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UAV-based Forest Fire Detection and Tracking Using Image Processing Techniques

Chi Yuan[1], Zhixiang Liu[2], and Youmin Zhang[3]

***Abstract*—In this paper, an unmanned aerial vehicle (UAV) based forest fire detection and tracking method is proposed. Firstly, a brief illustration of UAV-based forest fire detection and tracking system is presented. Then, a set of forest fire detection and tracking algorithms are developed including median filtering, color space conversion, Otsu threshold segmentation, morphological operations, and blob counter. The basic idea of the proposed method is to adopt the channel "a" in Lab color model to extract fire-pixels by making use of chromatic features of fire. Numerous experimental validations are carried out, and the experimental results show that the proposed methodology can effectively extract the fire pixels and track the fire zone.**

I. Introduction

Forests can purify water, stabilize soil, cycle nutrients, moderate climate, and store carbon. They can create habitat for wildlife and nurture environments rich in biological diversity. They can also contributes billions of dollars to the country's economic wealth. However, hundreds of millions of hectares of forests are unfortunately devastated by forest fire each year [1]. Forest fire has been constantly threatening to ecological systems, infrastructure, and public safety [2].

The current approach of forest fire detection is to use a single manned aerial vehicle, ground-based equipment, or satellites [3]. However, manned aerial vehicles are typically large and expensive with the necessity of skilled human pilots. Moreover, hazardous environments and operator fatigue can potentially threaten the life of the pilot. Ground-based measurement is generally limited in the range and maneuverability of surveillance. Although nowadays forest fire detection solely relies on satellite, satellite missions are usually expensive to construct and launch, and the fixed orbital satellites are also less flexible in their flight path and instrumentation/technology update [4]. Therefore, the deployment of small-scale UAVs for forest fire detection is a natural and increasingly realistic option [5]. UAVs can provide the following benefits: 1) cover wide areas, especially in cloudy weather; 2) work at day time, night, with long duration; 3) easily recoverable and relatively inexpensive; 4) in the case of electric UAVs, it is also a benefit to the environment; 5) carry different payloads for different missions; 6) cover target area efficiently [6, 28], and most importantly, missions can be achieved autonomously without or with minimal human pilot/operator's involvement.

As vision-based detection technique has advantages of supplying intuitive and highly real-time information, large detection range, as well as convenience for record, it has become a key component in the UAVs-based forest fire detection system [7]. A series of researches have focused on vision-based forest fire detection and image processing technique has been widely used with different segmentation methods. Most of the early researches detect fire by videos, then researchers gradually use cameras to do fire detection in the real situation. Vision-based fire detection usually makes use of three dominant features of fire: color, motion, and geometry [8]. Since color is the most dominant visual feature of fire, the color information is usually used as a pre-processing step in the detection of potential fire. Most of these methods take advantage of the discriminative properties in color space to obtain fire regions in the images [9, 10]. Chen *et al*. use color and motion features based on RGB (red, green, blue) model to extract real fire and smoke in video sequences [11]. [12] proposes a real-time algorithm which combines motion and color clues with fire flicker analysis on wavelet domain to detect fire in video sequences. In [13], a generic color model based on RGB color space, motion information, and Markov process enhanced fire flicker analysis are combined to create an overall fire detection system. In [14], a rule-based generic color model for flame pixel classification is presented and experimental results show that the detection performance is significantly improved. [15] presents an Otsu based method to detect forest fire and smoke and both fire and smoke areas are segmented together.

It is obvious that variety of vision-based methods primarily depends on image processing algorithms. In order to achieve the goals of automatic forest fire detection and tracking, this paper conducts a preliminary research on developing a set of image processing algorithms that is capable of effectively detecting and tracking forest fire. Through comparing and analyzing fire segmentation results of using different color space, it is found that segmentation with "channel a" of Lab color model (fire usually displays reddish color) has the most satisfied fire segmentation results. Experimental demonstrations are carried out in two scenarios, one is real forest fire images and the other is real-time fire images. Experimental results verify the proposed algorithms can not only test with real forest fire images but also perform well with the images collected by a UAV in lab environment.

The remainder of this paper is organized as: Section II addresses general description of the system architecture for forest fire detection using UAVs. Section III briefly presents

1 C. Yuan is a PhD student with the Department of Mechanical and Industrial Engineering, Concordia University, Montreal, Quebec H3G 1M8, Canada, chi_yua@encs.concordia.ca
2 Z. X. Liu is the PhD student with the Department of Mechanical and Industrial Engineering, Concordia University, Quebec H3G 1M8, Canada, l_zhixia@encs.concordia.ca
3 Y. M. Zhang is a Professor currently with the Department of Information and Control Engineering, Xi'an University of Technology, Xi'an, Shaanxi 710048, China and on sabbatical leave from the Department of Mechanical and Industrial Engineering, Concordia University, Quebec H3G 1M8, Canada, ymzhang@encs.concordia.ca

the image processing methods used for forest fire detection and tracking. Section IV discusses the experimental results. Conclusions are summarized in the last section.

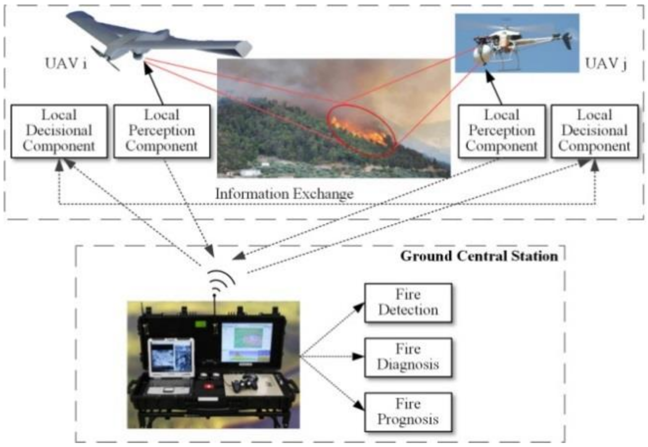

Fig. 1 Schematic illustration of UAVs forest fire detection system [26].

II. Architecture of UAV-based Forest Fire Detection and Tracking System

As illustrated in Fig. 1, a UAV-based forest fire detection system can be generally integrated into six main components: 1) UAV airframes and payloads (including sensors, communication devices, etc.) for fire detection and surveillance; 2) sensors fusion techniques and image processing techniques for rapid fire detection, decision-making, and localization; 3) guidance, navigation, control (GNC) module for single UAV and multiple UAVs to cover the fire areas; 4) cooperative localization, deployment, and control strategies of a fleet of UAVs with remote sensing sensors for optimal coverage of fire areas for the purpose of precise and rapid fire tracking, prediction, and assistance/guidance of firefighting; 5) autonomous path planning and re-planning strategies before and after fire being detected based on fire development condition; 6) ground station which contributes to ground computation, visualization for fire detection, tracking and prediction with automatic fire alarm, and safe and efficient operation of the UAVs system.

Generally, forest fire monitoring and detection mission is composed of three stages: fire search, fire confirmation, and fire observation [27]. In the fire search stage, a fleet of homogeneous or heterogeneous (fixed-wing and rotary-wing) UAVs with fire detection capabilities [16, 17] are commanded by the ground control center to patrol the surveillance area along respective preplanned path to search for the potential fire. Once a fire is detected, fire confirmation stage then starts. The control center sends other UAVs to confirm the alarm by using their sensors and meanwhile the UAV which has detected the fire alarm is commanded to hover at a safety distance from the fire spot. If the alarm is found to be false, then the fire search stage is resumed. If the alarm is confirmed, the fire observation is to begin [25]. In the fire observation stage, tasks of UAVs are re-planned to synchronously obtain images and data of the detected fire from different points of view [18] and deliver these information to ground station operator/firefighting manager or other UAVs with firefighting function [16, 17].

III. Fire Detection and Tracking Algorithms

Over the last decade, various image processing techniques have been developed for forest fire detection and tracking. In this paper, the main image processing algorithms implemented for automatic fire detection and tracking contain image collection, image preprocessing (including noise reduction, color model conversion), threshold segmentation, morphological operations and blob counter. The flowchart of the algorithms is briefly illustrated in Fig. 2.

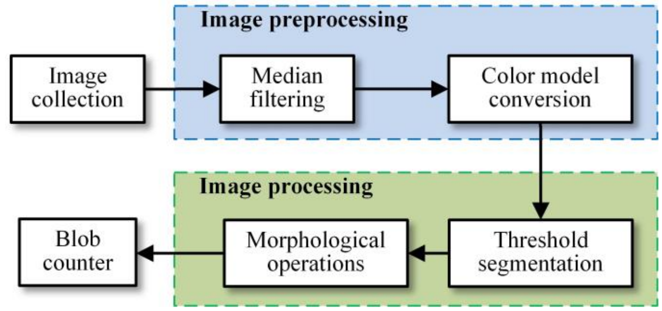

Fig. 2 Flowchart of fire detection and tracking algorithms.

A. Noise Reduction

Since impulse noises generated by sensor or communication errors usually corrupt images, noise reduction is essential for improving the results of subsequent processing such as image segmentation, morphological operations, and edge detection [19]. In this paper, median filter (a widely used nonlinear digital filtering technique) is adopted to eliminate noise in images due to its simplicity and capability of preserving image edges while removing noise [20].

B. Color Model Analysis and Conversion

Color is one of the dominant features of fire and the color information is widely used as a pre-processing step in the detection of potential fire. The discriminative properties in color space are generally utilized to obtain the fire regions. RGB (red, green, and blue) model, HSI (Hue, Saturation, and Intensity) model, HSV (Hue, Saturation, and Value) model, and Lab model are commonly adopted to represent images in corresponding color spaces. Generally, different segmentation results can be obtained using different color models.

Based on the existing researches on fire segmentation [7-15] and authors' extensive experimental results, Lab color model is chosen for the fire segmentation which is composed of three components: the luminance "L", the chrominance "a", and the chrominance "b". Channel "L" represents the luminance range from the darkest black ($L=0$) to the brightest white ($L=100$). Color channel "a" represents colors from red to green, with red at positive "a" values and green at negative "a" values. Color channel "b" represents colors from yellow to blue, with yellow at positive "b" values and blue at negative "b" values. The scaling of "a" and "b" values often run in the range from -128 to +127.

Lab color model analysis: In this paper, channel "a" of Lab color model is employed for fire segmentation due to: 1) it can exactly define the colors and Lab color space is an absolute color space which does not rely on input devices (camera) or output devices (monitors and printer) [21]; 2) it can represent more colors (even more than human eye's perceptual colors) so that more fire color information can be provided than other color spaces; 3) reddish colors are usually the dominant colors displaying in forest fire flames, whilst the reddish colors information can be well preserved and dominantly presented in "a" channel of Lab color model. Additionally, reddish fire flame possesses good discriminative effect in "a" channel of Lab color model through extensive fire images tests (as shown in Fig. 4); 4) it can effectively distinguish luminance from chrominance information using channel "a" such that it can reduce the influences from light. This is of significance to improve the fire segmentation results and enhance the algorithms' adaptability to environmental illumination; 5) it can dramatically reduce the computation burden of subsequent image processing when only information in channel "a" is processed.

Lab color model conversion: Because most visible range cameras have sensors detecting video in RGB format, there is a necessity of converting RGB model to Lab color model, which is described as follows:

$$\begin{aligned} L &= 116(0.299R + 0.587G + 0.114B)^{1/3} - 16 \\ a &= 500[1.006(0.607R + 0.174G + 0.201B)^{1/3} \\ &\quad - (0.299R + 0.587G + 0.114B)^{1/3}] \\ b &= 200[(0.299R + 0.587G + 0.114B)^{1/3} \\ &\quad - 0.846(0.066G + 1.117B)^{1/3}] \end{aligned} \tag{1}$$

where R, G, and B denote the values of red, green, and blue, respectively.

C. Fire Segmentation

Segmentation is an important step for fire detection. Its main objective is to differentiate fire pixels from background pixels. Thresholding is a frequently adopted technique to segment the fire regions in images, while Otsu method is one of the widely adopted thresholding approach for image segmentation.

Otsu method is a classic non-parametric and unsupervised adaptive threshold method. Whilst its principle is to automatically search out the appropriate image threshold. With image histogram information, Otsu image segmentation threshold can be dynamically determined by maximum variance between target and background. Based on the above-mentioned advantages, Otsu image segmentation method is employed in this paper to segment the fire from the captured images.

D. Morphological Operations

Although noise reduction, color model conversion, and fire segmentation have been applied, there still exist some small irrelative objects, which may affect the ultimate fire confirmation. In this paper, the solution to this is to employ the mathematic morphological operations to remove the small objects which are not target objects in the thresholding images.

Mathematic morphological operations contain a series of operators such as dilation, erosion, opening, and closing, which is capable of effectively removing small irrelative objects in the thresholding images. This paper applies dilation after erosion, since erosion can get rid of pixels on the object boundaries while dilation can add pixels.

The erosion operation E and dilation operation D between image set I and morphological element C can be separately illustrated as follows:

$$E = I \otimes C = \{(i,j) \mid C_{ij} \subseteq I\} \tag{2}$$

$$D = I \oplus C = \{(i,j) \mid [(\hat{C})_{(i,j)} \cap I] \neq \phi\} \tag{3}$$

where symbol "$\otimes$" denotes the erosion operation and symbol "$\oplus$" denotes dilation operation. (i, j) denote the coordinates of pixel in image I.

E. Fire Tracking

In this paper, blob counter approach is used for objects tracking due to the simplicity and effectiveness in application and great possibility for performance optimization. Blob counter is defined as a technique that tracks the number and direction of blobs traversing a certain passage or entrance per unit time. Its general working principle can be described as: 1) after segmentation and morphological operations, images are normally converted to binary images; 2) the connected component labeling algorithm [22] is then applied to identify the objects based on pixel connectivity. A specific area of interest is created for each object which is labelled with a different color and assigned with a set of coordinates; 3) after that, the tracked objects can be grabbed from the image, and their number, position, and dimension (height, width and shape) information can be obtained as well; 4) finally, the fire zone can be effectively tracked and located in the images [23]. It is worth noting that the fire tracking programme is implemented by adopting the blob counter class in Aforge (an open source image processing library) [24].

TABLE 1 SPECIFICATION OF USED CAMERA

Image device: 1/3-inch Sony super HAD color CCD	**Pixel:** 752 x 582 (NTSC)
Auto backlight compensation: On/OFF switchable	**Lens:** 3.6-6mm
Synchronization: Internal synchronization	**Input voltage:** DC12V
Horizontal resolution: 520TV lines	**Electric current:** 80mA±5mA
Minimum illumination: 0.1Lux/F1.2	**Electronic shutter:** Auto
S/N ratio: Greater than 48dB (AGC OFF/B/W OFF)	**PAL:** 1/50 to 1/100,000 seconds
White balance: Auto tracking white balance	**Power supply:** 12V/150mA

IV. EXPERIMENT AND TESTING RESULTS

In this section, two scenarios are employed for experimental validation:

(1) In Scenario 1, several sets of real aerial forest fire images are downloaded from website (as shown in Fig. 5) for verifying the effectiveness of the proposed detection method.

(2) In Scenario 2, an indoor test with real-time fire images collected by integrated UAV tools is carried out since forest fire perception in real-time deems crucial for early detection of fire. The main objective of this test is to verify the effectiveness of the proposed algorithms in both automatic fire detection and tracking. Fig. 3 presents an overview of the

whole system. A fire simulator is used to create simulated fire which is treated as the target object for detecting and tracking. A quadrotor helicopter UAV named Qball-X4 is used in the experiment. A camera is mounted at the bottom of this UAV in order to collect images from the ground. The camera's specification is listed in Table 1. In addition, a 5.8GHz 200mW transmitter and a 5.8G AV receiver are employed as the FPV wireless system, which is used for transmitting real time video images to the PC for image display and processing.

In these two scenarios, a PC (with Windows 7 Operating System; Intel Core i5 Processor; 4 GB Memory; 500 GB Hard Drive) is mainly used for image display and processing.

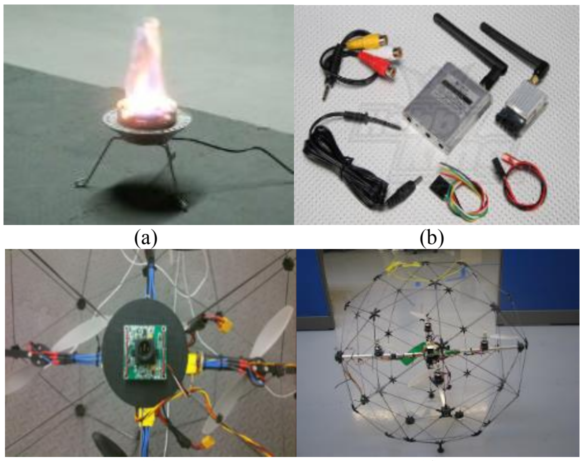

Fig. 3 Indoor test system: (a) fire simulator, (b) FPV wireless system, (c) installed camera, and (d) Qball-X4 UAV.

A. Scenario 1

Fig. 4 contains the sample images of forest fire in each channel of Lab, RGB and HIS models, it can be visually observed that fire region in channel "a" of Lab color model is most discriminative in the background.

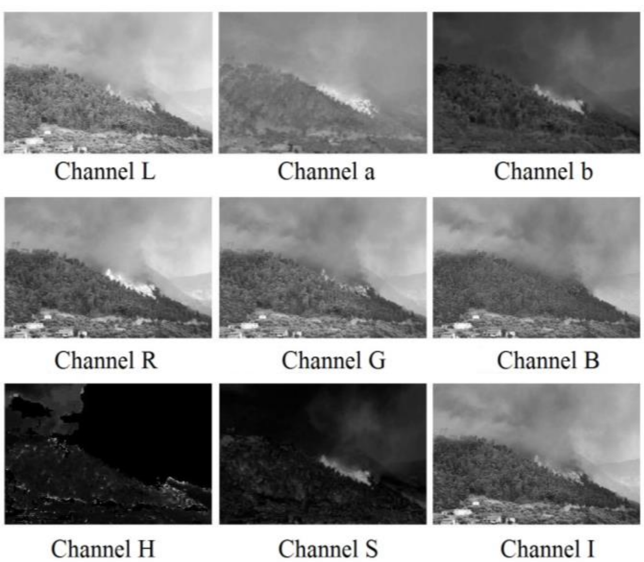

Fig. 4 (a) Sample images of different color channels.

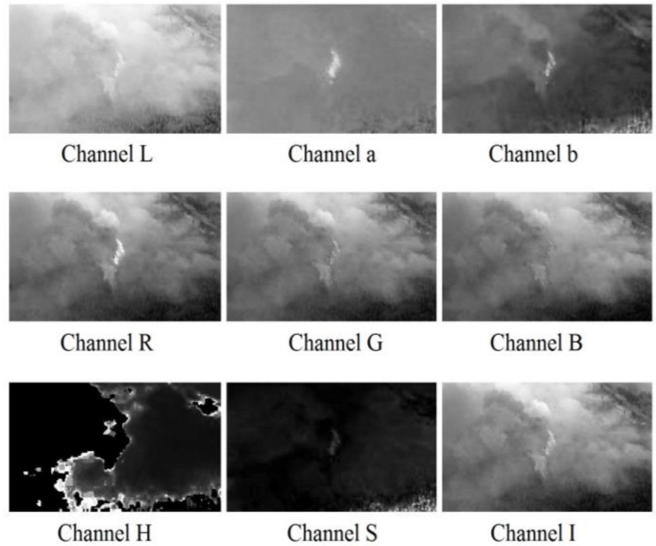

Fig. 4 (b) Sample images of different color channels.

In addition, through comparing and analyzing fire segmentation results of using these common color models, it is also found that segmentation with "a" channel of Lab color model has the most satisfactory fire segmentation results. Fig. 5 shows the Otsu segmentation results with channel "a" and Fig. 6 shows the results after morphological operations. All the results indicate that the proposed method performs well on forest fire pixels extraction.

B. Scenario 2

As displayed in Fig. 7, the proposed strategy can successfully achieve the goals of fire detection and tracking based on the real-time images collected by UAV.

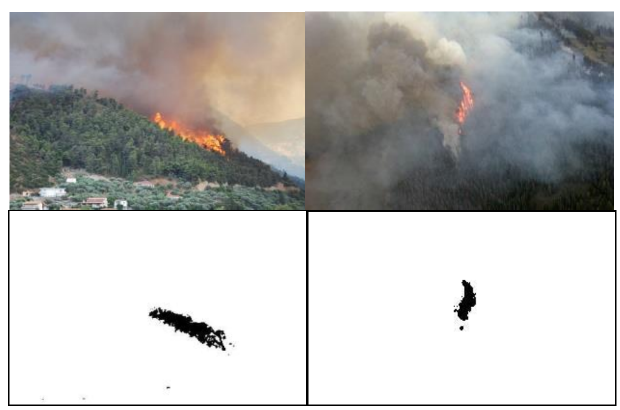

Fig. 5 Original images (top) and results of Otsu segementation (bottom).

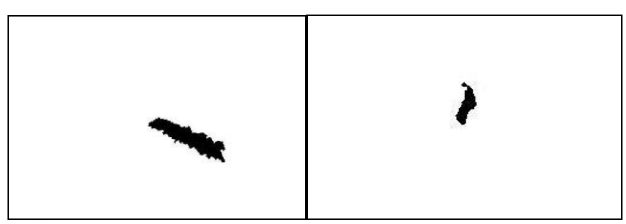

Fig. 6 Results of morphological operated images.

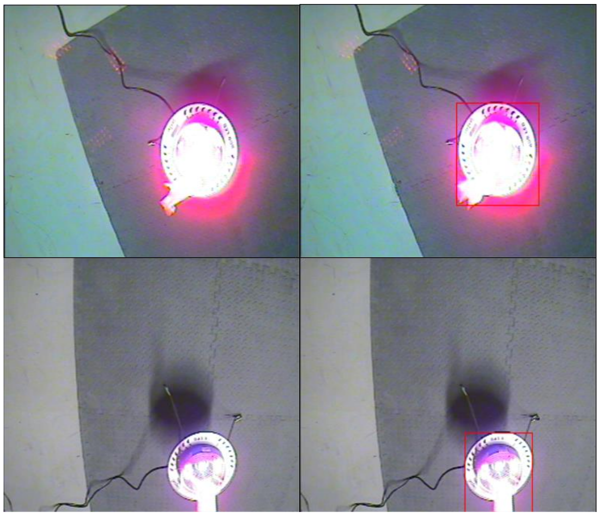

Fig. 7 Results of applying the detection and tracking strategy on a fire simulator: original images (left) and tracking results (right).

V. CONCLUSION

This paper proposes an approach for forest fire detection and tracking. Median filtering, color space conversion, Otsu threshold segmentation, morphological operations, and blob counter are applied to detect and track the potential fire in sequence. Several groups of preliminary experiments are carried out for detecting and tracking fire using a UAV in indoor lab environment. The experimental testing results demonstrate that superior performance can be achieved by using "a" channel of Lab color model in detecting forest fire in images. It is found that segmentation in "a" channel of Lab color model can provide the most satisfactory fire segmentation performance comparing with other color models. Future works can be extended to develop more robust image processing algorithms and translate the target fire image coordinates to the real position of the target which is used for fire localization.

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