Computer Vision-based Fire Detection using Enhanced Chromatic Segmentation and Optical Flow Model

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Abstract: Forests are one of the most important natural resources in the world. However, the occurrence of forest fires will burn plants and kill animals. Emergency incidents and events of fires can be dangerous and require quick and accurate decision-making. The use of computer vision for fire detection can provide an efficient solution to deal with these situations. We propose a combined method for detecting fire from a video sequence in monitoring and early fire detection operations. The method is based on motion detection methods, chromatic analysis and image segmentation. To improve the efficiency of the system, image pre-processing algorithms are proposed, and optical flow methods are used to detect the motion in fire video frames. We calculate the growth rate of the fire to reduce false-alarms. The proposed method has been tested on a very large dataset of fire videos captured by drones. It is assumed that the algorithm program is run on a computer that receives data from the camera of the drone that scans the required area. Experimental results demonstrate the effectiveness of our method while keeping their precision compatible with the existing methods.

Keywords: early fire detection; computer vision; image processing

1 Introduction

Forest fires are a powerful natural and anthropogenic factor that significantly changes the functioning and condition of forests. In countries where forests cover a large area, like Kazakhstan, forest fires are a national problem. Although Kazakhstan is a sparsely forested country, the area of the forest fund (the totality of all forests and land for forestry) is 30.4 million hectares, of which 13.3 million hectares are forested (11% of the country's territory). Up to 1000 forest fires are registered annually, covering areas up to 100 thousand hectares. On average, the amount of damage from forest fires per year is about 2.1 billion Kazak Tenge. Obviously, for many countries of the world with significant forest resources, including Kazakhstan, it is important to detect a fire as early as possible, determine its exact location and eliminate it. Therefore, it is very important to create a reliable and intelligent system for monitoring and early fire detection. Traditional fire detection systems include ground towers, aviation, and methods using satellite data. However, many such systems have a number of limitations in terms of cost, time, and space. For example, the use of satellite images makes it possible to detect fires on a continental scale, but they have large time constraints and are not applicable for early fire detection. At the initial stage of ignition, the fire is often not visible behind the barriers, and the smoke clouds often cool down too quickly to be detected. Therefore, it is necessary to use modern image processing tools that can significantly improve the efficiency of many existing systems. To overcome the limitations of traditional methods, unmanned aerial vehicle (UAV) technologies can extend traditional systems. For early forest fire detection, robotic devices such as UAVs can be used as surveillance and exploration devices. For example, one of the representatives of UAVs is quadrocopters. They are multifunctional devices that combine the automatic execution of a flight program from takeoff to landing, the transfer of the necessary information for fire detection, and the use of image data of controlled areas for subsequent computer data processing. They can be used to monitor large hard-to-reach areas such as woodlands, peat bogs, industrial sites, and more.

There are several ways to detect a fire based on information obtained in the form of images and video sequences. For example, an infrared thermal imaging camera, which is based on the detection of a stream of thermal radiation from a fire. To detect and localize wildfires, the system automatically locates hotspots using geo-referenced thermal images. Although the use of an infrared camera gives good results for fire detection, it is not recommended to use them on a drone for large scale use in fire detection systems due to their large size, weight and high cost. In recent years, there has been significant progress in digital data processing technology. At the same time, we have seen significant improvements in image and video processing capabilities, leading to greater use of computer vision systems for fire detection. The visual detection of fire in open spaces is very important for the early detection of fire. In most cases, the appearance and growth of a flame f fire can be considered a sign of an incipient fire, which, as a rule, appears as a bright spot of an indefinite changing shape against a relatively uniform darker image. To detect a fire, it is necessary to have knowledge of fire features (motion parameters, color characteristics, flickering effects) in order to correctly extract data from aerial photographs.

2 Literature Review

Fire detection systems based on machine vision typically extract three different fire data and use it for detection: color, motion, and geometry. The flame is the visible part of the fire and is made up of hot gases. The color of the flame is created by him as a result of burning materials. Depending on the substance and impurities outside, the color of the flame and the intensity of the fire will be different. However, in the case of forest fires, fire has a well-known red-yellow color. Many natural objects have colors similar to fire and can often be misidentified as flames. For this reason, it is very important to distinguish between such false alarms and real fires. Color-based detection methods are the simplest and most used methods for solving detection problems. These methods set the threshold values of the fire pixels after they have been converted to a specific color space. For example, the combination of RGB color space channels with a saturation component from the HSV (Hue, Saturation, Value) color space has been shown to be effective for extracting fire and smoke pixels [1]. The YCbCr color space was used to create a general chromaticity model for flame pixel classification [2]. The YUV color model has also been used for real-time fire detection based on the temporal variation of fire intensity due to the efficient separation of luminance from chrominance compared to the RGB color space [3]. However, the performance of color fire detection methods has been limited by the difficulty of characterizing the smoke, which in most cases strays into clouds. This problem was solved by attentional feature map in capsule networks [4]. Therefore, methods based on a combination of both color and the movement of fire or smoke increase the reliability of fire detection both indoors and outdoors [5]. For example, in [6], a combination of various flame characteristics (color, shape, and motion of the flame) obtained from video obtained by cameras was presented to reduce the number of false alarms caused by a fire. Khan et al. [7] proposed a video-based method using flame dynamics and static flame detection in a room using color, shape, and flame area. Their method may run into problems in early fire detection due to the steps of removing and then applying fire propagation characteristics. Seebamrungsat et al. [8] proposed a method based on the combination of HSV and YCbCr color spaces. Their system has additional color space conversions and is, therefore, better than methods using only one color space. But in their work, only the static characteristics of the fire are used and, therefore, the system is relatively weak and not stable enough. Chen et al. [9] improved the traditional fire detection methods by applying a flame flicker detection algorithm that was included in the algorithm for detecting fires in color video sequences. The test results show the good efficiency and reliability of the proposed algorithms. However, the calculation speed is quite slow, and is suitable for images with a low resolution, and may not be suitable for high-quality images. Kim et al. [10] used an ultra-spectral camera to distinguish flames from common light sources, which is one of the main limitations of ordinary cameras. According to the experimental results, they have achieved good results, but there may be limitations such as the higher cost of the camera. Y. Wang et al. [11] used a new video flame detection based on multi-feature fusion and double-layer XGBoost to increase the accuracy and robustness of flame recognition. The suggested technique enhances the detection rate and may be used in a variety of settings, according to the findings of experiments. Another method commonly used to detect temporal changes in flame boundaries is the wavelet transform [12, 13]. However, to gain satisfactory results in wavelet analysis, the frame rate of the input video sequence must be high, which limits its application. Deep learning has also become an active topic nowadays due to its high recognition accuracy in a wide range of applications. In the studies [14, 15, 16], a deep learning method for fire detection is used and high accuracy is achieved. We also conducted a study on the application of convolutional neural networks for fire detection in [17]. But there are certain limitations when using deep learning technology. For example, deep learning demonstrates better accuracy when working with big data, but it demands collecting a huge amount of actual fire samples taken with the UAV camera [18]. Also, deep learning requires more productive hardware for training, which takes more time.

Among the most recent studies, can be noted the work of Dang Nhu Dinh et al. [19], where they proposed combined fire detection techniques in RGB and YCbCr color spaces based on fire properties. They also propose using the correlation coefficient between consecutive frames to eliminate objects with fire-like color and diminish the vehicle shaking effect to ensure the accuracy of the proposed method in UAVs. P. Huang et al. [20] proposed a combined real-time intelligent fire detection and forecasting approach through cameras based on the computer vision method for practical application in high-fire-risk industries. V. L. Kasyap et al. [21] proposed early detection of forest fire using mixed learning techniques based on UAV composed of YOLOv4 tiny and LiDAR techniques. According to their data, the proposed model outperforms the traditional methods such as Bayesian classifiers, random forest, and support vector machines. But as noted above, there is still not enough data to create a dataset of actual fire samples taken with the UAV camera.

According to the information, which is discussed above, video-based fire detection has been rapidly explored and developed with current technology [22], but most existing fire detection methods need to be improved. In our previous work, we proposed a UAV-based system for monitoring forest fires, so in this research, the goal of our study is to optimize the existing methods and algorithms for analyzing images obtained from the UAV to monitor and detect a forest fire [23]. In this paper, we used the optical flow method for motion detection to isolate potential fire areas from other moving objects in the video frame. Optical flow is an important technique in motion analysis for computer vision-based systems. The proposed method uses fewer parameters than previous fire detection methods, making the process of fine-tuning automatic detection more intuitive.

3 Methods

The general structure of the proposed fire detection algorithm is shown in Fig. 1. The proposed model uses a combination of methods and algorithms for image processing using computer vision. The proposed algorithm can be divided into four steps. In the first stage, the input data is preprocessed for correct detection. Next comes flame region detection using the HSV color space. In the third stage, motion information is modeled by analyzing the temporal and spatial distributions via Optimal Mass Transport optical flow vectors. The last step of the algorithm is measuring the area of the regions extracted in the previous step.

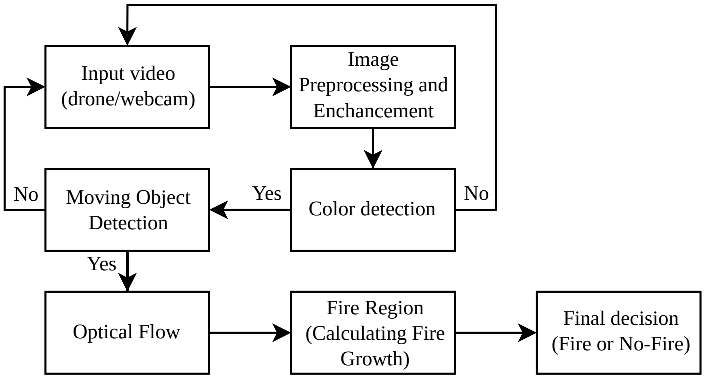


Figure 1
Workflow of the proposed model displaying the different phases

3.1 Image Pre-Processing

Image pre-processing is the stage of image enhancement and adjusting a digital image by changing its brightness, and contrast, removing noise and sharpening the image, and so on. The main goal of this stage is to bring out the details of the image so that the image is more suitable for processing and analysis. Our pre-processing step performs image filtering, contrast enhancement, and color processing. This project used the RGB and HSV color space. To detect a fire, the pixel of the fire area in RGB is explored. Then, for the HSV color space, the RGB image must be converted to HSV before the image can be analyzed. Image preprocessing will increase the reliability of data processing and recognition of the area of interest.

3.1.1 Image Smoothing Filtering

In the process of image formation, transmission, and reception, environmental noises, such as weather and light conditions, inevitably appear on images.

Therefore, before a fire is detected, the image should be smoothed and filtered. To filter and smooth a large number of images, this article applies Gaussian filtering to reduce image noise. Gaussian filtering is a classic way of smoothing images, in which image smoothing occurs by averaging pixels in the neighborhood, in which pixels at different positions are assigned different weights [24].

3.1.2 Contrast Enhancement

One of the main signs of the beginning of a forest fire is the appearance of a smoke cloud with an intensity exceeding the background intensity. Contrast enhancement is a step that is used to remove the effects of contrast variations from images due to varying light conditions. The contrast-enhancing technique is defined in the equations below [25]:

$$g(x,y)=\begin{cases} a_1 f(x,y), & f(x,y)<r_1 \\ a_2\left(f(x,y)-r_1\right)+s_1, & r_1 \geq f(x,y)<r_2 \\ a_3\left(f(x,y)-r_2\right)+s_2, & f(x,y)\geq r_2 \end{cases} \tag{1}$$

$$a_1=\frac{s_1}{r_1},\quad a_2=\frac{(s_2-s_1)}{(r_2-r_1)},\quad a_3=\frac{(L-s_2)}{(L-r_2)}. \tag{2}$$

where $g(x,y)$ presents the output image, $f(x,y)$ is the input pixel value; s_1, s_2, r_1, and r_2 are the contrast adjusting parameters; a_1, a_2, and a_3 are scaling factors for various grayscale regions and L is the maximum gray level value.

3.1.3 RGB to HSV Conversion

The conversion starts by obtaining red (R), green (G), and blue (B) values on a scale of 0 to 1 inclusive, and the largest and smallest of the R, G, B values with the difference between them. The variable $scale_x$ represents the channel scale, such as 255.

$$R=\frac{R'}{scale_r},\ G=\frac{G'}{scale_g},\ B=\frac{B'}{scale_b} \tag{3}$$

$$m_{\max}=\max(R,G,B) \tag{4}$$

$$m_{\min}=\min(R,G,B) \tag{5}$$

$$\Delta=m_{\max}-m_{\min} \tag{6}$$

To get the H (hue) values, we look at the largest of the R, G, B values. The two smallest values are subtracted and divided by the difference between the largest and smallest. Then, we normalize the hue by adding 0, 2, or 4. The resulting H is any real number, and the HSI to RGB conversion algorithm can work with any H value.

$$H = \begin{cases} undefined, \quad if\ \Delta = 0 \\ \dfrac{G-B}{\Delta}, \quad if\ m_{\max} = R \\ \dfrac{B-R}{\Delta} + 2, \quad if\ m_{\max} = G \\ \dfrac{R-G}{\Delta} + 4, \quad if\ m_{\max} = B \end{cases} \tag{7}$$

$$H^{'} = H \times scale_h \tag{8}$$

The saturation value S is the difference between the largest and smallest values of the color channel divided by the brightness. If V is 0, then the resulting saturation is 0.

$$S = \begin{cases} 0, \quad if\ V = 0 \\ \dfrac{\Delta}{V}, \quad otherwise \end{cases} \tag{9}$$

$$S^{'} = S \times scale_s \tag{10}$$

The value V is based on the brightest color channel.

$$V = m_{\max} \tag{11}$$

$$V^{'} = V \times scale_v \tag{12}$$

3.2 Color Segmentation using Multi-Color Space

Color is one of the static characteristics of fire and is the most important phenomenon for determining the flame of fire. To correctly detect a fire, it is necessary to know the color range of the fire. The color of the fire changes relatively little within a particular area and changes greatly when moving from one area to another. Most color-based fire detection methods use the RGB color space because almost all visible cameras have sensors that detect video in RGB format. In the RGB color model, each color appears in its primary spectral components: red, green, and blue. According to the RGB color histogram of the fire image, the value of the red channel of the flame is greater than the value of the green channel, and the value of the green channel is greater than the blue channel. Thus, the RGB model is more suitable for color, but not very suitable for describing the image as interpreted by a human. Therefore, the main disadvantage of the RGB color space is brightness dependence, which means if the brightness of the image changes, the fire pixel segmentation rules do not work properly. Also, it is not possible to separate a pixel value into intensity and chrominance components. Thus, there is a need to convert the RGB color space to another one where the separation between brightness and chrominance is large. The HSV color space is great for this. HSV is a cylindrical color model that converts RGB primaries to a color value that is easier for humans to understand, and those parameters are hue, saturation, and value.

3.2.1 RGB Color Space Segmentation

The RGB additive color model uses light to represent color. In this model, three colors – red, green, and blue – are mixed in various combinations to obtain different colors. Thus, by varying the amount of red, green, and blue, different colors can be created. The intensity of each of the red, green, and blue components are represented on a scale from 0 to 255, with 0 being the least intensity to the maximum intensity of 255. By studying the visual features of fire, it can be observed that fires have unique visual features. These features can be divided into static and dynamic characteristics, which are both used in the classification of fire pixels. In terms of static characteristics, fire displays a distinctive range of red-yellow colors depending on its temperature and this property makes color segmentation one of the most fundamental steps. The later decisions based on shapes and other features depend on how accurately true fire pixels are segmented out. Fire samples with different flame colors, environmental conditions, and backgrounds are collected and initially checked with the following rules:

$$\begin{gathered} R > R_T \\ R \geq G \geq B \\ \left(S \geq \left((255 - R) * \frac{S_T}{R_T} \right) \right) \end{gathered} \tag{13}$$

3.2.2 HSV Color Space Segmentation

Among various color systems, HSV color model is very suitable for human interpretation, since hue, saturation, and value components are intimately related to the way in which human beings perceive color. On the basis of human interpretations of fire features, it is reasonable to assume that the flame color belongs to certain ranges of HSV components. In order to obtain the threshold values to separate flame colors, the histograms shown in Figure 3 were generated for fire pixels of HSV components.

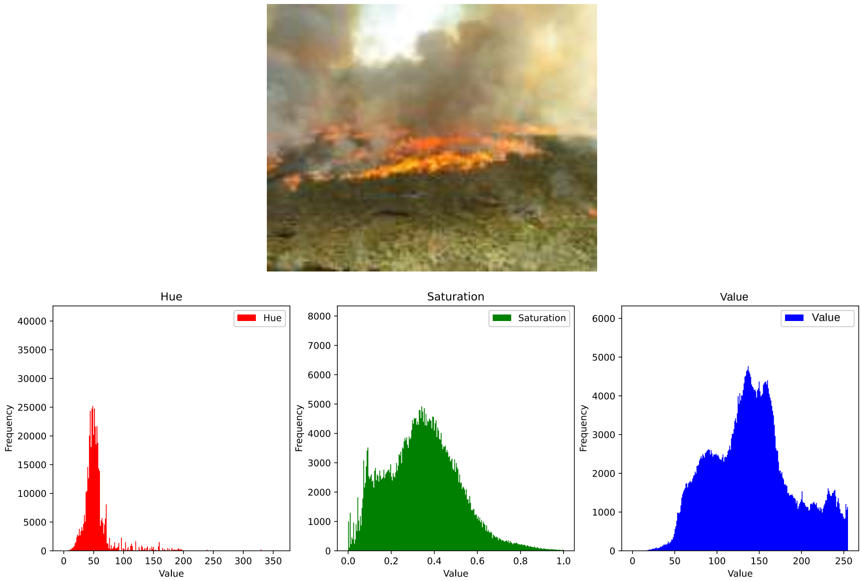


Figure 3
The input image and fire pixel histogram in HSV space

It can be concluded from Figure 3 that the fire pixels usually take much lower H values, but relatively higher S and V values. After a lot of experiments, the following decision rules to segment fire by HSV color space were defined. For flame detection, thresholds are used on each channel of the HSV color space for segmentation. For a brighter environment, the following rules are used:

$$\left.\begin{array}{r} 0^\circ \le I_H(x) \le 60^\circ \\ 32 \le I_S(x) \le 100 \\ 127 \le I_V(x) \le 255 \end{array}\right\} \tag{14}$$

For a darker environment of image:

$$\left.\begin{array}{r} 0^\circ \le I_H(x) \le 60^\circ \\ 20 \le I_S(x) \le 100 \\ 126 \le I_V(x) \le 255 \end{array}\right\} \tag{15}$$

3.3 Motion Detection

The proposed color models of flames detect fire regions well. However, various fire-like objects cause false positive alarms in real applications. Fires have dynamic features with a changeable shape as the airflow created by the wind can cause fluctuations and sudden movement of the fire. Some early studies consider fire-like moving objects as fire, but this method causes many false alarms, because fire-colored moving objects may all be falsely detected as fire. Red moving objects are subject to being considered flames. To reduce these false positive fire detection errors, it is reasonable to set the dynamic characteristics of the flame. To determine if the movement is caused by fire or a moving non-fire object, further analysis of the moving areas in the video sequence is needed. In this paper, we propose motion models for flames based on optical flow analysis. Optical flow is described as the two-dimensional distribution of visible motion velocities of brightness patterns in an image plane. This feature can be applied to estimate the local image pixel's movement and specify the velocity of each image pixel between adjacent images. Each pixel in the image corresponds to one velocity vector, and these velocity vectors compose an optical flow field.

3.3.1 Optimal Mass Transport Optical Flow

Classical optical flow models cannot represent the appearance of a fire because they depend on constant brightness. This problem is caused by rapid variation of intensity that exists in the combustion process and the chaotic motion produced by air turbulence. Taking into account the above conditions, the Optical Mass Transport (OMT) optical flow model is a suitable option for fire detection applications. In this work we apply OMT optical flow model due to its advantages in performing motion detection tasks with further dynamic analysis of moving areas, so that non-fire moving objects can be excluded. If the image capture camera is installed on the UAV that is in motion throughout the mission, the fire detection performance will be reduced because all objects in the field of view of the camera are moving. To solve this problem, this study proposes a novel approach to distinguishing the image variations caused by UAV motion and those caused by fire. The main idea of the proposed method is to estimate the discrepancies between the artificial optical flow and the OMT optical flow [26] and the elicitation of the fire pixels from the classified divergences. The structure of the proposed method is shown in Figure 4.

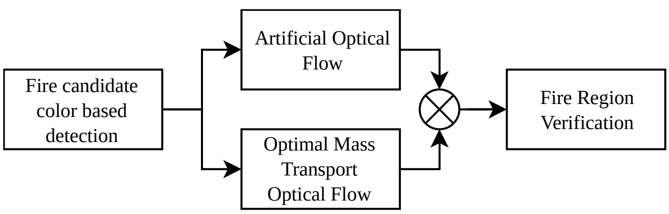


Figure 4
Basic architecture of the motion-based fire detection

3.3.2 Optical Flow Fire Feature Extraction

OMT fire motion pixels are defined as:

$$\Omega_e = \left\{ (x,y) \in \Omega : \left\| \vec{u}(x,y) \right\|_2 > c \cdot \max_{\Omega} : \left\| \vec{u} \right\|_2 \right\} \tag{16}$$

where $0 \le c < 1$ is selected so that an adequate number of pixels can be reserved, $\Omega \subset R^2$ represents an image region.

Two features can be extracted from OMT optical flow depending on dynamic texture of fire: f_1 measures the average magnitude; the directional value f_2 analyzes the motion directionality. They define the two-dimensional feature vector $F = (f_1, f_2)^T$. The given image region Ω and the OMT optical flow field in this region, the magnitude and directional characteristics are chosen through the following procedures [26]. The magnitude and directional characteristics are chosen through the following steps:

OMT Transport Energy per pixel: $f_1 = \underset{\Omega_e}{Mean}\left(\frac{I}{2} \left\| \vec{u}_{OMT} \right\|_2^2 \right).$ (17)

OMT Source Matching function is a quantification of how well the ideal source flow pattern matches the intended OMT flow field:

$$\vec{u}_T(x,y) = \begin{bmatrix} u_T(x,y) \\ v_T(x,y) \end{bmatrix} = \exp\left(-\sqrt{x^2+y^2} \right) \begin{bmatrix} x \\ y \end{bmatrix}. \tag{18}$$

The best matching computed OMT flow field with ideal source flow can be computed by:

$$f_2 = \max_{\Omega} \left\| \left(u_T * \frac{u_{OMT}}{\left\| \vec{u}_{OMT} \right\|_2} + \left(\upsilon_T * \frac{\upsilon_{OMT}}{\left\| \vec{u}_{OMT} \right\|_2} \right) \right) \right\| \tag{19}$$

where ($*$) means convolution.

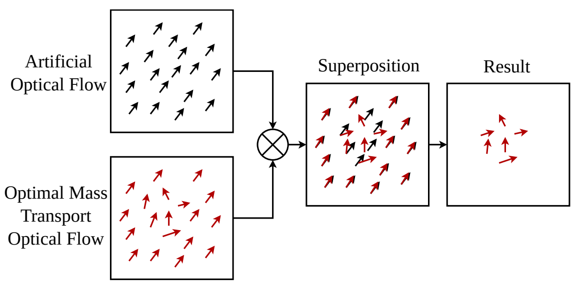


Figure 5
Illustration of the fire pixel identification

3.3.3 Motion Errors Estimation

After calculating two optical flows (an artificial optical flow for calculating camera movements and an OMT optical flow for estimating pixel movement), the next step is a comparison of these two obtained optical flows and calculating their differences. As shown in Figure 5, the artificial optical flow estimates the identical moving direction of the view in the image, while the OMT optical flow evaluates the movement of each pixel in the image. Then, these optical flows are combined into the same image, where if there is a fire in the scene, the OMT optical flow shows differences in motion between pixels.

3.3.4 Fire Region Tracking

On the basis of the estimated moving orientation of each pixel f_{OMT} utilizing the OMT optical flow and the calculated moving orientation of the camera f_α using the artificial optical flow. The difference between them can be acquired by $\Delta f = \left| f_\alpha - f_{OMT} \right|$. To reduce noise and some unexpected errors, f_α is chosen as the average value of the orientations of all pixels in the image. A simple approach to identifying fire pixels is comparing the angular deviations of each pixel with a properly chosen threshold. The decision rule for filtering the background and highlighting fire pixels is designed as follows:

$$P_{FM} = \begin{cases} 1, & if\ \Delta f > \overline{f}, \\ 0, & otherwise. \end{cases} \tag{20}$$

where P_{FM} is the binarized values of pixels obtained by applying the fire pixels motion decision making rule. If Δf outweighs the threshold $\overline{f}$, the pixel is classified as a fire pixel and is set to 1, otherwise the pixel is set to 0. The threshold value can be settled on the basis of the practical condition or by using advanced artificial intelligent methods, such as neural network or fuzzy logic.

3.4 Fire Region Growth Rate

Based on the fact that a hazardous fire grows over time, the area of flame is expected to increase. An example of the growth of the flame area during the burning of wood fuel is illustrated in Figure 6. First, we calculate the fire pixels between two consecutive frames using the following equation, which shows the fire is increasing or decreasing [27]:

$$FP_f = F\left(P(s)\right)_{i+1} - F\left(P(s)\right)_i \tag{21}$$

where F is the frame from the video and $P(s)$ is the number of fire pixels.

To identify the fire growth feature, the flame pixels in the video frames are calculated at regular time intervals and compared. To find the fire pixel difference between two frames at different time intervals, we use the following equation:

$$FP_t = F\left(P\left(s\right)\right)_{f(r)+1} - F\left(P\left(s\right)\right)_i \tag{22}$$

where $f\left(r\right)$ is the frame rate of the video and $P\left(s\right)$ is the segmented fire like pixels in the successive images. These results lead to the conclusion that the fire is likely to grow, and this increases the authentication of the real fire.

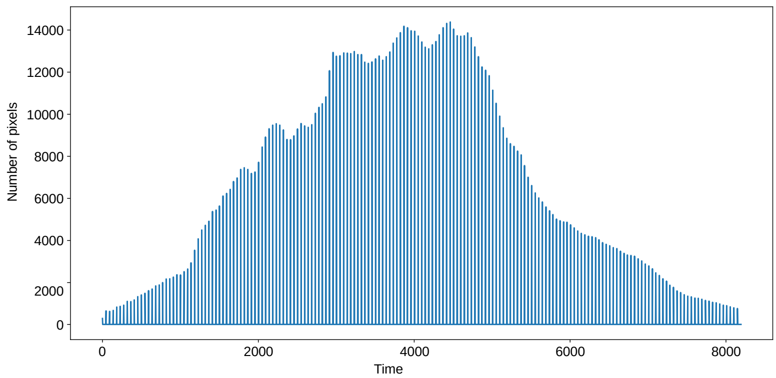


Figure 6
Graph of the amount of fire pixels extracted during the burning of wood fuel

4 Experimental Evaluation and Results

The proposed method has been tested on real cases. Tests have been run on a personal computer (NVidia GeForce RTX 2060 Super (Turing architecture) with 8 GB of graphics memory, AMD Ryzen 5 2600 processor with 3.9 GHz, 16 GB of DDR4 RAM). Our program was implemented using Python language and open-source computer vision libraries. The experimental evaluation was performed using 20 videos collected from multiple sources. Some videos in the dataset contain non-fire frames that are not visible to the eye. The video data frame rate varies from 20 to 30 fps, and the image resolution is a minimum 720 × 480 pixels. Table 1 describes the videos used in the experimental testing. Dataset contains aerial captured forest fires frames. The accuracy is calculated using the formula below:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{23}$$

We also calculated other metrics such as F1-score, precision, and recall. The F1-score is a weighted average of precision and recall, as these scores account for both false positives and false negatives. Precision is the ratio of correctly predicted positive results to the total number of positive solutions. Recall is the ratio of correctly predicted positive observations to all observations of the current class. The detection results were evaluated as follows [28]:

$$\mathrm{Pr}ecision = \frac{TP}{TP + FP} \tag{24}$$

$$\mathrm{Re}call = \frac{TP}{TP + FN} \tag{25}$$

$$F1 = \frac{2 \times \mathrm{Pr}ecision \times \mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call} \tag{26}$$

where TP - the number of true positives, TN - the number of true negatives, FP - the number of false positives and FN is the number of false negatives.

Table 1

The details of videos for experimental testing and performance evaluation

Input file	Resolution, px	Number of frames	Fire frames	Non-fire frames
Video file 1	640 x 480	278	278	0
Video file 2	640 x 480	325	321	4
Video file 3	1280 x 720	384	375	9
Video file 4	1280 x 720	292	292	0
Video file 5	640 x 480	658	657	1
Video file 6	480 x 480	364	364	0
Video file 7	720 x 480	741	697	44
Video file 8	640 x 480	365	365	0

Table 2

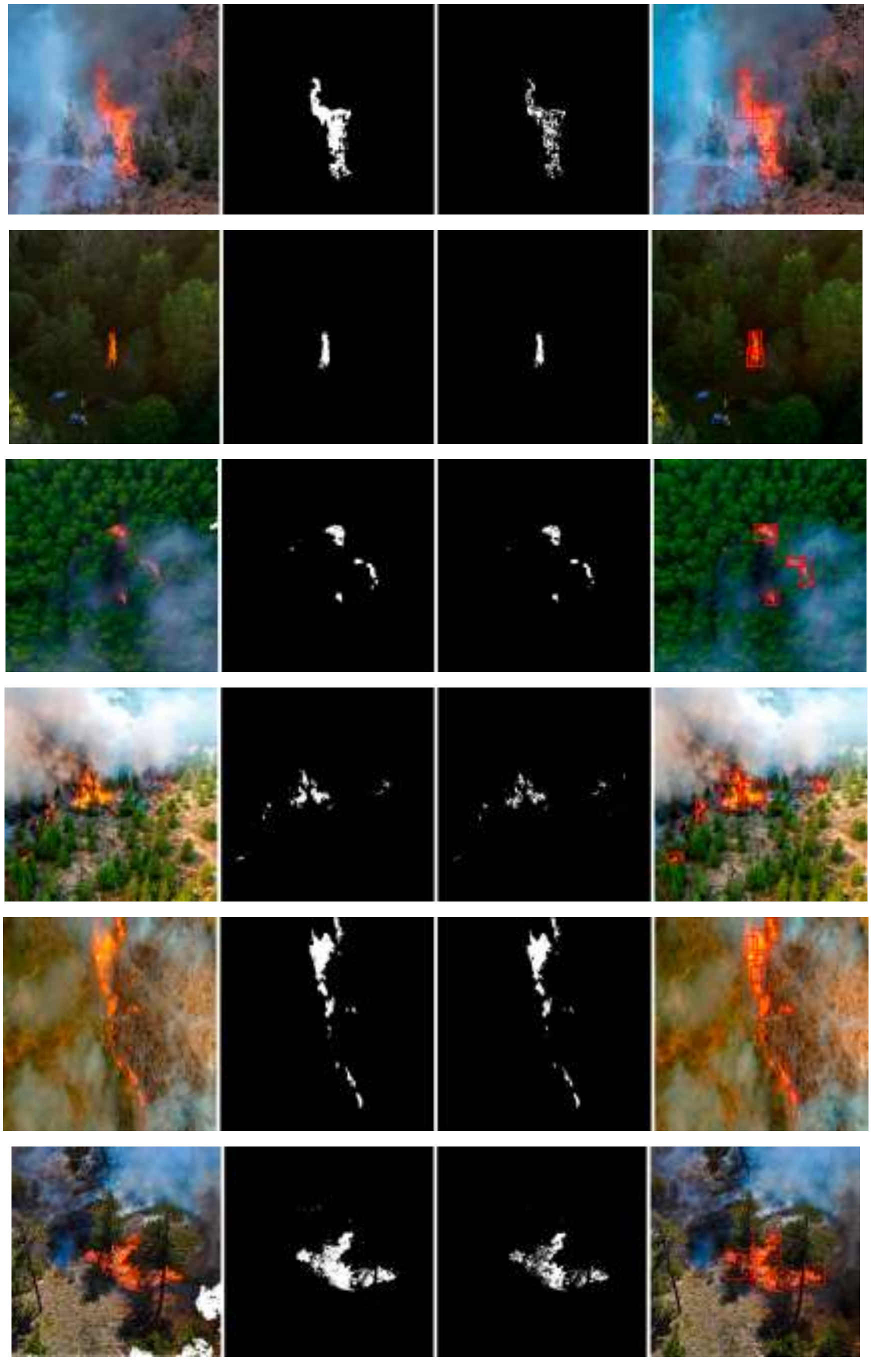
Average indicators of the proposed method

Proposed method	Accuracy, %	Precision, %	Recall, %	F1-score, %
	96.6	94.8	97.6	96.2

Table 3

Comparison of metrics in different techniques with the proposed method

Metric	D.-H. Lee et al. [1]	Khan et al. [7]	D. N. Dinh et al. [19]	**Our proposed method**
Accuracy, %	89.5	95.8	94.7	**96.6**
Precision, %	86.8	93.4	93.1	**94.8**
Recall, %	90.6	91.9	92.4	**97.6**
F1-score, %	88.7	92.6	92.7	**96.2**



(a) (b) (c) (d)

Figure 7

Experimental results of sample videos (a) Original images from video files (1-8), (b) results of color detection (c) optical flow analysis d) final results of fire tracking

Figure 7 shows examples of fire detection. Experimental results show that the accuracy of the method is 96.6%, which proves that our proposed method has higher accuracy and good performance in various scenes. From Table 2 it is clear that the precision and recall of the proposed method show the most satisfactory performance. Additionally, the performance of our proposed method with enhanced color segmentation and an optical flow analysis technique is compared with the model presented by F. Gong et al. [1], Khan et al. [7], and D. N. Dinh et al. [19]. The comparison table is given in Table 3. It can be clearly seen that the proposed method using the OMT optical flow achieved very high performance with 96.6% of accuracy respectively.

Conclusions

In this paper, we proposed a new fire detection method based on a combination of color spaces with optical flow motion detection and candidate region tracking in video captured by UAV. The key difference between the proposed method and existing studies is that our method first performs preprocessing stages followed by RGB and HSV color segmentation to detect fire-like pixels. Then, we provide segmented images to the OMT optical flow model to capture and track only the moving region in the video. Finally, we calculated the fire region growth rate in the video. Experimental results show the proposed method achieves an accuracy of around 96.6%, demonstrating the effectiveness and usefulness of the algorithm. The computational requirements of the proposed method are higher compared with those of the existing algorithms based on motion detection modeling. However, the proposed method is still considered suitable for early fire alarm systems. Future work will focus on performing the optical flow analysis step using a neural network that is trained directly on an aerial captured dataset containing fire signature vectors and creating a fuzzy logic for the detection of smoke generated by a fire in the visible image.

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