	inception4d	528	14×14		
12	inception4e	832	14×14		
13	pool4 (Max pooling)	832	7×7	3×3	2
14	inception5a	832	7×7		
15	inception5b	1024	7×7		
16	pool5 (Average pooling)	1024	1×1		
17	loss3-classifier (Softmax)	Output layer neurons: α			

Pooling Layer. In order to prevent over-fitting in network training, the input data size is sub-sampled in the pooling layer. This layer is written as pool in Table 2 and Table 3. Most deep networks apply the max-pooling method [63] to maintain important features. Some architectures (such as the last second layer of GoogleNet) use an average pooling method [61] to achieve recognition goals.

Inception. This layer consists of multiple convolution layers and pooling layers. It is a special processing layer that can prevent the problem of gradient disappearance in deep network training [61].

Fully Connected Layer. In a fully connected layer, neurons are related to each other due to interdependence. This layer applies dropout technology to avoid overfitting in network training. Like the convolution layer, the fully connected layer uses ReLU to activate the output of the layer.

Classification Layer. The classification layer includes the output of the fully connected layer, softmax and cross-entropy functions. In this paper, the number of output neurons α depends on the data set and hierarchical system, and is described in the experimental part. After outputting the neuron, the softmax of cross-entropy loss regression is used to obtain the final recognition result. The softmax [64] function is shown in formula (6), where $\boldsymbol{n}$ and $\boldsymbol{m}$ are indexes of category $\boldsymbol{c}$.

$$\text{Soft}\max = \frac{e^{c_n}}{\Sigma_m e^{c_n}}, \tag{6}$$

3.3 Fire Alarm System Combining Vegetation Features

In this subsection, we introduce our proposed system. The flowchart is shown in Fig. 6. There are two hierarchical methods for the system we propose. Like related works, the first method called ignition hierarchy aimed at fire detection. This method divides Fig. 3(a) into normal labels, and Fig. 3(b) and Fig. 3(c) into fire labels. When inputting an image, the ignition hierarchy detects fire. Then output the result label to decide the next step. Assuming that the label is normal, the system directly enters the step of disaster worsening analysis. Otherwise, the image is input to the second method called the vegetation hierarchy to analyze the image.

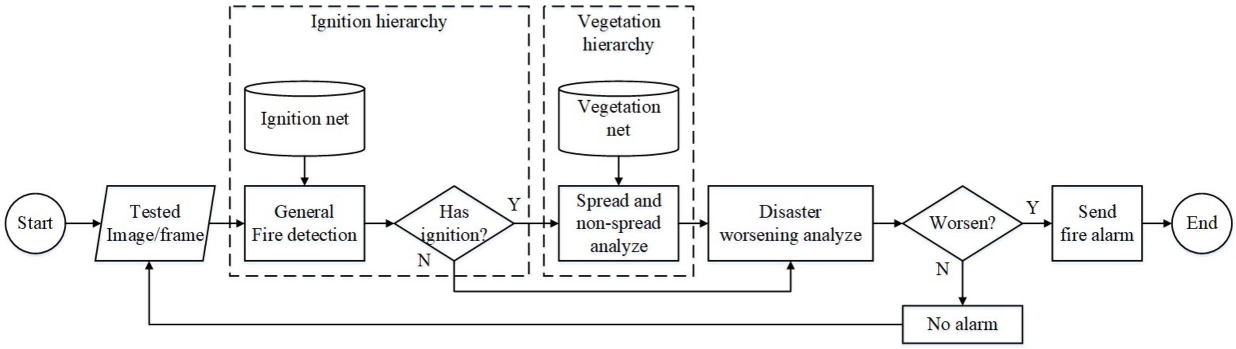


Fig. 6. Flow Chart of Proposed System

The work of the vegetation hierarchy is to analyze whether the fire is likely to spread. In this network training, the data set only uses data such as Fig. 3(b) and Fig. 3(c). Fig. 3(b) shows that the fire is easy to spread to class A vegetation. We label it as spread fire label. Fig. 3(c) shows the non-spread fire blocked by non-combustible materials. We label it as a non-spread fire label. The analysis results are all input to the disaster worsening analysis step for analysis. In the disaster deterioration analysis step, only the spread fire label was sent out a fire alarm, and the other labels were kept under observation. The following is a step-by-step description of the proposed system process:

- Input an image D_0 to proposed system.
- In ignition hierarchy, in order to detect fire in images, the CNN architecture of related works [60] and [61] is used to train the network $Net_I(.)$. Then the detection result label D_1 is obtained, which is represented by formula (7), where ϕ represents empty collection, in this step it is a normal label, and F is a fire label.

$$D_1 = \begin{cases} F, & \text{if } Net_I(D_0) = F \\ \phi & \text{otherwise} \end{cases}, \tag{7}$$

- When the first level structure output $D_1 = \phi$, it means that the input image is a non-fire normal image. Our proposed system takes D_1 as the input of disaster deterioration analysis. When $D_1 = F$, enter the vegetation hierarchy for further analysis.
- In vegetation hierarchy, the analysis network $Net(.)$ uses the same CNN as the ignition hierarchy for training. The analysis result label D_2 can be found in formula (8).

$$D_2 = \begin{cases} S \times D, & \text{if } Net_V(D_1) = S \\ D_1 & \text{otherwise} \end{cases}. \tag{8}$$

- The output of the vegetation hierarchy is directly used as the input of the disaster deterioration analysis step.

- In the disaster deterioration analysis, the input is integrated with formula (9). When the output A is 1, a fire alarm is sent. When A is not 1, no alarm will be sent.

$$A = D_t \wedge SF. \tag{9}$$

4 Experimental Results and Discussion

In this paper, we employ MATLAB R2019b to implement the proposed ignition and vegetation feature recognition network on 3.6 GHz Intal Core i7-4790HQ CPU and NVidia TITAN X GPU. The source of training unmanned aerial vehicle (UAV) image data comes from Google search, the size is form 224 × 224 to 5048 × 1568 pixels, and the total data is 692. According to the proposed pre-classification, spread fire images have 304, non-spread fire images have 85, and natural images have 303. Before training, each data is augmented by horizontally and vertically flipping and rotating 90 degrees. Training uses transfer learning to train the ignition and vegetation recognition network. The source of the test data is fire, smoke and other videos from the Bilkent EE signal processing team [65]. We extract images of this video every 20 frames as test data. The size of the test data is 256 × 256, 320 × 240 and 400 × 256, which is a total of 870 images. According to the proposed pre-classification, the spread fire image has 99, the non-spread fire image has 326, and the natural image has 445.

Table 4 is the comparison of validation accuracy between different datasets. Dataset A is a validation dataset labeled with three categories Normal, Spread Fire and Non-spread Fire ($\alpha = 3$). We directly use three types of neural networks for training. The verification accuracy of 0.8933 and 0.9267 were obtained in AlexNet and GoogleNet respectively. Next, the neural network training using ignition and vegetation hierarchies as proposed method ($\alpha = 2$). The ignition hierarchy is marked with normal and fire labels, while the vegetation hierarchy is marked with spread fire and non-spread fire labels. In the verification accuracy comparison, since the purpose of the network recognition of dataset A is equal to the two recognition network serial processing of dataset B and dataset C, the following description uses the serial processing result of dataset B and dataset C. In the verification accuracy rate of GoogleNet, dataset A obtains 0.9267, dataset B + dataset C obtains 0.8635 (0.9267×0.9318), and the result of dataset A is better than dataset B + dataset C. In the verification accuracy of AlexNet, dataset A gets 0.8933, dataset B + dataset C gets 0.9448 (0.9667×0.9773), dataset B + dataset C is better than dataset A. Considering the above results, dataset B + dataset C in AlexNet has the highest verification accuracy.

Table 4. Network Training Validation Accuracy of Different Datasets

Architecture	Average Processing Cost	Training Dataset	Validation Accuracy
AlexNet	23(ms)	Dataset A	0.8933
		Dataset B	0.9667
		Dataset C	0.9773
GoogleNet	28(ms)	Dataset A	0.9267
		Dataset B	0.9267
		Dataset C	0.9318

Dataset A: Normal, Spread Fire and Non-spread Fire
Dataset B: Normal and Fire (Spread and Non-spread Fire)
Dataset C: Spread Fire and Non-spread Fire

In this article, we defined the video data categories of the Bilkent database, as shown in Table 5. The test images are extracted from these videos every 20 frames. Table 6 shows the result of the data independence test in the Bilkent database. True positive rate (TPR) and false positive rate (FPR) are written as formula (10) and (11), respectively. The results indicate the accuracy of networks that are trained by different datasets. Among them, TPR and FPR of dataset A is the average of three categories.

$$TPR = \frac{TP}{(TP + FN)}, \tag{10}$$

$$FPR = \frac{FP}{(FP + TN)}, \tag{11}$$

Table 5. Bilkent Database Re-classification

Non-spread fire	Spread fire	Normal
40m_PanFire_20060824.avi	ForestFire1.avi	CarLights1.avi
barbeq.avi	controlled1.avi	CarLights2.avi
fBackYardFire.avi	controlled2.avi	Factory_Smoke_Output.avi
fire1.avi	controlled3.avi	Pelco_Colakli.avi
sBehindtheFence.avi	forest1.avi	Smoke_Manavgat_Raw.avi
sBtFence2.avi	forest2.avi	TunnelAccident1.avi
sMoky.avi	forest3.avi	TunnelAccident2.avi
sWasteBasket.avi	forest4.avi	TunnelAccident3.avi
sWindow.avi	forest5.avi	sParkingLot.avi
		sorgun1.avi

Table 6. The Result of System Accuracy Test using Bilkent Database

Architecture	Dataset	TPR	FPR
AlexNet	Dataset A	0.8825	0.0678
	Dataset B	0.9294	0.0360
	Dataset C	1.0000	0.0491
GoogleNet	Dataset A	0.6696	0.2009
	Dataset B	0.6706	0.1730
	Dataset C	0.6869	0.2883

The results of Table 6 are as below:

- In terms of image recognition accuracy, the accuracy of ignition and vegetation hierarchies is higher than that of the direct classification method. As shown in Table 4 the processing cost is close to real-time.
- The test is to select a network architecture suitable for training the proposed features. Due to discussion issues have not been mentioned in related work, and there are fewer pre-classified training materials. This result shows that a deep convolutional neural network architecture such as GoogleNet requires more training data to prevent overfitting. Therefore, this article mainly uses the recognition network trained by the AlexNet architecture, and discusses the following tests.

In image-based fire alarm related work, they usually only use ignition features to implement fire detection methods. However, related work generally only mentions the method of extracting the ignition features used between them or the procedure of how to speed up the processing, without discussing other factors. This makes the related work limited to extracting ignition features, so that the system they developed cannot solve the problem of false alarms in real fire alarms. The next experiment designed in this article is just like a real fire alarm situation. We use this experiment to show that the actual fire alarm uses only the ignition feature, and the difference between using ignition and other features as proposed in this article. Table 7 is a comparison of the fire alarm system method using only ignition hierarchy, both ignition and vegetation hierarchies, and related work. This comparison was still tested using the Bilkent database defined in Table 5. The results of Table 7 are as following:

Table 7. The Comparison of Correct Fire Alarm using Bilkent Database

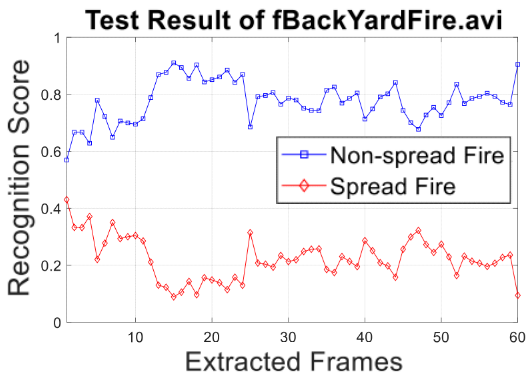
The Methods Used by Fire Alarm System	TP	FN	FP	TN	TPR	FPR
Seven Features [58]	99	0	397	374	100.00%	51.49%
Ignition Feature	99	0	312	459	100.00%	40.47%
Ignition and Vegetation Features	99	0	32	739	100.00%	4.15%

- In fire detection test, the TPR of our proposed hierarchical structure system and related works is 100.00% in Bilkent database. This result shows that the effectiveness of our proposed system is the same as the related work in true fire alarm.
- In FPR, it is first stated here that the method of related work [58] is not that bad methods cause 51.49% of FPR. In this experiment, the relevant work has such a high FPR precisely since of its very good detection effect. The reason for choosing Bilkent database for this experiment test data is that the

database has some flame data that will not be serious. These data have a certain relationship as the problem that this article wants to discuss. What this experiment wants to explain is that if the existing image fire alarm system only uses “fire detection work” as the standard. As soon as the system detects fire and smoke, it sends out an alarm, instead of observing whether the surrounding area really causes disasters. Automatic fire alarms will not be more advanced cause of this logical error. As in this experiment, only the ignition hierarchy is used, the FPR of the flame alarm is still 40.47%. In many related work, we have seen that image processing flame detection work has been pursuing the low FPR of flame detection, but there is no work to explore how experienced firefighters can judge whether a fire disaster is more serious. Therefore, this article attempts to propose a vegetation hierarchy, just like when experienced firefighters see a flame, they will assess whether the disaster is more serious based on the surrounding environment. The experimental results confirmed that the flame alarm system of the vegetation hierarchy successfully reduced the FPR of this experiment from 40.47% to 4.15%.

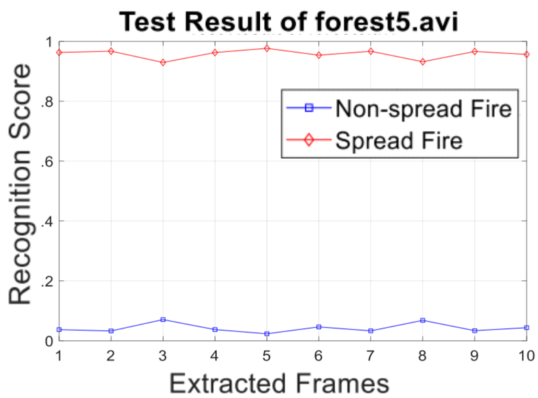
Fig. 7 and Fig. 8 are our case descriptions illustrating the success and failure of using the system to detect. Fig. 7 is the result of the successful display of the test data analysis. Fig. 7(a) is the non-spread fire video fBackYardFire.avi in the pre-classification, and Fig. 7(b) is the analysis result of the video. Fig. 7(c) and Fig. 7(d) are the spread fire video forest5.avi and its corresponding analysis results. In Fig. 7(b) and Fig. 7(d), when the analysis is successful, the lines represented by non-spread fire and spread fire will not have any intersection.

(a) The part of fBackYardFire.avi



(b) The Analysis Result of (a)

(c) The part of forest5.avi

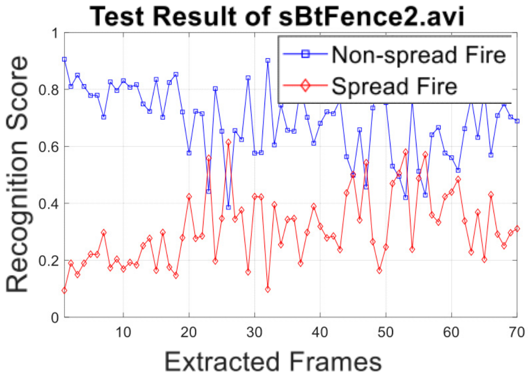


(d) The Analysis Result of (c)

Fig. 7. The Successful Analysis Result of Non-spread Fire and Spread Fire

Fig. 8 is the display result of the miscellaneous part analysis failure. Fig. 8(a) is a part of the frame extracted from the non-spread fire data sBt-Fence2.avi in the Bilkent database. And Fig. 8(b) is the analysis diagram corresponding to the video. In the analysis of the video, 63 frames received the correct non-spread fire labels, and 7 frames received the wrong spread fire labels. From the explanation of the video content, it can be explained that the use of CNN can reduce most of the environmental interference to extract the vegetation features needed for recognition. However, when the image interference exceeds a certain level, CNN cannot accurately extract the features needed for recognition. This shows that the vegetation features change greatly due to environmental interference, and even CNN cannot completely ignore the interference to extract vegetation features.

(a) The part of sBtFence2.avi



(b) The Analysis Result of (a)

Fig. 8. The Failed Analysis Result of Non-spread Fire and Spread Fire

Based on the experimental results of related work, the experiments designed in this paper show that the related work of image-based fire alarms is limited to the case of extracting ignition features. In this experiment, we propose to use vegetation features derived from the traditional fire triangle extension. Although experiments show that CNN cannot completely ignore environmental interference, the vegetation features we implemented using it can still assist the ignition feature to reduce FPR. The experimental results show that we use the vegetation feature to assist the ignition feature is an effective method. The vegetation feature reduces the FPR of the fire alarm from 40.47% using only the ignition feature to 4.15%. This result shows that in the fire alarm system, the vegetation feature is an auxiliary feature that needs to be paid attention to, rather than treating it as noise and filtering it out.

5 Conclusion

In recent work related to image-based flame detection, research methods focus on extracting ignition features. The purpose of these related work is to reduce the FPR of flame detection to detect fires early and to send fire alarms at the same time. However, the related work so far has been limited to extracting ignition features. This situation makes that when wildfire occurs today, firefighters still need to evaluate the fire alarm through the screen to determine the correctness of the fire alarm. Generally, related work only mentions the method of extracting ignition features used between them or the process of how to speed up the processing, but there is no related work to explore why firefighters can confirm whether it is the correct fire alarm by observing the screen. In order to correct this logical error, we learned from the literature [52] the extension of the traditional fire triangle in time and space, and then tried to find features different from related work. In this article, we propose vegetation features that are different from related work based on the extended fire triangle. The vegetation feature is a feature that is quite susceptible to environmental influences, so that related work does not discuss it and regards it as noise to be removed. However, if we carefully examine how firefighters can judge whether a fire disaster has occurred with high accuracy, we can get that vegetation features are actually a kind of auxiliary judgment features, and are not regarded as noise as related work. Therefore, we try to propose vegetation features as an important feature for reducing false alarms in this paper.

As mentioned earlier, vegetation features are a feature that is quite susceptible to environmental influences. In order to implement this feature, this paper uses deep learning CNN with features that are not easily affected by environmental factors as an important classifier [55-57]. In the experiment, we selected the Bilkent database flame database to design the experiment that has the flame data which will not severely. We developed Table 6 to pre-classify the flame data of the Bilkent database, and used the pre-classified data to perform experiments. Among them, the vegetation feature of the image is the vegetation that appears at the same time as the ignition feature. Such images are classified as spread fire in this article. Through CNN to train the classification of design experiments, we complete the common flame detection work "ignition hierarchy" such as related work and the "vegetation hierarchy" proposed in this article to prevent false alarms of fire alarms. In the experiment, we chose to achieve quite effective flame detection related work in recent years [58] for comparison. The comparison results are shown in Table 8, and this result is also as we expected. Related work [58] has a very effective fire point feature detection effect, so that in this design experiment, the highest FPR is obtained. This result proves that the fire related work has not found the problems found in this article. The test in this article also confirmed that only using the ignition hierarchy with the ignition features of the relevant work can also obtain an FPR as high as 40.47%. However, after the vegetation hierarchy proposed in this article has vegetation feature analysis, the experimental results reduced FPR from 40.47% to 4.15%. The result of this sharp drop in FPR shows that vegetation features have a certain importance in the fire alarm system, rather than processing noise as described in the related work.

Acknowledgements

The authors would like to thank several anonymous reviewers and the editor for their comments and suggestions.

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