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REVIEW

A survey on technologies for automatic forest fire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques

Chi Yuan, Youmin Zhang, and Zhixiang Liu

Abstract: Because of 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 fire fighting technology has shown increasing promise. This paper presents a systematic overview of current progress in this field. First, a brief review of the development and system architecture of UAV systems for forest fire monitoring, detection, and fighting 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. The final section outlines existing challenges and potential solutions in the application of UAVs to forest firefighting.

Key words: forest fire, fire monitoring, detection, and fighting, image processing, remote sensing, unmanned aerial vehicles.

Résumé : Étant donné qu'ils sont rapidement manœuvrables, qu'ils ont un grand rayon d'action opérationnel et qu'ils offrent une meilleure sécurité pour le personnel, les véhicules aériens sans pilote (UAV) équipés de systèmes de vision ont un potentiel énorme pour surveiller, détecter et combattre les feux de forêt. Au cours de la dernière décennie, la technologie de lutte contre les feux de forêt qui utilise des UAV s'est avérée de plus en plus prometteuse. Cet article présente un aperçu complet des progrès actuels dans ce domaine. D'abord, une brève revue du développement et de l'architecture des systèmes de surveillance, de détection et de combat des feux de forêt qui utilisent des UAV est présentée. Ensuite, les technologies reliées à la surveillance, à la détection et au combat des feux de forêt sont brièvement passées en revue, incluant celles qui sont associées à la détection, au diagnostic et au pronostic des feux, à l'élimination de la vibration des images et au contrôle coopératif des UAV. La dernière section décrit les défis actuels et les solutions potentielles liés à l'utilisation des UAV dans la lutte contre les feux de forêt. [Traduit par la Rédaction]

Mots-clés : feu de forêt, surveillance, détection et combat des feux, traitement des images, télédétection, véhicules aériens sans pilote.

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, which 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 (McAlpine and Wotton 1993; Martínez-de Dios et al. 2008). Although wildfires do help to form new forests, it is difficult to make sure that uncontrolled fires do not spread into places that may threaten sensitive ecological systems or human infrastructure and lives (Hirsch and Fuglem 2006). Forest fires have become a serious natural danger (Mandallaz and Ye 1997; Kolarić et al. 2008); therefore, fighting forest fires is considered to be one of the most important roles in the protection and preservation of natural resources (Gonzalez et al. 2006; Kolarić et al. 2008).

Early detection and suppression of forest fires are crucial to minimizing the destruction that the fires may cause due to their rapid convection propagation and long combustion cycle (Lin et al. 2014). Massive efforts have been put into monitoring, detecting, and rapidly extinguishing 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 (Vipin 2012).

Remote sensing has become one of the most frequently utilized tools for effective forest survey and management (Leckie 1990; Chisholm et al. 2013). 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 (Vipin 2012). 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 (Den Breejen et al. 1998). However, each of these systems presents different technological and practical problems. Ground measurement equipment may suffer from

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C. Yuan, Y.M. Zhang, and Z.X. Liu. Department of Mechanical and Industrial Engineering, Concordia University, 1455 de Maisonneuve Blvd. West, Montreal, QC H3G 1M8, Canada.
Corresponding author: Youmin Zhang (e-mail: youmin.zhang@concordia.ca).

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Table 1. The characteristics of reviewed UAVs forest fire monitoring, detection, and fighting systems.

Field test type	References	UAV class	Onboard cameras (resolution)	Engine power	Payload capacity (kg)
Near operational	Ambrosia et al. 2003	1 fixed-wing	1 thermal (720×640)	Fuel	340
Operational	Ambrosia et al. 2011	1 fixed-wing	4 mid-IR (720×640)	Fuel	>1088
Near operational	Martínez-de Dios et al. 2005	2 rotary-wing	1 visual (320×240)	Fuel	3.5
		1 airship	1 IR (160×120)	Electric	
Operational	Van Persie et al. 2011	1 fixed-wing	1 visual	Fuel	—
		1 rotary-wing	1 IR		
Near operational	Tranchitella et al. 2007	1 fixed-wing	1 visual	Fuel	<34
			1 IR		
Near operational	Ambrosia and Zajkowski 2015	2 fixed-wing	1 visual	Fuel	25
			1 IR	Fuel	250
Near operational	Esposito et al. 2007	2 fixed-wing	1 visual (1920×1080)	Fuel	250
			1 thermal (160×120)		
			1 NIR (752×582)		
			1 VNIR (128×128)	Electric	<2.6
Near operational	Jones 2003; Jones et al. 2006	1 fixed-wing	1 visual (720×480)	Gas	0.68
Near operational	Pastor et al. 2011	1 rotary-wing	2 visual (4000×2656; 2048×1536)	Fuel	907
			1 thermal (320×240)		
Near operational	Restas 2006	1 fixed-wing	1 visual	Electric	—
Near operational	Charvat et al. 2012	1 fixed-wing	1 visual (656×492)	Electric	5.5

Note: IR, infrared; NIR, near-IR; VNIR, visible–NIR; —, not mentioned.

limited surveillance ranges. Satellite systems are less flexible in their path planning and technology updates, and their temporal and spatial resolution may be too low for detailed data capture and operational forest fire fighting (Olsson et al. 2005). Manned aerial vehicles are typically large and expensive. Moreover, the life of the pilot can be potentially threatened by hazardous environments and operator fatigue (Beard et al. 2006).

Unmanned aerial vehicles (UAVs) with computer vision based remote sensing systems are an increasingly realistic option, providing rapid, mobile, and low-cost alternatives for monitoring, detecting, and even fighting forest fires. The integration of UAVs with remote sensing techniques are also able to meet the critical spatial, spectral, and temporal resolution requirements (Everaerts 2008; Berni et al. 2009), offering the potential to serve as a powerful supplement to existing methods (Olsson et al. 2005; Hunt et al. 2008). In addition, UAVs allow the execution of long-term, monotonous, and repeated tasks beyond human capabilities. This has led to increased worldwide attention to UAV forest fire applications in recent years (Ambrosia and Zajkowski 2015; Merino et al. 2015; Shahbazi et al. 2014; Sharifi et al. 2014; Bosch et al. 2013; Merino et al. 2012, etc.).

This paper reviews existing UAV-based forest fire monitoring, detection, and fighting technologies, with an emphasis on monitoring and detection techniques as forest fire fighting using UAVs has not yet received much attention in the literature. Section 1 assesses the advantages of applying UAVs in forest fire fighting. Section 2 reviews several monitoring, detection, and fighting systems and outlines a general description of these kinds of systems. Section 3 focuses on key technologies that can be applied to automatic forest fire monitoring, detection, and fighting, as well as summarizing some of the more challenging research and development issues in this field. Finally, section 4 concludes with suggestions of possible future directions for computer vision based forest fire fighting through the use of UAVs.

2. General description of UAV-based forest fire fighting systems

2.1. Review of the development of UAV-based forest fire monitoring, detection, and fighting systems

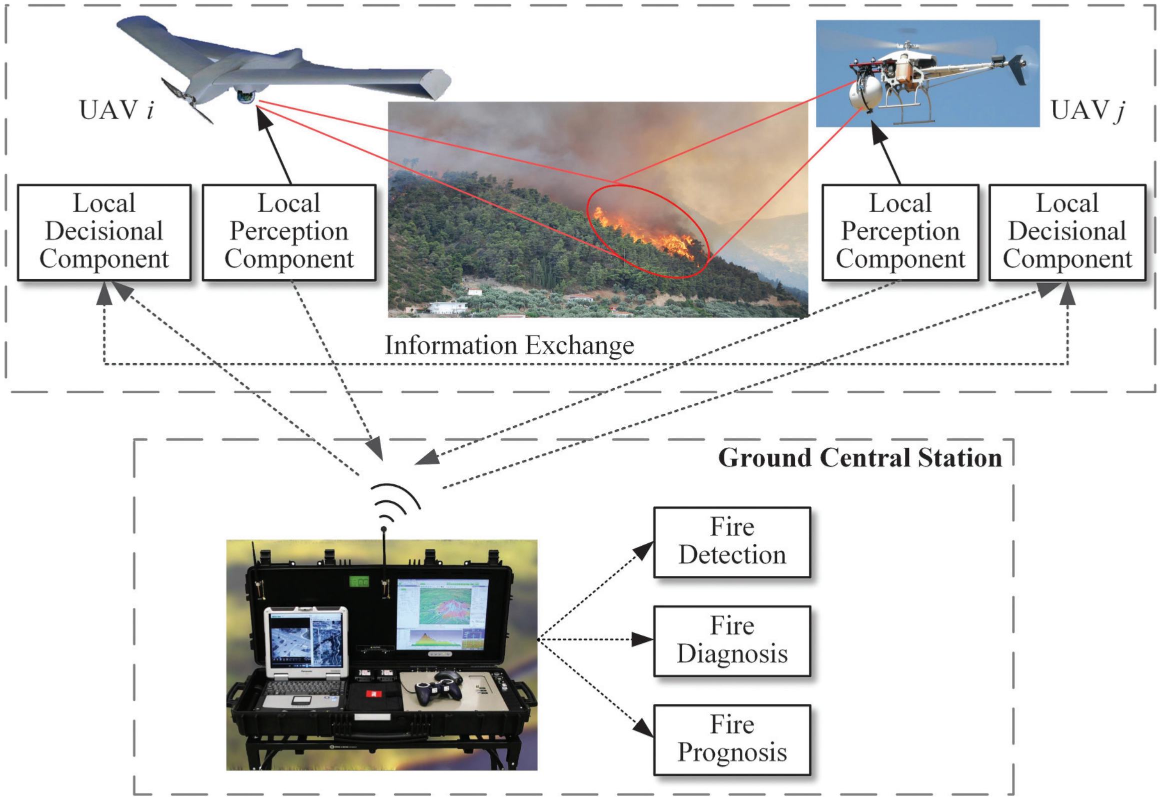
Recent decades have seen tremendous progress in the field of automatic forest fire fighting technologies (Ambrosia and Zajkowski 2015; Merino et al. 2015). Despite this, few research papers until now have considered the application of UAVs in this field. Most research has been carried out in the United States and Europe. Table 1 provides a brief overview of existing UAV-based forest fire fighting systems.

The earliest application of UAVs for gathering information on forest fires can be traced back to 1961 by the United States Forest Services (USFS) Forest Fire Laboratory (Wilson and Davis 1988). In 1996, a "Firebird 2001" UAV with a visual camera and an onboard imaging system was used for forest fire imaging in Missoula, Montana (Ambrosia and Zajkowski 2015). Later, between 2003 and 2010, a Wildfire Research and Applications Partnership (WRAP) project was conducted by the USFS and National Aeronautics and Space Administration (NASA), which was intended to augment underserved forest fire applications (Ambrosia et al. 2011; Tranchitella et al. 2007). In 2006, the NASA "Altair" and the "Ikhana" (Predator-B) UAVs demonstrated their capabilities in supporting near-real-time forest fire imaging missions in the western United States (Ambrosia et al. 2011). In 2011, with the support of the West Virginia Department of Forestry (WVDF) and NASA, a research team from the University of Cincinnati used the Marcus "Zephyr" UAV system to test the capability of its forest fire detection systems (Charvat et al. 2012). Moreover, in the First Response Experiment (FiRE) project (Ambrosia 2002), wildfire detection was demonstrated by an unmanned aerial system (UAS), verifying the efficacy of using UAVs for real-time disaster data collection. Overall data collection, telemetry, geoprocessing, and delivery were achieved within 15 min using this system.

While the FiRE project used a single, powerful UAV with sophisticated sensors, another project undertaken in Europe used a team of low-cost UAVs with onboard visual and infrared cameras instead. In this project, UAVs worked as local sensors supplying images and data at close ranges. Experiments using multiple UAVs for surveillance, detection, localization, confirmation, and measurement of forest fires have also been carried out (Ollero et al. 2005; Martínez-de Dios et al. 2007; Merino et al. 2012, 2015). The first regulated use of a UAV in fire service was done in Hungary in 2004, testing the system's ability to detect forest fires (Restas 2006). Additionally, Pastor et al. (2011) validated the use of a Sky-eye UAV system to detect forest fires in Spain. In 2011, two UAVs with visual and infrared cameras were deployed to evaluate their ability to detect and localize two real fire scenarios in the Netherlands (Van Persie et al. 2011).

In addition to the practical testing of UAVs, there has also been a significant amount of simulated research on their fire monitoring and detection abilities. Casbeer et al. (2006) investigated the practicality of using a team of low-altitude, low-endurance UAVs

Fig. 1. Conceptual UAV-based forest fire monitoring, detection, and fighting system.



for cooperative surveillance and tracking of the propagation of large forest fires. A numerical propagation model for forest fire monitoring and detection was verified in simulation using a dynamic UAV model with six degrees of freedom. Despite this, verification of UAV effectiveness in actual forest fire fighting activities is still required in future investigations. One recent test saw a team of Lockheed Martin and Kaman UAVs successfully demonstrate their ability to aid in fire extinguishing operations (UAS VISION 2014), although technical details on this operation have not yet been made available.

Although the aforementioned 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 and sensors, and algorithms for autonomous guidance, navigation, and control (GNC), as well as on using UAVs in combination with other remote sensing techniques. It is this urgent need that necessitates the writing of this survey paper, which aims to motivate further research and development in this important field.

2.2. General system design architecture and requirements of UAV-based automatic forest fire monitoring, detection, and fighting systems

Based on the above 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 and 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.

Terminologies for forest fire monitoring and detection are not yet clearly defined, with even different definitions within the literature. To avoid confusion, definitions for forest fire monitoring, detection, diagnosis, and prognosis are provided in this review by following established traditions in the more general field of condition monitoring, fault detection, and diagnosis (Zhang and Jiang 2008).

Forest fire monitoring is defined as monitoring for the possible occurrence of fire before it has occurred, whereas 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.

To achieve these goals, UAV-based forest fire monitoring, detection, diagnosis, and prognosis systems typically includes the following: (*i*) various frames and sensors, including global positioning system (GPS) receivers, inertial measurement units (IMUs), and cameras, all of which aid in firefighting; (*ii*) specific algorithms and strategies for fire monitoring, detection, diagnosis, and prognosis; (*iii*) GNC systems for both single and multiple UAVs; (*iv*) cooperative localization, deployment, and control systems for UAV fleets to optimally cover fire areas (such systems are based on the real-time information provided by the onboard visual (for daytime) and infrared (for both nighttime and daytime) monitoring sensors and their associated image and (or) signal processing algorithms); and (*v*) a dedicated ground station that includes equipment for communication, ground computation, vi-

Table 2. Vision-based techniques for forest fire monitoring, detection, and fighting using UAVs in near-operational field.

Detection method	Spectral bands	Resolution	Used features	Detection objects: Flame	Detection objects: Smoke	Geolocation	Propagation prediction	Image stabilization	References
Georeferenced uncertainty mosaic	IR	320×240	Color	√	×	√	√	√	Bradley and Taylor 2011
Statistical data fusion	Visual Mid-IR	752×582 256×256	Color	√	×	√	√	√	Martínez-de Dios et al. 2011
Training method	IR	160×120	Color	√	×	×	×	√	Martínez-de Dios and Ollero 2004
Training method	Visual Far-IR	320×240 —	Color	√	×	√	×	√	Merino et al. 2005, 2006
Training method	Visual Far-IR	320×240 —	Color	√	×	√	√	√	Merino et al. 2010, 2012
—	Visual IR	720×640 —	Color	√	×	√	×	—	Ambrosia 2002; Ambrosia et al. 2003
Genetic algorithm	IR	320×240	Color	√	×	×	×	×	Kontitsis et al. 2004
Training method	Visual IR	752×582 160×120	Color	√	×	√	×	—	Martínez-de Dios et al. 2005; Martínez-de Dios et al. 2006
—	Visual IR	— —	Color	√	×	√	×	—	Ollero et al. 2005; Ollero and Merino 2006; Maza et al. 2010, 2011

Note: IR, infrared; √, considered; ×, not considered; —, not mentioned.

sualization of fire detection, tracking, and prediction with automatic fire warning or alarm, as well as all equipment necessary for the safe and efficient operation of UAVs.

UAV forest fire fighting missions can generally be broken down into three stages: fire search, fire confirmation, and fire observation (Merino et al. 2010). 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 and (or) heterogeneous (fixed wing and rotary wing) search UAVs (Sharifi et al. 2014, 2015*b*) are deployed to patrol the surveillance region along respective preplanned 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 and (or) firefighting managers or service UAVs to better guide firefighting efforts.

3. Technologies used in automatic forest fire monitoring, detection, and fighting UAVs

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 (Li et al. 2013). 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.

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, e.g., image vibrations induced by their flight and cooperative control of multiple UAVs, they nevertheless offer some potentially transferable insights into UAV-based forest fire fighting applications due to their common issues in fire detection using vision-based technologies. To reduce the cost of devices and personnel and save experimental time, the effectiveness of various fire detection approaches are normally tested and verified in advance based on forest fire videos. Only afterwards are the specific practical issues (image vibration, etc.) affecting onboard images considered and solved. Because of this, it is highly possible that these detection methodologies can also be applicable for UAVs conducting operational and (or) near-operational forest fire detection missions.

3.1. Vision-based technologies for automatic forest fire detection

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 as either visual or infrared fire detection systems (Çetin et al. 2013). Fire detection can be divided into either flame detection or smoke detection in terms of the actual object being detected (Li et al. 2013). Most importantly, the color, motion, and geometry of the fire constitute the three dominant characteristic features of fire detection (Çelik et al. 2007*b*).

3.1.1. Fire detection with visual images

In Tables 3 and 4, color, motion, and geometry of the detected fire are commonly used in the existing investigation, with color being used mostly in segmenting the fire areas (Rudz et al. 2009; Mahdipour and Dadkhah 2012). As outlined in Table 3, considerable effort has gone into the development of offline video-based fire detection. Chen et al. (2004) use color and motion features based on an RGB (red, green, blue) model to extract real fire (flame) and smoke in video sequences. Töreyin et al. (2005) propose a real-time algorithm combining motion and color clues with fire flicker analysis on wavelet domain to detect fire in video sequences. Töreyin et al. (2006*a*) combine a generic color model based on RGB color space, motion information, and Markov process enhanced fire flicker analysis to create an overall fire detection system. Later, the same fire detection strategy is employed to detect possible smoke samples, which is used as an early alarm for fire detection (Töreyin et al. 2006*b*). In Çelik and Demirel (2009), a rule-based generic color model for flame pixel classification is

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

Detection method	Resolution	Adopted features			Detection objects		References[a]
		Color	Motion	Geometry	Flame	Smoke	
Statistic method	320×240 400×255	√	×	×	√	×	Cho et al. 2008
Fuzzy logic	256×256	√	×	×	√	×	Çelik et al. 2007*b*
Support vector machine	—	√	√	√	√	×	Zhao et al. 2011
Fuzzy logic	320×240	√	√	√	×	√	Ho and Kuo 2009
Wavelet analysis	320×240	√	√	√	√	×	Töreyin et al. 2006*a*
Computer vision	320×240	√	√	×	√	×	Qi and Ebert 2009
Wavelet analysis	320×240	√	√	×	√	×	Töreyin et al. 2005
Rule-based video processing	—	√	√	×	√	√	Chen et al. 2004
Fourier transform	—	√	√	×	√	×	Jin and Zhang 2009
Bayes and fuzzy C-means	—	√	√	×	√	×	Duong and Tuan 2009
Adaptable updating target extraction	—	√	√	×	√	×	Hou et al. 2010
Histogram-based method	—	√	√	×	√	×	Philips et al. 2002
Fuzzy-neural network	—	√	√	×	√	×	Hou et al. 2009
Statistical method	176×144	√	×	×	√	×	Çelik et al. 2007*a*
Fuzzy finite automata	—	√	√	×	√	×	Ham et al. 2010
Gaussian mixture model	320×240	√	√	×	√	×	Chen et al. 2010
Histogram back projection	—	√	×	×	√	×	Wirth and Zaremba 2010
Wavelet analysis	—	√	√	×	×	√	Töreyin et al. 2006*b*
Adaptive decision fusion	—	√	√	×	×	√	Günay et al. 2012
Accumulative motion model	—	×	√	×	×	√	Yuan 2008
Image processing method	—	√	√	×	×	√	Surit and Chatwiriya 2011
Neural network	320×240	√	√	×	×	√	Yu et al. 2010

Note: √, considered; ×, not considered; —, not mentioned.
[a]None of these referenced studies addressed issues about fire propagation prediction, geolocation, or image vibration elimination.

presented, with experimental results showing significant improvement in detection performance. In Günay et al. (2009), an approach based on four subalgorithms for wildfire detection at night is addressed and an adaptive active fusion method is adopted to linearly combine decisions from subalgorithms. Finally, Günay et al. (2012) develop an entropy-functional-based online adaptive decision fusion framework, the application of which is to detect the presence of wildfires in video.

Most of the above-mentioned research focuses on the detection of forest fires by flame, whereas smoke is also an important feature in the early and precise detection of forest fires. Tables 3 and 4 show some studies that focus on smoke detection. Chen et al. (2006) continue their work from Chen et al. (2004), proposing a chromaticity-based static decision rule and a diffusion-based dynamic characteristic decision rule for smoke pixel judgment. Experimental results indicate that this approach can provide an authentic and cost-effective solution for smoke detection. In Yu et al. (2009), a real-time smoke classification method using texture analysis is developed, and a back-propagation neural network is adopted as a discriminating model. Experiments prove that the proposed method is capable of differentiating smoke and non-smoke videos with both a quick fire alarm and low false alarm rate. Yuan (2008) designs a smoke detection system utilizing an accumulative motion model based on integral images by fast estimation of the smoke motion orientation to reduce the rate of false alarms, as the estimation accuracy can affect subsequent critical decisions. Hence, smoke orientation is accumulated over time to compensate for inaccuracy. A fuzzy logic method is employed to detect smoke in a real-time alarm system in Ho and Kuo (2009). Spectral, spatial, and temporal features are used for extracting smoke and for helping with the validation of smoke. Experimental results show that smoke can be successfully detected in different circumstances (indoor, outdoor, simple or complex background image, etc.). Although the results are promising, further development is still needed to integrate such findings with existing surveillance systems and implement them in actual operations. An approach using static and dynamic characteristic analysis for forest fire smoke detection is proposed by Surit and Chatwiriya (2011). Zhang et al. (2007) present an Otsu-based method to detect fire and smoke while segmenting fire and smoke together from the background. In Yu et al. (2010), a color-based decision rule and an optical flow algorithm are adopted for extracting the color and motion features of smoke, with experimental results showing significantly improved accuracy of video smoke detection.

Although various forest fire and smoke detection methods have been developed experimentally, at present, only a few have been carried out in near-operational environments (see Table 2). Most of these have been conducted by a research team from the University of Seville in Spain. These experiments use multiple UAVs, with color information chosen as the key fire detection feature.

Many researchers in recent years have adopted intelligent methods to reduce false alarm rates and the cost of sensors. As illustrated in Table 3, the adopted algorithms (Çelik et al. 2007*b*; Hou et al. 2009; Yu et al. 2010; Ham et al. 2010, etc.) include artificial neural networks, fuzzy logic, and fuzzy neural networks. Experimental results show that although these approaches can effectively detect fires, the majority of them have not been tested on UAVs or in real forest fire scenarios.

3.1.2. Fire detection with infrared images

As infrared images can be obtained in conditions of either weak or no light and smoke is transparent in infrared images, it is therefore practical to employ infrared cameras for monitoring and detecting fires in both daytime and nighttime conditions.

Tables 2 and 4 summarize research studies done using infrared cameras for fire detection. Merino et al. (2005) and Martínez-de Dios et al. (2005) make use of infrared images to generate binary images containing fire regions while reducing false alarm rates by using a training-based threshold selection method (Martínez-de Dios and Ollero 2004) as the appearance of a fire is a high intensity area in infrared images. In Bosch et al. (2013), decision fusion is applied in infrared imaging for judging the occurrence of forest fires, allowing a variety of anticipated features of the fire to be obtained, including short-term persistence and long-term increase. Pastor et al. (2006) develop an infrared image processing

Table 4. Fire monitoring, detection, and fighting methodologies using visual and infrared cameras.

			Validations			Adopted features			Detection objects				
Detection method	Spectral bands	Resolution	Outdoor	Indoor	Offline	Color	Motion	Geometry	Flame	Smoke	Propagation prediction	Geolocation	References[a]
Training method	Visual Mid-IR	752×582 256×256	×	√	×	√	×	×	√	×	√	√	Martínez-de Dios et al. 2006
Training method	Visual Mid-IR	— —	√	×	×	√	×	×	√	×	√	√	Martínez-de Dios et al. 2008
Images matching	Visual IR	— —	√	×	×	√	√	√	×	√	×	√	Ollero et al. 1999; Arrue et al. 2000
Data fusion	Visual IR	— —	×	√	×	√	—	—	√	√	×	×	Bosch et al. 2013
Neural networks	IR	—	×	√	×	√	√	×	√	×	×	×	Huseynov et al. 2007
Dynamic data driven	Multispectral IR	—	×	×	√	√	×	√	√	×	√	×	Ononye et al. 2007
Training method	Visual IR	— —	√	×	×	√	×	√	√	×	√	√	Martínez-de Dios et al. (2008)

Note: IR, infrared; √, considered; ×, not considered; —, not mentioned.
[a]None of these referenced studies addressed issues about image vibration elimination.

method based on linear transformations for precisely calculating the rate of spread (ROS) of forest fires, while a threshold value searching criterion is utilized to identify the flame front position. Ononye et al. (2007) depict a multispectral infrared image processing method. Based on a sequence of image processing tools and the dynamic data-driven application system (DDDAS) concept, the proposed method is capable of automatically attaining the forest fire perimeter, active fire line, and fire propagation tendency. A multiple artificial neural networks (ANNs) model for an infrared flame detection system is devised in Huseynov et al. (2007). The experimental results demonstrate that the proposed method can contribute to faster training and improvement of the classification success rate.

One problem associated with processing images from infrared cameras is that miniaturized cameras still have low sensitivity (Martínez-de Dios et al. 2005). This requires an increase in detector exposure periods to produce higher quality images. In addition, the high-frequency vibration of UAVs can cause blurring in the images, which remains a major challenge in their development.

3.1.3. Fusion of visual and infrared images

To improve the accuracy, reliability, and robustness of fire detection algorithms and to reduce the rate of false alarms, visual and infrared images can be fused together, generally through the use of fuzzy logic, intelligent, probability, and statistical methods (as illustrated in Tables 2 and 4).

Arrue et al. (2000) have designed a false alarm reduction system comprised of infrared image processing, ANNs, and fuzzy logic. In this system, matching the information excessiveness of visual and infrared images is utilized to confirm forest fire alarms. Martínez-de Dios et al. (2006) integrate infrared and visual cameras for fire front parameter measurement by taking advantage of both visual and infrared image processing techniques, whereas experimental validations are only conducted in a laboratory. In addition, Martínez-de Dios et al. (2008) describe a forest fire perception system built on computer vision techniques. Visual and infrared images are combined to calculate a three-dimensional (3D) fire perception model, allowing the fire evolution to be visualized by remote computer systems.

Although different approaches to image information fusion have been addressed in the existing research, the issue of how to optimize the number of features that are utilized in fire detection is still a challenge. Solving this issue would not only reduce the computation burden of onboard computers, but also decrease both the cost of the hardware and the rate of false alarms.

3.2. Vision-based technologies for automatic forest fire diagnosis and prognosis

The most common mission undertaken in UAV-based forest fire diagnosis is to produce fire geolocated alarms, whereas the most common mission in fire prognosis is to predict the fire's propagation, which is sufficient to meet the requirements of operational forest firefighting.

3.2.1. Geolocation of fire – fire diagnosis

After the fire is detected and its information is extracted from images, the segmented fire area requires geolocation information for measuring its geometrical features such as fire front location, fire site width and perimeter, flame length and height, inclination angle, coordinates of burnt areas, and location of hotspots (Martínez-de Dios et al. 2011; Casbeer et al. 2005, 2006). Such measurements, together with the projection of gathered images onto a terrain map, are essential for planning effective and efficient firefighting strategies (Shahbazi et al. 2014).

UAVs are currently being employed in the automatic geolocation of forest fires due to their wide coverage, spectral resolution, and safety (Rossi et al. 2010). Existing automatic geolocation studies have mainly been conducted by adopting the multisensory fusion technique for providing the information before, during, and after wildfires, using onboard vision and telemetry sensors and navigation units (GPS, IMUs) (Shahbazi et al. 2014). Meanwhile, the location of the UAVs themselves is known through the use of GPS. The orientation of the UAV's camera is computed by composing the orientation angles of the pan and tilt system with the orientation angles of the UAV airframe, which is estimated by IMUs and compasses. If a camera is calibrated and a digital elevation map is available, it is possible to obtain the georeferenced location of an object in the common global coordinate frame from its position on the image plane (Merino et al. 2006).

The past decade has seen considerable effort in the field of geolocation. Direct geolocation via navigation information is the most time-effective way to automatically conduct the mission (Shahbazi et al. 2014). Besides this, generating real-time orthorectification and a geocoded mosaic is of great significance for improving the accuracy of automatic geolocation in UAV systems (Li et al. 2011; Chou et al. 2010; Wu and Zhou 2006; Qian et al. 2012). Orthorectified mosaics of the fire area can be combined with the geolocated UAV images to produce geospatial data for quick action on time-critical fire events (Zhou et al. 2005; Wu and Zhou 2006; Zhou 2009; Van Persie et al. 2011; Shahbazi et al. 2014). The position, ROS, and height of the fire front can also be measured by adopting a 3D vision-based instrumentation with visual cameras and navigation sensors (Rossi et al. 2010).

In practice, numerous potential sources of error may result in inaccurate 3D information. For example, smoke may occlude the fire scene, while the accuracy of navigation sensors and platforms may affect the measurement of forest fires. As proposed in Mostafa and Schwarz (2001) and Habib et al. (2006), proper calibration of the platform and camera orientation is of great significance for improving the accuracy of geolocation. Digital elevation models (DEMs), ground control points (GCPs), and planimetric and topographic maps are all potential choices for this application (Shahbazi et al. 2014). Computing the errors of object localization by considering the terrain map and errors in the position and orientation of cameras is described in Martínez-de Dios et al. (2011). In addition, to decrease the effect of smoke, multiple heterogeneous UAVs mounted with different kinds of sensors (visual and infrared cameras) are deployed for geolocating in the field experiment (Merino et al. 2006; Martínez-de Dios et al. 2011).

Unfortunately, existing research studies to date have only been carried out in either laboratory or near-operational environments (Rossi et al. 2010; Merino et al. 2006; Martínez-de Dios et al. 2011). Research and testing in operational firefighting conditions is still needed for further investigation.

3.2.2. Propagation prediction — fire prognosis

Predicting the behavior of fire propagation is essential for developing quick, effective, and advanced forest fire fighting strategies. Hence, it is important to know the evolution of the fire front, as well as other properties of the fire such as ROS, fire front location, flame height, flame inclination angle, fire site width, etc. ROS, in particular, is one of the most significant parameters in the characterization of forest fire behavior, as it is directly associated with fire intensity (Byram 1959) and flame front geometry (Anderson 1968), two key indicators of the danger levels of fire propagation.

Numerous new methodologies have been developed in recent decades based on discrete or continuous fire monitoring with the aid of visual and infrared cameras (Pastor et al. 2006). Infrared image processing, visual and infrared image fusion, and stereovision are all applied in the literature to better provide fire propagation information (Pastor et al. 2006; Martínez-de Dios et al. 2006, 2008; Ononye et al. 2007; Rossi et al. 2010).

In addition, many intelligent algorithms have also been adopted (Jaber et al. 2001; Alonso-Betanzos et al. 2003; HomChaudhuri and Kumar 2010), including genetic algorithms, expert-, knowledge-, and rule-based systems, and ANNs. These approaches are extensively applied in forest fire prognosis because of their high accuracy, multifunctionality, and reliability in different surroundings.

Karafyllidis (2004) adopts cellular automation for predicting the spread of forest fires. A dedicated parallel processor that can work as part of a decision support system is developed by a genetic algorithm. Olivas (2003) represents a knowledge-based system (KBS) for forest fire prediction and firefighting decision support. To estimate the extent and spread of wildfires, a fuzzy segmentation algorithm that can map fire extent, active fire front, and hot burn scar is proposed in Li et al. (2007). In Fowler et al. (2009), a suitable fuzzy rule based system is employed to fulfill forest fire size prediction, with both these fuzzy rules and membership functions automatically evolved through genetic algorithms. In Wendt (2008), a robust data storage and retrieval system is devised to calibrate input variables for data-driven forest fire prediction. To improve the effectiveness and efficiency of forest fire spread predictions, an enhanced prediction scheme that uses recent fire history and optimization techniques is described in Abdalhaq et al. (2005), while Denham et al. (2008) address a dynamic data driven genetic algorithm.

3.3. Image vibration elimination

One practical issue in image capture and processing is that inescapable turbulences and vibrations of UAVs during flight may change a camera's position and result in frequent image motion and blurring images affecting detection results and even leading to detection failure. To decrease the failure alarm rate, image antivibration should be considered. Electromechanic systems are helpful in eliminating such vibrations, but these systems are usually heavy and expensive and produce a residual vibration of their own (Merino et al. 2010).

Although smaller and less expensive gimbal systems have recently been developed, a simple and low-cost image processing approach that can be used for image motion calculation and elimination is still in high demand. Existing research on this topic is still scarce, with Ferruz and Ollero (2000), Ollero et al. (2004), and Merino et al. (2010) constituting the few identified investigations of this problem.

3.4. Cooperative control of UAVs in forest fire monitoring, detection, and fighting

Because forest fires are highly sophisticated and nonstructured, it is crucial to use multiple sources of information at different locations. Furthermore, the rate at which this information is updated may be unsatisfactory if only a single UAV is deployed for either a single, large-scale forest fire or for multiple forest fires.

More efficient forest fire monitoring, detection, and even fighting can be achieved when a fleet of multiple UAVs are deployed instead of a single UAV (Chao and Chen 2012; Sharifi et al. 2014, 2015*a*). However, this also requires that more practical algorithms for task assignment and cooperative control for multiple UAVs be developed. These algorithms are intended to achieve efficient cooperation between vehicles for optimal coverage, as well as deployment for the most efficient fire detection, tracking, and prediction in the cases of large, multiple, and simultaneous fire events.

Several simulations have demonstrated the effectiveness of different methods for UAV coordination (Alexis et al. 2009; Casbeer et al. 2005, 2006; Phan and Liu 2008; Kumar et al. 2011). Despite this, experimental or near-operational works with teams of UAVs are still underdeveloped (Beard et al. 2006; Bradley and Taylor 2011; Merino et al. 2005, Merino et al. 2006; Sujit et al. 2007), and no operational implementation can be identified in the literature at present. Numerous technical challenges must be solved prior to any practical implementation and application of forest fire monitoring, detection, and fighting strategies using multiple UAVs.

4. Conclusions and future work

Through a comprehensive review of the existing literature on the development of UAVs with computer-vision systems, it is apparent that these systems can be used to avoid the drawbacks of other land- and space-based approaches. Their potential benefits for forest fire detection, diagnosis, and prognosis are also demonstrated.

Because forests are highly complex and nonstructured environments, the use of multiple sources of information at different locations is critical. The related issue of using vision sensors and GPS systems to determine fire location is complicated, with very few researchers addressing this problem. To implement practical, useful applications, UAVs with longer endurance are also required. In addition, 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 causing either false alarms or alarm failure. Existing research has demonstrated that the combination of infrared and visual images can contribute to robust forest fire detection, including high detection probability, low false alarm rates, and enhanced adaptive capabilities in various environmental conditions. However, there is still the challenge of optimizing an appropriate number of features in image information fusion. Meanwhile, miniaturized infrared cameras usually have very low sensitivities, which can also lead to fire alarm failure; thus longer detector exposure periods are also needed to generate higher quality images. Finally, the vibration and motion of UAVs often blur images and cause image capture failure. Therefore, both hardware and software techniques for image stabilization and vibration reduction are worthy of further investigation.

Compared with their use in forest fire monitoring and detection, research and development on UAV-based fire extinguishment is still scarce and lacking in detailed techniques. However, there is a trend and demand towards more research and development of complete solutions for forest fire monitoring, detection, and fighting. Thus, we can expect to see the further development of this area in the future.

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