Vision-based Fire Detection for Forest Firefighting Using Unmanned Aerial Vehicles

—Doctoral Thesis Research Proposal

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Abstract

Due to their rapid maneuverability, extended operational range, and improved personnel safety, Unmanned Aerial Vehicles (UAVs) with vision-based systems have great potential for monitoring, detecting and fighting forest fires. Over the last decade, UAV-based forest firefighting technology has shown increasing promise. In this proposal report, a systematic overview of the development and system architecture of forest fire monitoring, detection and fighting UAV systems is first provided, associated with existing challenges and potential solutions in the application of UAVs to forest firefighting. Next, technologies related to UAV forest fire monitoring and detection are presented. Thirdly, the detailed forest fire monitoring and detection strategies and research for this PhD thesis work are outlined. Finally, the future PhD thesis work are given, and their corresponding expected solutions are also generally addressed.

Keywords: Forest fire; Firefighting; Image processing; Unmanned Aerial Vehicles (UAVs).

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1 Introduction

Forests play a number of important roles in nature. They can purify water, stabilize the soil, cycle nutrients, moderate climate, and store carbon. They also provide habitats for wildlife and nurture environments rich in biological diversity. Economically, forests sustain the forest products industry that supports hundreds of thousands of jobs and contributes billions of dollars to a country's economic wealth. Unfortunately, every year millions of hectares of forest are destroyed by forest fires and hundreds of millions of dollars are spent to extinguish these fires [1]. Although wildfires do help to form new forests, it is difficult to make sure uncontrolled fires do not spread into places which may threaten sensitive ecological systems or human infrastructure and lives. Forest fires have become a serious natural danger [2]. Fighting forest fires is therefore considered as one of the most important roles in the protection and preservation of natural resources [2].

Early detection and suppression of forest fires are crucial to minimize the destruction that the fires may cause due to their rapid convection propagation and long combustion cycle [3]. Massive efforts have been put into monitoring, detection, and rapid extinguishment of forest fires before they become too large. Traditional forest fire monitoring and detection methods employ either mechanical devices or humans to monitor the surroundings, but these methods can be both dangerous and costly in terms of the required human resources [4].

Remote sensing technique has become one of the most frequently utilized tools for effective forest survey and management [5]. Current remote sensing approaches to forest fire monitoring and detection can be grouped into three categories: ground-based systems, manned aerial vehicle-based systems, and satellite-based systems. However, each of these systems presents different technological and practical problems. Ground measurement equipment may suffer from limited surveillance ranges. Satellite systems are less flexible in their path planning and technology updates, while their temporal and spatial resolution may be too low for detailed data capture and operational forest fire fighting [6]. Manned aerial vehicles are typically large and expensive. Moreover, the life of the pilot can be potentially threatened by hazardous environments and operator fatigue [7].

Unmanned Aerial Vehicles (UAVs) with remote sensing systems are an increasingly realistic option, providing rapid, mobile, and low-cost alternatives for forest fire monitoring, detection, and even fighting. The integration of UAVs with remote sensing techniques are also able to meet the critical spatial, spectral, temporal resolution requirements [8,9], offering the potential to serve as a powerful supplement to existing methods [6, 10]. In addition, UAVs allow the execution of long-time, monotonous and repeated tasks beyond human capabilities. This has led to increased worldwide attention to UAV forest fire applications in recent years [11–14, 16].

Traditional point-sensors detect heat or smoke particles and are quite successful for indoor fire detection. However, they cannot be applied in large open spaces, such as in forests. Rapid advances in electronics, computer science and digital camera technologies have allowed computer-vision-based remote sensing systems to provide a promising substitute for conventional forest fire monitoring and detection systems [4]. As vision-based detection technique has advantages of supplying intuitive and highly real-time information, large detection range, as well as convenience for recording, it has become a key component in the UAVs based forest fire detection system [17]. A series of researches have focused on vision-based forest fire detection with different image processing methods. Most of the researches detect fire by videos, then researchers gradually use visual 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 [50]. Since color is the most dominant visual features 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 spaces to obtain fire regions in the images [19, 20]. Variety of vision-based methods primarily depends on image/video processing algorithms. In order to achieve the goals of automatic forest firefighting using UAVs, this research aims to design and develop novel vision-based forest fire detection schemes that is capable of effectively detecting and alarming forest fires with application to UAV-based forest firefighting systems.

The remainder of this PhD thesis proposal is organized as follows: The background, motivation and pertinent literature review of forest firefighting are briefly presented in Section 2. The thesis scope and objectives are discussed in Section 3. Section 4 is devoted to the research methodologies. The timeline for appropriate completion of the proposed thesis is drawn in Section 5. Finally, anticipated significance of the work is presented in Section 6.

2 Background, Motivation, and Review of Forest Firefighting Using UAVs

2.1 Background: General System Design Architecture and Requirements

Based on the review of the existing literature and research, the basic elements of a general UAV-based forest fire surveillance and fighting system can be illustrated in Fig. 1, which covers the functions of monitoring (finding a potential fire), detection (triggering an alarm to inform firefighting operators or initialize further diagnosis and prognosis), diagnosis (determining the fire's location, extent, and tracking its evolution), and prognosis (predicting the future evolution of the fire based on real-time wind and firefighting conditions). These functions are conducted using either a single UAV or a team of UAVs (with different kinds of sensors) along with a central ground station. The objectives are to use UAVs to track fires, predict their evolution and provide real-time information to human firefighters and/or to execute firefighting with UAVs.

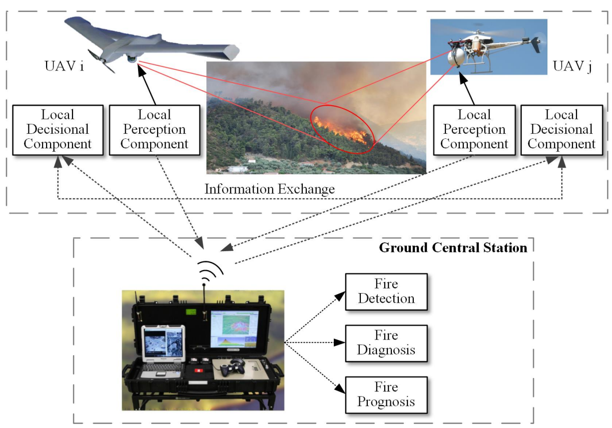

Figure 1: Illustration of UAVs-based forest fire monitoring, detection, and fighting system.

Terminologies for forest fire monitoring and detection are not yet clearly defined and with even different definitions within the literature. To avoid confusion, definitions for forest fire monitoring, detection, diagnosis, and prognosis are provided here by following established traditions in the more general field of condition monitoring, fault detection and diagnosis [32]. Forest fire monitoring is defined as monitoring for the possible occurrence of fire before it has occurred, while fire detection is the detection of an actual fire in progress. Because smaller fires are easier to control and extinguish, detection must be done as fast and as early as possible. Fire diagnosis aims to find detailed information about the fire, such as its location and extent. Fire prognosis aims to track and predict the evolution of a fire in real time using information provided by the onboard remote monitoring sensors installed on UAVs.

In order to achieve these goals, UAV-based forest fire monitoring, detection, diagnosis, and prognosis system typically includes the following: 1) various frames and sensors, including Global Positioning System (GPS) receivers, Inertial Measurement Units (IMUs), and cameras, all of which aid in firefighting; 2) specific algorithms/strategies for fire monitoring, detection, diagnosis, and prognosis; 3)autonomous guidance, navigation and control (GNC) systems for both single and multiple UAVs; 4) cooperative localization, deployment, and control systems for UAV fleets in order to optimally cover fire areas. Such systems are based on the real-time information provided by the onboard visual (for day-time) and infrared (for both night-time and day-time) monitoring sensors and their associated image/signal processing algorithms; 5) a dedicated ground station which includes equipment for communication, ground computation, visualization of fire detection, tracking and prediction with automatic fire warning/alarm, and necessary equipment for the safe and efficient operation of UAVs.

UAV forest firefighting missions can generally be broken down into one of three stages: fire search, fire confirmation, and fire observation [33]. In the fire search stage, the ground control station divides the mission for each UAV according to the characteristics of terrain, and the capabilities of individual UAVs including their onboard sensors. Following this, either a single UAV or a fleet of homogeneous/heterogeneous (fixed-wing and rotary-wing) search UAVs [16, 34] are deployed to patrol the surveillance region along respective pre-planned paths. Meanwhile, fire segmentation methods are applied on each UAV to automatically identify fire by employing the fire detection sensors including visual and infrared cameras. The fire confirmation stage begins after a fire is detected. The ground control station commands the search UAV(s) to hover at a safe distance, while other UAVs are also sent to the detected fire location to make confirmation if needed. The fire observation stage starts if the fire is confirmed to be real; otherwise the fire search stage is resumed. In the fire observation stage, UAVs are commanded to continuously obtain information about the fire. This requires multiple synchronous images be obtained by the UAVs from different points of view. These are then delivered to ground operators/firefighting managers or service UAVs to better guide firefighting efforts.

2.2 Motivation

Recent decades have seen tremendous progress in the field of automatic firefighting technologies [11, 12]. Despite this, few research papers until now have considered the application of UAVs in this field. Most research has been carried out in the United States and Europe. Table 1 provides a brief overview of existing UAV-based forest firefighting systems.

Table 1: Characteristics of reviewed UAVs forest fire monitoring, detection and fighting systems

Test Types	**References**	**UAV Class**	**Onboard Cameras (Resolution)**	**Engine Power**	**Payload Capacity**
Near operational	[21]	1 fixed-wing	1 thermal (720×640)	Fuel	$340kg$
Operational	[22]	1 fixed-wing	4 mid-IR (720×640)	Fuel	$> 1088kg$
Near operational	[23]	2 rotary-wing; 1 airship	1 visual (320×240); 1 IR (160×120)	Fuel; Electric	$3.5kg$
Operational	[24]	1 fixed-wing; 1 rotary-wing	1 visual; 1 IR	Fuel	—
Near operational	[25]	1 fixed-wing	1 visual 1 IR	Fuel	$< 34kg$
Near Operational	[11]	2 fixed-wing	1 visual; 1 IR; 1 visual (1920×1080)	Fuel	$25kg$; $250kg$
Near operational	[26]	2 fixed-wing	1 thermal (160×120); 1 NIR (752×582); 1 VNIR (128×128)	Electric	$< 2.6kg$
Near Operational	[27, 28]	1 fixed-wing	1 visual (720×480)	Gas	$0.68kg$
Near operational	[29]	1 rotary-wing	2 visual (4000×2656; 2048×1536); 1 thermal (320×240)	Fuel	$907kg$
Near Operational	[30]	1 fixed-wing	1 visual	Electric	—
Near operational	[31]	1 fixed-wing	1 visual (656×492)	Electric	$5.5kg$

Note: (-) Not mentioned; IR: Infrared; NIR: Near IR; VNIR: Visible-NIR.

Although the existing research demonstrates the possibility of using UAVs to detect and even extinguish forest fires, development of such systems, including related hardware, software and application strategies, is still minimal. Further investigation is needed on all aspects of their use, including suitable system platforms, remote sensing payloads/sensors, and algorithms for GNC, as well as using UAVs in combination with other remote sensing techniques. It is this urgent need that motivates further research and development in this important field. In addition, UAV-based forest fire detection remains difficult, given the chance of smoke blocking the images of the fire, or the chance for analogues of flame characteristics, such as sunlight, vegetation, and animals, or the vibration and motion of cameras mounted on UAVs to cause either false alarms or alarm failure. How to reduce false alarm rates, increase high detection probability, and enhanced adaptive capabilities in various environmental conditions to improve the reliability and robustness of forest fire detection also worth further investigation.

2.3 Brief Review on Applications of Vision-based Forest Firefighting

The advantages of vision-based techniques, including the capture of intuitive, informative, and reliable, real-time data, a large detection range, and convenient verification and recording abilities, have made them a major research topic in the field of forest fire monitoring and detection [17]. As shown in Table 2, the past decade has seen a series of research studies conducted using vision-based UAV systems for forest fire monitoring and detection in near-operational field tests, though actual firefighting tests remain scarce.

Table 2: UAVs-based forest fire monitoring, detection and fighting in near-operational field

Detection Method	Spectral Bands	Resolution	Used Features	FD	SD	GL	PP	IS	References
Georeferenced uncertainty mosaic	IR	320×240	Color	√	×	√	√	√	[35]
Statistical data fusion	Visual Mid-IR	752×582 256×256	Color	√	×	√	√	√	[36]
Training method	IR	160×120	Color	√	×	×	×	√	[37]
Training method	Visual Far-IR	320×240 —	Color	√	×	√	×	√	[38, 39]
Training method	Visual Far-IR	320×240 —	Color	√	×	√	√	√	[15, 33]
—	Visual IR	720×640 —	Color	√	×	√	×	—	[21, 40]
Genetic algorithm	IR	320×240	Color	√	×	×	×	×	[41]
Training method	Visual IR	752×582 160×120	Color	√	×	√	×	—	[23, 42]
Training method	Visual IR	— —	Color	√	×	√	×	—	[43, 44]

Note: (√) considered; (×) not considered; (FD) Flame Detection; (SD) Smoke Detection; (GL) Geolocation; (PP) Propagation Prediction; (IS) Image Stabilization.

In addition, there are a number of other studies of other platforms and offline videos used to monitor and detect fires, as illustrated in Tables 3 and 4. Although these methodologies were not originally intended for UAV application, and do not consider problems associated with UAVs, such as image vibrations induced by their flight and cooperative control of multiple UAVs, they nevertheless offer some potentially transferable insights into UAV-based forest firefighting applications due to their common issues in fire detection with utilized vision-based technologies. In order to reduce the cost of devices and personnel and save experimental time, the effectiveness of various fire detection approaches are normally tested and verified based on forest fire videos in advance.

Over the last decade, image processing techniques have become widely used for forest fire detection. Based on the spectral range of the camera used, vision-based fire detection technologies can generally be classified into either visual fire detection or infrared fire detection systems [71], while fire detection can be divided into either flame detection or smoke detection in terms of the actual object being detected [17]. Most importantly, the color, motion, and geometry of the fire constitute the three dominant characteristic features of fire detection [62].

Table 3: Offline video fire monitoring and detection methodologies using visual cameras

Detection Method	Resolution	Color	Motion	Geometry	FD	SD	References
Statistic method	320 × 240 400 × 255	√	×	×	√	×	[49]
Fuzzy logic	256 × 256	√	×	×	√	×	[50]
Support vector machine	—	√	√	√	√	×	[51]
Fuzzy logic	320 × 240	√	√	√	×	√	[52]
Wavelet analysis	320 × 240	√	√	√	√	×	[53]
Computer-vision	320 × 240	√	√	×	√	×	[54]
Wavelet analysis	320 × 240	√	√	×	√	×	[55]
Rule-based video processing	—	√	√	×	√	√	[56]
Fourier transform	—	√	√	×	√	×	[57]
Bayes and fuzzy C-Means	—	√	√	×	√	×	[58]
Adaptable updating target extraction	—	√	√	×	√	×	[59]
Histogram based method	—	√	√	×	√	×	[60]
Fuzzy-neural network	—	√	√	×	√	×	[61]
Statistical method	176 × 144	√	×	×	√	×	[62]
Fuzzy Finite Automata	—	√	√	×	√	×	[63]
Gaussian mixture model	320 × 240	√	√	×	√	×	[64]
Histogram back projection	—	√	×	×	√	×	[65]
Wavelet analysis	—	√	√	×	×	√	[66]
Adaptive decision fusion	—	√	√	×	×	√	[67]
Accumulative motion model	—	×	√	×	×	√	[68]
Image processing method	—	√	√	×	×	√	[69]
Neural network	320 × 240	√	√	×	×	√	[70]

Note: (√) considered; (×) not considered; (—) not mentioned; (FD) Flame Detection; (SD) Smoke Detection.

3 Scope and Objectives

This research aims to design and develop novel fire detection schemes with application to UAV-based forest firefighting at both flame detection and smoke detection levels. In particular, the proposed research plan is organized around the following research objectives:

1. Design and develop fire flame detection techniques with both visual and infrared images.

2. Design and develop fire smoke detection techniques with both visual and infrared images.

3. Design and develop information fusion (including visual and IR images) schemes/strategies to improve the reliability and robustness of fire (flame and smoke) detection.

4. Design and develop decision fusion (including flame and smoke) schemes/strategies to further improve the reliability and robustness of fire detection.

To sum up, the proposed research (as shown in Fig. 2) is primarily expected to synthesize advanced levels of fire monitoring and detection capabilities/techniques in UAV-based forest firefighting system which in turn can guarantee the reliable and satisfactory performance of forest fire detection at both smoke and flame levels. The schemes and strategies expected from this research proposal will be verified by a series of aerial images/videos in the presence of forest fire scenarios.

4 Research Methodologies

This section presents the research methodologies for the proposed research. The presented algorithms /schemes in this section are generic and can be applied to forest fire detection at both flame detection and smoke detection levels (see Fig. 3). The proposed algorithm uses both color and motion features, and the combination of the two features will greatly enhance the forest fire detection reliability. Color

Table 4: Fire monitoring and detection methodologies using visual and infrared cameras

Detection Method	Spectral Bands	Resolution	OV	IV	OLV	CF	MF	GF	FD	SD	PP	GL	References
Training method	Visual Mid-IR	752 × 582 256 × 256	×	√	×	√	×	×	√	×	√	√	[42]
Training method	Visual Mid-IR	— —	√	×	×	√	×	×	√	×	√	√	[1]
Images matching	Visual IR	— —	√	×	×	√	√	√	×	√	×	√	[45,46]
Data fusion	Visual IR	— —	×	√	×	√	—	—	√	√	×	×	[14]
Neural networks	IR	—	×	√	×	√	√	√	×	×	×	×	[47]
Dynamic Data-Driven	Multi-spectral IR	—	×	×	√	√	×	√	√	×	√	×	[48]
Training method	Visual IR	— —	√	×	×	√	×	√	√	×	√	√	[1]

Note: (√) considered; (×) not considered; (—) not mentioned; (OV) Outdoor validation; (IV) Indoor validation; (OLV) Offline validation; (CF) Color feature; (MF) Motion feature; (GF) Geometry feature; (FD) Flame Detection; (SD) Smoke Detection; (GL) Geolocation; (PP) Propagation Prediction; (IS) Image Stabilization.

features are extracted using color-based decision rules and motion features are extracted with optical flow which is an important technique in motion analysis for machine vision. In the following, the fire detection methodologies with application to UAV-based forest fire detection are presented and discussed.

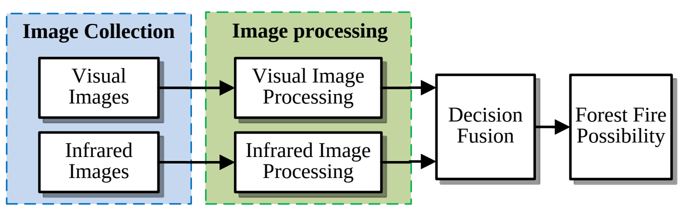

Figure 2: Schematic diagram of overall vision-based forest fire detection system.

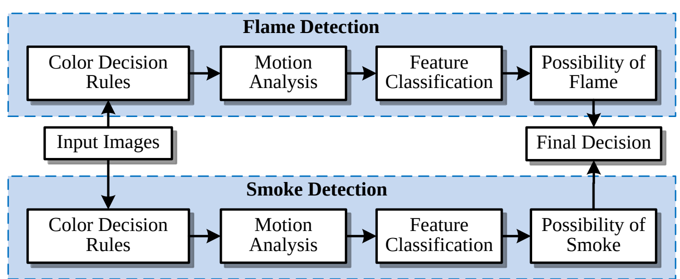

Figure 3: Schematic diagram of visual-based forest fire detection scheme.

4.1 Color-based Decision Rules

Color detection is one of the first detection techniques used in vision-based fire detection and is still popular by far in almost all detection methods [71]. The majority of the color-based approaches in fire detection make use of RGB (Red, Green and Blue) color model, sometimes in combination with HSI (Hue, Saturation, Intensity) model [54,56,64,67]. It is obvious that color cannot be used by itself to detect fire because of the variability in color, density, lighting, and background. However, the color information can be used as a part of a more sophisticated system. In this proposal, the color-based decision rules are used to determine candidate fire (flame and smoke) regions.

4.1.1 Flame Color-based Decision Rules

In the point of general fires [72], the flames usually display reddish colors and the color shows range from red to yellow [56]. It is reported that RGB values of flame pixels are in red-yellow color range indicated by the rule ($R > G > B$). The conditions in HSI color model are as follows:

$$\begin{cases} \text{Condition 1:} & 0^o \leq H \leq 60^o; \\ \text{Condition 2:} & \text{Brighter environment: } 30 \leq S \leq 100, \\ & \text{Darker environment: } 20 \leq S \leq 100; \\ \text{Condition 3:} & 127 \leq I \leq 255. \end{cases} \tag{1}$$

where H, S, and I are the hue, saturation and intensity values of a specific pixel, respectively.

4.1.2 Smoke Color-based Decision Rules

Smokes are always generated with a burning fire and have various quantities and colors because of burning different combustible fuels. For forest fire smoke, they usually display some greyish colors, which can be classified into two gray level regions: light-gray and dark-gray. This implies that three components R, G and B of the smoke are very close to each other [71]. Therefore, these grayish colors can be described with I (intensity) component of HSI color model. The intensity of light-gray region and dark-gray region ranges from L_1 to L_2, and D_1 to D_2, gray levels, respectively. Thus, the condition $R \pm r = G \pm g = B \pm b$ and $L_1 \leq I \leq L_2$ and $D_1 \leq I \leq D_2$ where $0 \leq r,\ g,\ b \leq a$, can be used as one decision function of smoke recognition, when considering chromatic analyses. In the above condition, those values of a, L_1, L_2, D_1 and D_2 depend on statistical data of experiments [56].

4.2 Motion-based Detection Methods

Fire motion analysis is needed for achieving more accurate systems. Flame and smoke are moving objects with the changeable shapes due to the fact that airflow caused by wind will make fire oscillate or move suddenly [56]. This dynamic feature of fire make moving object detection widely used in vision-based fire detection to eliminate the disturbance of stationary non-fire objects. Some of the early research simply classified fire-colored moving objects as fire but this approach leads to many false alarms, because falling leaves in autumn or fire-colored ordinary objects, etc., may all be incorrectly classified as fire. To determine if the motion is caused by fire or an ordinary moving object, further analysis of moving regions in video is necessary. Well-known and effective algorithms are background subtraction methods, temporal differencing, and optical flow analysis [71].

These methods make use of either temporal or spatial information. Background subtraction is popularly used in the situation that camera is stationary and the background is relatively static. Temporal differencing is highly adaptive to dynamic environments, but generally does a poor job of extracting the complete shapes of certain types of moving objects [74]. Therefore, optical flow analysis is adopted in this proposal since it can achieve success of motion detection in the presence of camera motion or background changing i.e., it can detect the motion accurately even without knowing the background [74]. It is very suitable for UAV-based forest fire detection since the camera has motion and the background is changing in this situation.

4.2.1 Classical Optical Flow

Optical flow is an approximation of the local image motion and specifies how much each image pixel moves between adjacent images, which is the process of establishing a common geometric frame of reference from two or more data sets from the same or different imaging modalities taken at different times. Optical flow, on the other hand, transforms the image sequence into estimated motion fields, allowing for a more insightful extraction of features.

The main optical flow constraint equation (the brightness constancy assumption) can be represented as follows:

$$\frac{d}{dt}I = \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \frac{\partial I}{\partial t} = I_x u + I_y v + I_t = 0 \tag{2}$$

where $I(x, y, t) = I(x + u\delta t, y + v\delta t, t + \delta t)$ is a sequence of intensity images with spatial coordinates $(x, y) \in \Omega$ and time variable $t \in [0, T]$. The flow vector $(u, v) = (x_t, y_t)$ points into the moving direction of the pixel (x, y).

Point-wise method is adopted here applying conditions per pixel instead of constant neighborhoods. This method is to minimize the following function:

$$\int_{\Omega}\int_{0}^{T} r_{data}(I, u, v) + \alpha r_{reg}(u, v) dtdxdy \tag{3}$$

where the data term r_{data} is the error from the optical flow constraint Eq. (2) and the regularization term r_{reg} quantifies the smoothness of the flow field. The constant α controls regularization. Moreover, the data and regularization terms are selected as:

$$\int_{\Omega}\int_{0}^{T} (I_x u + I_y v + I_t)^2 + \alpha(||\nabla u||_2^2 + ||\nabla v||_2^2) dtdxdy \tag{4}$$

4.2.2 Motion Detection of Flame

1. *Optimal Mass Transport (OMT) Optical Flow*:

   Classical optical flow models are inadequate to model the appearance of fire due to their dependence on brightness constancy ($\frac{d}{dt}I = 0$). This is caused by two reasons:

   - Due to fast pressure and heat dynamics, rapid change of intensity occurs in the burning process, fire thereby does not satisfy the intensity constancy assumption of Eq. (2).
   - Turbulent such as non-smooth and motion field may be caused since smoothness regularization is counter-productive to the estimation of fire motion.

   Considering the above-mentioned reasons, the Optimal Mass Transport (OMT) optical flow can be a suitable choice [75]. In OMT, the optical flow problem is treated as a generalized mass (which denotes image intensity I) transport problem, where a mass conservation is enforced by the data term. The conservation law can be formulated as:

$$I_t + \nabla \cdot (\vec{\mathbf{u}} I) = 0 \tag{5}$$

   where $\vec{\mathbf{u}} = (u, v)^T$. Therefore, the intensity I is replaced by mass density.

   Similar to standard optical flow, the OMT optical flow model minimizes the total energy according to:

$$\min_{\vec{\mathbf{u}}} \frac{1}{2}\int_{\Omega}\int_{0}^{T} (I_t + \nabla \cdot (I\vec{\mathbf{u}}))^2 + \alpha||\vec{\mathbf{u}}||_2^2 I dtdxdy \tag{6}$$

   subject to the boundary conditions $I(x, y, 0) = I_0(x, y)$ and $I(x, y, 1) = I_1(x, y)$, where I_0 and I_1 are given gray-scale images. The transport energy $||\vec{\mathbf{u}}||_2^2 I$, which is the consumption required to move mass from one location at $t = 0$ to another at $t = 1$, represents the regularization term in Eq. (6). The solution to this minimization problem can be obtained through discretizing Eq. (6):

$$\min_{\vec{\mathbf{u}}} \frac{\alpha}{2}(\vec{\mathbf{u}}^T \hat{I} \vec{\mathbf{u}}) + \frac{1}{2}(I_t + [D_x I D_y I]\vec{\mathbf{u}})^T (I_t + [D_x I D_y I]\vec{\mathbf{u}}) \tag{7}$$

where $\vec{\mathbf{u}}$ is a column vector containing u and v, and $\hat{I}$ is a matrix containing the average intensity values $(I_0 + I_1)/2$ on its diagonal. The derivatives are discretized by $I_t = I_1 - I_0$ and the central-difference sparse-matrix derivative operators D_x and D_y.

$$\min_{\vec{\mathbf{u}}} \frac{\alpha}{2}(\vec{\mathbf{u}}^T \hat{I} \vec{\mathbf{u}}) + \frac{1}{2}(A\vec{\mathbf{u}} - b)^T (A\vec{\mathbf{u}} - b) \tag{8}$$

where $A = [D_x I \ D_y I]$ and $b = -I_t$.

The solution of Eq. (8) can then be obtained:

$$\vec{\mathbf{u}} = (\alpha \hat{I} + A^T A)^{-1}(A^T b) \tag{9}$$

In addition, the generalized mass of a pixel can be represented by its similarity to a center fire color in the HSI color space $(H, S, I^* \in [0, 1])$. The center fire color can be properly chosen as $H_c = 0.083$, $S_c = I_c = 1$, which denotes a fully color-saturated and bright orange. Then, the generalized mass can be achieved as:

$$I = f(\min\{|H_c - H|, 1 - |H_c - H|\}) \cdot S \cdot I^* \tag{10}$$

where f is the logistic function

$$f(x) = 1 - (1 + \exp(-a \cdot (x - b)))^{-1} \tag{11}$$

and $a = 100$, $b = 0.11$.

2. *Optical Flow Feature Extraction*:

   Since our concern is moving objects which are pixels in motion, thus these essential pixels $(\Omega_e \subset \Omega)$ can be defined as:

$$\Omega_e = \{(x, y) \in \Omega : ||\vec{\mathbf{u}}(x, y)||_2 > c \cdot \max_{\Omega} ||\vec{\mathbf{u}}||_2\} \tag{12}$$

   where $0 \le c < 1$ is selected such that sufficient number of pixels can be retained, $\Omega \subset \Re^2$ denotes an image region.

   In this report, two features $f_i : \vec{\mathbf{u}} \mapsto \Re, i = 1, 2$ defining the two dimensional feature vector $F = (f_1, f_2)^T$ are chosen to conduct feature extraction. To be specific, the magnitude feature f_1 measures mean magnitude, while the directional feature f_2 is to analyze motion directionality.

   Therefore, given the image region Ω and the OMT optical flow field in this region, the magnitude and directional features are selected according to the following procedures.

   (a) OMT Transport Energy:

$$f_1 = \underset{\Omega_e}{Mean}\left(\frac{I}{2}||\vec{\mathbf{u}}_{OMT}||_2^2\right) \tag{13}$$

   This feature is to measure the mean OMT transport energy per pixel in a subregion.

   (b) OMT Source Matching: For rigid motion, the flow field tends to be comprised of parallel vectors indicating rigid translation of mass. This feature is designed to quantify how well an ideal source flow template matches the computed OMT flow field, which is designed as:

$$\vec{\mathbf{u}}_T(x, y) = \begin{pmatrix} u_T(x, y) \\ v_T(x, y) \end{pmatrix} = \exp\left(-\sqrt{x^2 + y^2}\right) \begin{bmatrix} x \\ y \end{bmatrix} \tag{14}$$

   Then, the best match can be obtained by:

$$f_2 = \max_{\Omega} \left| (u_T * \frac{u_{OMT}}{||\vec{\mathbf{u}}_{OMT}||_2}) + (v_T * \frac{v_{OMT}}{||\vec{\mathbf{u}}_{OMT}||_2}) \right| \tag{15}$$

where $*$ denotes convolution.

4.2.3 Motion Detection of Smoke

Normally, smoke appears before flame. Fire detection in this case gives an earlier fire alarm. Additionally, smoke detection also provides enhanced fire alarm reliability. Comparing to flame, the extraction of smoke's visual features introduces more complicated and challenging issues since smoke is a random motion that abundantly changes in size and shape.

Based on the classical optical flow Eq. (2), an additional constraint is introduced for the optical flow estimation. Their solution assumes a locally constant flow that (u, v) is constant in a small neighborhood Ω. Within this neighborhood the following term is minimized:

$$\sum_{(x,y)\in\Omega} W^2(x)(I_x u + I_y v + I_t)^2 \tag{16}$$

Here, $W(x)$ is a weighting function that favors the center part of Ω. The solution to Eq. (16) is given by:

$$\mathbf{A}^T\mathbf{W}^2\mathbf{A}\mathbf{v} = \mathbf{A}^T\mathbf{W}^2\mathbf{b} \tag{17}$$

The motion feature extraction is then performed as follows:
Average of velocity:

$$a_n = \frac{1}{n}\sum_{i=1}^{n}\sqrt{d_{xi}^2 + d_{yi}^2} \tag{18}$$

Variation of velocity:

$$b_n = \frac{1}{n}\sum_{i=1}^{n-1}(\sqrt{d_{xi}^2 + d_{yi}^2} - a_n)^2 \tag{19}$$

Average of orientation:

$$c_n = \frac{1}{n}\sum_{i=1}^{n} e_i \tag{20}$$

Variation of orientation:

$$d_n = \frac{1}{n-1}\sum_{i=1}^{n}(e_i - c_n) \tag{21}$$

while

$$e_i = \begin{cases} \arctan(\frac{d_{yi}}{d_{xi}}), & \text{for } d_{xi} > 0, d_{yi} > 0 \\ \pi - \arctan(\frac{d_{yi}}{d_{xi}}), & \text{for } d_{xi} > 0, d_{yi} > 0 \\ \pi + \arctan(\frac{d_{yi}}{d_{xi}}), & \text{for } d_{xi} < 0, d_{yi} < 0 \\ 2\pi - \arctan(\frac{d_{yi}}{d_{xi}}), & \text{for } d_{xi} > 0, d_{yi} < 0 \end{cases} \tag{22}$$

5 Timeline

The following table outlines the progress and timeline for accomplishing the objectives of the PhD study.

6 Anticipated Significance of the Work and Future Work

6.1 Conclusion

The merits of this proposed research can be reflected by an anticipated significant contribution to the realization of a new concept and technology of UAV-based forest firefighting. The knowledge and experience

Table 5: Timelines for PhD study

Main Tasks	2012-2013			2013-2014			2014-2015			2015-2016		
	F	W	S	F	W	S	F	W	S	F	W	S
Coursework	>	>	>									
Literature Review	>	>	>	>								
Comprehensive Examination					>							
Flame Detection at Visual Level					>	>	>					
Smoke Detection at Visual Level						>	>	>				
Flame Detection at IR Level								>	>			
Smoke Detection at IR Level									>	>		
Experimental Setup and Validation									>	>		
Synthesis of Research Results and Analysis										>	>	
Publications					>	>	>	>	>	>	>	>
Thesis Writing											>	>

Note: **S**: summer; **F**: fall; **W**: winter semesters; IR: Infrared; $>$: available.

gained in this research not only can be used in forest fire detection for UAV-based firefighting, but also will be transferable towards other firefighting applicaiton such as fire suveilliance of oil fields, pipelines, electric lines and nuclear power plants, and public area which significantly contribute to infrastructure and public safety. Although the tasks and objectives of proposed research are targeted mainly for UAV-based forest fires detection, the developed technologies and techniques can be directly or straightforwardly adopted for other manned/unmanned mobile forest fire detection platform. To sum up, the proposed research project will create a vigorous collaborative environment, which in the long-term is expected to evolve into innovative projects enhancing natural resources and environmental sustainability and protection, safety and security of society, reduce the economic losses and save more lives due to fires.

The results of the research proposed here will be disseminated in the form of conference and journal publications, as well as technical reports. Some preliminary parts of the proposed research in particular UAV-based forest fire detection are completed and results are presented in several journal papers [76–78] and conference papers [79–86].

6.2 Future Work

1. Because vision-based detectors still suffer from a significant amount of missed detections and false alarms due to changing environmental conditions and the target characteristics, thus the combination of different fire features (flame and smoke) worth further investigation. Support Vector Machine (SVM) will be adopted to correctly classify the different extracted features, learn the class separation (classification) boundaries, and effectively determine the probability of forest fire.

2. To avoid the disadvantages of visual sensors and reduce false alarm rates, the use of infrared imaging sensors instead of only dealing with ever more complex visual fire detection algorithms, will be carried out in the future research.

3. In order to verify the practical effectiveness of the studied research, an experimental platform (see Fig. 4) is currently under development, and outdoor test will be conducted in the near future.

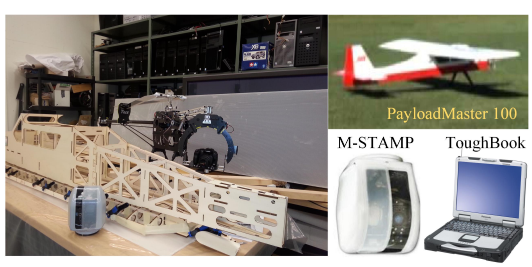

Figure 4: Experimental platform.

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7 Appendix: Progress to Date

With respect to the presented timeline (Table 5) in Section 5, this section provides a brief review of the progress to date of the PhD thesis work.

1. Due to their rapid maneuverability, extended operational range, and improved personnel safety, UAVs with vision-based systems have great potential for monitoring, detecting and fighting forest fires. Over the last decade, UAV-based forest firefighting technology has shown increasing promise.

   The above statement motivated this research proposal of UAV-based forest fire detection which is a key component of UAV-based forest fire fighting system. Based on identified literatures relevant to UAV-based firefighting systems, a survey paper [76] for the review to the state-of-the-art technologies and techniques in this area with a total of cited 121 references has been written and published in the *Canadian Journal of Forest Research*. The preliminary conference version of the paper has been presented as a conference paper [79]. This paper presents a systematic overview of current progress in this field. First, a brief review of the development and system architecture of forest fire monitoring, detection and fighting UAV systems is provided. Next, technologies related to UAV forest fire monitoring, detection, and fighting are briefly reviewed, including those associated with fire detection, diagnosis and prognosis, image vibration elimination, and cooperative control of UAVs. Finally, the existing challenges and potential solutions in the application of UAVs to forest firefighting are also outlined.

2. A set of forest fire detection and tracking algorithms (see Fig. 5) are developed including median filtering, color space conversion, threshold segmentation, morphological operations, and blob counter.

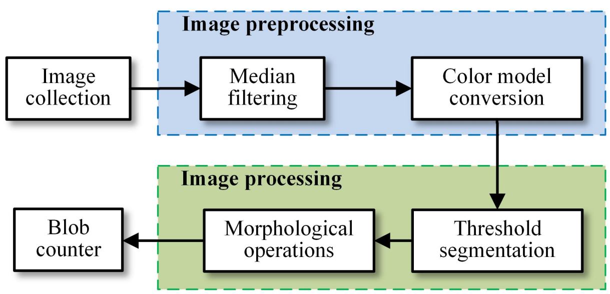


Figure 5: Flowchart of fire detection and tracking algorithms.

Table 6: Specification of used camera

Image device: 1/3-inch Sony super HAD color CCD	**Pixel**: 752×582 (NTSC)
Auto backlight compensation: On/OFF switchable	**Lens**: $3.6 - 6mm$
Synchronization: Internal synchronization	**Input voltage**: DC $12V$
Horizontal resolution: 520 TV Lines	**Electric current**: $80mA5mA$
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 seconds
White balance: Auto Tracking White Balance	**Power supply**: $12V/150mA$

   First, several sets of real aerial forest fire images are adopted for verifying the effectiveness of the proposed detection method. Next, 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. 6 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 6. In addition, a 5.8 GHz 200 mW transmitter and a 5.8 G receiver are employed as the wireless system, which is used for transmitting real time video images to the PC for image display and processing. This 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.

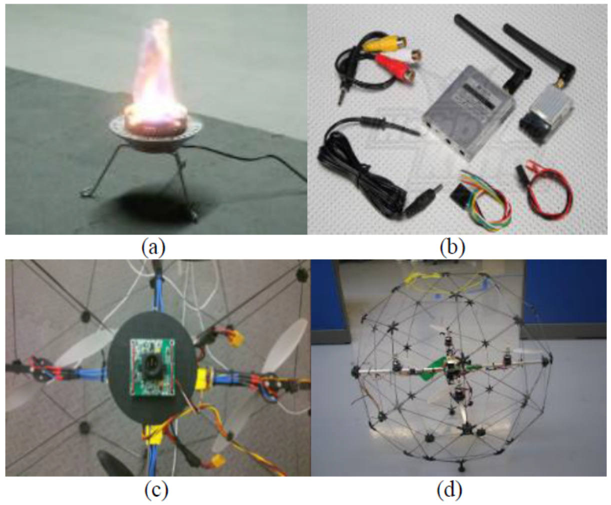


Figure 6: Indoor test system: (a) fire simulator, (b) wireless system, (c) installed camera, and (d) UAV.

The samples of experimental results are shown in Fig. 7, Fig. 8, and Fig. 9, which demonstrate that the proposed strategy can successfully achieve the goals of fire detection and tracking based on the real-time images collected by UAV. Future works are still deserved, which 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. The developed algorithm and testing results have been presented in a conference paper [80].

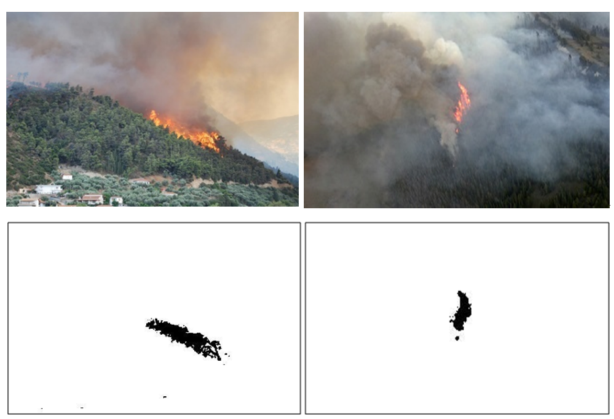


Figure 7: Original images (top) and results of segmentation (bottom).

3. A method of forest fire detection and tracking based on optical flow (see Fig. 9) are developed including color filtering, optical flow estimation, threshold segmentation, morphological operations, and blob counter.

   This approach can detect and track fires in aerial video sequence using optical flow estimation. The color filter help find the candidate region of fire-colored pixels. The optical flow estimation technique is adopted to estimate the motion vectors in each frame of the video sequence. Through

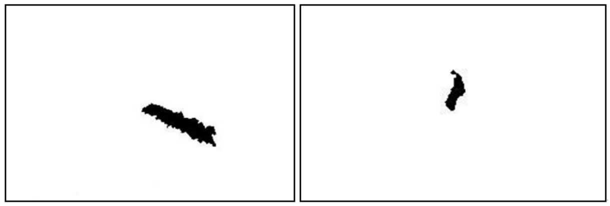


Figure 8: Results of morphological operated images.

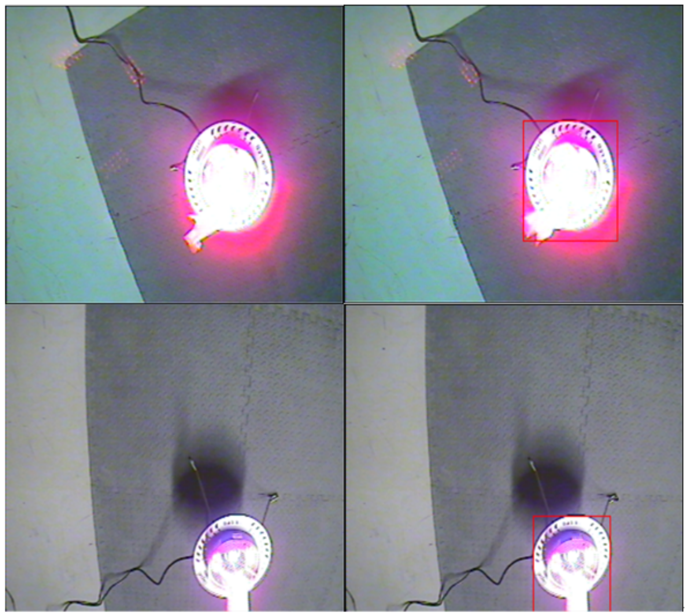


Figure 9: Results of applying the detection and tracking strategy on a fire simulator: original images (left) and tracking results (right).

thresholding and performing morphological operations on the motion vectors, binary images are produced. Finally, the fires are located in each binary image using the Blob counter. Results of forest fire detection and tracking are shown in Fig. 11.

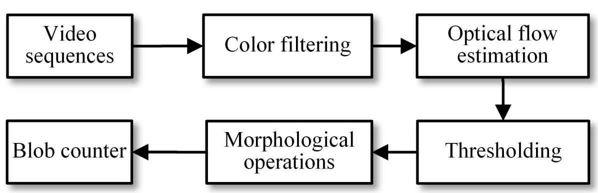
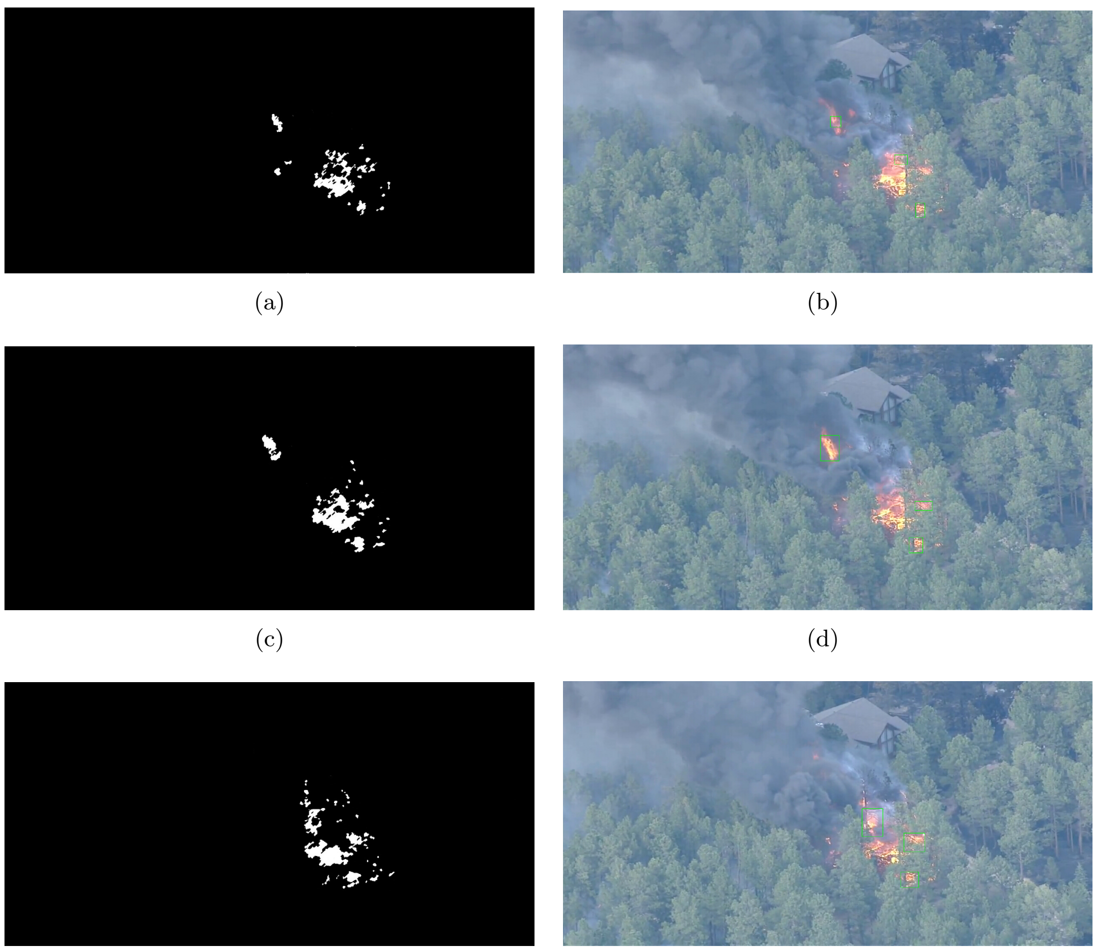


Figure 10: Procedure of forest fire detection and tracking.



(a) (b) (c) (d) (e) (f)

Figure 11: Samples of experimental results: thresholding results (left) and tracking results (right).