# Forest Fire Detection with Color Features and Wavelet Analysis Based on Aerial Imagery

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***Abstract*—Unmanned aerial vehicles (UAVs), equipped with vision-based systems, can be used for forest fire monitoring and detection due to their low cost, fast response capability, and high safety. This paper proposes a novel approach to forest fire detection, which uses the color characteristics of the images taken by the UAVs and uses wavelet analysis to further process. Firstly, according to the color characteristics of forest flame and smoke, a low computational cost algorithm is adopted to extract pixels from its related regions. In order to correct the inaccuracy of color feature extraction, a two-dimensional discrete wavelet transform (DWT) is implemented to distinguish flame and the smoke area from other high-frequency noise signals. Multiple sets of experiments have proved that the algorithm proposed can effectively detect the forest flame and smoke part of the image. The good performance is anticipated to significantly improve the accuracy of forest fire detection on the basis of less computational cost and can perform real-time detection on the UAVs platform.**

***Index Terms*—Unmanned aerial vehicles, forest fire, color characteristics, wavelet transform, real-time detection**

## 1. Introduction

Forest plays a crucial role in nature. They can keep the soil fertile and stable, purify water and air, regulate climate through photosynthesis, and maintain biodiversity. From an economic perspective, forests can provide huge employment opportunities and economic benefits for society [1]. Current environmental conditions, unfortunately, have recently been producing more severe and frequent wildfires, causing sizable areas of forest loss every year [1, 2]. Therefore, forest fires fighting is seen as one of the most significant roles in the preservation of natural resources and the protection of personal and property security [3]. Particularly, in view of the rapid spread of forest fires and the long burning time, early prevention of forest fires is the main way to reduce the damage caused by fires.

A lot of efforts have been devoted to the issue of forest fire detection. Traditional forest fire monitoring and detection methods are mainly based on watchtowers, which not only adds additional labor demand but also increases the potential operational risks of observers. With the development of technology, ground fire monitoring systems, manned aircraft and satellites have been widely used in the past few decades. However, there are different problems in these systems. Ground monitoring systems are usually built at specific locations and subject to the environment. Manned aircraft are usually bulky and costly; in addition, the safety of pilots constantly threatened by complex environments and bad weather. The cost of satellite systems is extremely high, and less flexible for maintaining, develop and technology update; at the same time, their spatial-temporal resolution is often difficult to meet the requirements of detailed data capture and detection of forest fires [1].

The integration of unmanned aerial vehicles (UAVs) with remote sensing technology, as a promising alternative to traditional and current forest fire detection methods, has been the most powerful tool for forest fire detection applications and attracted widespread attention from many scholars around the world [1, 4]. They can not only meet critical spatio-temporal and spectral resolution requirements [5], but also enable the execution of long-term, repetitive missions beyond human capabilities. Overall, UAVs with computer vision detection technology delivers intuitive, highly real-time information that can easily cover a wide range of observations with reduced development costs. Based on the information above, many related research activities on forest fire monitoring and detection based on UAVs, in recent years, have been carried out [2, 6–11].

In the existing research, vision-based fire detection techniques are usually based on three characteristics: color, motion and geometric [12]. In particular, most researchers tend to combine the color and dynamic characteristics of the flame to provide a more reliable recognition. To the best of our knowledge, one of the first works on fire detection based on image processing was proposed by [13]. In this document, threshold processing is used in the region of interest (ROI) to distinguish between the flame region and the non-flame region to save computational cost. The RGB (Red, Green, and Blue) / HIS (Hue, Saturation, Intensity) color model was used in [14], dynamically analyzing the disorder characteristics of the flame and verifying the possibility of fire. A support vector machine (SVM) based flame detection scheme is used in [15] to remove non-flame pixel regions by using a luminance map. In addition, the SVM is also used in [16] for the extraction of the flame region, which reduced the false alarms caused by fire-colored moving

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objects. However, its classifiers are hardly real-time due to the excessive computational cost of the SVM. [9–11] solved the problem of effectively extracting fire pixels by taking advantage of the Lab color model which can clearly show the color features of the fire. For further accuracy of forest fire detection, image texture analysis is broadly used by researchers. Töreyin et al. proposed some theoretical analysis for forest fire based on wavelet transformation, and introduced an image bandpass filter briefly [17]. Then, a more systematic flame detection scheme was presented in [18]. Later, based on the former work, Gubbi et al. performed wavelet analysis on the smoke region and applied DCT, DWT, CWT to the image [19]. Chen et al. performed wavelet analysis on the region which is separated from static background [20]. In [21], the second-order wavelet transformation was carried out and did briefly digital analysis. To distinguish forest smoke and foggy weather, wavelet analysis is used in [22]. What is more, infrared images are used in [10], which greatly improves the accuracy of forest fire detection.

Although a variety of fire detection methods have been developed, only several studies refer to forest fire and few relative experiments have used UAVs for forest fire monitoring and detection [2, 4, 7, 9–11]. Typically, vision-based fire detection methods are applied with stationary camera, separating moving flames from the static background. However, due to the motion characteristics of the drone, the method of extracting the forest fire area in the image using the motion feature becomes incapable. In the application of the UAVs, objects in the captured images are all moving, which is the main factor that causes difficulties in detection [23]. To solve this problem, Kolesov et al. proposed optimal mass transport (OMT), a detection theory that can be applied to dynamic background [24]. Then, Mueller et al. proposed a more specific formula for OMT [25]. [11] extracted the flame based on the Lab color space, adopted both OMT and traditional optical flow for the further process. Unfortunately, due to the complex operation procedure and high computational cost, optical flow algorithm have poor performance in real-time detection.

To solve the problems above, this paper proposes a forest fire detection method based on UAVs, using color characteristics and wavelet analysis. The method mainly uses the color and texture features of the image to reduce the computational cost of the algorithm, improve the robustness and speed, achieve the effect of real-time image detection.

The algorithm will be divided into three steps.

- First extract the pixels suspected of forest fire with the RGB color features.
- Then use the color characteristics of the smoke to extract the suspected smoke pixels in the image.
- Combine the pixels extracted in steps 1st and 2nd as $D_{fs}$. With the continuous characteristics of fire and smoke in the image, filtering out the discontinuous noise points in the $D_{fs}$ by comparing the high-frequency energy values after wavelet transformation.

The arrangements for the rest of this paper are as follows. The color extraction algorithm for forest flames will be explained in Section 2. Section 3 will introduce the color extraction algorithm of smoke and the wavelet analysis of images. The experimental results of the algorithm are listed in Section 4 and discussed briefly. Finally, concluding remarks and future works are drawn in the last section.

## 2. Color model of forest fire

As one of the early applications of vision-based forest fire detection, the color model of the flame has been widely used [26]. Generally, the flame image, with bright shade, will show a reddish tint among red and yellow. So the color range of the flame can be described as the interval between them. The extraction of forest flames mainly to use Forest Fire Detection Index (FFDI) [27] and morphological operations.

### 2.1. Image preprocessing

To remove the effects of illumination in the image, The first step is RGB normalization. Therefore, all components are first normalized by the sum of RGB, leading to the following expression:

$$r_n = \frac{255 \times R}{R+G+B}, g_n = \frac{255 \times G}{R+G+B}, b_n = \frac{255 \times B}{R+G+B} \quad (1)$$

where $r_n$, $g_n$ and $b_n$ represent the normalized RGB components.

### 2.2. Forest fire area extraction

Woebbecke et al. proposed five different color indexes for plant classification in [28]. In this paper, we define the VBI (vegetative background index) with (2) as the pixel region for extracting green vegetation in the background.

$$VBI = 2g_n - r_n - b_n \quad (2)$$

As a result of the literature [27], the RGB values of the forest flame region have the following relationship:

$$r_n > g_n \wedge r_n > b_n \quad (3)$$

Thus, similar to the VBI operation method, the following formula of the fire index (FI) is proposed:

$$FI = 2r_n - g_n - b_n \quad (4)$$

FI, as it is, could be very sensitive to small flame pixels as long as the environment does not contain similar colors. In view of the characteristics of early forest fires, it is necessary to extend FI to the vegetation background. forest fire index (FFI) is a combination of FI and VBI. On the one hand, the flame area would be more prominent through FI. On the other hand, the noise impact of the forest vegetation background can be reduced by VBI. In order to obtain greater flexibility and increase the importance of the flame region, a weighting factor $\alpha$ is introduced.

$$FFI = \alpha \times FI - VBI \tag{5}$$

Here, the value of parameter $\alpha$ is between 1 and 2 ($1 < \alpha \leq 2$). In our experiments, $\alpha = 1$.

In order to detect RoI more stably and accurately, the previously obtained forest flame area is binarized. So it is necessary to set the threshold for binarizing the image which is presented as a gray value in FFI. Threshold $T_F$ is created, as shown in (6), by averaging the standard deviations of FI and VBI.

$$T_F = \frac{\alpha \cdot \sigma_{FDI} + \sigma_{VBI}}{\alpha + 1} \tag{6}$$

In FFI, the pixel whose value is greater than or equal to TF is set to 1, otherwise 0 is executed. The binarized matrix is denoted as FFI'.

### 2.3. Morphological operation

Since there is still a lot of noise in the binarized matrix FFI', the image morphology operation is used. Eroding has been carry out, in the first step, to eliminate the noise in the image. To recover the edge eroded, dilating is followed by. The matrix used for morphological operation, as shown in Fig. 1, is $5 \times 5$.

| | | | | |
|---|---|---|---|---|
| 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 1 | 1 | 1 |
| 0 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 0 | 0 |

Figure 1: Morphological matrix.

The result of the morphological operation is named after $D_{FI}$. If the original image is $D_o$, the forest fire region $D_f$ would be computed as follow:

$$D_f = D_{FI} \wedge D_o \tag{7}$$

## 3. The extraction of forest fire and smoke

Mostly, the smoke is observed more easily at the beginning in forest fires. Obvious fire spots will be detected when fires cause a certain range of damage. Therefore, the detection of smoke is more significant in early forest fire prevention.

In this section, smoke area $D_s$, which were extracted based on the color features of itself [29, 30], is combined with the flame region $D_f$ to generate the forest flame and smoke area $D_{fs}$. Due to the large number of noise points in $D_{fs}$, wavelet analysis is used in the latter half of this part.

### 3.1. Calibrate smoke area based on color feature

The smoke usually displays grayish colors during the burning process. Such color can be classified into light-gray and dark-gray, which can be described with I (intensity) component of HSI color model. At the same time, the characteristics above also imply that three components R, G and B of the smoke pixels are equal or so. Therefore, the smoke area will be judged according to the following conditions.

$$(|R - G| < \beta) \wedge (|G - B| < \beta) \wedge (|R - B| < \beta) \tag{8}$$

$$(R > 120) \wedge (B < 230) \tag{9}$$

$$I = \frac{R + G + B}{3} \tag{10}$$

$$(80 < I < 150) \vee (150 < I < 220) \tag{11}$$

Where $10 < \beta < 40$. Equations (8), (9) and (11) are denoted as $rule1$, $rule2$ and $rule3$ respectively. The decision for extracting $D_s$ from $D_o$ is deduced by followings:

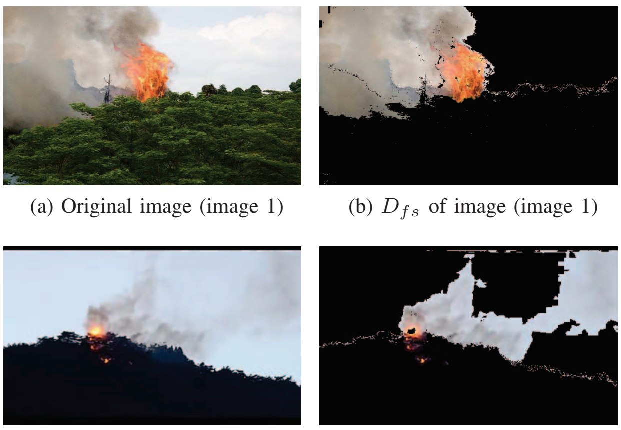
**if** $(rule1)$ **and** $(relu2)$ **and** $(relu3)$**= true then**
    $D_s$
**end if**

Combine $D_f$ with $D_s$ and record it as the flame smoke area $D_{fs}$.

$$D_{fs} = D_f \vee D_s \tag{12}$$

### 3.2. Image filtering based on wavelet transform

Since the results of forest fire and smoke detection based on color model are not reliable, further image filtering measure is needed. In this application, the background of image is mainly forest, which contains few fire-like parts. Unlike continuous and grayish area of smoke, the non-fire pixels are shown in Fig. 2, which imply there are more high-frequency energy in noise. Therefore, DWT is introduced in further process.



(a) Original image (image 1) (b) $D_{fs}$ of image (image 1)

(c) Original image (image 2) (d) $D_{fs}$ of image (image 2)

Figure 2: Original image and extracted forest fire area.

In this part, discrete wavelet transform (DWT) is applied to the grayscale maps of $D_{fs}$ and $D_o$ respectively, and then an approximation image and three high-frequency images are obtained, which are recored as LL, LH, HL and HH. The energy images of $D_{fs}$ and $D_o$ are denoted as $E_{fs}$ and $E_o$ respectively, which can be calculated by using (13).

$$E = LH^2 + HL^2 + HH^2 \tag{13}$$

The energy image is divided by a fixed block of $l \times l$, in our experiments, $l$ is 2 or 4. The energy in each block is calculated using (14).

$$E_{nk} = \sum_{(i,j) \in Block_k} E(i,j) \tag{14}$$

Where $E_{nk}$ describes the energy value of $Block_k$. If $E_{nk,fs}$ ($k$th block in the $E_{fs}$) has a higher value than $E_{nk,o}$ ($k$th block in the $E_o$), $E_{noise}$ (the energy of noise) would be generated as follows:

**if** $E_{nk,fs} > E_{nk,o}$ **then**
    $E_{nk,noise} = 1$
**else**
    $E_{nk,noise} = 0$
**end if**

At the same time, $E_{fsn}$(total blocks of $E_{nk,fs}$) is binarized for later operation.

**if** $E_{nk,fs} > 0$ **then**
    $E_{nk,fs} = 1$
**else**
    $E_{nk,fs} = 0$
**end if**

$E_{result}$, which is the result of filtering $E_{noise}$ out, is calculated using (15).

$$E_{result} = E_{fsn} - E_{noise} \tag{15}$$

The image was wavelet transformed at the beginning of this section, reduced to $\frac{1}{4}$ of the original. As a consequence, $E_{result}$ should be enlarged by $4l^2$ times to obtain a mask $E_r$ equal in size to the original image. By combining $E_r$ and $D_{fs}$, the final forest fire and smoke region $D_{result}$ can be produced as (16).

$$D_{result} = E_r \wedge D_{fs} \tag{16}$$

## 4. Experiments

### 4.1. Forest fire detection system based on UAV

As illustrated in Fig. 3, a typical UAV-based forest fire detection system consists of a single UAV and ground station. The UAV is equipped with a visible/infrared camera for image acquisition, and the onboard computer carried by UAV can perform local real-time image processing and mission planning. The data transmission system is responsible for the transmission of image data and flight commands. The ground station would detect and diagnose forest fire, after receiving the image and position transmitted by the drone in real time. On the other hand, the ground terminal can send considered operational command to the drone. This system combines real-time and wireless fire detection. Different algorithms could be implemented on this platform, which provides a more reliable guarantee for forest fire detection.

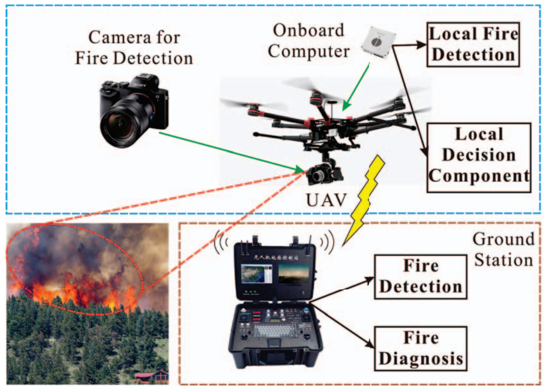



Figure 3: General concept of the UAV-based forest fire detection system.

### 4.2. Scenarios description

The forest flame video on the network (https://www.kaggle.com/csjcsj7477/firedetectionmodelkeras) is used for the method proposed above. The resolution of the video is $400 \times 240$. The average detection time per frame is 0.175 (s), which can basically meet the real-time requirements. The computer configuration used is shown in Table 1.

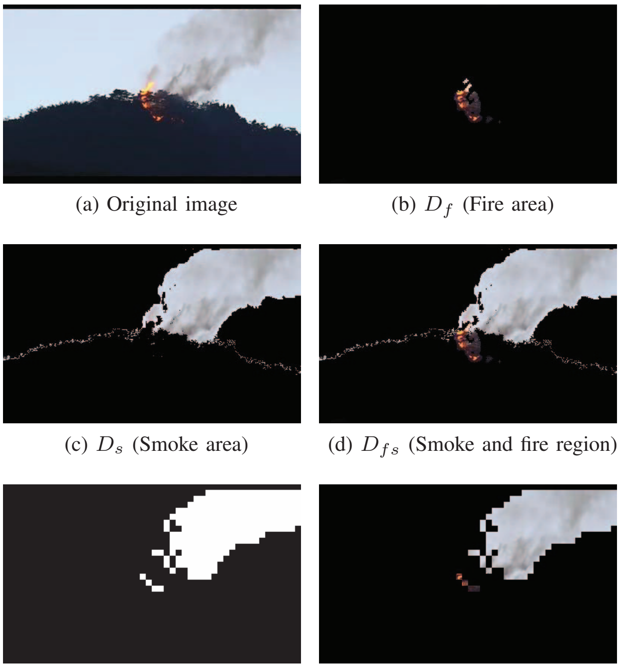
TABLE 1: Configuration of the computer

| Parameter | Description |
|---|---|
| Onboard Computer | DJI MANIFOLD |
| CPU | NVIDIA 4-Plus-1 ARM Cortex-A15 |
| RAM | 2GB DDR3L |
| System Environment | Ubuntu 14.04LTS |

### 4.3. Results

Fig. 4 reflects the effect of the algorithm proposed in this paper. It can be observed that the color model based algorithm has a significant effect on forest flames and smoke extraction. Comparing Fig. 4d with Fig. 4f, the effect on the small clutter filtering of wavelet transform can be observed.

Besides, the parameter $l$ in 3.2 has an effect on the final result. As shown in Fig. 5, it can be observed that the larger $l$ is, the more effectively of the filter, but at the same time it will erode a part of the fire and smoke region. On the contrary, more details of the forest fire could be remained with a smaller $l$, while it may result in filtering incompletely.

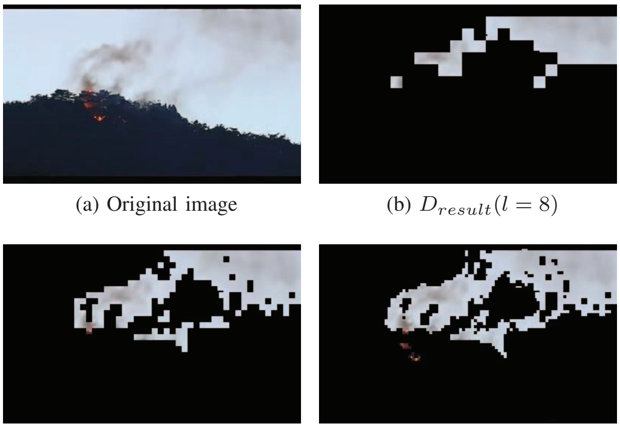


(a) Original image (b) $D_f$ (Fire area)

(c) $D_s$ (Smoke area) (d) $D_{fs}$ (Smoke and fire region)

(e) $E_r$ (Binarized mask) (f) $D_{result}$ (Final result)

Figure 4: Experimental results of sample frame



(a) Original image (b) $D_{result}(l = 8)$

(c) $D_{result}(l = 4)$ (d) $D_{result}(l = 2)$

Figure 5: Experimental results with changing $l$

## 5. Conclusions

This paper aims at providing an efficient and reliable method for forest fire detection that could be implemented on UAVs. Therefore, color features and wavelet transformation are used to improve the reliability of detection. A color model based fire and smoke detection method, which intended to effectively identify the suspicious forest fire regions with high accuracy, is firstly devised. In order to solve the noise points, the wavelet analysis approach is implemented. Proved by the experimental results, the method has the characteristics of high speed and accuracy, which could be used as a real-time application on-board.

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